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

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Abstract

Despite unprecedented progress in developing COVID-19 vaccines, global vaccination levels needed to reach herd immunity remain a distant target, while new variants keep emerging. Obtaining near universal vaccine uptake relies on understanding and addressing vaccine resistance. Simple questions about vaccine acceptance however ignore that the vaccines being offered vary across countries and even population subgroups, and differ in terms of efficacy and side effects. By using advanced discrete choice models estimated on stated choice data collected in 18 countries/territories across six continents, we show a substantial influence of vaccine characteristics. Uptake increases if more efficacious vaccines (95% vs 60%) are offered (mean across study areas=3.9%, range of 0.6% to 8.1%) or if vaccines offer at least 12 months of protection (mean across study areas=2.4%, range of 0.2% to 5.8%), while an increase in severe side effects (from 0.001% to 0.01%) leads to reduced uptake (mean=-1.3%, range of -0.2% to -3.9%). Additionally, a large share of individuals (mean=55.2%, range of 28% to 75.8%) would delay vaccination by 3 months to obtain a more efficacious (95% vs 60%) vaccine, where this increases further if the low efficacy vaccine has a higher risk (0.01% instead of 0.001%) of severe side effects (mean=65.9%, range of 41.4% to 86.5%). Our work highlights that careful consideration of which vaccines to offer can be beneficial. In support of this, we provide an interactive tool to predict uptake in a country as a function of the vaccines being deployed, and also depending on the levels of infectiousness and severity of circulating variants of COVID-19.

1 Introduction

The COVID-19 pandemic has resulted in significant mortality and morbidity (Chaudhry et al., 2020; WHO, 2021b), and has galvanised unprecedented investment in the development and distribution of COVID-19 vaccines, at a pace not previously seen (Kyriakidis et al., 2021). Over the course of 2021 and going into 2022, vaccine distribution has gathered speed around the world (though not for example in Africa), and high rates of vaccination have been achieved in a growing number of (mainly high income) countries. However, as no vaccine is likely to guarantee immunity (i.e. 100% efficacy), the share of the population that needs to be vaccinated is higher than the levels of 70% and 80% (see e.g. Kwok et al., 2020; Prowse et al., 2020) typically estimated to be needed for herd immunity. This remains a distant target in many countries, while at the same time, the emergence of new variants poses further risks.

The success of vaccination programmes depends on public engagement and vaccine acceptance, making it important to understand public preferences and uptake of vaccines. Information on uptake amongst those people offered a vaccine so far (as opposed to absolute numbers of vaccines administered) is difficult to obtain, with the potential of upwards bias due to many (but not all) countries prioritising vulnerable groups for early vaccination, where uptake might be higher. In addition, comparing vaccination rates across countries leads to another potential source of bias as access to vaccination varies substantially, especially in developing countries. This then motivates a focus on potential vaccine uptake in the overall population.

Extensive coverage has been given to differences across countries in how willing individuals are to be vaccinated, with e.g. Lazarus et al. (2021) reporting that *"71.5% of participants reported that they would be very or somewhat likely to take a COVID-19 vaccine"* but that *"differences in acceptance rates ranged from almost 90% (in China) to less than 55% (in Russia)"*. There is also interest in how this might vary across population subgroups (BBC, 2021; Glenza, 2021; Razai et al., 2021; Robinson et al., 2021) and over time (Biddle et al., 2021), and the role of misinformation in that context (Depoux

et al., 2020; Loomba et al., 2021).

Particular attention has been paid to the reasons for vaccine hesitancy and resistance (Dror et al., 2020; Karlsson et al., 2021; Machingaidze and Wiysonge, 2021), and also looking at ways to increase vaccine uptake (Campos-Mercade et al., 2021; Finney Rutten et al., 2021). The reluctance of people to receive recommended vaccines has been widely studied before the pandemic, for example through the '5C model of the drivers of vaccine hesitancy' (Betsch et al., 2018). Its general conclusions are expected to be applicable to the COVID-19 vaccine; nevertheless, some specificities arise. In this line, Solís Arce et al. (2021) analyse COVID-19 vaccine acceptance across 15 survey samples covering 10 low and middle-income countries, and find, contrary to the previous literature that stresses altruistic behaviour, that COVID-19 vaccine acceptance is mainly explained by an interest in personal protection, while concern about side effects is the most common reason for hesitancy.

Statistics on likely vaccine uptake are often produced on the basis of answers to simple binary (or Likert scale) questions about vaccine acceptance (see e.g. Kessels et al., 2021), and ignore the potential role of vaccine characteristics. A complication in this context is that the vaccines that are offered to people vary across countries and even across population subgroups within countries. Given the differences across vaccines in terms of efficacy and side effects, an important question arises as to how uptake behaviour might depend on the vaccine on offer. This is especially important as more results emerge in relation to vaccine efficacy (cf. Polack, 2020; Sahin et al., 2021), protection duration (Pfizer, 2021), and the risk of side effects for specific vaccines (cf. Sadoff et al., 2021). Especially the latter has attracted much attention in the context of blood clots with the Oxford-AstraZeneca (Greinacher et al., 2021; Wise, 2021) and Johnson & Johnson vaccines (Mahase, 2021). There is already real-world evidence of individuals willing to defer their vaccination until a more desirable vaccine is offered to them (Ward, 2021). As more such results emerge (Menni et al., 2021), they potentially influence the public's willingness to be vaccinated, with implications for herd immunity (cf. Lim and Zhang, 2020).

The present paper is concerned with understanding the tradeoffs people are prepared to make when deciding whether or not to be vaccinated. Gaining such insights is especially crucial in the context of closing the gap between the levels of vaccination already achieved and those required for herd immunity. We hypothesise that the a priori willingness to accept COVID-19 vaccination varies across individuals, but that crucially, this willingness is affected by the characteristics of the vaccines on offer, as well as the levels of infectiousness and severity of circulating variants of COVID-19. Furthermore, the way in which vaccine efficacy and the risk of side effects impact vaccine uptake may again vary across individuals, within and across countries.

We show how to predict the impact of vaccine characteristics on vaccine uptake in the population, and compare this across 18 study areas, spanning all six inhabitable continents and variations in terms of healthcare systems, GDP and socio-cultural contexts. As the first of its kind in terms of the scope of research questions covered and geographic breadth, this cross-national study harnesses results from a stated choice (SC) survey to provide evidence on: (1) predicted uptake of vaccination against COVID-19 (including for vaccines with the efficacy and safety characteristics of those currently in circulation) and exploration of vaccine hesitancy and resistance; (2) preferences and trade-offs between different vaccine characteristic; (3) the public's willingness to pay for faster access to vaccines or to wait longer for safer or more efficacious vaccines.

Literature is emerging on some of these questions in isolation for some countries. For example, studies have explored preferences over characteristics of hypothetical COVID-19 vaccines and have predicted uptake in individual countries (e.g. Borriello et al., 2021; Craig, 2021; Kaplan and Milstein,

2021; Kreps et al., 2020; Leng et al., 2021; McPhedran and Toombs, 2021; Motta, 2021; Schwarzinger et al., 2021; Tervonen et al., 2021), but none seem to have explored and compared preferences and predicted uptake across multiple countries. Furthermore, there has been a lack of emphasis on prediction, while a major output of our research is the ability to make forecasts of uptake of vaccination against COVID-19. Alongside the predictions made in the paper itself, we provide an online scenario testing tool that allows for deeper insights, including studying settings of greater relevance to individual study areas.

The global nature of the pandemic means that generating evidence on these pressing questions from the perspective of individual countries, and comparing similarities and differences across countries is of paramount importance, and provides useful inputs to vaccine policy. While our findings relate to data collected during the first year of the COVID-19 pandemic, they will remain relevant as new variants of COVID-19 emerge, and as countries engage in further rounds of vaccinating their population, leading to an ongoing need to understand vaccine acceptance.

2 Materials and Methods

2.1 Data

2.1.1 Survey

The initial questionnaire was developed for the United Kingdom, Australia and the United States, and then translated into other languages for non-English speaking study areas. The translation was carried out by native researchers in each country, and double checked by another researcher fluent in both English and the local language. Minor content adjustments reflecting differences in health systems, population and cultural characteristics, or due to data protection requirements were also made. Ethical approval was obtained first in the United Kingdom and then for subsequent data collection in other study areas.

Stated choice component

The core part of the survey was a stated choice (SC) component, often referred to as discrete choice experiments in the health literature. SC surveys are an established technique for capturing data on preferences in hypothetical choice scenarios (cf. Louviere et al., 2000). They present respondents with a set of scenarios that involve a choice between at least two options at a time, described using a set of attributes or product characteristics, with the levels for these attributes varying across scenarios. SC surveys are used commonly across numerous fields of research, including in advice to policy makers (cf. Mahieu et al., 2017). Some recent examples of their use in the context of the present journal are Chen et al. (2021); Oedingen et al. (2021); Wang et al. (2021). SC surveys have also been previously used for understanding vaccination choices in a pandemic context (Determann et al., 2016, 2014), including for COVID-19 (Mouter et al., 2022). A key distinction of SC surveys compared to more direct types of questions is that they face respondents with (hypothetical) multi-attribute multi-alternative settings in which they are asked to make choices, allowing analysts to disentangle the influence of different attributes, or in our case, vaccine characteristics, on choice. Respondents face scenarios with differences in the attribute levels, allowing the estimation of flexible models that capture the relative importance of different vaccine characteristics. The use of such models then additionally allows an analyst to capture how this relative importance of individual vaccine characteristics might vary across

people. SC surveys also differ from conjoint analysis (CA), as explained in detail by Louviere et al. (2010), as they have a clear behavioural foundation, are consistent with economic demand theory, yield outputs that are suitable for understanding the role of individual attributes in decision making, and enable analysts to predict choices in settings with different attribute level combinations.

With the data collection primarily taking place prior to widespread vaccine availability, respondents were asked to imagine a situation where a number of vaccines for COVID-19 have been developed and where these vaccines have undergone all required testing and have received regulatory approval from the health authorities. Participants were informed that vaccination reduces the risk of infection, while it also decreases risk of serious illness should a vaccinated person become infected. Participants were then faced with six hypothetical vaccination choice scenarios. In each choice scenario, they were presented with two different vaccines. These were described on the basis of five key vaccine characteristics, namely:

