Ambiguity and Vaccination Decisions*

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Abstract

Despite the scientifically documented benefits both to oneself and society, many people still refuse or hesitate to take the vaccines. We propose that the latter "wait and see" approach is consistent with ambiguity aversion. As the advent of new vaccines will always lag their respective disease, the distribution of adverse side effects to vaccination will appear more uncertain than averse consequences of disease. Using an established experimental model of vaccination, the Interactive Vaccination (I-Vax) Game from Böhm et al. (2016), we introduce uncertainty to the distribution of side effects in the Ambiguity Treatment. Consistent with the general intuition of ambiguity aversion, relative to treatment without ambiguity, subjects in the Ambiguity Treatment vaccinate less often. Additionally, the effect is concentrated in the first half of the experiment when distribution of side effects is less known. We separately elicit subjects' ambiguity attitudes and find that ambiguity-averse subjects vaccinate less, ambiguity-seeking subjects vaccinate more, and ambiguity-neutral subjects show little change, with these differences dissipating in the second half of the experiment. Finally, we examine the relationship between elicited ambiguity attitudes and COVID-19 attitudes and vaccination decisions.

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1 Introduction

Vaccination is considered to be one of the greatest public health achievements. A high vaccination uptake rate is necessary to reduce the prevalence of vaccine-preventable diseases (VPDs), including cholera, Ebola, diphtheria, or COVID-19. However, many people still refuse or hesitate to take the vaccine (Dubé et al., 2013, 2015; Jacobson et al., 2015; Sallam, 2021; Troiano and Nardi, 2021; Khubchandani et al., 2021). Surveys assess that the estimates of Americans' vaccine hesitancy about COVID-19 are between 25-34% (Khubchandani et al., 2021).

The World Health Organization (WHO) defined vaccine hesitancy as "the delay in acceptance or refusal of vaccination despite the availability of vaccination services" (World Health Organization, 2014). Focusing on the former (delay), and not the latter (refusal), this paper posits that this "wait and see" attitude toward vaccines could be explained by ambiguity aversion (Ellsberg, 1961). Related evidence shows that individuals with lower tolerance for uncertainty are less likely to vaccinate and more likely to delay vaccination decisions (Gillman et al., 2022). Due to its nature, vaccine development inevitably lags behind the emergence of new infectious diseases. Even in the most successful cases, such as with COVID-19, there is typically a one-year delay. Consequently, the distribution of risk of the virus becomes known, while the distribution of potential side effects of the vaccine may not yet be fully disclosed. Thus, the virus represents a known risk, whereas the vaccine may seem ambiguous. The concerns over the Janssen (Johnson & Johnson) COVID-19 vaccine, as highlighted by the FDA in April 2021, could be an example.

To test our conjecture, we follow a previously used experimental paradigm to model vaccination decisions, the Interactive Vaccination (I-Vax) Game (Böhm et al., 2016), which builds on a broader experimental literature studying vaccination behavior in strategic settings on institutional interventions and herd immunity perceptions (Betsch and Böhm, 2016; Betsch et al., 2017). Our control, the No Ambiguity Treatment, is taken directly from the No Framing treatment of Böhm et al. (2016). Subjects make vaccination decisions over 20 rounds, with adverse outcomes from disease and vaccine side effects governed by known risks. Our innovation is to introduce ambiguity into this design through a novel Ambiguity Treatment. The distribution of adverse disease outcomes remains known, while the distribution of adverse vaccine side effects is no longer disclosed, making the vaccination option ambiguous.

We develop three predictions about how ambiguity affects vaccination decisions. First, we expect lower rates of vaccination overall in the Ambiguity Treatment. Second, we expect the treatment differences between the No Ambiguity and Ambiguity Treatments to manifest in the early rounds of the experiment. For after several rounds of play, the distribution of side effects will become more apparent to subjects reducing ambiguity. Third, we expect subjects, based on their underlying ambiguity attitudes to respond differentially between treatments.

