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Temporal stability of preferences: The case of COVID-19 vaccines in Australia and New Zealand

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ABSTRACT

This paper introduces a novel two-level Latent Class (LC) structure to investigate the temporal stability of preferences, allowing individuals to switch classes over time. The model is used to investigate the temporal stability of COVID–19 vaccine preferences in Australia (AUS) and New Zealand (NZ) during 2020-2021. Through online experiments on vaccine choices, stated choice data is collected across three waves from the general population in both countries. The LC estimation identifies three distinct preference classes: an “Impatient” group, with greater sensitivity to waiting time (AUS: 46%, NZ: 31%), a “Price Sensitive” group (AUS: 41%, NZ: 56%), and a “Vaccine Hesitant” group (AUS: 13%, NZ: 13%). Across waves, preferences for COVID-19 vaccines remain stable, with the probability of respondents remaining in the same class over three waves being 0.62 for Australia and 0.61 for NZ. Changes in preferences are significantly linked to variations in individuals’ socioeconomic status and COVID–19 policy responses during the survey period.

1. Introduction

Stated choice (SC) surveys, such as Discrete Choice Experiments (DCEs), are commonly used in applied economics as one-off experiments for exploring preferences in decision-making. What is less common is the use of a panel of DCEs (Song et al., 2022). Taking a longitudinal approach through repeated experiments opens up the ability to explore the stability of preferences in the face of exogenous shocks. This investigation focuses on the temporal stability of preferences, i.e., the stability of estimated marginal utility over time. We demonstrate this using the case study of preferences for COVID-19 vaccines in Australia and New Zealand (NZ).

The usefulness of one-off DCEs to inform future public health planning rests on the assumption that vaccine preferences are stable over time. A handful of studies have tested the reliability of this assumption across different settings and periods. While studies have demonstrated stable preferences for medical services (Allanson et al., 2020; Bryan et al., 2000; San Miguel et al., 2002; Salkeld et al., 2005; Skjoldborg et al., 2009), exogenous shocks and changing choice environments across waves can also impact the stability of such preferences. To date, only a handful of studies investigate such topics, with most evidence in the domain of vaccine priority (Luyten and Kessels, 2023) and vaccine preferences (Daziano and Budziński, 2023; Huang et al., 2024; Kong et al., 2025). These studies found stable preferences during and after the pandemic. However, there has been no published evidence on the switching behavior of vaccine preferences, which will be the focus of this paper.

Although the COVID-19 pandemic represented a major shock to global public health and the economy, prompting unprecedented investment in developing and distributing COVID-19 vaccines, vaccine preference may remain stable during this time due to stable intention to get vaccinated, social norm on vaccination, and attitudes toward COVID-19 vaccine (Chambon et al., 2022). However, the rapid changes in micro and macro conditions before and after the pandemic may have also challenged the assumption of stable preferences for COVID-19 vaccines. For example, Daziano and Budziński (2023) conducted a DCE over five distinct waves in the US from October 2020 to October 2021. They found that the vaccination rates increase the probability of vaccine hesitancy and thus may discourage people from getting vaccinated. This evidence is consistent with free-riding behavior. Some countries mandated vaccination for high-risk age groups or occupations, possibly shifting individuals’ preferences in such groups. News

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about the potential side effects of some vaccines may have deterred some consumers from vaccination. During the pandemic, Australia and NZ implemented various national and jurisdictional health policies, such as non-essential business and school closures, and limiting domestic and international travel. These policies have been shown to have immediate impacts on the macroeconomic conditions. For example, Australian underemployment hit a historic high of 13.8% with over 800,000 reported jobs loss, prompting the government to introduce a new wage subsidies program (Australian Bureau of Statistics, 2021). A similar program was implemented from March 2020 in NZ to minimize job losses over the many lockdowns (Fyfe et al., 2023).

Longitudinal DCEs, in which the same individual is asked to state their preferences at different time points of the pandemic, can be used to test the stable preferences assumption. However, this type of data raises the possibility of heterogeneity in preferences across individuals (inter-individual) alongside changes in preferences over time at the level of individual respondents (intra-individual). An increasing number of studies have demonstrated the presence of intra-individual variations in repeated choice surveys that collect multiple responses during a single wave (Hess and Rose, 2009; Hess and Train, 2011; Hess and Giergiczny, 2015; Becker et al., 2018; Song et al., 2022). The common practice to account for such heterogeneity is through a Mixed Multinomial Logit (MMNL) framework with two layers of integration, but this is achieved at a high computational cost (Hess and Train, 2011). Moreover, the MMNL model cannot provide a behavioral explanation for intra-respondent preference heterogeneity. Song et al. (2022) proposed a two-layer latent class modeling (LC) framework to overcome these two limitations. Building upon their framework, we apply a novel two-level LC approach, with S behavioral classes, where each individual is allocated probabilistically to the S^W possible combinations of such classes across W waves. For example, when the data covers two waves and the model identifies two classes, the individuals can be allocated to any of the $2^2 = 4$ combinations, including (i) Class 1 in both waves, or (ii) Class 2 in both waves, or (iii) Class 1 in Wave 1 but Class 2 in Wave 2, or (iv) Class 2 in Wave 1 but Class 1 in Wave 2. Switching behaviors are identified based on combination of (iii) and (iv).

We implement the model to investigate the temporal stability of COVID-19 vaccine preferences in Australia and NZ across three data waves ($W = 3$). We contribute to the existing literature in two ways. First, we provide a novel modeling approach to account for heterogeneity in preferences across both individuals and time, allowing the identification of class-switching behavior (i.e., when respondents switch classes in the follow-up waves). Second, our study is the first to provide evidence of the stability of vaccine preferences and to explore the sources of intra-individual preference in Australia and NZ.

The structure of the paper is as follows. The next section describes the methodology, including the survey design, data collection, and modeling strategy. Section 3 reports our estimation results, and the paper ends with a discussion of the key findings.

2. Methods

2.1. Survey design

The initial survey has been developed for a multi-national project (Hess et al., 2022), where only minor adjustments reflecting differences in health systems, population, and cultural characteristics has been made in the survey development. The core part of the survey is a SC component, in which participants are asked to imagine a situation where some COVID-19 vaccines have been developed, undergone required testing, and received regulatory approval from health authorities. Participants are informed that vaccination reduces the risks of infection and the risk of serious illness once infected. Participants are each faced with six hypothetical choice sets. In each set, they are presented with two different vaccine options.

Each vaccine option is described by five vaccine characteristics (risk of infection, risk of serious illness, protection duration, risk of mild and severe side effects), two non-vaccine characteristics (population coverage as a percentage, and international travel exemptions), waiting time for a free vaccine (in months), and fee to pay if they could obtain vaccination immediately. The attribute levels are summarized in Table A.1, where only the levels for the fee attribute for paid vaccination varied across countries, with values adjusted based on cost of living indices and local insights on the cost of other vaccinations. For a detailed description of the attribute and levels, please refer to Hess et al. (2022).

2.2. Data collection

An online survey has been developed to collect the data in Australia (AUS) and New Zealand (NZ). Participants have been recruited from the general population through multiple approaches, including the use of professional market research companies, and social media advertising.