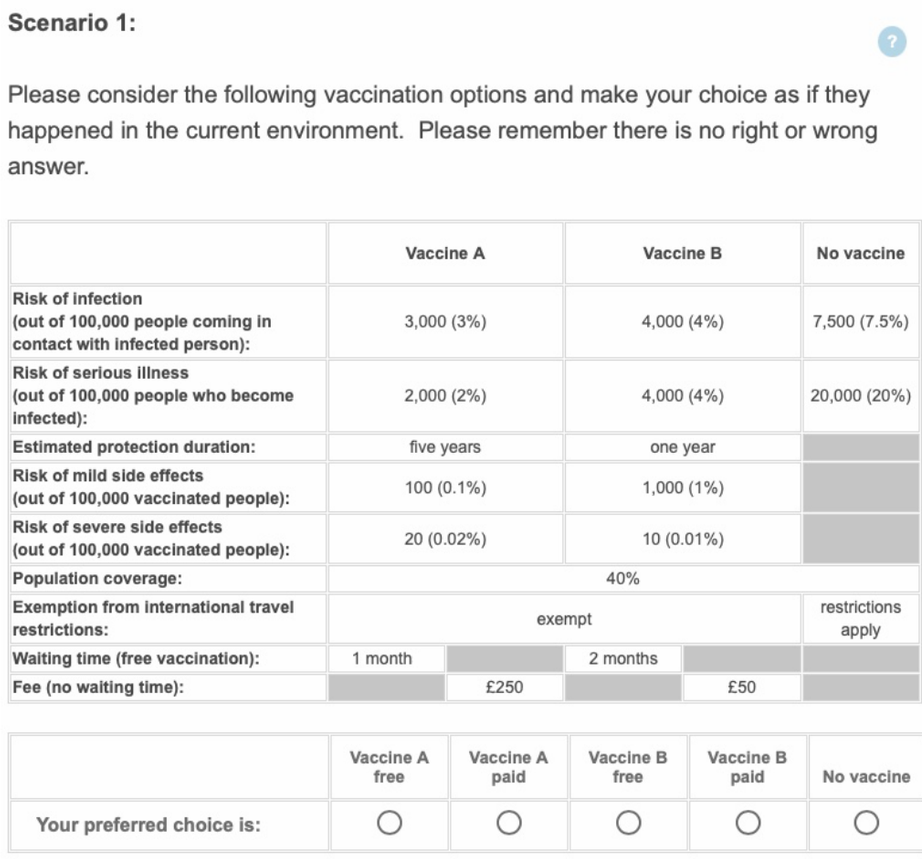
Risk of infection: The number out of every 100,000 vaccinated people who would still get infected when coming in contact with an infected person.
Risk of serious illness: The number out of every 100,000 vaccinated people who, if infected, would develop serious symptoms.
Estimated protection duration: The expected length of time that the protection provided by the vaccine would last before a new course of vaccination was needed.
Risk of mild side effects: The number of people out of 100,000 that could suffer mild side effects from the vaccine (such as numbness or a rash at the injection site, or a headache).
Risk of severe side effects: The number of people out of 100,000 that could suffer severe side effects from the vaccine (such as an allergic reaction requiring further medical treatment).

While the performance of vaccines is generally measured in terms of efficacy, i.e., the reduction in risk that a vaccine gives, the interpretation of this is subjective in the face of an unknown baseline risk. In the survey, we instead presented respondents with risk levels with and without vaccination, so as to give a baseline against which to measure vaccine performance. In the later model application, we then translated the results into efficacy. Using r_{vacc} and r_{unvacc} to be the risks (e.g. for infection) with and without vaccination, respectively, efficacy would be calculated as $\frac{r_{vacc}-r_{unvacc}}{r_{unvacc}}$. This has the added advantage that, after model estimation, predictions of vaccine uptake can be generated for cases with different base line risks, which is not the case when using efficacy alone in a survey.

To further test whether vaccine uptake was also influenced by non-vaccine specific characteristics, two additional scenario attributes were included that related to:

Population coverage: The share of the population that have already been vaccinated.
Exemption from international travel restrictions: Whether being vaccinated would give individuals exemption from current COVID-19 travel restrictions.

Finally, respondents were told that, given the need to vaccinate very large parts of the population, and limits on supply, there would be a wait before they could receive a vaccine. However, they could also obtain vaccination immediately by paying a one-off fee. While paid access has been ruled out for now in most countries, developments in that direction have taken place in some countries, for example with paid access being allowed in Pakistan, and attracting substantial demand despite high costs (Hassan, 2021). At the same time, excess vaccine availability in some countries has led to vaccine tourism, with people from Latin America paying substantial amounts of money to travel to the United States



Scenario 1:

Please consider the following vaccination options and make your choice as if they happened in the current environment. Please remember there is no right or wrong answer.

	Vaccine A	Vaccine B	No vaccine
Risk of infection (out of 100,000 people coming in contact with infected person):	3,000 (3%)	4,000 (4%)	7,500 (7.5%)
Risk of serious illness (out of 100,000 people who become infected):	2,000 (2%)	4,000 (4%)	20,000 (20%)
Estimated protection duration:	five years	one year	
Risk of mild side effects (out of 100,000 vaccinated people):	100 (0.1%)	1,000 (1%)	
Risk of severe side effects (out of 100,000 vaccinated people):	20 (0.02%)	10 (0.01%)	
Population coverage:	40%		
Exemption from international travel restrictions:	exempt		restrictions apply
Waiting time (free vaccination):	1 month	2 months	
Fee (no waiting time):	£250	£50	

	Vaccine A free	Vaccine A paid	Vaccine B free	Vaccine B paid	No vaccine
Your preferred choice is:	○	○	○	○	○

Figure 1: Example of SC scenario

for vaccination (Reuters, 2021). While this is different from regulated paid access in a person's home country, it highlights a high willingness to pay by some for faster access to vaccination in countries where universal access is not yet guaranteed. The two additional attributes were:

Waiting time: How long people need to wait to obtain the vaccine for free
Fee: How much people would need to pay to obtain the vaccine immediately

Each scenario thus involved the choice between five possible options, namely free or paid versions of either of the two vaccines, and the option of not being vaccinated. An example choice scenario is shown in Figure 1.

The attribute levels for the different scenarios were varied across scenarios according to a D-efficient design (cf. Rose and Bliemer, 2014) produced using NGene (Choicemetrics, 2018), with 36 rows divided into six blocks. In the absence of reliable previous studies, the priors used in the design gave equal weight to each of the attributes and only recognised their directionality (e.g., that higher risk would imply reduced utility). The attribute levels used are summarised in Table 1, where only

the levels for fee attribute for paid vaccination varied across study areas, with values adjusted on the basis of cost of living indices as well as local insights on the cost of other vaccinations.

Table 1: Levels used in experimental design for Stated Choice (SC) scenarios

		Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**	**Without vaccine**
	Risk of infection out of 100,000 people	500 (0.5%)	1,500 (1.5%)	3,000 (3%)	4,000 (4%)	5,000 (5%)	-	7,500 (7.5%)
	Risk of illness out of 100,000 people	2,000 (2%)	4,000 (4%)	6,000 (6%)	10,000 (10%)	15,000 (15%)	-	20,000 (20%)
	Estimated protection duration	five years	two years	one year	6 months	Unknown	-	-
	Population coverage	More than 80%	60%	40%	20%	Fewer than 10%	-	-
	Risk of mild side effects out of 100,000 people	100 (0.1%)	500 (0.5%)	1,000 (1%)	5,000 (5%)	10,000 (10%)	-	-
	Risk of severe side effects out of 100,000 people	1 (0.001%)	5 (0.005%)	10 (0.01%)	15 (0.015%)	20 (0.02%)	-	-
	Exemption from international travel restrictions	no restrictions	no exemptions	-	-	-	-	Restrictions on international travel
	Waiting time (for free option)	2 weeks	1 months	2 months	3 months	6 months	-	-
Cost (for paid option)	AU (AUD)	40	100	200	350	450	700	-
	BR (BRL)	40	200	400	800	1,000	1,600	-
	CL (CLP)	3,000	13,500	27,000	54,000	69,000	108,000	-
	CN (CNY)	50	250	500	950	1,200	1,900	-
	CO (COP)	20,000	100,000	200,000	420,000	530,000	850,000	-
	DE (EUR)	10	50	110	220	270	450	-
	DK (DKK)	100	500	1,010	2,020	2,520	4,030	-
	EC (USD)	10	40	80	150	200	300	-
	ES (EUR)	10	45	90	180	230	360	-
	FR (EUR)	10	60	120	240	300	485	-
	HK (HKD)	110	560	1,100	2,200	2,800	4,500	-
	JP (JPY)	1,680	8,400	16,800	33,600	42,000	67,200	-
	KR (KPW)	18,000	90,000	180,000	360,000	450,000	720,000	-
	NA (NAD)	186	464	928	1,624	2,088	3,931	-
	NZ (NZD)	20	100	200	400	500	800	-
	UK (GBP)	10	50	100	200	250	400	-
	US (USD)	15	60	125	250	300	500	-
	ZA (ZAR)	186	464	928	1,624	2,088	3,931	-

It is important to note that while the survey gave individuals a choice between two vaccine options and the choice not to be vaccinated, the real-world situation in many countries will be one where a single vaccine is offered to individuals and they choose to accept vaccination or not. Alternatively, in some countries, people are now being offered a choice between different vaccines, or where the vaccine available depends on which location they choose for vaccination. Similarly, paying for faster access is not an option in real-world settings at present in the study areas. These scenarios again differ from what was presented in the survey. However, it is important to note that the SC scenarios need not mimic the real-world situation, as long as they present respondents with choices that could reasonably arise in the future. The aim of the data collection is not to understand vaccine acceptance in a specific scenario but to elicit sensitivities to individual vaccine characteristics. This includes the sensitivity to cost, which can be used to understand the willingness to accept out-of-pocket expenses for faster vaccination, where this could include, for example, travel costs to a nearby country with easier access to vaccines, an issue that might return again in future if vaccines targeted at new variants are initially in short supply.

Presenting individuals with multi-alternative and multi-attribute scenarios allows us to collect rich data on which to estimate models that capture the differential impact on utility of individual vaccine characteristics. Model results can thus be used to make predictions of vaccine acceptance in scenarios that are different from those used in data collection, including single vaccine cases, as well as those where paid access is not an option. We show this in model application (Section 3.3 and Section 3.4). This is a key advantage of using stated choice scenarios and models of choice behaviour based on utility maximisation, as opposed to simply measuring the likelihood of vaccine acceptance in specific scenarios.

Identification of vaccine-resistant individuals

Much has been made in the literature about the existence of different segments of individuals when it comes to vaccine acceptance (see e.g. Edwards et al., 2021), often dividing people into a group that

would definitely accept vaccination, a group with varying levels of hesitancy about vaccination, and a group that is resistant to vaccination, more colloquially referred to as anti-vax. Often, this segmentation is performed on the basis of answers to questions about the likelihood of vaccine acceptance. As our study presented each respondent with six separate vaccine choice scenarios, we were able to segment individuals on the basis of their observed choices. We return to this in detail in Section 3.1, but one point already needs addressing at this stage, namely how to distinguish between individuals who are truly *resistant* to vaccination and those who are simply *hesitant* and require the right *incentive*, such as being offered a vaccine that is acceptable to them. In our work, respondents who never chose a vaccination option across their six choice tasks were asked a follow-up question about their reasons for not accepting any vaccine, which was worded as follows: *"We noticed that across all the choices we presented you with, you never chose one of the vaccines. Which of the following options best describes your reason for that?"*. Respondents had the option of selecting *"The options presented to me were not good enough compared to not being vaccinated"*, in which case they were deemed to be open to vaccination per se, if the right vaccine was made available. On the other hand, we classified as vaccine resistant any respondents who selected one or more of the other answers, which were *"The options presented to me were not good enough compared to not being vaccinated"*, *"I do not believe in the benefits of vaccination"*, *"Enough other people will accept vaccination so I will benefit from herd immunity"*, *"I have already been infected with COVID-19 and believe I have developed natural immunity"*, and *"I prefer obtaining immunity naturally without vaccination"*.

2.1.2 Sampling

Data collection covered 18 study areas, across all six inhabited continents, with a final combined sample size of 13,128 individuals. The 18 countries and territories included in the study are as follows:

Africa: Namibia (NA), South Africa (ZA)
Asia: China (CN), Hong Kong Special Administrative Region of the People's Republic of China (HK), Japan (JP), South Korea (KR)
Europe: Denmark (DK), France (FR), Germany (DE), Spain (ES), United Kingdom (UK)
North America: United States (US)
Oceania: Australia (AU), New Zealand (NZ)
South America: Brazil (BR), Chile (CL), Colombia (CO), Ecuador (EC)

Different recruitment methods were used across study areas, with some combining multiple approaches, including the use of professional market research companies, social media advertising, printed media advertising and the involvement of local citizen panels or distribution via government, local authority or university lists. In many of the study areas, the main incentive for participant recruitment was a prize draw or a fixed incentive such as a voucher. While several of the study areas used a survey company to seek a broad representability of the sample, this was not the case elsewhere, and during the subsequent analysis, the results were reweighted to bring them in line with the real age and gender distribution in the relevant population (and, for local reasons, also by ethnicity in New Zealand).