We find confirmation of all three predictions. Subjects in the ambiguity treatment are 3 percentage points less likely to vaccinate. The effect is more pronounced (4 pp) over the first half of the experiment and insignificant in the second half. Using an Ellsberg task elicitation of ambiguity attitudes to proxy for subjects' underlying ambiguity attitudes the effects become more pronounced. In the first half of the experiment, relative to the No Ambiguity Treatment, ambiguity averse subjects decrease their rate of vaccination by 10.8 pp; ambiguity seeking subjects increase their rate by 19.8 pp. Ambiguity neutral subjects do not significantly change. The effects are mitigated and insignificant by the second half of the experiment. Taken together, these results suggest that ambiguity matters most when subjects have the least experience with the side-effect distribution: behavior initially responds in systematically different directions according to independently elicited ambiguity attitudes, but these differences fade as experience accumulates.

Böhm et al. (2016) classifies subjects along the Social Value Orientation scale (Murphy et al., 2011) and characterizes subjects by a binary proself/prosocial. They find generally that prosocial subjects are more likely to vaccinate than proselfs. We characterize subjects by the same measure and find our main results on ambiguity are robust controlling for this measure. While prosocials subjects are not necessarily higher vaccinators in our data, low rates of vaccination from other players make the choice to vaccinate more lucrative. In general we find that proselfs are much more responsive to strategic components of the game than prosocials, which suggests the differences across type may be tougher to disentangle. Indeed, even after controlling for ambiguity attitudes, we find that proself types are 15.9 pp less likely to vaccinate under ambiguity than prosocials.

Böhm et al. (2016) also find that subjects are more responsive to past side effects from vaccination rather than bad disease outcomes and attributed it to omission bias (Spranca et al., 1991; Ritov and Baron, 1999; Kahneman and Tversky, 1982). We generally find that experiencing a side effect last round is more robust a predictor of play than a bad disease outcome. Our results suggest that ambiguity may intensify this response: under ambiguity, adverse side effects to vaccination can also lead subjects to update beliefs about the initially unknown side-effect distribution. Consistent with this interpretation, the response to side effects is largest in magnitude in the first half of the Ambiguity Treatment.

At the end of our experiment, we surveyed our subjects on their general attitude toward vaccines, their attitude toward COVID-19 vaccination, and whether they had been vaccinated for COVID-19. Through structural equation modeling using the former two terms as mediators, we look to see if any of our experimental data might be predictive of an individual's COVID vaccination. Using our overall sample, we find no indication of any predictors of this decision, only the mediator COVID-19 attitude is highly predictive of this decision. However, consistent with the theme of this paper when we focus on the earlier half of our experimental subjects, ambiguity aversion attitude is a predictor of COVID attitude, indirectly affecting the decision to vaccinate. This is consistent with recent evidence showing that ambiguity aversion is associated with lower COVID-19 vaccination intentions (Simonovic et al., 2025).

While these estimates rely on several strong assumptions and we are cautious on direct interpretation, we see it as a test case of how ambiguity attitude might be analyzed in regards to vaccination decision.

There is a wealth of literature on how ambiguity affects medical decisions. Attema et al. (2018) reveal that individuals tend to be more pessimistic in medical decisions under ambiguity than under risk. Courbage and Peter (2021) theoretically demonstrate that the probability of side effects and the efficacy of the vaccine reduce the take-up rate of ambiguity averse individuals. Blaisdell et al. (2015) finds ambiguity about the outcomes of childhood immunization is an important factor in parental vaccine hesitancy. Han et al. (2018) reveal that communicating scientific uncertainty about VPD risk and vaccine effectiveness leads to ambiguity aversion.

The rest of the paper is structured as follows: Section 2 presents the experimental design and procedure. Section 3 develops the strategic framework and derives the experimental predictions. Section 4 reports the experimental results, and Section 5 provides the concluding remarks.

2 Experimental Design

2.1 I-Vax Game

We adopted the Interactive Vaccination (I-Vax) Game from Böhm et al. (2016) as the key framework for our study. They found that individuals respond to the interactive incentive structure by making strategic vaccination decisions. In our study, we employed two versions of the I-Vax Game as distinct treatments: the *No Ambiguity treatment*, which is identical to the standard I-Vax Game of Böhm et al. (2016), and the *Ambiguity treatment*. 120 subjects were enrolled in the No Ambiguity treatment, while another 120 took part in the Ambiguity treatment.