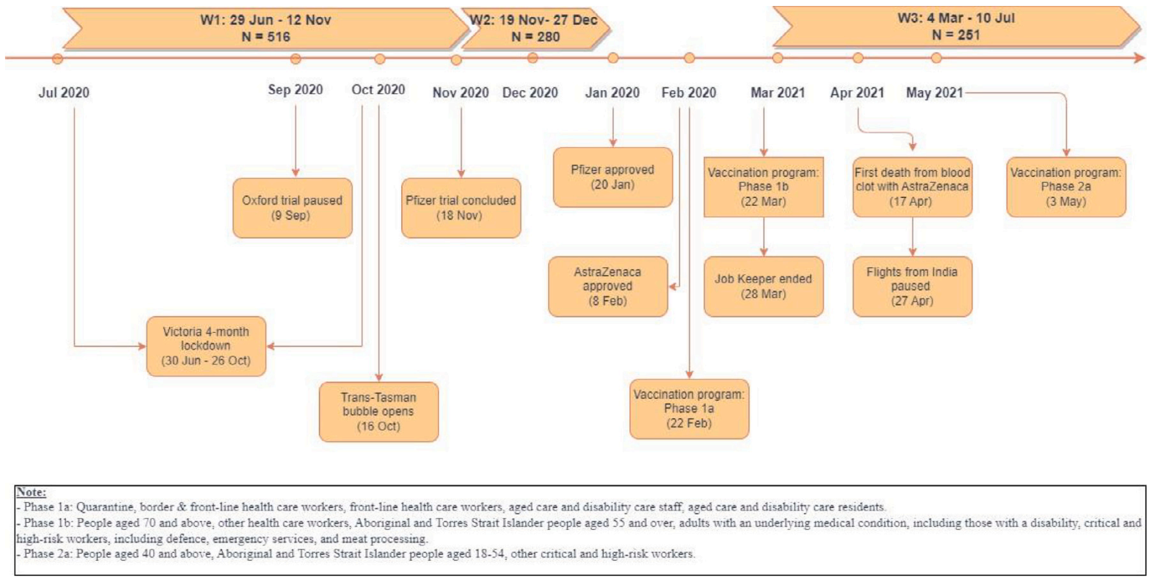
The data collection for Wave 1 started in July 2020 for Australia and August 2020 for NZ. The data comprises 674 Australian and 835 NZ respondents from the general population. Participants have also been asked whether they would like to be contacted for a follow-up survey. In Australia, those who have agreed to be contacted for the follow-up after Wave 1 are sent the Wave 2 and Wave 3 surveys to complete. All participants in the NZ survey are automatically sent Wave 2; and, upon responding to Wave 2 survey, are automatically sent Wave 3. Therefore, the AUS sample contains respondents who responded in (i) Only Wave 1, (ii) Wave 1 and Wave 2, (iii) Wave 1 and Wave 3, or (iv) all three waves. Table A.2 reports the number of observations for the Australian sample for each possibility. The waves are spaced two to four months apart, covering a critical period when preferences for COVID-19 vaccines may have been influenced by macro changes in the political environment (e.g., lockdown), the initial introduction of COVID vaccines, and the emergence of new variants (see Fig. 1). During the same period, micro condition changes such as age, presence of new health conditions, or employment status could also have influenced individuals' preferences to COVID-19 vaccines.

Following Hess et al. (2022), we exclude individuals who complete the survey in less than 11 min in Wave 1 ($\sim 21\%$ in AUS and $\sim 15\%$ in NZ), and further remove individuals who are test cases (AUS: 1 case; NZ: 0 case). Therefore, our final sample is an unbalanced panel of 516 Australians and 710 NZ respondents. The attrition rate over time is 41.6% in Wave 2, and 53.4% in Wave 3 for the Australian data, and 32.7% in Wave 2, and 55.6% in Wave 3 for the NZ data. If the attrition is not random (i.e., vaccine-hesitant people dropping out of the survey), then our estimation could be biased. However, we conduct a Heckman selection analysis and find no evidence of selection bias within our sample (see Appendix A4). Therefore, we present our estimation using the unbalanced sample, as this includes the most comprehensive and complete information.

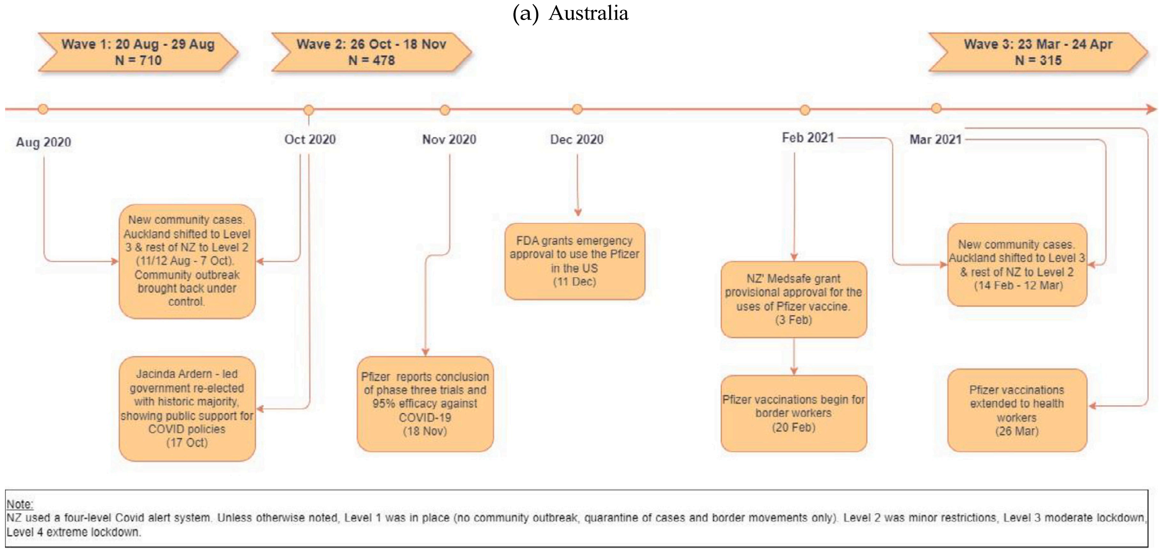
2.3. Modeling strategy

2.3.1. Exploratory analysis of the choice data

We start with an exploratory analysis of the raw choice data to understand changes in individuals' choices over time. We allocate individuals to one of three categories based on their responses to the six choice tasks within each experiment/wave. The existing literature contains many definitions of vaccine hesitancy (Acharya et al., 2025; Bussink-Voorend et al., 2022). Since our study focuses mainly on the transition between different preference groups identified through the LC-NL model, it is particularly important to understand whether people switch from Pro-vaccine or Trader to Vaccine Hesitant. Therefore, we developed the following classifications. If an individual always selects a vaccine option, they are classified as "Pro-vaccine". If an individual never selects a vaccine, they are classified as "Vaccine Hesitant". If



(a) Australia



(b) New Zealand

Fig. 1. Survey timeline.

an individual selects a mix of no vaccine and vaccine, some of the time, they are classified as "Traders". We then conduct paired t-tests for differences in these categories across waves. As a robustness check, a partially-overlapping sample t-test is also conducted and the results remain similar to the paired t-tests (Derrick and White, 2022).