The data collection started in summer 2020, and continued until the start of March 2021. As shown in Figure 2, the bulk of the data collection took place in August and September 2020, where, in most cases, this was after the first wave of the pandemic for the concerned study areas. The timing of data collection varied across study areas, with data collection taking place later in some study areas,

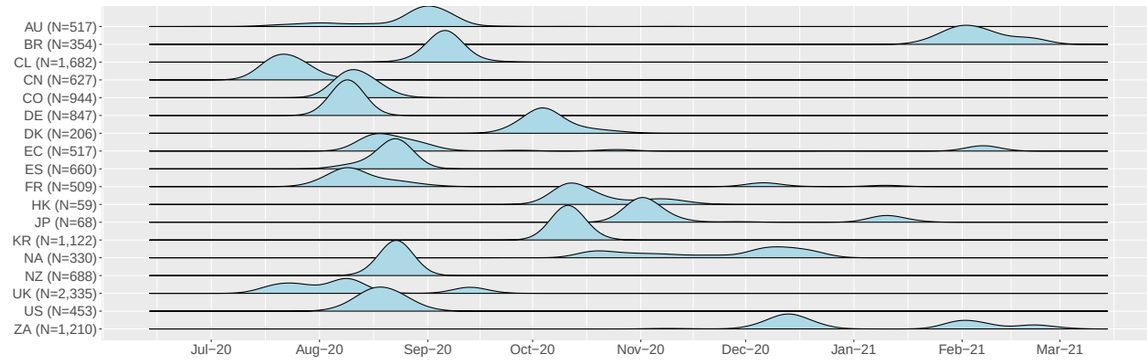


Figure 2: Overview of data collection across study areas and time

partly also reflecting the worldwide progression of the pandemic. Sample sizes also varied substantially across study areas, with only small sample sizes for Hong Kong and Japan, a point we return to later on in the analysis.

2.2 Modelling work

A carefully designed multi-stage analysis was undertaken, going from estimation to prediction, with key steps outlined in the following subsections, and further details provided in the online supplementary material (cf. Sections A.2 and A.3). All models were estimated using maximum likelihood routines in Apollo v0.2.5 (Hess and Palma, 2019).

2.2.1 Ordered logit analysis of vaccine uptake behaviour

Let $Y_{n,c,t}$ be a binary variable indicating whether individual n in study area c chose a vaccine option in scenario t (with $t = 1, \ldots, 6$). We first computed for each individual in the data the rate of vaccine uptake across the six scenarios, i.e. $Y_{n,c} = \sum_{t=1}^{6} \frac{Y_{n,c,t}}{6}$ for individual n in study area c. As this is an ordinal variable, with seven categories $Y_{n,c} \in \left\{0, \frac{1}{6}, \frac{2}{6}, \ldots, 1\right\}$, we used an Ordered Logit (OL) model (cf. Greene, 2014), with the utility for vaccination for individual n in study area c given by:

$$V_{n,c} = \delta_c + \sum_{l=1}^{L} \kappa_l q_{n,c,l} + \sum_{m=1}^{M} \gamma_{m,c} z_{n,c,m}, \tag{1}$$

where:

- δ_c is a study area-specific constant (to be estimated), capturing the mean effect of omitted variables, which would include, for example, differences across areas related to cultural aspects, policy/regulation regarding tackling pandemic, as well as media effects;
- $\kappa = \langle \kappa_1, \ldots, \kappa_L \rangle$ is a vector of parameters to be estimated, capturing the impact of study area-specific variables $q_{n,c} = \langle q_{n,c,1}, \ldots, q_{n,c,L} \rangle$ at the time of respondent n completing the survey, including for example the current R (reproduction) number; and

- $\gamma_c = \langle \gamma_{1,c}, \ldots, \gamma_{M,c} \rangle$ is a vector of parameters to be estimated, capturing the impact of person-specific variables $z_{n,c} = \langle z_{n,c,1}, \ldots, z_{n,c,M} \rangle$, including for example age, gender, education and current health.

Some components in the vector γ_c were study area-specific, such as age and gender, while generic parameters were used for other, such as for example whether an individual suffered from a chronic health condition. In addition to the above parameters, the use of the OL model relies on the estimation of threshold parameters for the different levels of vaccine uptake, as described in detail in the online supplementary material (cf. Section A.2.1), which also explains how the model was used to make predictions of vaccine uptake, and to investigate the impact of decision maker and study area characteristics on uptake.

2.2.2 Latent class analysis of disaggregate vaccine preferences

The core empirical work concerned the analysis of the disaggregate level data from the SC survey, i.e., modelling the choices between the five options presented in individual SC scenarios. Based on the OL analysis, two key decisions were made. First, we excluded individuals classified as vaccine-resistant (for who we set $vr_{n,c} = 1$) from the data during estimation. These individuals were identified as making choices independent of the characteristics of the vaccine and should thus not contribute to the estimation of parameters relating to the role of individual vaccine characteristics. To recognise the existence of this segment of the population, the predictions from the models were reweighted accordingly in application (cf. Section A.3.1). Second, given the OL findings about differences across study areas (in terms of baseline preferences and the role of age, gender and education), this analysis made use of study area-specific models.

Given the likely high levels of heterogeneity in preferences even within a study area, we used Latent Class (LC) models (cf. Hess, 2014; Kamakura and Russell, 1989) to analyse the data. In general terms, for person n in study area c, we write the deterministic component of utility for alternative i in choice scenario t and in class s as:

$$V_{n,c,i,t,s} = \delta_{c,i,s} + \beta_{c,s}{}' x_{n,c,i,t}, \tag{2}$$

where $\delta_{c,i,s}$ is the constant used in class s (out of S_c classes) for alternative i in study area c, $x_{n,c,i,t}$ is a vector of attributes describing alternative i as faced by individual n in study area c in choice situation t, and $\beta_{c,s}$ is the associated vector of parameters to be estimated for class s. Some distinctions arise across alternatives and across attributes, as follows:

- For the constants, we used the no vaccine option as the base, normalising its constant to zero. Separate constants were estimated for free and paid vaccine options, along with an effects coded position constant to distinguish between the left and right vaccine in the survey. Just as in the OL model, the study area-specific constants also help capture the role of differences across areas related to cultural aspects, etc.
- For the no vaccine option, the only attributes that entered the utility function were the risk of infection and the risk of illness, using the baseline levels from Table 1.
- After initial tests for non-linearity, all attributes were treated as continuous, with two exceptions. For protection duration, a separate term was estimated for unknown protection duration, alongside the continuous term for known durations, while the travel exemption attribute, which has only two levels, was dummy coded (using no exemption as the base).

To capture potentially greater substitution between the different vaccine options than switching between vaccine and no vaccine, the discrete choice model in each class was of the Nested Logit (NL) type (cf. Train, 2009, chapter 4), grouping together the vaccine options into one nest. Let $Y_{n,c,i,t} = 1$ if individual n in study area c chooses option i in task t, and 0 otherwise. With option 5 being the no vaccine option, we then have that the probability of the observed choice for individual n in study area c and task t, conditional on latent class s, is given by:

$$P_{n,c,t,s}\left(\Omega_{LC,s}\right) = \frac{\sum_{j=1}^{4} Y_{n,c,t,j} \cdot e^{\frac{V_{n,c,j,t,s}}{\lambda_s}} \left(\sum_{k=1}^{4} e^{\frac{V_{n,c,k,t,s}}{\lambda_s}}\right)^{\lambda_s - 1} + Y_{n,c,t,5} \cdot e^{V_{n,c,5,t,s}}}{\left(\sum_{j=1}^{4} e^{\frac{V_{n,c,j,t,s}}{\lambda_s}}\right)^{\lambda_s} + e^{V_{n,c,5,t,s}}}, \tag{3}$$

where $\Omega_{LC,s}$ groups together all the parameters for class s, namely the δ and β terms from Equation 2, and the nesting parameter λ_s, with $0 < \lambda_s \leq 1$, $\forall s$. As the membership in the classes is latent, the likelihood for the observed sequence of choices for person n is given by a weighted average across S classes, using the class allocation probabilities as weights. The likelihood function for study area c is then given by:

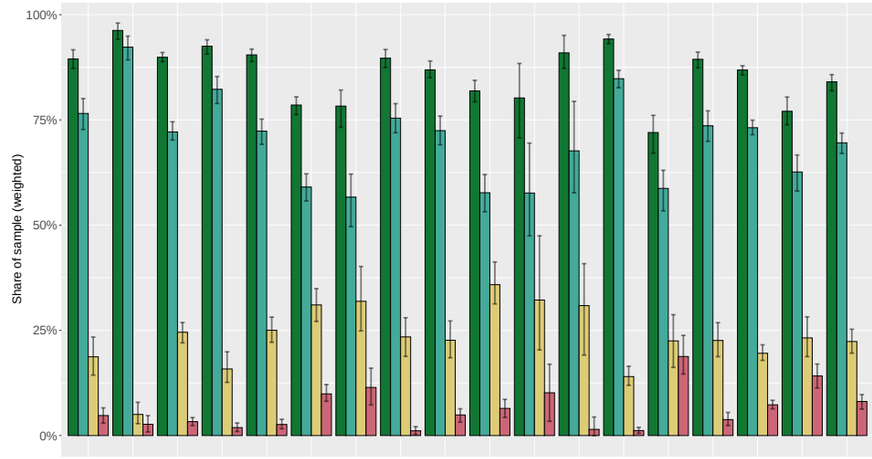
$$L\left(\Omega_{LC}\right) = \prod_{n=1}^{N_c} \left[\sum_{s=1}^{S_c} \pi_{n,c,s} \prod_{t=1}^{6} P_{n,c,t,s}\left(\Omega_{LC,s}\right)\right]^{1 - vr_{n,c}}, \tag{4}$$

where Ω_{LC} groups together all model parameters, and where $\pi_{n,c,s}$ is the class allocation probability for individual n in study area c for class s. The use of the exponent $1 - vr_{n,c}$ ensures that vaccine-resistant individuals do not contribute to the estimation of model parameters. Further details for the LC model are provided in the online supplementary material (cf. Section A.3.1), looking at estimation, recalibration and prediction, including the use of individual-level posterior class allocation probabilities.

2.2.3 Scenario tool

To allow further insights and wider use of results, an online tool is made available alongside the paper at https://stephanehess.shinyapps.io/COVID19_Shiny/. This tool allows users to simultaneously predict the uptake of different vaccines across all 18 study areas, for custom scenarios with up to three vaccines being available at the same time, where the user can configure the characteristics of these vaccines in terms of efficacy, protection duration, risk of side effects, waiting time and cost, as well as changing the levels of infectiousness and severity of circulating variants of COVID-19. An example for a three vaccine case is presented in Figure 3, showing a situation with a choice between a high efficacy/low risk of side effects vaccine and a lower efficacy/higher side effects vaccine, but where the former is only available either with a three months waiting time or a fee of £100, and the latter has a longer protection duration. The tool returns the predicted uptake both as a barchart (as in Figure 3) and as a table.