2.1.1 No Ambiguity Treatment

In the standard I-Vax Game, subjects play in groups of 12 over 20 rounds. In each round, they are endowed with 100 points and decide whether to get vaccinated or not. Their payoff of each round depends on their own decision and other group members' decisions.

Each vaccinated subject pays a fixed cost $c^{fixed} = 5$. Also, vaccinated subjects might incur a side effect, with a probability of $p_1 = 0.3$. In the case of the side effect, the point loss would be $21, 36, 51$ with probabilities of $0.5, 0.4, 0.1$. Figure 1 shows each consequence and its probability.

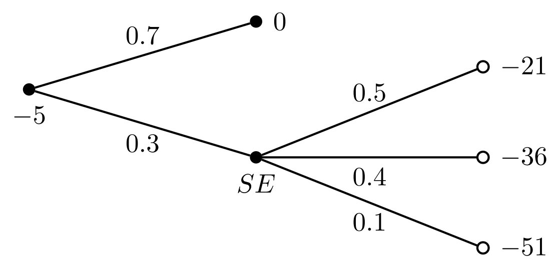


Figure 1: Consequences and probabilities of vaccination

On the other hand, each unvaccinated subject could contract the disease in each round. The probability of having the disease (p_0) depends on the number of other subjects in their group who get vaccinated: The greater the number of vaccinated people, the lower the probability of point loss for unvaccinated subjects. (See Figure 2.) In the case of the disease, the point loss would be 35, 60, or 85 with probabilities of 0.5, 0.4, and 0.1, respectively.

2.1.2 Ambiguity Treatment

In addition to the standard I-Vax setting, we added an additional treatment, where ambiguity exists in the vaccination option. The possible consequences and probabilities of the side effect are different from the standard I-Vax Game, while other features are identical.

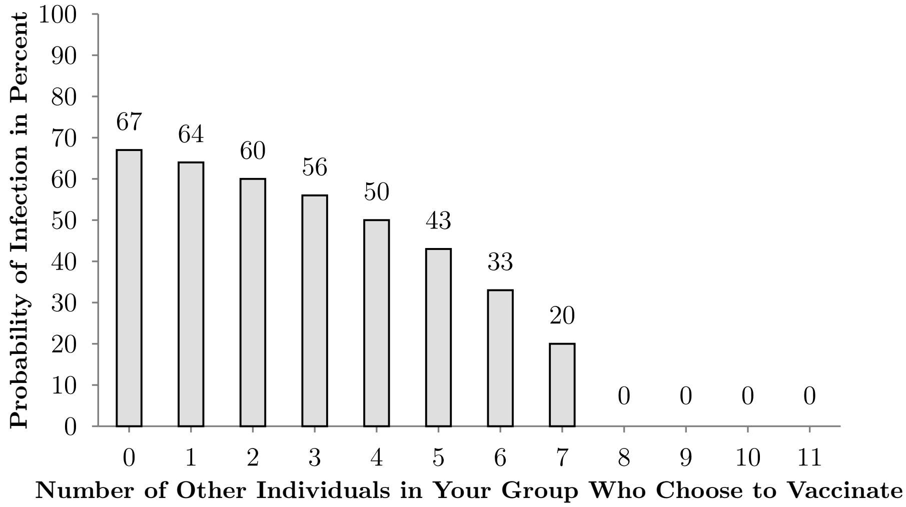


Figure 2: How p_0 is determined based on other subjects' decisions

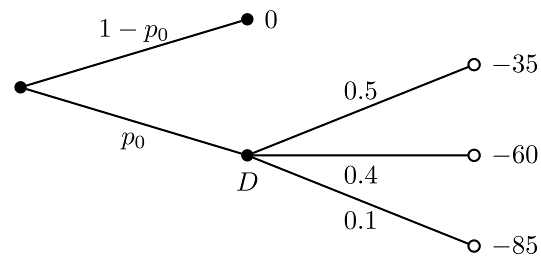


Figure 3: Consequences and probabilities without vaccination

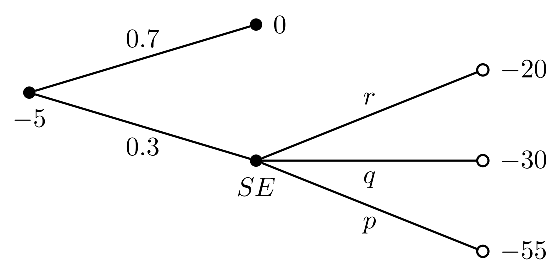


Figure 4: Consequences and probabilities of vaccination

In this treatment, the values of p, q, r are unknown. The only restriction about these parameters is $p < 0.5$. This restriction implies that the loss from vaccination conditional on a side effect, including the fixed vaccination cost, first-order stochastically dominates the loss from disease.[1]