2.3.2. *Behavioral model: wave-specific without heterogeneity*

Next, we estimate the choice model for a wave-specific analysis without accounting for random heterogeneity. For person i in country c, the deterministic component of utility for alternative n in choice scenario t_w (in wave w) is written as:

$$V_{i,c,n,t_w} = \delta_{c,n} + \beta_c{}' x_{i,c,n,t_w}, \tag{1}$$

where $\delta_{c,n}$ is the constant for alternative n in country c, x_{i,c,n,t_w} is a vector of attributes describing alternative n as faced by individual i in country c in choice situation t_w, and β_c is the associated vector of parameters to be estimated. In line with Hess et al. (2022), we use the no vaccine option as the base, normalizing its constant to zero, and estimate separate constants for free (ASC_{free}) and paid vaccine (ASC_{paid}) options. For the "no vaccine" option, the only attributes that entered the utility function are the risks of infection and illness, using the fixed baseline levels. All attributes are treated as continuous, except for the dummy coded travel exemption attribute, while an additional penalty for unknown duration is included alongside the continuous duration attribute.

The underlying model structure is in line with the work of Hess et al. (2022), using a Nested Logit (NL) model (Train, 2009) to capture potentially greater substitution between the different vaccine options, thus grouping together the vaccine options into one nest. A schematic tree representation of our modeling strategy can be seen in Fig. 2.

Let $Y_{i,c,n,t_w} = 1$ if individual i in country c chooses option n in choice scenario t in wave w, and 0 otherwise. With option 5 being the no vaccine option, we then have that the probability of the observed choice for individual i in country c and task t_w, is given by:

$$P_{i,c,n,t_w}(\Omega_c) = \frac{\sum_{n=1}^{4} Y_{i,c,n,t_w,j} \cdot e^{\frac{V_{i,c,n,t_w}}{\lambda}} \left(\sum_{n=1}^{4} e^{\frac{V_{i,c,n,t_w}}{\lambda}}\right)^{\lambda-1} + Y_{i,c,5,t_w} \cdot e^{V_{i,c,5,t_w}}}{\left(\sum_{n=1}^{4} e^{\frac{V_{i,c,n,t_w}}{\lambda}}\right)^{\lambda} + e^{V_{i,c,5,t_w}}}, \tag{2}$$

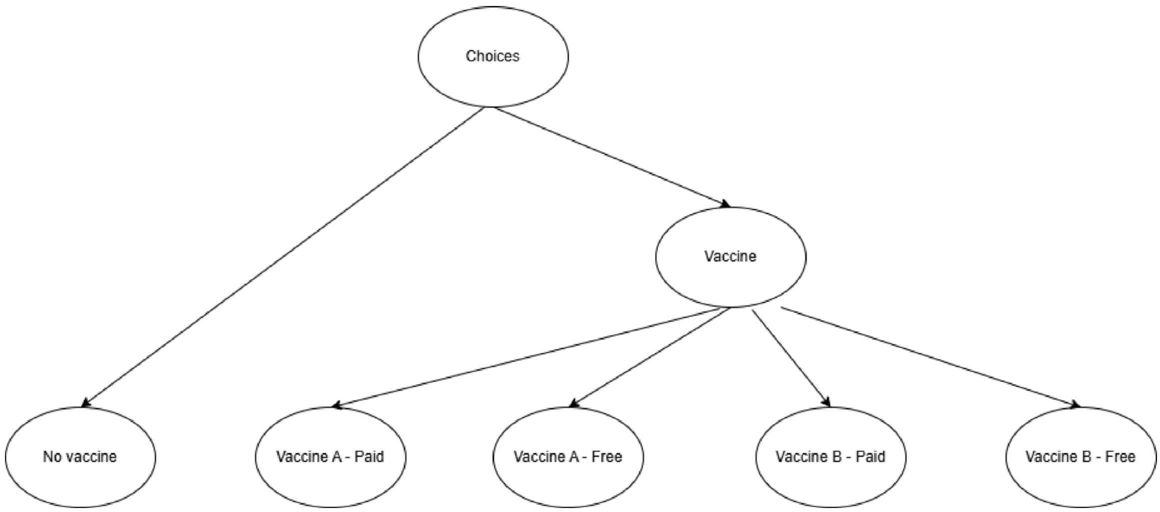


Fig. 2. A schematic tree representation of the choice model.

where Ω_c groups together all the parameters, namely the δ and β terms from Eq. (1), and the nesting parameter λ, with $0 < \lambda \leq 1$. λ is a measure of the degree of independence in unobserved utility among the alternatives under the "vaccine" nest, namely: free Vaccine A, paid Vaccine A, free Vaccine B, and paid Vaccine B.

2.3.3. Test for preference stability

To test for the stability of preferences, we estimate wave-specific NL models (Eq. (2)) and follow the procedure proposed by Swait and Louviere (1993) to test poolability across all waves of data, specifically testing if preferences and scale are stable across waves. First, we perform a visual test by plotting the estimated coefficients of common attributes in one wave against another. We obtain these estimated coefficients using the NL model to account for potential substitution between the different vaccine options, as outlined in the previous section. If the coefficients are clustered around a line, it is suggestive evidence that preferences are potentially stable across waves. If the slope of the line differs from a 45-degree line, this indicates that scale between the waves are different. This plot can also help identify if preferences for specific attributes (specific coefficients) have changed, by observing points that noticeably diverge from the line. The steps for performing this test and described as follows:

- Estimate the NL models for each wave and save the log likelihood (LL) for each wave as LL_1, $LL2$, and LL_3.
- Estimate the pooled NL model from all three waves. Since the pooled model assumes equal scale and preference parameter, we obtained the LL for the stable-preference model: LL_{pool}.
- Conduct a Likelihood Ratio (LR) test for whether the preference parameters are the same. The test statistic is calculated as $-2[LL_{pool} - (LL_1 + LL_2 + LL_3)]$. This can be compared to a χ^2 critical value, with $2K$ degrees of freedom, where K is the numbers of parameters used per wave.
- If the test is rejected, we conclude that preferences are not stable across waves.

2.3.4. Latent class model without switching behavior

We extend the NL model in Eqs. (1) and (2) to allow for LC structure. The motivation to use a LC structure (Hess, 2024) to analyze the data was driven by the expected high levels of heterogeneity in preferences even within a study area, in line with the work in Hess et al. (2022). We first rewrite the deterministic component of utility in Eq. (1) so that it is specific to latent class s, by using:

$$V_{i,c,n,t_w,s} = \delta_{c,n,s} + \beta_{c,s}{}' x_{i,c,n,t_w}. \tag{3}$$

From this, we then rewrite the probability of choice in Eq. (2) as, $P_{i,c,t_w,s}$ for class s.