Figure 3: Online scenario tool: https://stephanehess.shinyapps.io/COVID19_Shiny/



	units	AU	BR	CL	CN	CO	DE	DK	EC	ES	FR	HK	JP	KR	NA	NZ	UK	US	ZA
Overall vaccine uptake	%	89.5	96.3	89.9	92.5	90.5	78.5	78.3	89.7	86.9	81.9	80.2	90.9	94.2	72.0	89.4	86.9	77.1	84.1
Share likely to accept any reasonable vaccine	%	76.5	92.3	72.1	82.3	72.3	59.1	56.7	75.4	72.5	57.7	57.6	67.6	84.8	58.7	73.6	73.1	62.6	69.6
Share open to vaccination depending on characteristics	%	18.7	5.0	24.5	15.8	25.0	31.0	31.9	23.4	22.7	35.8	32.2	30.9	14.0	22.5	22.6	19.5	23.2	22.3
Share of vaccine−resistant individuals	%	4.8	2.7	3.3	1.9	2.6	9.9	11.4	1.1	4.9	6.5	10.2	1.5	1.2	18.8	3.8	7.3	14.2	8.1

Figure 4: Overview of vaccine uptake in SC survey (95% confidence intervals by bootstrapping from data)

3 Results

3.1 Overview of vaccine uptake behaviour

Given the use of the same underlying design (which took differences in the cost of living into account), the overall vaccine uptake in the SC survey can be compared across study areas. We computed four key metrics for this purpose, with the results, expressed in percentages, shown in Figure 4.

We first look at the average vaccine uptake in each study area, i.e. the proportion of choice tasks in which respondents selected one of the vaccine options. We observe a wide variation of vaccine uptake across areas, with the lower numbers in some study areas being partly in line with past evidence (cf. de Figueiredo et al., 2020). While the uptake proportions for Denmark and Germany are lower than

expected, it should be noted that, at the time of data collection, the number of deaths relative to population size in these two countries was still much lower than in many other European countries.

The overall vaccine uptake in a given study area arises as a result of a mix of three patterns of preferences, namely respondents who always choose a vaccine across their six scenarios, respondents who choose a vaccine in some but not all scenarios, and respondents who never choose a vaccine. Figure 4 shows that individuals who always choose a vaccine across their six tasks, independent of the characteristics of the vaccine, form the largest group in all countries, but with a wide range, from 56.7% for Denmark to 92.3% in Brazil. The second largest group is formed of individuals who are open to vaccination, but where their decision depends on the characteristics of the vaccine. We include in this group individuals who choose a vaccine in some of the six choice tasks they faced as well as individuals who never never chose a vaccine but indicated that this was due to the characteristics of the available vaccines (cf. Section 2.1.1). This combined group accounts for around one in five individuals overall, but reaches shares as high as one third of respondents in some countries. From a policy perspective, this group of individuals is key to ensuring a sufficiently high level of vaccine uptake in a population to achieve herd immunity, and the findings highlight the importance of vaccine characteristics in this context, given that these individuals choose to be vaccinated only if the available vaccine meets their desired characteristics.

The final group is of particular concern in relation to herd immunity, and relates to a growth in vaccine resistance in many countries (see also de Figueiredo et al., 2020; Ward et al., 2019). This share of *vaccine-resistant* individuals (i.e., those who never choose a vaccine and indicate that they would not do so independent of vaccine characteristics) ranges from very low values (below 5% in Australia, Brazil, Chile, China, Colombia, Ecuador, Japan, New Zealand, South Korea, Spain) to a high value of 18.8% for Namibia, and 14.2% for the United States. Notwithstanding the lack of consistency with the closely related South Africa, the high share of vaccine-resistant individuals in Namibia could be seen to relate to a lack of information and clarity surrounding vaccination, a lack of trust in the vaccination procurement and dissemination process, and the presence of underlying beliefs that fuel the anti-vaccination behaviour (cf. Tulloch et al., 2021). Indeed, Namibia is the only country in which the answer *"I do not believe in the benefits of vaccination"* was the most commonly chosen reason for respondents who never choose a vaccine across their six tasks (29.5% compared for example to 12.7% for the United States).

It is of interest to compare these numbers with those reported elsewhere. For example, Ward et al. (2020) reported that *"almost a quarter of French adults would not get vaccinated against COVID-19"*. Our predicted uptake of 81.9% for France is not entirely out of line with that reported by Ward et al. (2020). However, we show that this uptake is strongly influenced by the vaccine characteristics in that it varies across choice tasks, with only a much smaller share of individuals being completely unwilling to be vaccinated, where our share of 6.5% is quite similar to the 7.9% reported by Ward et al. (2020) as *"certainly"* refusing vaccination. Overall, the results highlight the benefit of surveys that not only describe the properties of vaccines (as opposed to simple yes/no questions about vaccination intentions) but also vary them within and across individuals so as to allow analysts to uncover the influences on vaccine uptake.

3.2 Impact of area and respondent characteristics

We next use the ordered logit (OL) model discussed in Section 2.2.1 to understand the drivers of differences in the likelihood of accepting a COVID-19 vaccination across individuals within a study area

and across study areas. The final model specification was arrived at after testing for numerous other effects, where a number of omissions from the final results are worth highlighting. First, no consistent meaningful pattern was observed for income. Second, attempts were made to include race/ethnicity in the models, even though the possible categories are highly specific to study areas. In the end, an impact of race/ethnicity could be conclusively proven only in two cases; namely a 3.4% higher probability of vaccine acceptance for Asian respondents in the United States (vs White), and a 10.8% lower probability for vaccine acceptance for Whites in South Africa (vs Blacks), a finding supported by Alexander et al. (2021). For these two cases where race was found to have an impact, the samples were already representative in terms of ethnicity split, and no further reweighting was thus needed. Results of a separate analysis on the US data suggested that other factors, potentially institutional, are driving the vaccination rates for these groups (cf. van den Broek-Altenburg et al., 2021). Given this limited evidence, race/ethnicity was not included in the final model. Third, while there is at some evidence of a relationship between political ideology/party affiliation and vaccine resistance, such a variable is difficult to construct in an internationally comparable way and associated questions were not included in our survey due to ethics regulations in several of the participating study areas. Detailed estimation results are presented in the online supplementary material (cf. Section A.2.2).

To interpret the OL results, we look at person (Figure 5) and area-specific (Figure 6) effects, each time focussing on the impact of a single characteristic while controlling for all other effects. In particular, we compared predictions using two versions of the data, changing only the attribute of interest (cf. online supplementary material, Equation 7 in Section A.2.1 for details on the prediction calculations). Using gender as an example, we would compare predictions made with a version of the data where everyone is treated as female and a version where everyone is treated as male. Comparing the predictions for women and men would give a biased account of the role of gender given correlations with other characteristics.

COCONEL Group (2020); Dror et al. (2020); Kreps et al. (2020); Wouters et al. (2021) find on average lower vaccine acceptance for women than men. Our model similarly predicts a lower uptake for women than for men in Chile, Ecuador and especially the United States, while there is also reduced uptake for women, but with slightly wider confidence intervals, for Colombia, Germany and the United Kingdom. The opposite is however the case for Brazil, while the larger positive effect for women in Denmark, France and Namibia is accompanied by very wide confidence intervals. For education, having a university degree would in general increase the predicted probability of vaccine uptake, but the confidence intervals for this effect are again wide for most countries. A notable exception is Namibia, where we see a substantially lower uptake rate for individuals with a degree. The overall positive impact of education is in line with the findings of Craig (2021), who however also noted a general lack of impact of socio-demographics. A generic treatment across study areas of the role of health and exposure shows that suffering from a chronic health condition has the biggest impact on predicted uptake, while exposure to infection risks on either public transport (PT) or air travel similarly raises the predicted willingness to be vaccinated (where for the latter, travellers may also already have perceived a vaccine as being a legal requirement for travel in future). A diverse pattern emerges for age, where we show the differences in predicted uptake for different ages, compared to a 45 year old. Across the majority of study areas, we see higher predicted uptake for both younger and older individuals, where this is especially striking for Denmark, with differences of over 20% at both ends of the distribution. The same pattern is not repeated throughout, where, for example, for the United States, the probability only bottoms out at a later stage (around 60) before rising again, but coming nowhere near the predictions for younger age groups. This finding is contrary to that reported

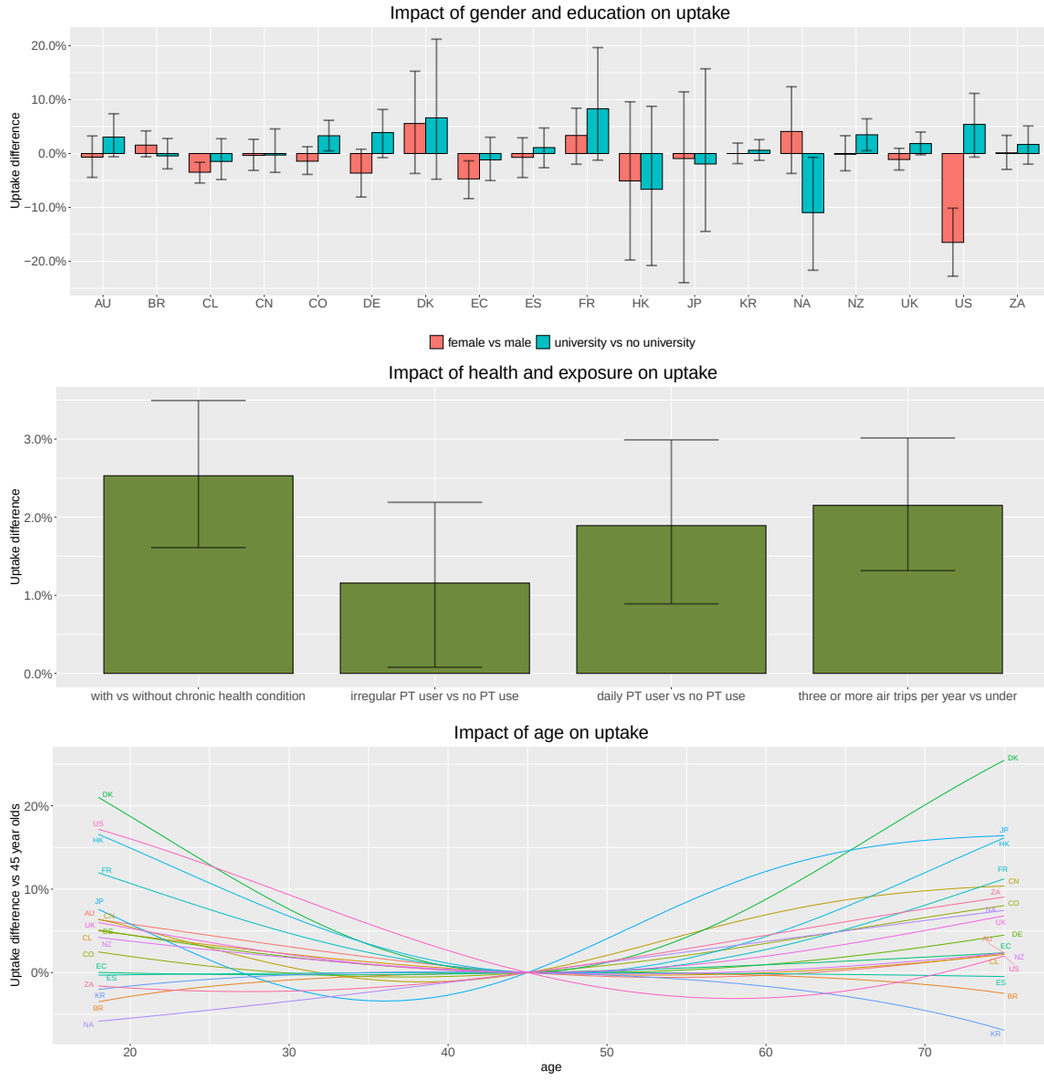


Figure 5: Impact of person characteristics on predicted uptake from OL model (where shown, 95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)