2.2 Social value orientation (SVO)

To measure preference for allocation between oneself and others, we use social value orientation (SVO) slider measure (Murphy et al., 2011). Subjects make 6 allocation decisions of decomposed games, allocating points between themselves and an unknown other subject. Responses for 6 decisions yield a single angle index, classifying the subject as prosocial, individualistic, or competitive. The allocation choice sets are reported in Appendix A.4.

2.3 Ambiguity Attitude

We elicited ambiguity attitudes by using two questions from Ellsberg (1961).

> Consider there is a bag containing 90 ping-pong balls. 30 balls are blue, and the remaining 60 balls are either red or yellow in unknown proportions. The computer will draw a ball from the bag. The balls are well mixed so that each ball is as likely to be drawn as any other. You will bet on the color that will be drawn from the bag.

Subjects chose their preferred options between A & B and between C & D. Table 1 shows the options.

If the submitted choices are A and D, the preference is considered to be a consequence of ambiguity aversion. Also, B and C represent ambiguity seeking preference, and the other choices show ambiguity neutral.

[1]Let $\widetilde{SE}$ denote the loss from vaccination conditional on a side effect, including the fixed vaccination cost of 5. In the Ambiguity treatment, $\widetilde{SE} \in \{-25, -35, -60\}$ with probabilities (r, q, p), where $p + q + r = 1$ and $p < 0.5$. Let D denote the loss from disease without vaccination, so that $D \in \{-35, -60, -85\}$ with probabilities $(0.5, 0.4, 0.1)$. Then $\widetilde{SE}$ first-order stochastically dominates D. To see this, note that $\widetilde{SE}$ assigns less probability to sufficiently severe losses: its worst outcome -60 occurs with probability $p < 0.5$, whereas D assigns probability 0.5 or more to losses of -60 or worse and additionally includes the strictly worse outcome -85. Moreover, $\widetilde{SE}$ places additional mass on the strictly better outcome -25, which is not present in D. Hence $F_{\widetilde{SE}}(x) \leq F_D(x)$ for all x.

Options	
Option A	receiving 100 points if a blue ball is drawn.
Option B	receiving 100 points if a red ball is drawn.
Option C	receiving 100 points if a blue or yellow ball is drawn.
Option D	receiving 100 points if a red or yellow ball is drawn.

Table 1: Ellsberg questions

2.4 Vaccination Attitude

After completing the SVO slider tasks, the I-Vax Game, and the Ellsberg questions, subjects completed a post-experiment questionnaire measuring their general attitudes toward vaccination, attitudes toward COVID-19 vaccination, and COVID-19 vaccination status. The exact questions and response scales are reported in Appendix A.3. The questionnaire also collected age, gender, and major.

2.5 Procedure

A total of 240 subjects participated in 20 sessions — 10 under the Ambiguity Treatment and 10 under the No Ambiguity Treatment — conducted from March to September 2022 at the Texas A&M Economic Research Laboratory. Subjects were recruited from a database using ORSEE (Greiner, 2015). The experiments were conducted using z-Tree (Fischbacher, 2007). Decisions in both the I-Vax Game and the Ellsberg task were incentivized and included in the random payment procedure. On average, each session lasted 30 minutes, and subjects earned \$18.87, including a \$10 show-up fee. The experimental instructions are provided in Appendix A.1.

3 Strategic Vaccination Decisions

We consider the experimental environment described above, which follows the strategic structure of the I-Vax game in Böhm et al. (2016). In this setting, the expected payoff from vaccination is constant, while the expected payoff from remaining unvaccinated increases with the number of vaccinated individuals due to herd immunity. This generates a threshold best response: a rational individual prefers vaccination when infection risk is sufficiently high, and remaining unvaccinated otherwise. To characterize this benchmark, we assume linear utility over experimental points, as in the standard I-Vax analysis.