In the model without switching behavior, we assume that class membership remains constant across waves at the person level. As the membership in the classes is latent, the likelihood for the observed sequence of choices for person i is given by a weighted average across S classes, using the class allocation probabilities as weights. The likelihood function for the NL model with LC in country c is then given by:

$$L\left(\Omega_{LC,c}\right) = \prod_{i=1}^{N_c} \left[\sum_{s=1}^{S} \pi_{i,c,s} \prod_{w=1}^{W} \prod_{t_w=1}^{6} P_{i,c,t_w,s}\left(\Omega_{c,s}\right) \right], \tag{4}$$

where $\Omega_{LC,c}$ groups together all model parameters, N_c are the numbers of participants each country, and W are numbers of waves. Note that this formulation includes a product across the three waves, where any individual not taking part in all waves will only contribute observations for some of the waves.

The class allocation weights $\pi_{i,c,s}$ are given a logit probability, with:

$$\pi_{i,c,s} = \frac{e^{\alpha_{c,s}}}{\sum_{r=1}^{S} e^{\alpha_{c,s}}}, \tag{5}$$

where, for normalization, we set $\alpha_{c,1} = 0$. The class allocation probabilities in our model are specified as constant, i.e., they do not vary as a function of characteristics of the individual.

2.3.5. Latent class model with switching behaviors

Although the above LC model can capture the heterogeneity across respondents, it cannot capture any potential changes in preferences over time at the level of individual respondents. This is the motivation for our LC model with class switching across waves.

Re-using the earlier notation, we now have:

$$L\left(\Omega_{LC,c}\right) = \prod_{i=1}^{N_c} \left[\sum_{s_1=1}^{S} \sum_{s_2=1}^{S} \sum_{s_3=1}^{S} \pi_{i,c,s_1 s_2 s_3} \prod_{w=1}^{W} \prod_{t_w=1}^{6} P_{i,c,t_w,s_w}\left(\Omega_{c,s_w}\right) \right], \tag{6}$$

where s_1, s_2, s_2 denotes the latent class in Waves 1,2, and 3. This specification differs from the earlier model in that we now have a sum across S^W different classes, with each combination of the S classes across W waves being possible. The within-class likelihood then still uses a product across the 18 choices for an individual, but, depending on the combination of classes that applies, uses different parameters in the different waves.

The class allocation weights $\pi_{i,c,s_1 s_2 s_3}$ now relate to the probability assigned to a combination of classes across waves, and are again specified in our model as a logit probability, with:

$$\pi_{i,c,s_1s_2s_3} = \frac{e^{\alpha_{c,s_1s_2s_3}}}{\sum_{r_1=1}^{S}\sum_{r_2=1}^{S}\sum_{r_3=1}^{S} e^{\alpha_{c,r_1r_2r_3}}}, \tag{7}$$

where, for normalization, we set $\alpha_{c,111} = 0$. The only difference in terms of number of parameters compared to the standard model is the estimation of a larger number of parameters in the class allocation model (two parameters in the standard LC model vs. 26 parameters in the new model).

2.3.6. Relating micro and macro factors to switching behaviors

Estimating how micro factors (e.g., age, employment) and macro factors (e.g., COVID-19 policy) influence switching behaviors can provide insights for policy. This can be examined by including these variables in the class allocation function (Eq. (7)). However, including more variables led to computational issues since our model already included many parameters (26 class-specific constants). Moreover, this one-step approach could result in mis-specified models (Nylund-Gibson and Masyn, 2016). Thus, we opt to estimate a simpler model without these characteristics, and in our post-estimation analysis we explore how these characteristics relate to the switching behaviors, using the estimated posterior class allocation probabilities and the Fractional Multinomial Logit (FMNL) model (Papke and Wooldridge, 1996). We detail the steps to obtain the final results below.

Firstly, we calculate the conditional class allocation probabilities, resulting in 27 class probabilities per individual. We classify these 27 class probabilities into five major groups: Stayers, Pro-vaccine to Vaccine Hesitant, Vaccine Hesitant to Pro-vaccine, Switchback, and Pro-Switchers. Stayers are individuals who stayed in the same classes across three waves. Pro-vaccine to Vaccine Hesitant are people who switched from any vaccine option to the "no vaccine" option. Vaccine Hesitant to Pro-vaccine are individuals who switched from the "no vaccine" option to any vaccine option. Switchback are individuals who switched back to their original choices over time. Pro-switchers switched during the survey period but only switched among the vaccine options. The group probabilities are calculated as a sum of the class probabilities. For example, the probability of being a Stayer is a sum of the probabilities of being in Class 111, Class 222, and Class 333.

The next step involves matching the individuals' group probabilities with their baseline micro and macro characteristics. Micro parameters include individual demographics (gender, age), education, household income, employment, health status, and trust. Macro variables include the daily Oxford stringency index at the country level, a composite measure of nine COVID-19 responses, e.g., lockdown. The higher the score, the stricter the response. Other macro variables have been used in addition to the stringency index, including numbers of COVID-19 cases and deaths. However, these variables are highly correlated with the stringency index. Thus, only the stringency index is used to avoid potential multicollinearity.

Lastly, we model the group probabilities as a function of these micro and macro characteristics using the FMNL model. Although the LC model with switching behavior used all available information (i.e., unbalanced panel), the FMNL estimation only used the balanced panel to ensure the individual macro and micro characteristics were available across all three waves.

3. Results

3.1. Sample statistics

In both countries, the average age of respondents is the late 40 s, with the samples significantly older across waves. Over half of the respondents are females in both countries. Although the gender composition in the Australian sample remain relatively stable, there are significantly fewer female respondents in Wave 3 of the NZ survey. The average household income for both samples decrease over time, potentially reflecting the significant increase in numbers of retirees in both samples and the decline in Australian working respondents. These descriptive statistics are summarized in Appendix Tables A.3 and A.4.

Our surveys also collect information on individuals' risk perception and attitudes toward COVID-19 and general societal issues. Risk perceptions and attitudes are somewhat similar between the two countries, except for the estimated population share of people who have been infected and the estimated risk of death if infected with COVID-19. Australian respondents have a higher perceived risk, estimating higher COVID-19 prevalence and risk of death than NZ respondents. Over time, more respondents in both countries believe that COVID-19 infection leads to symptoms but fewer thought it will lead to more severe consequences, e.g., illnesses, hospitalization, or death.

While the perceived risk of death and the population share of infected people are stable in NZ, Australian respondents expected COVID-19 infections to become more prevalent (i.e., a higher population share of infected people) but less severe (i.e., lower own death risks) across three waves. Overall, attitudes toward COVID-19 and general societal issues also change significantly. In both countries, respondents are less concerned with COVID-19 and the impacts of COVID-19 on various aspects of their lives and society over time. We present these statistics in Appendix Tables A.5 and A.6.

Since our data have considerable attrition rates, we estimate a Heckman selection model as a robustness check for selection bias (Cameron and Trivedi, 2010). This model statistically tests whether participation in the follow-up surveys is random. If non-random, the factors determining participation in the follow-up surveys may be correlated with the factors determining their choices of COVID-19 vaccines, violating the assumption of independent and identically distributed errors. In both countries, we note that unobserved factors, which influence selection into subsequent waves, are negatively associated with individuals choosing "no vaccine". However, these parameters are statistically non-significant, indicating that our estimated choice models do not suffer from selection bias. We summarize the test and its results in Appendix A4.