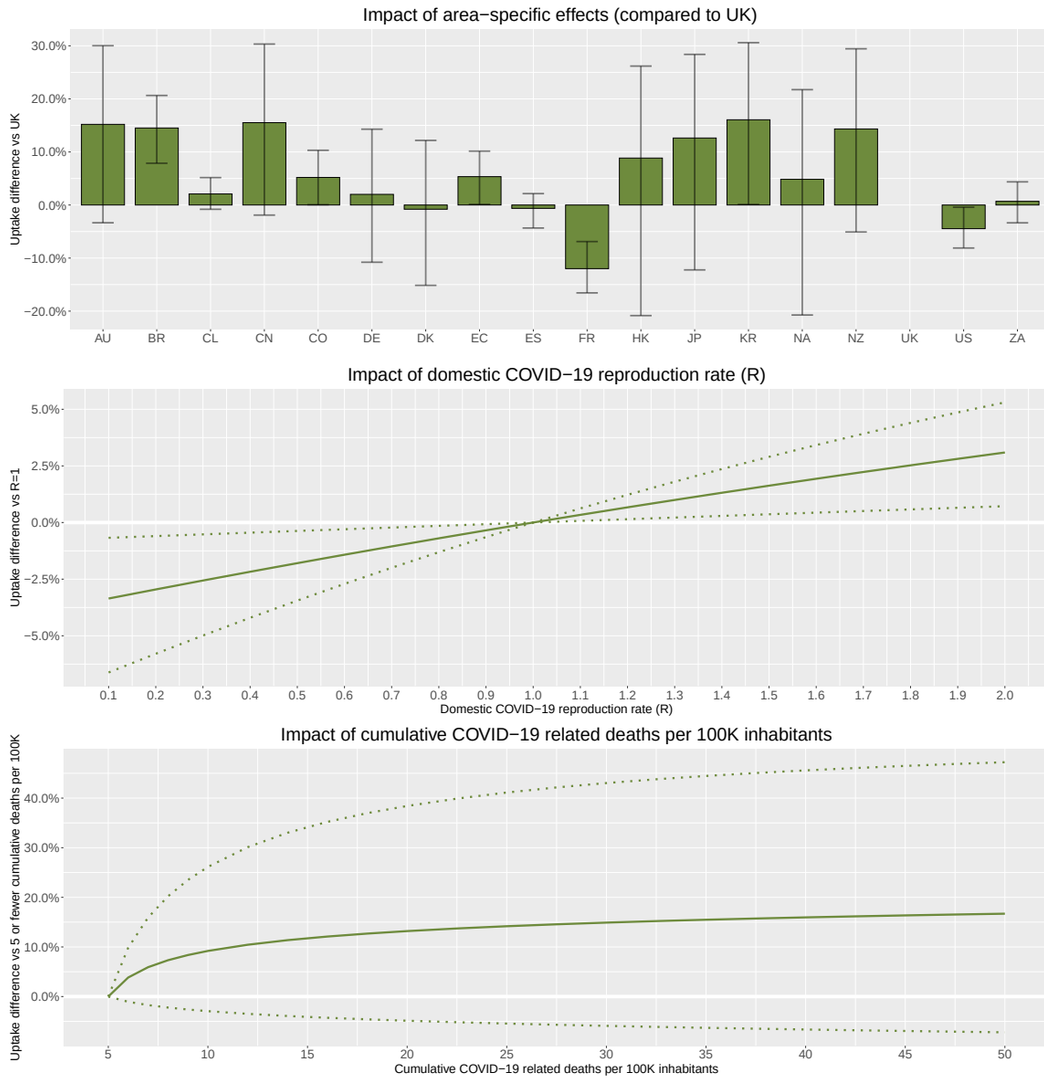


Figure 6: Impact of study area and pandemic characteristics on predicted uptake from OL model (where shown, 95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)

in COCONEL Group (2020), where younger and older people were less open to vaccination. However, in our study, the higher predicted uptake for younger individuals is also not universal, looking for example at the result for Namibia, while age has very little effect in some study areas, e.g., Spain. The findings in relation to age have potentially high policy relevance given the diverse risk patterns that are emerging for vaccines for different age groups (Greinacher et al., 2021; Menni et al., 2021).

We next turn to the study area and pandemic characteristics, shown in Figure 6. After controlling for other variables, and using the United Kingdom as the base (given it has the largest sample), we see a reduction in uptake for France (cf. Ward et al., 2020) and the United States, with substantial increases (with varying levels of confidence) in the case of Australia, Brazil, China, New Zealand or South Korea. These findings differ somewhat from the uptake rates in Figure 4, highlighting the importance of disentangling the study area effects from other effects. There were substantial differences across study areas in the state of the pandemic at the time of data collection, and the impact of this was captured in the OL model through the role of the reproduction number and the cumulative number of COVID-19 related deaths. We see that, increases over a base reproduction number of 1 lead to increased vaccine uptake, with the opposite applying for reductions. Similarly, as the number of COVID-19 related deaths increases in a study area (compared to 5 or fewer per 100K inhabitants), so does the predicted vaccine uptake, although the estimate for this effect has a wide confidence interval.

3.3 Impact of vaccine characteristics

To illustrate the differences in the impact of individual vaccine characteristics (such as efficacy and risks) and how these may vary across study areas, we look at the marginal effects of individual characteristics, based on Latent Class (LC) models (cf. Section 2.2.2, with detailed estimation results presented in the online supplementary material in Section A.3.2). Given the lack of clear trends in the effects of population coverage and the travel exemptions across study areas, these two attributes were excluded from the calculations, with an additional calibration (as per Equation 12 in Appendix A.3.1) carried out to replicate the baseline market shares in the estimation data.

Our analysis looks at two different baseline scenarios. In the first, a single low efficacy vaccine (60% efficacy for both infection and illness), with unknown protection duration, low levels of mild (0.1%) and severe (0.001%) side effects is offered, without wait and without payment. In the second baseline scenario, an additional vaccine is introduced, with a higher efficacy (95%) but a three months wait time.

Figure 7 presents the findings for the single vaccine case, where we focus on changes in efficacy, protection duration, and risk of side effects, and where the differences in vertical scale of the graphs need to be borne in mind.

- For efficacy, we look at an increase from 60% to 95%, and we investigate this separately as efficacy against infection and illness, as well as for a joint improvement for both, where the latter of course has a larger impact. A point to note here is that, in the survey, the unvaccinated risk of illness if infected was set to 20%, while the risk of of infection when coming in contact with an infected person was set to 7.5%. As a result, an improvement in the efficacy for infection has a lower impact on the *absolute* risk of infection than a corresponding improvement in the efficacy for illness. This is however counteracted to some extent by the fact that, for many (but not all) study areas, the relative sensitivity to the risk of infection is higher than the

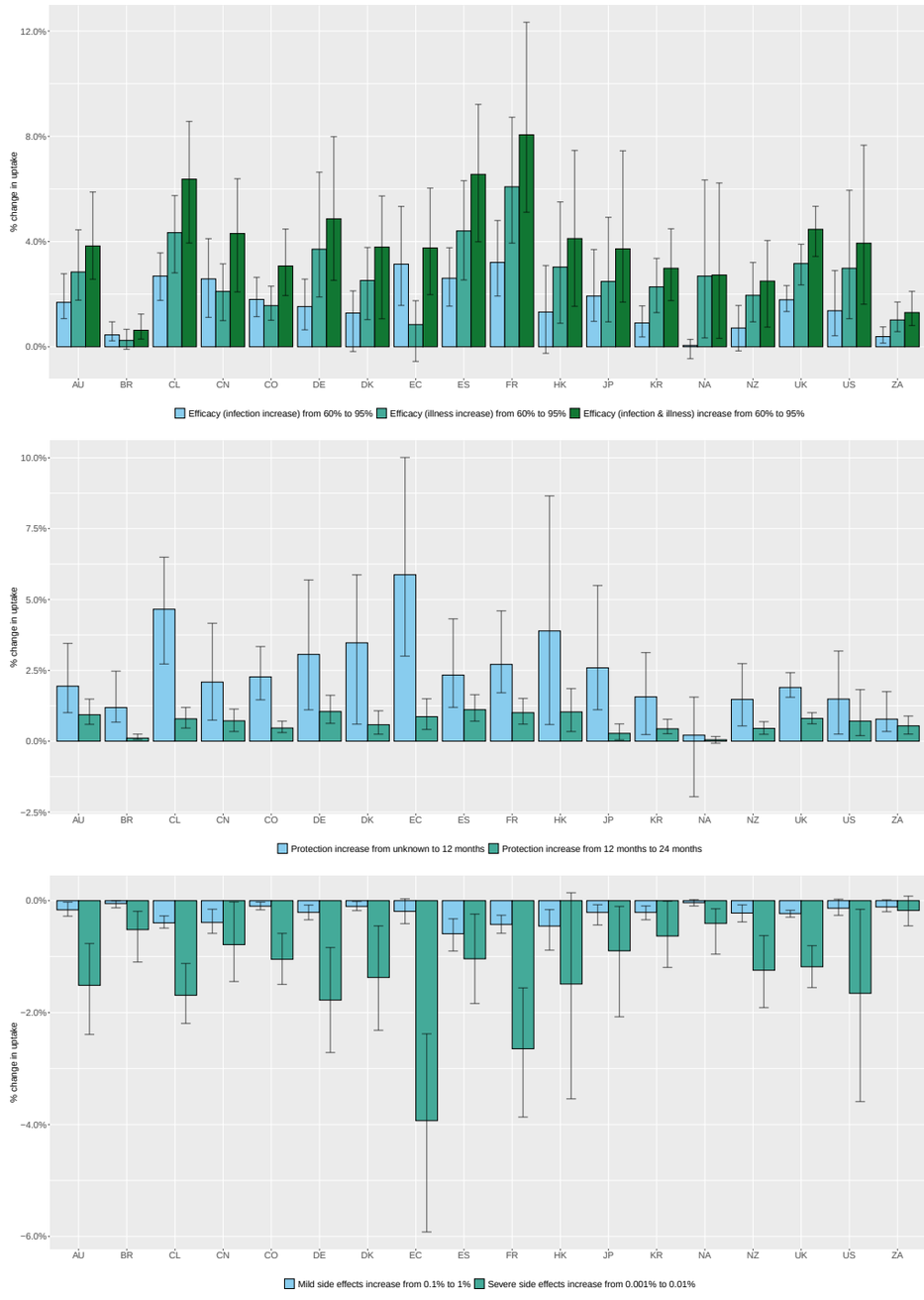


Figure 7: Marginal effects: single vaccine case (95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)