In the No Ambiguity Treatment, the expected loss from vaccination is fixed at

$$5 + 0.3 \times (0.5 \cdot 21 + 0.4 \cdot 36 + 0.1 \cdot 51) = 14,$$

while the expected loss from non-vaccination is $50p_0(n)$, where 50 is the expected loss conditional on infection. A risk-neutral individual therefore chooses to vaccinate if and only if

$$14 < 50\, p_0(n),$$

or equivalently when $p_0(n) > 0.28$. In our design, this implies vaccination when at most six of the other group members vaccinate, and non-vaccination otherwise, yielding a Nash equilibrium of 7 out of 12 individuals (58.3%) (Böhm et al., 2016).

In the Ambiguity Treatment, the probabilities of the side-effect outcomes are unknown, with the only restriction that the probability of the most severe outcome is less than 0.5. Let

$$\Theta = \left\{\theta = (r, q, p) \in \mathbb{R}^3_+ : r + q + p = 1,\ p < 0.5\right\}$$

denote the set of possible distributions over the three side-effect losses. For a given $\theta \in \Theta$, define the expected loss conditional on a side effect as

$$m(\theta) = 20r + 30q + 55p.$$

The expected payoff from vaccination conditional on θ is therefore

$$\pi_V(\theta) = 95 - 0.3m(\theta),$$

while the expected payoff from remaining unvaccinated is

$$\pi_N(n) = 100 - 50p_0(n).$$

To distinguish beliefs about the unknown side-effect distribution from attitudes toward ambiguity, we use the smooth ambiguity framework of Klibanoff et al. (2005). Subject i has a subjective second-order belief μ_i over Θ and evaluates the vaccination option according to

$$V_i = \phi_i^{-1}\left(\int_\Theta \phi_i\big(\pi_V(\theta)\big)\, d\mu_i(\theta)\right),$$

where ϕ_i is increasing and its curvature captures the subject's attitude toward ambiguity. A concave ϕ_i represents ambiguity aversion, a linear ϕ_i ambiguity neutrality, and a convex ϕ_i ambiguity seeking.

For comparison, define

$$\bar{\pi}_{V,i} = \int_\Theta \pi_V(\theta)\, d\mu_i(\theta),$$

which is the valuation of vaccination by an ambiguity-neutral subject with the same beliefs. By Jensen's inequality,

$$V_i \begin{cases} < \bar{\pi}_{V,i}, & \text{if subject } i \text{ is ambiguity averse,} \\ = \bar{\pi}_{V,i}, & \text{if subject } i \text{ is ambiguity neutral,} \\ > \bar{\pi}_{V,i}, & \text{if subject } i \text{ is ambiguity seeking,} \end{cases}$$

whenever the perceived ambiguity is nondegenerate and the relevant curvature is strict. Because the non-vaccination option involves known probabilities, subject i

chooses to vaccinate when

$$V_i > 100 - 50p_0(n),$$

or equivalently when

$$p_0(n) > \frac{100 - V_i}{50}.$$

Thus, holding beliefs about the side-effect distribution fixed, ambiguity aversion raises the infection-risk threshold required for vaccination relative to ambiguity neutrality, while ambiguity seeking lowers it.

To connect this comparative static directly to the No Ambiguity Treatment, consider a mean-matched benchmark in which the subject's belief about the unknown side-effect distribution has the same expected side-effect loss as in the No Ambiguity Treatment:

$$\int_{\Theta} m(\theta)\, d\mu_i(\theta) = 30.$$

Under this benchmark,

$$\bar{\pi}_{V,i} = 95 - 0.3(30) = 86,$$

which is exactly the expected payoff from vaccination in the No Ambiguity Treatment. It follows that an ambiguity-averse subject values vaccination at less than 86, an ambiguity-neutral subject at 86, and an ambiguity-seeking subject at more than 86. Equivalently, the infection-risk threshold for vaccination is above 0.28 for an ambiguity-averse subject, equal to 0.28 for an ambiguity-neutral subject, and below 0.28 for an ambiguity-seeking subject. Under this benchmark, the introduction of ambiguity therefore reduces the incentive to vaccinate for ambiguity-averse subjects, leaves it unchanged for ambiguity-neutral subjects, and increases it for ambiguity-seeking subjects.