3.2. Exploratory analysis of the choice data

3.2.1. Vaccine preferences categorization

Table 1 reports the vaccine preference categories across three waves in Australia and NZ. We report the results of paired t-tests for differences in these categories across waves in the last two columns.

In Wave 1, most respondents are classified as "Pro-vaccine" (AUS: 76.02%, NZ: 74.79%), followed by "Traders" (AUS: 17.21%, NZ: 21.76%). Approximately seven percent of the Australian respondents are "Vaccine Hesitant", while the proportion of this group is slightly lower in the NZ sample (5%). In Australia, the sample of "Vaccine Hesitant" remains relatively stable across waves. A similar pattern is observed for NZ data, except for an increase to almost 7% in Wave 3. There are fewer respondents classified as "Pro-vaccine" in Australia across all waves. In NZ, numbers of "Pro-vaccine" decrease in Wave 2 and increased again in Wave 3. These changes are not statistically significant; however, we observe a significant difference in the proportion of "Traders" in both countries. While the changes in the "Trader" sample in Australia is likely to be driven by the decrease in the "Pro-vaccine" sample, the changes in NZ is spread between small increases in the proportions of respondents in the Pro-vaccine and Vaccine Hesitant categories. Overall, there are small differences in vaccine preference groups between Wave 2 and Wave 3 in both countries, except for "Traders" group in New Zealand.

3.2.2. Vaccine preference by age

Since vaccine roll-out is based on age in both countries, we also show the distributions of vaccine uptake for each age group and each wave (see Appendix Tables A.7 and A.8). Overall, there are no significant changes in the respondents who always choose the status quo

Table 1
Vaccine preferences across waves.

	W1	W2	W3	Test for difference-in-mean		
				W1 vs. W2	W1 vs. W3	W2 vs. W3
Australia						
Pro-vaccine	76.02%	71.17%	71.43%	−4.85%	−4.59%	0.26%
Trader	17.21%	23.13%	21.43%	5.92%**	4.22%	−1.70%
Vaccine hesitant	6.77%	5.69%	7.14%	−1.08%	0.37%	1.45%
Observations	**516**	**280**	**251**			
New Zealand						
Pro-vaccine	74.79%	73.43%	78.41%	−1.36%	3.62%	4.95%
Vaccine hesitant	4.51%	4.81%	6.98%	0.30%	2.47%	2.17%
Observations	**710**	**478**	**315**			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

across ages. However, in both countries, we observe a rise of older adults (aged 70 years and above) being classified as “Pro-vaccine”. This pattern likely reflects the vaccine roll-out, as this age group is among the first to receive COVID-19 vaccines. In addition, Australian respondents aged 40–49 are more likely to switch from “Pro-vaccine” to “Traders” in later waves. Contrarily, the same age group in NZ is less likely to be “Traders” in later waves.

3.2.3. Vaccine hesitant behavior

For the “Vaccine Hesitant” group, respondents are also asked in the survey why they do not choose a vaccine option. Using this information, we explore the changes in the reasons for choosing the no-vaccine option across waves. The results are summarized in Appendix Tables A.9 and A.10.

In both countries, the most reported reason in Wave 1 for not choosing the vaccine option is “*believing the vaccines needed more testing*”, followed by the preference to obtain natural immunity without vaccination. However, this pattern changes slightly in later waves. Although the most commonly reported reason do not change, the second most common reason for not choosing vaccination changes to “*not believing in the benefits of vaccinations*”. Fewer respondents state preferring to obtain natural immunity as their reason in later waves.

3.3. Swait-Louviere test

A formal test for preference stability is performed with detailed estimation results and the visual test summarized in Appendix A5. For both countries, the Swait–Louviere test rejects the null hypothesis that preferences are stable at all common levels of significance (Test statistic $= 190.18 > \chi_{26,0.95} = 38.9$ (AUS) and $190.18 > \chi_{26,0.95} = 38.9$ (NZ)). The Wald test for coefficient equality across three waves is also rejected, suggesting that the preference for the COVID-19 vaccine is less likely to be stable over time. As a sensitivity check, we repeat the test for the balanced sample (i.e., the sample of respondents who answered all three waves). The null hypothesis that preferences are stable across waves is also rejected. This result is consistent with our previous finding that attrition is unlikely to affect our results. As part of the modeling process, we have also estimated a scaled model to account for potential scale heterogeneity. Overall, we detect minor scale differences across waves. However, the estimates from the scaled models are not too different from the pooled model, which does not account for scale differences. We also calculate the marginal rates of substitution (MRS) based on the willingness to wait, and we find the magnitude and directions of the attributes to be very similar between the two models. Since our paper also focuses on examining the changes in preferences and measuring the transitioning between different classes, there is little benefit to account for scale in this application. For model parsimony and simplicity, we opted to report only the pooled model in the main results.

3.4. Latent class estimation without switching behavior

We estimate Eq. (4) for up to five classes, and the three LC models are chosen based on the Akaike information criteria (AIC) and the Bayesian information criteria (BIC) for Australia. We also estimate a three-class model for NZ to allow for consistency of interpretation of LC models between countries. Based on the goodness-of-fit test, the NZ estimation uses a generic nesting parameter λ, while the AUS estimation uses a class-specific nesting parameter $\lambda_s, s = 1, 2, 3$. We summarize the AIC and BIC for up to five LC estimations in Appendix Figure A.3. We report the preferred LC-NL estimation in Table 2.

Our preferred LC-NL model identifies three classes, which are described as follows:

- **Class 1** or “Price Sensitive” is characterized by greater sensitivity to price. The estimated coefficient on “Fee” is significantly negative and largest in magnitude and MRS across three classes. Moreover, the significantly positive ASC_{free} coefficient in this class indicates that respondents in this group have strong preferences for the “free vaccine” option.
- **Class 2** or “Vaccine Hesitant” is dominated by the “no vaccine” option. The ASCs for this class are significantly negative at all common levels of significance, indicating that individuals in this group strictly prefer the “no vaccine” over any vaccine option (regardless of paid or free).
- **Class 3** or “Impatient” always prefer “vaccine” over “no vaccine” options, as shown by the significantly positive ASCs for free and paid vaccine alternatives. Individuals in this group are also the most sensitive to waiting time for vaccine access, as its estimated utility weight on “waiting time” is the largest among the three classes.

In both countries, there are higher probabilities of being classified as “Price Sensitive” (AUS: 46%, NZ: 56%), followed by “Impatient” (AUS: 40%, NZ: 31%). “Vaccine Hesitant” is the smallest of both countries’ samples (AUS: 14%, NZ: 13%).

There are some similarities between the two countries regarding their preferences for vaccines. Specifically, all classes prefer longer protection duration (if known), lower risks of severe side effects, and lower costs to obtain the vaccine. Population coverage is significant only in the “Price Sensitive” and “Impatient” groups. For both Australian and NZ estimations, the risk of severe side effects is the most important attribute in all classes but relatively more important for “Price Sensitive” than other classes. “Vaccine Hesitant” in both countries are similar, except for the waiting time and risk of serious illness. In both countries, “Vaccine Hesitant” prefers shorter waiting times and lower risk of serious illness, but these attributes are only statistically significant in Australia.