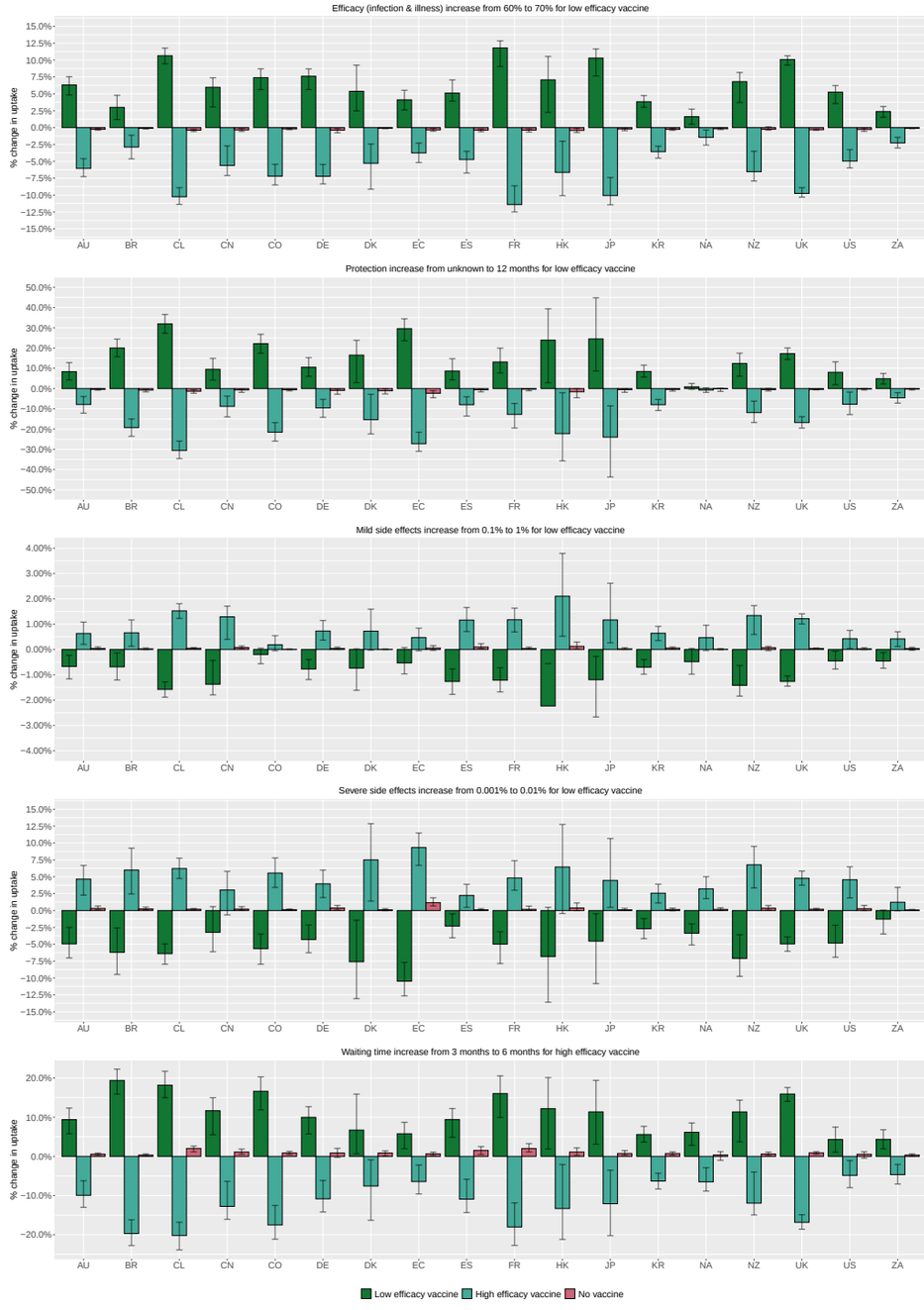


Figure 8: Marginal effects: two vaccines case (95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)

sensitivity to illness. In combination, we see that the impact (on uptake) of increases in efficacy for infection is lower than that for efficacy for illness, except for 4 out of the 18 study areas (Brazil, China, Colombia, Ecuador). The differences across study areas are quite pronounced, in terms of overall effect (contrasting e.g. Brazil and South Africa with Chile, France or Spain), and also in terms of relative importance of the two efficacy measures (contrasting for example Ecuador with Germany).

- Moving from an unknown protection duration to a protection duration of 12 months has a noticeably larger impact than moving from 12 months to 24 months on protection, showing the importance of having some certainty about the length of protection a vaccine offers.
- For side effects, we looked at increases in mild side effects from 1 in $1,000$ to 1 in 100, and increases in severe side effects from 1 in $100,000$ to 1 in $10,000$. Despite the fact that there is a factor of 100 difference in the size of these increases for mild and severe side effects, the impact of increases in severe side effects on uptake is still larger for all study areas. However, major differences arise across study areas, with the importance attributed to severe side effects (relative to mild side effects) being much smaller for China, South Africa and Spain than for other study areas, and much higher for Ecuador than for others.

Figure 8 presents the findings for the two vaccine case. The impact we see for changes in the characteristics of the low efficacy vaccine (first four panels of Figure 8) are universally larger (on average over five times larger) than the corresponding changes in Figure 7, noting that for efficacy, we now look at a 10% increase. This shows that the choice between vaccines is more *deterministic* than the choice vaccinating or not, and the impact of vaccine characteristics consequently plays a larger role for the former. While individuals in most countries are unlikely to (in the short term at least) face a choice between different vaccines at the same time, they may have the option of waiting in order to obtain a more desirable vaccine. Our finding is consistent with anecdotal evidence from countries like Germany and Italy where many have refused the AstraZeneca vaccine in the hope of getting a different one in the future. This is an indication of the fact that our data, largely collected before the vaccination campaign was rolled out, is predictive of what actually happened later. A final comparison in Figure 8 concerns an increase in the waiting time for the high efficacy vaccine - the major changes in vaccine shares that are observed as a result of this change reflect the urgency that individuals attach to rapid vaccination, even at the expense of reduced efficacy.

We noted above that the choice between vaccines is influenced by the vaccine characteristics much more so than the decision whether to accept vaccination or not. Crucially, this also means that, in a situation where multiple vaccines with acceptable characteristics are available (even if one of these has a longer wait), there is little or no impact on overall vaccine uptake of changes to individual vaccines. For example, while joint improvements in both levels of efficacy for the low efficacy vaccine lead to an average increase in its predicted share by 6.4% across study areas, overall vaccine uptake only increases by 0.3%, i.e. the vast majority of the gain in share for one vaccine comes from a reduction in share for the other vaccine. Similarly, increasing the waiting time for the high efficacy vaccine leads to an average drop in the share for the high efficacy vaccine by 11.7%, where this is however almost all shifted towards the low efficacy vaccine, with overall uptake only reducing by 0.9%. This would imply that in a situation with multiple vaccines being on offer, changes to one vaccine will not substantially impact overall vaccine uptake, but lead to a change in the relative uptake between the different vaccines. Note that this is slightly different from the situation where additional vaccines are added to the mix, a point we return to in Section 3.4.

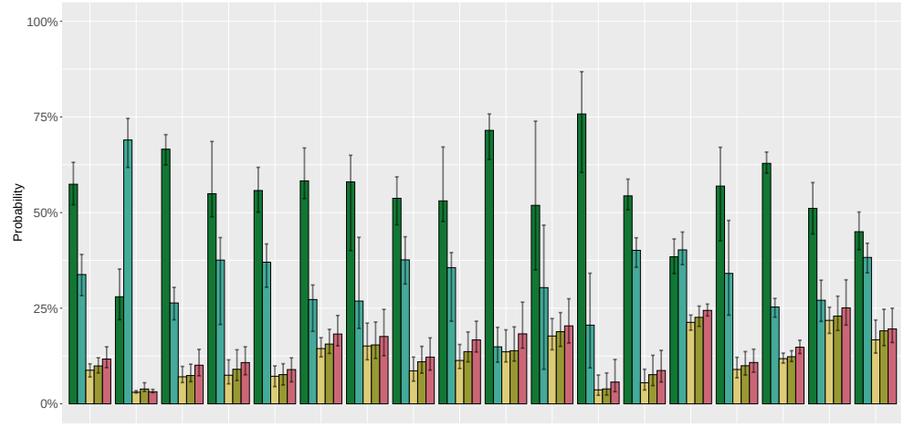
3.4 Scenario testing

The analysis thus far has looked at understanding the sources of heterogeneity in preferences within and across study areas and over time, as well as the role of vaccine characteristics in changing uptake. We now bring together these different strands of analysis by looking at predictions of vaccine uptake under different possible scenarios. We present the results for three such scenarios, with different vaccines being available in each, where the online scenario test tool (cf. Section 2.2.3) can be used for other scenarios, including with differing levels of infectiousness and severity of circulating variants of COVID-19. Each time, we use a baseline risk of infection and illness for unvaccinated people as used in the survey.

Our first scenario (Figure 9) looks at a situation when two vaccines are available; one is a high efficacy (95%) vaccine, while the other is a low efficacy (60%) vaccine. Both vaccines have low risks of mild (0.1%) and severe (0.001%) side effects, offer 6 months protection (in line with Pfizer, 2021), and are available for free, but the high efficacy vaccine has a three month wait. We see a larger share for the higher efficiency vaccine across all study areas except Brazil and Namibia, where individuals value being vaccinated immediately more on average than the increase in efficacy they could obtain for waiting. Across study areas, there is extensive heterogeneity in the overall uptake (mean of 88.7%, ranging from 78.1% for the United States to 97% for Brazil), as well as the relative share for the high efficacy vaccine (mean of 62.3%, ranging from 28.9% for Brazil to 82.7% for France). In all study areas, the removal of either vaccine leads to a small increase in the share of individuals choosing not to be vaccinated, reflecting the fact that having multiple options available makes it more likely that one of these has characteristics that are acceptable, where the criteria of what makes a vaccine acceptable vary across individuals. While this increase is modest in most areas, we see that especially the availability of the higher efficacy vaccine leads to non-trivial impacts on uptake, with increases for example by 4.7% for France and 5.4% for Spain.

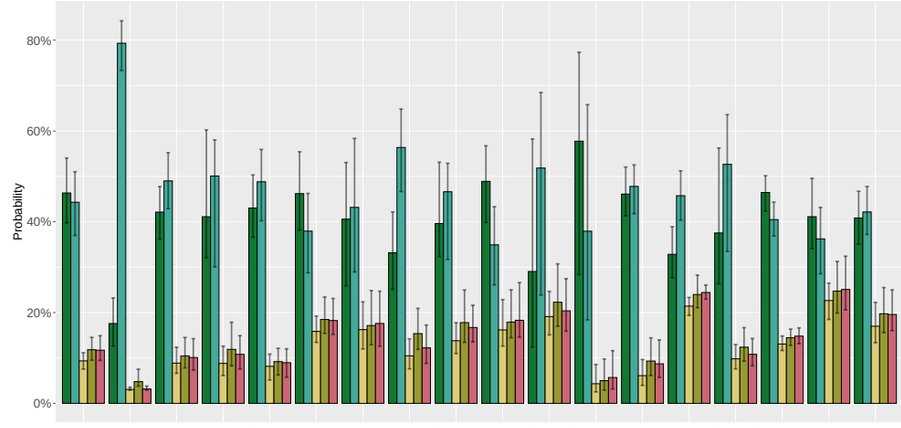
Our second scenario (Figure 10) studies the trade-offs between efficacy and side effects, looking at a situation where the risk of side effects is higher for the high efficacy vaccine, with rates of 5% for mild side effects and 0.015% for severe side effects (*vs* 0.1% and 0.001%, respectively, for the low efficacy vaccine). We see a notable drop in the share for the higher efficiency vaccine compared to the first scenario in Figure 9, highlighting a strong response to side effects. There is extensive heterogeneity in the size of the reductions (mean of 14.6%, ranging from 4.2% for South Africa to 24.4% for Chile), but across study areas, the changes are almost exclusively direct shifts from the higher efficacy to the lower efficacy vaccine, as opposed to an increase in the probability of no vaccination (mean reduction in vaccine uptake is only 1.1%, with the largest reduction in vaccine uptake being 2.6% for France). While, in common with scenario 1, the vaccine uptake rate only changes minimally if the lower efficacy vaccine is removed, the impact of removing the lower efficacy vaccine is now on average greater than the impact of removing the higher efficacy but higher risk of side effects vaccine. This suggests that adding a higher efficacy vaccine will only offer increases in uptake if there is not an associated increase in the risk of side effects and/or waiting time.