The mean-matched assumption provides a useful benchmark for interpreting the direction of the treatment effects. More generally, if subjects hold different beliefs about the unknown side-effect distribution, the model does not necessarily imply a zero treatment effect for ambiguity-neutral subjects. The more general comparative static is that, holding beliefs fixed, ambiguity aversion lowers the valuation of vaccination relative to ambiguity neutrality, while ambiguity seeking raises it.

The model also provides a natural interpretation of how the effect of ambiguity may change with experience. The side-effect distribution remains fixed throughout the experiment, and observed side-effect outcomes provide information about the initially unknown distribution. Let μ_{it} denote subject i's belief in period t. As subjects gain information, their beliefs about the side-effect distribution may become less dispersed. If this learning primarily reduces uncertainty about the distribution without substantially changing its mean, the gap between V_i and the ambiguity-neutral valuation $\bar{\pi}_{V,i}$ becomes smaller. Thus, the effect of ambiguity attitudes on vaccination should be strongest when the side-effect distribution is least known and weaken as subjects gain experience.

These comparative statics motivate the predictions tested in the experiment.

3.1 Predictions

Building on the framework above, we expect ambiguity aversion to be sufficiently prevalent that the introduction of ambiguity reduces vaccination on average. Consequently, we expect lower vaccination rates in the Ambiguity Treatment than in the No Ambiguity Treatment.

Prediction 1. *Vaccination rates will be lower in the Ambiguity Treatment than in the No Ambiguity Treatment.*

The distribution of adverse side effects to vaccination is constant throughout the experiment. As subjects gain experience with the vaccine, they receive information about the initially unknown side-effect distribution. If this experience reduces perceived ambiguity, the effect of ambiguity on vaccination should become weaker over time. Given the predicted negative average treatment effect, we therefore expect the treatment difference to be larger in the first half of the experiment.

Prediction 2. *The lower vaccination rate in the Ambiguity Treatment will be more pronounced in periods 1–10 than in periods 11–20.*

The preceding predictions concern the average treatment effect, but the model also implies heterogeneity according to subjects' ambiguity attitudes. Experimental evidence documents substantial heterogeneity in ambiguity attitudes, including ambiguity-neutral and ambiguity-seeking individuals (e.g., Trautmann and van de Kuilen, 2015; Baillon et al., 2018; Brown et al., 2026). Holding beliefs fixed, ambiguity-averse subjects value the ambiguous vaccination option less than ambiguity-neutral subjects, while ambiguity-seeking subjects value it more. Under the mean-matched benchmark above, this implies a negative treatment effect for ambiguity-averse subjects, no treatment effect for ambiguity-neutral subjects, and a positive treatment effect for ambiguity-seeking subjects.

Prediction 3. *Relative to the No Ambiguity Treatment, ambiguity-averse subjects will vaccinate less under ambiguity, ambiguity-seeking subjects will vaccinate more, and ambiguity-neutral subjects will show little or no change.*

4 Results

Table 2 reports subject-level summary statistics by treatment. For the most part, the treatments do not differ on features. However, the Ambiguity treatments were run one later dates of the year and involved slightly younger subjects. Survey responses on vaccination attitude, COVID-19 attitude and COVID-vaccination status are more positive for the No Ambiguity control though only differ significantly on vaccination status. These differences may reflect differences in age which is positively correlated with all three variables.

Table 3 reports the distribution of ambiguity attitudes elicited from the Ellsberg task. Overall, 52.1% of subjects are classified as ambiguity averse, 36.3% as ambiguity neutral, and 11.7% as ambiguity seeking. The distribution is similar across

	No Ambiguity	Ambiguity	Total
Day of 2022	136.20	179.40	157.80***
(1–365)	(61.56)	(77.40)	(73.06)
Age	21.55	20.48	21.01**
(in years)	(4.60)	(2.13)	(3.62)
Female	0.50	0.55	0.53
(binary)	(0.50)	(0.50)	(0.50)
Economics major	0.12	0.18	0.15
(binary)	(0.32)	(0.39)	(0.36)
Proself (SVO)	0.44	0.42	0.43
(binary)	(0.50)	(0.50)	(0.50)
SVO angle	23.03	24.35	23.69
(-16.26–61.39)	(14.82)	(13.84)	(14.32)
Vaccination attitude	80.31	75.86	78.08
(1–100)	(25.30)	(30.11)	(27.84)
COVID-19 attitude	4.09	3.84	3.97
(1–5)	(1.12)	(1.26)	(1.19)
COVID-19 vaccinated	0.91	0.82	0.87*
(binary)	(0.29)	(0.38)	(0.34)
Observations	120	120	240