Table 2
LC-NL estimation, without switching behavior.

	Class 1: Price sensitive		Class 2: Vaccine hesitant		Class 3: impatient	
	AUS (46%)	NZ (56%)	AUS (14%)	NZ (13%)	AUS (40%)	NZ (31%)
ASC_free	1.141***	1.362***	−1.184***	−1.062***	0.985***	1.581***
	(0.354)	(0.232)	(0.436)	(0.385)	(0.343)	(0.356)
ASC_paid	−0.702*	0.685**	−1.843***	−2.236***	1.208***	1.743***
	(0.393)	(0.285)	(0.757)	(0.491)	(0.371)	(0.362)
Risk of infection	−0.138***	−0.097***	−0.012	−0.023	−0.179***	−0.067***
	(0.030)	(0.022)	(0.021)	(0.026)	(0.035)	(0.014)
Risk of serious illness	−0.115***	−0.068***	−0.023	−0.032*	−0.083***	−0.050***
	(0.015)	(0.011)	(0.019)	(0.017)	(0.017)	(0.012)
Unknown protection	−0.068	−0.072	0.106	−0.074	−0.177	−0.036
	(0.113)	(0.053)	(0.102)	(0.124)	(0.128)	(0.073)
Protection duration	0.018***	0.013***	0.006**	0.004*	0.016***	0.013***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Risk of mild side effects	−0.065***	−0.040***	−0.010	−0.010	−0.044***	−0.027***
	(0.012)	(0.007)	(0.009)	(0.012)	(0.012)	(0.008)
Risk of severe side effects	−36.40***	−20.19***	−19.22***	−18.20**	−30.76***	−11.83***
	(6.753)	(4.266)	(6.051)	(7.512)	(7.371)	(4.445)
Waiting time	−0.034***	−0.016***	−0.003	−0.013***	−0.054***	−0.028***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.008)	(0.006)
Fee	−0.005***	−0.005***	−0.001*	−0.002**	−0.002***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Population coverage	0.015*	0.017***	0.003	0.000	0.001	0.019*
	(0.008)	(0.006)	(0.002)	(0.002)	(0.007)	(0.010)
Travel exemption	−1.105**	−0.184	−0.242	−0.036	−0.246	−0.771
	(0.535)	(0.348)	(0.252)	(0.169)	(0.363)	(0.502)
λ	1	0.594***	0.408**	0.594***	1	0.594***
	(.)	(0.081)	(0.190)	(0.081)	(.)	(0.081)
α	0	0	−1.234***	−0.586***	−0.168	−1.507***
	(.)	(.)	(0.150)	(0.140)	(0.123)	(0.133)

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. λ is a nesting parameter for the "vaccine" group. Standard errors are clustered at the individual level, reported in parenthesis. Numbers of respondents = 516 (AUS) and 710 (NZ). Log-likelihood = −7,388.67(AUS) and −10,347.71 (NZ).

3.5. Latent class estimation with switching behavior

We report the estimation of the LC-NL model with switching behavior in Table 3. Three classes are identified for each wave, resulting in $3^3 = 27$ different combinations. The parameters of attributes and the ASCs are weighted and reported for each class. Parameters $\alpha_{c,s_1s_2s_3}$ represent the constant in the class allocation functions, with $s_1s_2s_3$ representing the class in each wave. For example, α_{123} represents the constant for the group where Class 1 is identified in Wave 1, Class 2 in Wave 2, and Class 3 in Wave 3. Thus, "Stayers" groups' constants are $\alpha_{111}, \alpha_{222}$, and α_{333}, and the other constants characterize the "Switchers" groups. For ease of analysis, we fix some of the $\alpha_{s_1s_2s_3}$ to a small value (−10) if their contribution to the sample is less than 0.1%.

Overall, the estimated parameters and class structures in the LC-NL model with switching behaviors are similar to the LC-NL model without switching behavior, even though the two models are estimated independently. The LC-NL model with switching behavior also identifies three distinct classes in each wave: "Price Sensitive", "Vaccine Hesitant", and "Impatient", with similar characteristics to those identified in the LC-NL estimation without switching behaviors. Preferences changes are measured as changes in the identified classes across the three waves. Across waves, preferences for COVID-19 vaccines remain stable, with the probability respondents remaining in the same class across three waves being 0.62 for Australia and 0.61 for NZ. NZ respondents have higher probabilities of switching from any of the pro-vaccine classes (i.e., "Vaccine Hesitant" and "Impatient") to "Vaccine Hesitant" than AUS respondents. Similar patterns are observed in the probability of switching back to Wave 1's identified preference classes. Interestingly, the likelihood of respondents switching from "Vaccine Hesitant" to any pro-vaccine classes is five times higher in Australia (0.4) compared to NZ (0.08).

3.6. Characteristics of switchers and non-switchers

Table 4 summarizes the estimation described in Section 2.3.6. Using the conditional probabilities estimated from Eq. (7), we can relate micro and macro factors to the switching behavior of five different groups: "Stayers", "Pro switchers", "Pro to Vaccine Hesitant" "Hesitant to Pro vaccine", and "Switch back".

There are variations in how these factors influence switching behaviors. In both countries, class-switching behaviors are significantly associated with micro-factors, such as household income, changes in employment status, mental health status, and trust in social media and healthcare providers for vaccine information. For instance, compared to "Stayers", "Pro-vaccine to Hesitant", and "Hesitant to Pro-vaccine" in Australia are less likely to report being out of work during COVID-19. However, they are also more likely to report worse physical health after the pandemic. Trusting family and friends as a source of vaccine information is not a significant determinant of switching behaviors in both countries. Interestingly, age, gender, chronic health conditions, and trusting traditional media for vaccine information significantly correlate with switching behaviors in Australia but not NZ. Likewise, trusting government websites or campaigns is a significant determinant in NZ rather than Australia.

We use the country-level daily stringency index to capture the macro-factors impacting the switching behaviors. The stringency index is a composite measure of nine of the COVID-19 policy responses, including school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport,

Table 3
LC-NL estimation, with switching behavior.