An interested reader may also consider the situation where the risk of side effects is higher for the low efficacy vaccine as opposed to the high efficacy vaccine, in line with the blood clots issues with the Oxford-AstraZeneca (Greinacher et al., 2021; Wise, 2021) and Johnson & Johnson vaccines (Mahase, 2021) vaccines. Such a test, easily run with the online scenario tool, shows a notable increase in the share for the higher efficiency vaccine compared to the first scenario in Figure 9, highlighting a strong response to side effects (mean of 10.7%, ranging from 3.8% for South Africa to 16.5% for Hong Kong).



	units	AU	BR	CL	CN	CO	DE	DK	EC	ES	FR	HK	JP	KR	NA	NZ	UK	US	ZA
High efficacy, low risk of side effects, wait 3 months	%	57.4	28.0	66.6	54.9	55.8	58.3	58.0	53.7	53.1	71.5	51.9	75.8	54.4	38.4	56.9	62.9	51.1	45.0
Low efficacy, low risk of side effects, no wait	%	33.8	69.0	26.4	37.6	37.0	27.3	26.9	37.6	35.6	14.9	30.4	20.6	40.1	40.2	34.1	25.3	27.1	38.3
No vaccine	%	8.8	3.0	7.1	7.5	7.2	14.4	15.1	8.6	11.3	13.6	17.7	3.7	5.5	21.3	9.0	11.8	21.8	16.7
No vaccine if only high efficacy available	%	9.9	3.9	7.4	9.0	7.6	15.6	15.4	11.0	13.7	13.9	18.9	3.9	7.6	22.6	10.0	12.3	22.9	19.1
No vaccine if only low efficacy available	%	11.7	3.2	10.1	10.8	9.0	18.2	17.6	12.2	16.7	18.3	20.4	5.7	8.7	24.4	10.8	14.8	25.1	19.6

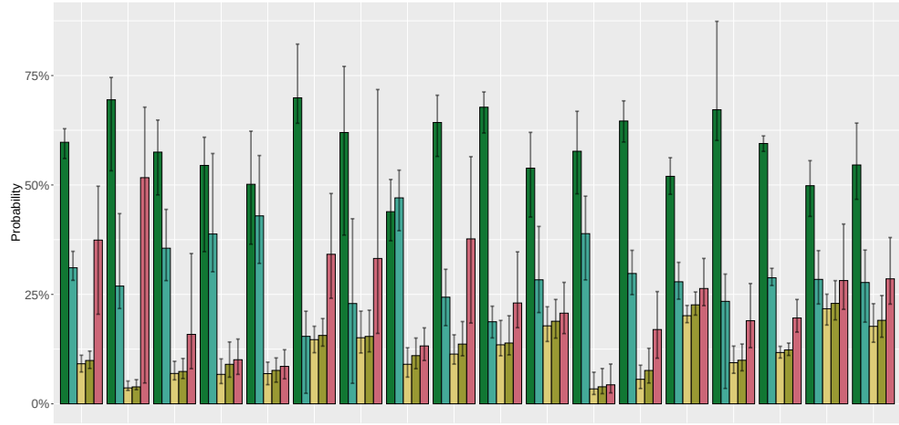
Figure 9: Prediction scenario 1: high efficacy vaccine with three month wait *vs* low efficacy vaccine with immediate access, both with low risk of side effects (95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)



	units	AU	BR	CL	CN	CO	DE	DK	EC	ES	FR	HK	JP	KR	NA	NZ	UK	US	ZA
High efficacy, high risk of side effects, wait 3 months	%	46.3	17.6	42.1	41.1	43.0	46.2	40.6	33.2	39.6	48.9	29.1	57.8	46.1	32.8	37.5	46.4	41.1	40.8
Low efficacy, low risk of side effects, no wait	%	44.3	79.3	49.0	50.1	48.8	37.9	43.2	56.4	46.6	34.9	51.8	37.9	47.8	45.7	52.7	40.5	36.2	42.2
No vaccine	%	9.4	3.1	8.9	8.8	8.2	15.9	16.2	10.5	13.8	16.2	19.1	4.3	6.1	21.4	9.8	13.1	22.6	17.0
No vaccine if only high efficacy available	%	11.8	4.8	10.5	11.9	9.2	18.5	17.1	15.4	17.8	17.9	22.3	5.0	9.3	24.0	12.4	14.4	24.7	19.7
No vaccine if only low efficacy available	%	11.7	3.2	10.1	10.8	9.0	18.2	17.6	12.2	16.7	18.3	20.4	5.7	8.7	24.4	10.8	14.8	25.1	19.6

Figure 10: Prediction scenario 2: high efficacy vaccine with three month wait but high risk of side effects *vs* low efficacy vaccine with immediate access and low risk of side effects (95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)

In that scenario, removing the high efficacy/low risk of side effects vaccine leads to a more marked



	units	AU	BR	CL	CN	CO	DE	DK	EC	ES	FR	HK	JP	KR	NA	NZ	UK	US	ZA
High efficacy, wait 3 months, no fee	%	59.8	69.5	57.5	54.5	50.2	69.9	62.0	43.9	64.3	67.8	53.8	57.7	64.6	52.0	67.2	59.5	49.8	54.6
High efficacy, no wait, pay £100	%	31.1	26.9	35.6	38.8	42.9	15.4	22.9	47.1	24.4	18.8	28.3	38.9	29.8	27.9	23.4	28.8	28.4	27.7
No vaccine	%	9.2	3.6	6.9	6.7	6.9	14.7	15.1	9.0	11.4	13.5	17.8	3.4	5.6	20.1	9.4	11.7	21.7	17.7
No vaccine if only option with wait available	%	9.9	3.9	7.4	9.0	7.6	15.6	15.4	11.0	13.7	13.9	18.9	3.9	7.6	22.6	10.0	12.3	22.9	19.1
No vaccine if only paid option available	%	37.4	51.7	15.9	10.1	8.6	34.2	33.2	13.2	37.7	23.0	20.7	4.3	17.0	26.4	19.0	19.6	28.2	28.6

Figure 11: Prediction scenario 3: high efficacy, low risk of side effects vaccine with three month wait *vs* immediate access for £100 or equivalent (95% confidence intervals by bootstrapping from parameter distribution using asymptotic variance-covariance matrix)

increase in the rate of vaccine refusal by an average of 5.3% across study areas, with especially large increases for France (9.9%) and Spain (9%). The flipside of this finding is of course that the addition of a higher quality vaccine has the potential to substantially increase the rate of vaccine uptake.

Our third scenario (Figure 11) looks at a situation where only the high efficacy vaccine with low risk of side effects is available, but people can now choose to pay for immediate access to avoid the three month wait, where the fee was set to £100, which was adjusted by cost of living indices for other study areas. We predict that a sizeable share of individuals who are willing to be vaccinated would choose to pay to avoid the three month wait (mean of 33.5%, ranging from 18.1% in Denmark to 51.7% in Ecuador). While the addition of a paid option gives some choice to individuals, it is in the present scenario not predicted to substantially impact overall vaccine uptake (mean of 1.1%, ranging from 0.2% for Brazil to 2.5% for Namibia). The removal of the free vaccine however would lead to a substantial drop in vaccine uptake (mean of 12.4%, ranging from 0.9% for Japan to 48% for Brazil).

4 Conclusions

The multi-national study presented in this paper is unique in terms of both its coverage of geographic regions and countries (18 countries and territories from all six inhabitable continents) and in its breadth of analysis. Our use of a consistent survey and econometric analysis across countries allows for detailed comparison and insights across the globe.

Despite the considerable heterogeneity in the study areas involved, and the domestic stage and experience of the pandemic at the time of data collection, we found some meta commonalities across all areas. Importantly, characteristics of vaccines matter, both in terms of the decision to be vaccinated

or not, and in the choice between different vaccines. As such, the likelihood of accepting any given vaccine, or the likelihood of accepting vaccination per se if just a single vaccine is offered, increases with efficacy (both for infection and illness reductions) and decreases with waiting time or the risk of side effects. There is also an overall preference for free vaccination as opposed to paid vaccination, all else equal.

Moving beyond these meta findings, we find considerable heterogeneity across and within countries, in terms of specific vaccine preferences per se, and the role of individual vaccine characteristics. While there are some similarities across areas, for example in terms of the largely consistent pattern of reductions in the risk of infection being valued more highly than reductions in the risk of illness, major differences arise too. This relates to the relative importance of different vaccine characteristics varying across countries, as well as the baseline preferences for vaccination per se, and the willingness to pay for faster access.

Finding reasons for the differences between countries always involves a degree of speculation and future work is needed to investigate the exact reasons, for example through in-depth interviews or focus groups. Nevertheless, it seems safe to say that the complex mix of culture, political ideology, information, trust in government and perceived risks all are likely to play a role, an issue studied in a wider response to COVID-19 context for example by van den Broek-Altenburg and Atherly (2021). Notwithstanding a slower rollout and lower access to vaccines, our findings for Namibia for example are supported by the fact that, in Africa, only about 8% of individuals were fully vaccinated by December 2021, and the slow vaccine uptake has been attributed partially to mistrust and misinformation (Jerving, 2021; WHO, 2021a). There is also evidence from other developing countries, notably Papua New Guinea, that beliefs can play a major role in vaccine hesitancy or outright opposition (Macdonald, 2021).

Alongside trust and cultural effects, a possible reason for the differences could be the perceived risk levels, where our findings from the OL analysis show a link between exposure and vaccination uptake (cf. Figure 5 and 6), a result also supporting the predicted high vaccine uptake for Brazil. Interestingly, we also find groups of study areas with similar results, possibly explained by their similar experiences of and response to the pandemic, geographical proximity or cultural links. For example, we see strong similarities between Colombia and Ecuador. Similarly, results are very consistent between Australia and New Zealand, which reflects the similarity in experience for these two countries, including their generally risk-averse responses to the pandemic and high control of infections through non-vaccine policies at the time of our data collection. Finally, the high predicted uptake in East Asia could relate to a general tendency in that area for more conservative attitudes and government obedience.

Within each study area (with the exception of the small samples for Hong Kong and Japan), we additionally uncover substantial heterogeneity across individual respondents, again both in their preferences for individual vaccine characteristics, and in their overall willingness to be vaccinated. A key implication of our work is that some individuals clearly will accept any reasonable vaccine, while others are resistant to be vaccinated or indeed fundamentally opposed to vaccination. Importantly, we found a third group who are open to vaccination only if the characteristics of the vaccine are right for them. What defines "right" differs across individuals as well as across study areas, but efficacy is of especially great importance, as is a low risk of severe side effects. It is this third (and quite large) group of individuals who will be crucial in any efforts to achieve herd immunity.

A major output of the research is the ability to make predictions of uptake of vaccination against COVID-19. While the paper itself only looks at three such scenarios, the online scenario testing tool at https://stephanehess.shinyapps.io/COVID19_Shiny/ allows for deeper insights, including

studying settings of greater relevance to individual study areas, and for future variants of COVID-19, with different levels of infectiousness and severity. Our findings show that for vaccines with a performance similar to what is currently available, a large majority of the population would accept to be vaccinated. However, the levels of uptake we predict are not guaranteed to be sufficiently high to achieve herd immunity. Greater availability of the most highly performing vaccines may be needed to achieve that objective, as well as concerted efforts to reduce the share of vaccine-resistant individuals in the population. Uptake increases if more efficacious vaccines (95% vs 60%) are offered (mean increase across study areas=3.9%, range of 1.2% to 7.0%), while an increase in severe side effects (from 0.001% to 0.01%) leads to reduced uptake (mean=-1.4%, range of -0.2% to -4.5%). Additionally, a large share of individuals (mean=57.5%, range of 28.1% to 76.7%) would prefer to delay vaccination by 3 months to obtain a more efficacious (95% vs 60%) vaccine, and this increases further if the low efficacy vaccine has a higher risk (0.01% instead of 0.001%) of severe side effects (mean=62.3%, range of 33.8% to 81.2%). Given the large amount of heterogeneity, no single vaccine is likely to be acceptable to all individuals, and our scenarios show that the availability of more than one vaccine at the same time may lead to a further small increase in overall vaccine uptake. Finally, in the context of recent developments to permit paid access to vaccines in some countries (Hassan, 2021), or of people paying substantial amounts of money to travel to countries with easier vaccine availability, we note that a non-trivial share of the population would indeed be willing to pay for faster access, but this provides little benefit in terms of overall vaccine uptake, as these individuals are likely to accept waiting if no paid access is available.