Table 2: Subject-level summary statistics across treatment. Stars indicate where No Ambiguity and Ambiguity treatments differ on value on a two-sample t-test: $*p < 0.1, **p < 0.05, ***p < 0.001$.

treatments, and a chi-squared test does not reject equality of the ambiguity-type distributions across the No Ambiguity and Ambiguity Treatments ($\chi^2(2) = 0.655$, $p = 0.721$).

	No Ambiguity	Ambiguity	Total
Ambiguity averse	64 (53.33%)	61 (50.83%)	125 (52.08%)
Ambiguity neutral	44 (36.67%)	43 (35.83%)	87 (36.25%)
Ambiguity seeking	12 (10.00%)	16 (13.33%)	28 (11.67%)
Observations	120	120	240

Table 3: Distribution of elicited ambiguity attitudes by treatment. The distribution does not differ significantly across treatments ($\chi^2(2) = 0.655$, $p = 0.721$).

4.1 Main treatment effects

Figure 5 presents vaccination rates by ambiguity treatment over the 20 rounds of the experiment. The rate of vaccination in the ambiguity treatment (49.7%) is slightly lower than in no ambiguity (52.7%), however both values fall well below the Nash

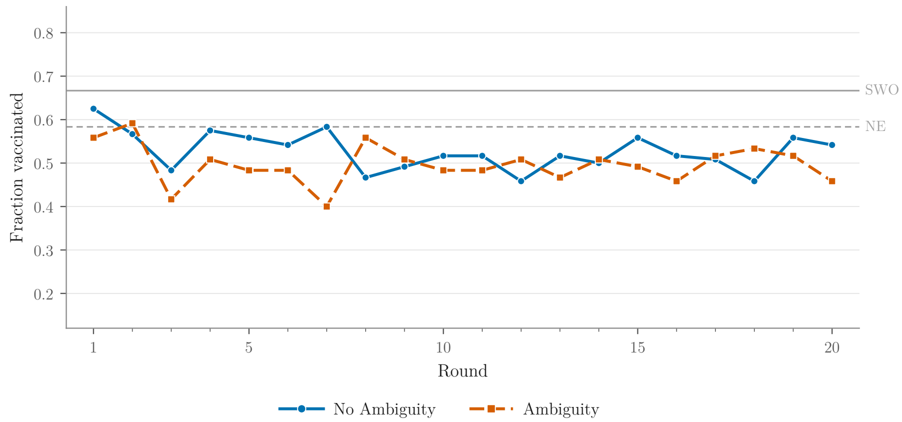


Figure 5: Vaccination rates by treatment over each round of the experiment. Dashed horizontal line: Nash equilibrium (NE $= 7/12$). Solid horizontal line: social welfare optimum (SWO $= 8/12$).

equilibrium prediction (58.3%) and the social optimum (SWO, 66.7%).

Table 4 provides complementary regression results from five specifications of a linear probability model with subject random effects. The general specification is:

$$V_{it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_i + \boldsymbol{\gamma}'\left(\mathbf{X}_i \times B_t\right) + u_i + \varepsilon_{it}, \tag{1}$$

where V_{it} is an indicator for whether subject i chooses to vaccinate in round t, $\mathbf{X}_i$ is a vector of time-invariant subject characteristics (treatment assignment, ambiguity attitude, SVO type, and their interactions), B_t is a second-half indicator (rounds 11–20), u_i is a subject random effect, and ε_{it} is the idiosyncratic error. Standard errors are clustered at the session level.