	Class 1: Price sensitive		Class 2: Vaccine hesitant		Class 3: Impatient	
	AUS	*NZ*	*AUS*	*NZ*	*AUS*	*NZ*
ASC_free	1.107***	1.193***	−3.297***	−2.569**	0.963**	1.360***
	(0.299)	(1.115)	(0.818)	(0.211)	(0.421)	(0.**315**)
ASC_paid	−1.006**	0.891***	−4.254***	−4.361***	1.646***	1.644***
	(0.394)	(0.280)	(0.881)	(1.249)	(0.449)	(0.305)
Risk of infection	−0.126***	−0.086***	0.137	0.134	−0.204***	−0.098***
	(0.024)	(0.016)	(0.095)	(0.111)	(0.038)	(0.023)
Risk of illness	−0.108***	−0.074***	−0.059	−0.031	−0.076***	−0.050***
	(0.013)	(0.012)	(0.040)	(0.042)	(0.020)	(0.012)
Unknown protection	−0.086	−0.095*	0.552	−0.061	−0.167	−0.069
	(0.093)	(0.056)	(0.460)	(0.524)	(0.141)	(0.080)
Protection duration	0.017***	0.013***	0.011**	0.005	0.018***	0.015***
	(0.002)	(0.002)	(0.005)	(0.006)	(0.003)	(0.003)
Risk of mild side effects	−0.053***	−0.041***	−0.021	0.018	−0.057***	−0.031***
	(0.010)	(0.007)	(0.026)	(0.034)	(0.013)	(0.009)
Risk of severe side effects	−35.99***	−19.4***	−50.12**	−42.76*	−31.68***	−15.35***
	(5.966)	(4.120)	(23.38)	(21.93)	(8.052)	(5.116)
Waiting time	−0.032***	−0.016***	−0.024	−0.012	−0.056***	−0.036***
	(0.005)	(0.004)	(0.019)	(0.016)	(0.008)	(0.008)
Cost	−0.004***	−0.013***	−0.001	0.0004	−0.003***	−0.002***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.0004)
Population coverage	0.012*	0.020***	0.012*	0.004	0.008	0.017*
	(0.007)	(0.007)	(0.008)	(0.007)	(0.013)	(0.009)
Travel exemption	−0.643*	−0.221	0.312	0.466	−0.652	−0.922*
	(0.354)	(0.361)	(0.468)	(0.414)	(0.564)	(0.493)
λ	1	0.668***	0.490**	0.668***	1	0.668***
	(.)	(0.094)	(0.177)	(0.094)	(.)	(0.094)
$\alpha_{s_1 11}$	0	1.211***	−2.556***	−2.049***	−0.754***	−0.201
	(.)	(0.180)	(0.360)	(0.466)	(0.194)	(0.235)
$\alpha_{s_1 21}$	−3.373***	−1.489***	−10.00	−2.831***	−3.440***	−2.975***
	(0.599)	(0.383)	(.)	(0.651)	(0.702)	(0.785)
$\alpha_{s_1 31}$	−2.257***	−1.414***	−10.00	−10.00	−10.00	−0.360
	(0.417)	(0.374)	(.)	(.)	(.)	(0.298)
$\alpha_{s_1 12}$	−1.884***	−1.650***	−4.394***	−3.384***	−10.00	−1.956***
	(0.313)	(0.424)	(0.988)	(1.159)	(.)	(0.509)
$\alpha_{s_1 22}$	−2.766***	−2.197***	−1.914***	−1.303***	−10.00	−10.00
	(0.430)	(0.483)	(0.238)	(0.279)	(.)	(.)
$\alpha_{s_1 32}$	−3.958***	−10.00	−10.00	−10.00	−4.505**	−10.00
	(1.057)	(.)	(.)	(.)	(2.235)	(.)
$\alpha_{s_1 13}$	−2.822***	−10.00	−10.00	−10.00	−10.00	−10.00
	(0.532)	(.)	(.)	(.)	(.)	(.)
$\alpha_{s_1 23}$	−10.00	−10.00	−10.00	−10.00	−10.00	−10.00
	(.)	(.)	(.)	(.)	(.)	(.)
$\alpha_{s_1 33}$	−3.306***	−1.520***	−10.00	−3.997***	−0.527**	0
	(0.700)	(0.389)	(.)	(1.013)	(0.207)	(.)

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. λ is a nesting parameter in each class. $\alpha_{s_1 s_2 s_3}$ with $s_1 s_2 s_3 = \overline{1,3}$ are the constants in the class allocation functions. Standard errors are clustered at the individual level, reported in parenthesis. Numbers of respondents = 516 (AUS) and 710 (NZ). Log-likelihood = −6,957.52 (AUS) and −9,783.97 (NZ).

stay-at-home orders, public information campaigns, restrictions on internal movements; and international travel controls. The higher the index, the stricter the policy responses. We find that stringency index is significantly associated with class-switching behaviors in both countries, except for the "Pro-switchers". While the effects of macro-factors on the likelihood of being in the "Pro-vaccine to Hesitant" group is similar across the countries, it differs for "Hesitant to Pro-vaccine" and "Switchbacks". Specifically, stricter policy responses are positively correlated with the likelihood of being "Hesitant to Pro-vaccine" in Australia. However, the relationship was reversed in NZ.

4. Discussion and conclusion

Although some papers have found stable preferences for vaccine over time (Hofman et al., 2014; Walsh et al., 2020; Daziano and Budziński, 2023), others have shown that exogenous shocks and changing choice environments between DCEs can influence the stability of preferences for medical services (Allanson et al., 2020; Bryan et al., 2000; San Miguel et al., 2002; Salkeld et al., 2005; Skjoldborg et al., 2009). Longitudinal DCEs, in which the same individual is asked to state their preferences at different time points, can be used to test the stable preferences assumption. However, this type of data raises the possibility of heterogeneity in preferences across individuals (inter-individual) and changes in preferences over time at the level of individual respondents (intra-individual). This paper applies a novel LC model to examine preference changes, measured as switching in preference classes at different time points. The model is then applied to investigate the temporal stability of COVID-19 vaccine preferences in Australia and NZ.

The LC model identifies three preference classes: the "Impatient" group, which had greater sensitivity to waiting time for the vaccine (AUS: 46%, NZ: 31%), the "Price Sensitive" group (AUS: 41%, NZ: 56%), and the "Vaccine Hesitant" group (AUS: 13%, NZ: 13%). Our identified classes are similar with studies of DCEs in 21 countries (Antonini et al., 2025; Hess et al., 2022). We find some similarities between the two countries for COVID-19 vaccine preferences. Specifically, respondents in all classes prefer longer protection duration (if known), lower risk of severe side effects, and lower costs to obtain the vaccine. These findings are similar to Daziano and Budziński (2023). Among the significant vaccine characteristics, the risk of severe side

Table 4
Characteristics of switchers - Fractional multinomial logit model.