It appears that the highest quality vaccines, which would be most preferred by individuals according to the results of our study, have the largest supply constraints, at least in some countries. This raises questions about how best to ration and prioritise supply. Should the lower efficacy/higher side effect vaccines which are in higher supply and which our results suggest are acceptable to a large proportion in each of our study areas be used first, with more *appealing* vaccines reserved to encourage uptake by those people who are more hesitant, as others are likely to accept any vaccine? This approach is hampered by the fact that it is difficult to a priori identify which part of the population is more likely to be willing to be vaccinated, given that common demographics are not strong predictors of uptake. It is also difficult to reconcile with a policy response taken in many countries to reserve the higher efficacy/lower side effects vaccine for younger people who have been found to be more exposed to side effects. There are also international implications, with the optimal distribution of vaccines not being in line with domestic policy and vaccine protectionism, which has led to the higher quality vaccines not being accessible to areas where they may make a greater contribution to achieving herd immunity. Furthermore, if the likelihood of accepting vaccination depends on the characteristics of the vaccine offered, as shown in our study, then our findings also have important implications for when a different vaccine is used for the second dose in case of shortages, or for a booster shot, where mixing vaccine types is now common practice.

Finally, a crucial component of a globally successful vaccination campaign could be improved messaging, as highlighted for example by Beckman et al. (2021); Merkley and Loewen (2021); Rief (2021). Earlier work by Chanel et al. (2011) stressed the beneficial impact on vaccine uptake of information provided by medical staff as opposed to media and internet, a finding repeated by Solís Arce et al. (2021) in a COVID-19 context. Our country-specific conclusions can be useful for the design of messaging to address remaining COVID-19 vaccine hesitancy and/or resistance. Most crucially, the high impact of side effects and vaccine efficacy on uptake in our scenario testing suggest that objective messaging stressing the rarity of potential severe side effects of vaccination and highlight-

ing the reduction in risk of hospitalisation and death may contribute to a decrease in hesitancy. As pointed out by Machingaidze and Wiysonge (2021), the reasons for COVID-19 vaccine acceptance and hesitancy/resistance remain complex. They stress the balance in communicating what is known and acknowledging the uncertainties that remain, mainly through open communication of all involved agents such as researchers, pharmaceutical manufacturers and policy makers. The results from the present paper may allow these agents to quantitatively understand the factors influencing vaccine acceptance, thus potentially paving the way for better and more targeted messaging.

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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 12 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).

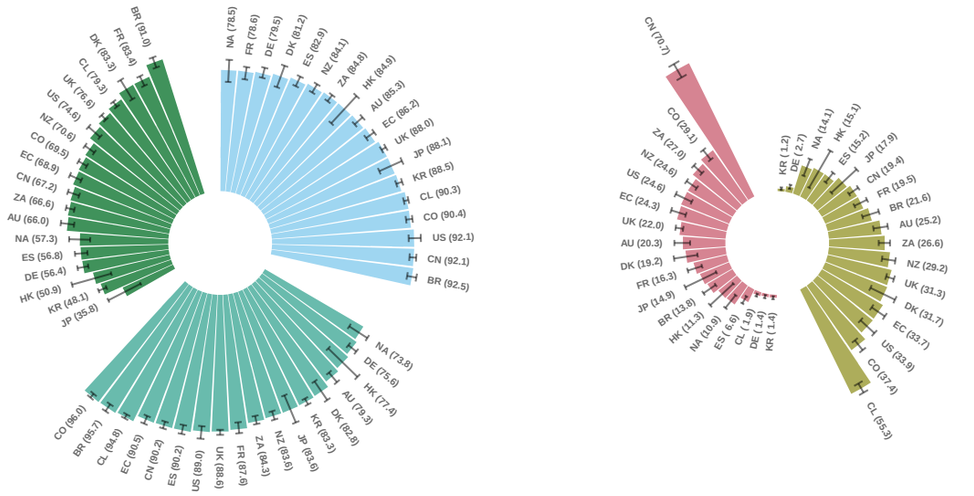
A.2 Ordered logit analysis

A.2.1 Ordered logit analysis: additional theory

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

$$L\left(\Omega_{OL}\right)=\prod_{c=1}^{C}\prod_{n=1}^{N_c}\sum_{s=0}^{S}I\left(Y_{n,c}=\frac{s}{6}\right)\left[\frac{e^{\tau_{s+1}-V_{n,c}}}{1+e^{\tau_{s+1}-V_{n,c}}}-\frac{e^{\tau_{s}-V_{n,c}}}{1+e^{\tau_{s}-V_{n,c}}}\right], \tag{5}$$

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



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

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 5 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 1.

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:

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

The predicted vaccine uptake in a given study area, conditional on study area and person character-

istics, is then calculated as:

$$Y_c\left(\widehat{\Omega}_{OL}, q_c, Z_c\right) = \frac{\sum_{n=1}^{N_c} Y_{n,c}\left(\widehat{\Omega}_{OL}, q_{n,c}, z_{n,c}\right)}{N_c}, \tag{7}$$

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 2.

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 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 4 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:

$$\pi_{n,c,s} = \frac{e^{\alpha_{c,s}}}{\sum_{k=1}^{S_c} e^{\alpha_{c,k}}}, \tag{8}$$

Table 2: 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

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:

$$\widetilde{\pi}_{n,c,s} = \frac{\widehat{\pi}_{n,c,s} \prod_{t=1}^{6} \widehat{P}_{n,c,t,s}}{\sum_{k=1}^{S_c} \widehat{\pi}_{n,c,k} \prod_{t=1}^{6} \widehat{P}_{n,c,t,k}}, \tag{9}$$

where $\widehat{P}_{n,c,t,s}$ and $\widehat{\pi}_{n,c,s}$ are the within class probabilities from Equation 3 and class allocation probabilities from Equation 8, 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:

$$\widetilde{P}_{c,i} = \frac{\sum_{n=1}^{N_c} w_{n,c} \left(1 - vr_{n,c}\right) \sum_{s=1}^{S_c} \widetilde{\pi}_{n,c,s} \widehat{P}_{n,c,s,i}}{\sum_{n=1}^{N_c} w_{n,c}}. \tag{10}$$

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:

$$P_{LC-nv,c,base} = \frac{\sum_{n=1}^{N_c} w_{n,c}\,(1 - vr_{n,c}) \sum_{s=1}^{S_c} \widetilde{\pi}_{n,c,s} \sum_{t=1}^{6} \widehat{P}_{n,c,t,s,5}}{\sum_{n=1}^{N_c} w_{n,c}\,(1 - vr_{n,c})}, \tag{11}$$

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

$$\delta_{c,5,adjusted} = \delta_{c,5,base} + \ln\left(\frac{NV_c}{P_{LC-nv,c,base}}\right), \tag{12}$$

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 10 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 3 and 4. 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 13 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

Table 3: 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 4: 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)

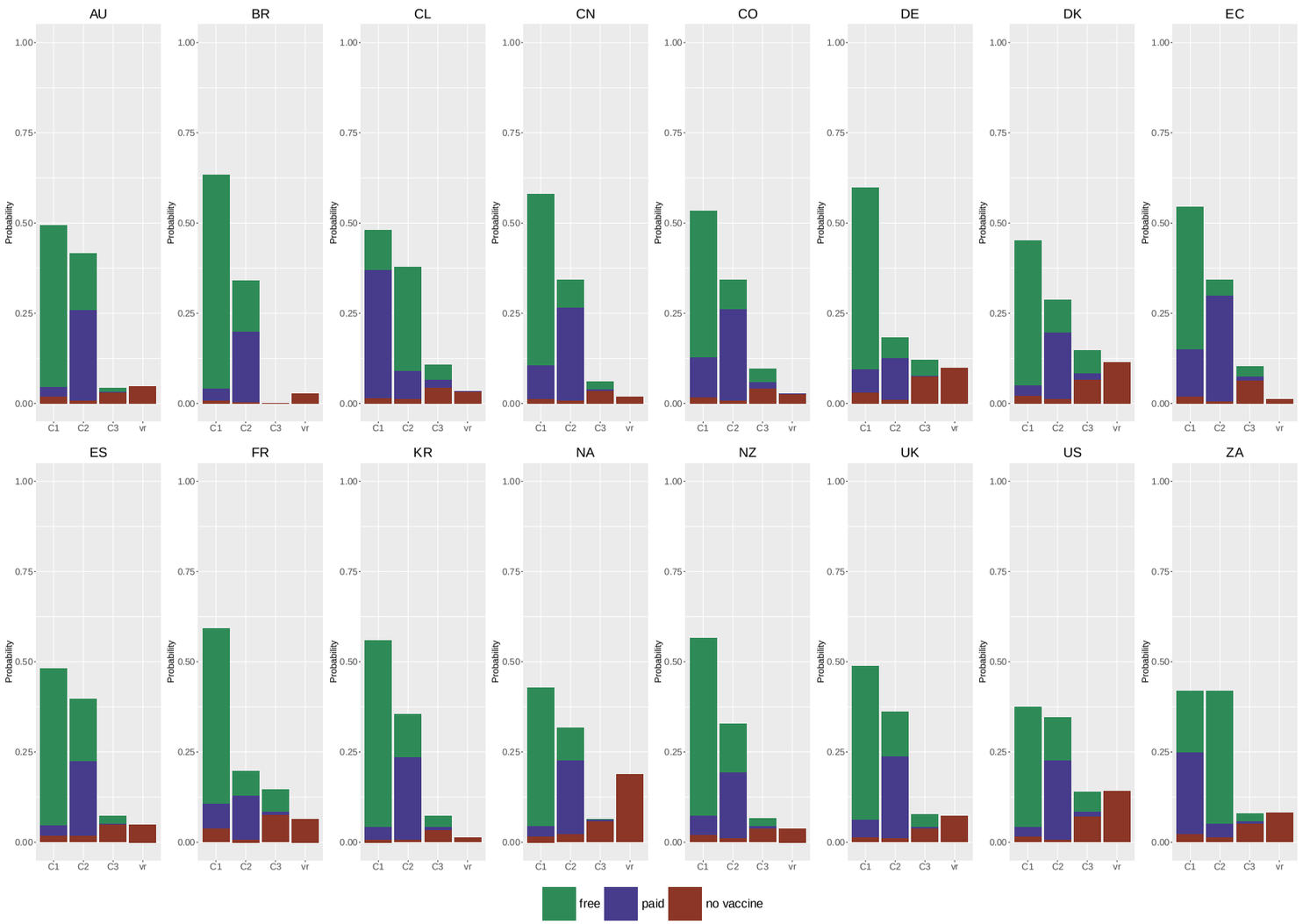


Figure 13: Class sizes and predicted choices within classes in overall data (height shows class weight)

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, with it only clearly exceeding the size of the smallest non-*vr* class in Namibia.

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