Compared to Stayer	Hesitant to Pro-vaccine		Switchback		Pro-vaccine to Hesitant		Pro-switcher	
	AUS (14%)	*NZ (3%)*	*AUS (6%)*	*NZ (4%)*	*AUS (4%)*	*NZ (6%)*	*AUS (12%)*	*NZ (26%)*
Constant	−14.70*	84.45**	−38.26***	32.52	−31.80***	−59.55*	−4.783	19.45
	(8.644)	(32.82)	(12.47)	(28.40)	(10.58)	(32.45)	(21.19)	(18.12)
Demographics								
Age	−0.012	0.016	0.012	0.015	−0.016	−0.012	0.036**	0.000
	(0.013)	(0.028)	(0.018)	(0.020)	(0.013)	(0.014)	(0.018)	(0.008)
Male	−0.020	0.001	0.986*	−0.049	1.115	−1.105	−0.658	0.268
	(0.394)	(0.818)	(0.510)	(0.549)	(0.717)	(0.621)	(0.573)	(0.242)
Household income (AUD1,000)	0.007**	−0.014	0.005	−0.014***	0.005	−0.004	−0.005	−0.001
	(0.003)	(0.009)	(0.004)	(0.004)	(0.005	(0.005)	(0.004)	(0.002)
At least Bachelor degree	−0.165	0.523	0.579	−0.116	1.224**	−0.206	0.190	0.353
	(0.383)	(0.747)	(0.624)	(0.576)	(0.578)	(0.569)	(0.501)	(0.252)
Employment status								
Out of work	1.024	−11.21***	−3.915***	−12.92***	−9.809***	−14.71***	−15.79***	−1.375**
	(0.825)	(1.113)	(1.248)	(1.112)	(1.537)	(0.890)	(1.064)	(0.606)
Became employed	0.770	3.196**	0.049	1.477	−5.780***	0.231	0.018	−0.147
	(0.652)	(1.531)	(1.147)	(1.394)	(1.217)	(1.103)	(1.734)	(0.568)
Health status								
Any health conditions	−0.293	1.105	−0.731	0.534	−1.262**	0.396	−0.798	0.053
	(0.397)	(0.892)	(0.556)	(0.605)	(0.586)	(0.484)	(0.504)	(0.239)
Worse physical health	0.964**	−6.235***	0.515	−0.289	2.461**	0.623	1.486*	0.016
	(0.408)	(1.743)	(0.757)	(0.858)	(0.958)	(1.041)	(0.833)	(0.435)
Worse mental health	−0.051	−4.679***	−1.081**	0.086	−0.782	−0.178	0.398	0.093
	(0.399)	(0.828)	(0.542)	(0.730)	(0.773)	(0.849)	(0.610)	(0.324)
Macro context								
Stringency index	0.174	−1.219***	0.459***	−0.491	0.336**	0.832*	0.053	−0.293
	(0.114)	(0.464)	(0.164)	(0.391)	(0.137)	(0.458)	(0.284)	(0.253)
Trust the following sources for information about vaccines								
Government website/campaign	0.232	−2.429***	0.306	1.038	0.933	−1.929**	0.065	0.845**
	(0.566)	(0.855)	(0.644)	(0.744)	(1.184)	(0.747)	(0.711)	(0.373)
Social media	0.140	0.063	−5.584***	−10.14***	1.636	1.364	0.295	0.279
	(0.639)	(1.539)	(0.746)	(1.289)	(1.334)	(1.313)	(0.902)	(0.561)
Traditional media	0.159	0.004	0.864	0.001	−1.872*	−0.997	0.661	−0.289
	(0.448)	(0.751)	(0.555)	(0.538)	(0.973)	(0.776)	(0.718)	(0.256)
Friends and family	−0.097	−1.115	0.260	0.298	0.008	0.741	0.422	0.022
	(0.441)	(1.126)	(0.636)	(0.695)	(0.899)	(0.711)	(0.597)	(0.269)
GP/healthcare provider	−0.093	0.459	−0.659	−1.522*	2.801**	−0.563	−3.347***	−0.201
	(0.711)	(1.102)	(0.749)	(0.836)	(1.314)	(0.715)	(0.875)	(0.488)
Numbers of respondents	**202**	**315**	**202**	**315**	**202**	**315**	**202**	**315**

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

effects has the highest utility weight in each class, suggesting its relative importance over other characteristics. Our findings are also consistent with a systematic review of preferences for various vaccines using choice-based experiments (Diks et al., 2021).Therefore, our findings are not limited to only COVID-19 vaccine, but it is applicable to other vaccination programs, suggesting that public campaigns for future annual vaccination could focus on the specific attributes that individuals in these classes consider to be important, e.g., risk of side effects or efficacy.

Although we find evidence of switching behaviors, most preferences for vaccines remain stable with the probability of being "Stayer", the group with the same identified preference classes across the three waves, being 0.62 in Australia and 0.61 in NZ. These findings are consistent to ones investigating the temporal stability of preferences for HPV and flu vaccination in the US and Netherlands (Hofman et al., 2014; Walsh et al., 2020). From the model, we identify four different types of switchers. Out of the switchers, the probability of being in "Pro-switcher" (i.e., switching between pro-vaccine classes) in NZ is 0.67. In contrast, the probabilities of Australian switchers being "Pro-switcher" and "Hesitant to Pro-vaccine" are somewhat equal. For policy makers, these findings suggest that most consumers would continue to prefer vaccine over no-vaccine after one year. More importantly, during this period, some Vaccine Hesitant switched to Pro-vaccine, thereby policies targeting this group of population may increase the country's vaccination rates over time.

We also find evidence that household income, employment status, physical and mental health status, the COVID–19 stringency index, and trust in social media and healthcare providers for vaccine information can be significant determinants of preference instability. For example, having any health conditions may lower the chances of switching from pro-vaccine to hesitant. This is consistent with the findings of Daziano and Budziński (2023). Trust in government as an information source has mixed effects for vaccine acceptance in NZ, but it does not significantly influence the switching behaviors in Australia.

There is also evidence that stricter public health policy responses, measured using the stringency index, were significantly associated with class switching. Regarding policy implications, our study has broader relevance not only for planning COVID-19 vaccination strategies but also for guiding vaccination efforts in response to future pandemics of a similar nature. It provides critical information for effective vaccination program planning in the face of emerging health crises. For example, we find that having stricter COVID–19 policy responses is associated with an increased likelihood of switching from Pro-vaccine to Hesitant in both countries. Stricter stringency index is associated with decreased chances of switching from hesitant to pro-vaccine in New Zealand, but the relationship is not significant in Australia. This is consistent with findings from Borga et al. (2022).

Our study is not without a limitation. Since the stringency index includes a range of COVID-19 policy responses, it is not enough to inform policymakers on a specific decision, e.g., whether a local school lockdown can influence vaccine preferences. Moreover, the timeline for our data collection is just three time points over a course of a year, which may be quite short throughout the fast-evolving pandemic situation. Hence, future research using our LC framework could explore these factors in greater detail - with potentially longer time horizons so that the data has enough temporal and geographical variations to be identified.

As far as we are aware, our study is the first study to examine the switching of preferences for a COVID–19 vaccine using a longitudinal DCE using a LC modeling framework. Our approach is a significant departure from existing studies in that it introduces a novel LC structure to assess if and how people switch across different preference classes. Overall, we find that switching occurs in approximately 30% of the sample, within which the majority switched between pro-vaccine classes or from vaccine-hesitant to pro-vaccine. Our findings also show that switching behavior is significantly associated with both macro and micro factors.

CRediT authorship contribution statement

My Tran: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Robbie Maris:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Stephane Hess:** Writing – original draft, Methodology, Funding acquisition, Data curation, Conceptualization. **Zack Dorner:** Writing – review & editing, Supervision, Funding acquisition, Formal analysis, Data curation. **Elisabeth Huynh:** Writing – review & editing, Investigation, Data curation. **Kathryn Glass:** Writing – review & editing, Investigation. **Emily Lancsar:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.socscimed.2025.118417.

Data availability

The data that has been used is confidential.

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