In line with Prediction 1, specification (1) indicates the Ambiguity Treatment reduces the rate of vaccination by 3.0 percentage points (pp) ($p = 0.093$) relative to the No Ambiguity Treatment. Specification (2) indicates the predicted magnitude of this effect is roughly double in the first half (-4.2 pp, $p = 0.021$) than the second half (-1.9, $p = 0.379$). This result is consistent with our hypothesized effect of ambiguity (Prediction 2) and the premise of this paper of how ambiguity may generate

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Chooses to Vaccinate				
Ambiguity	-0.030*	-0.042**	0.198**	0.042	0.254***
Treatment (A)	(0.018)	(0.018)	(0.084)	(0.035)	(0.089)
Second half (B)		-0.028**	0.000	-0.061***	-0.015
(rounds 11–20)		(0.013)	(0.084)	(0.017)	(0.088)
SVO: proself (C)				0.106*	0.069
				(0.059)	(0.056)
Ambig. attitude:			0.278***		0.252***
averse (D)			(0.085)		(0.081)
Ambig. attitude:			0.162**		0.147**
neutral (E)			(0.067)		(0.073)
A × B		0.023	-0.100	0.053*	-0.091
		(0.017)	(0.100)	(0.032)	(0.109)
A × C				-0.194***	-0.159**
				(0.068)	(0.066)
A × D			-0.306***		-0.290***
			(0.102)		(0.100)
A × E			-0.212**		-0.204*
			(0.106)		(0.110)
B × C				0.076*	0.091***
				(0.041)	(0.034)
B × D			-0.050		-0.083
			(0.101)		(0.098)
B × E			-0.002		-0.022
			(0.095)		(0.090)
A × B × C				-0.068	-0.078
				(0.067)	(0.064)
A × B × D			0.142		0.176
			(0.117)		(0.114)
A × B × E			0.137		0.158
			(0.122)		(0.118)
Constant	0.527***	0.541***	0.333***	0.494***	0.322***
	(0.011)	(0.010)	(0.061)	(0.029)	(0.059)
Observations	4800	4800	4800	4800	4800
Subjects	240	240	240	240	240
Sessions	20	20	20	20	20
R^2 (overall)	0.001	0.001	0.015	0.016	0.025

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Main regressions.

vaccine hesitancy rather than vaccine avoidance altogether. The ambiguity serves as a deterrent for vaccination when the distribution of the side effects are unknown, after a few draws some of the ambiguity is resolved and the deterrent effect is mitigated.

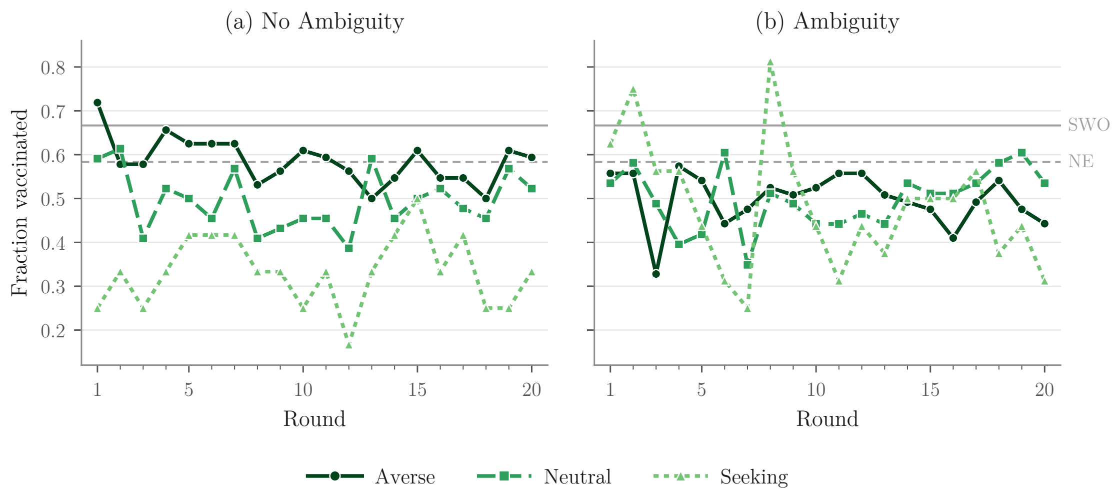


Figure 6: Vaccination rates over time by ambiguity attitude, separate panels for each treatment.

Prediction 3 states that the effect of the Ambiguity Treatment should have a differential effect among ambiguity attitude types: averse, neutral and seeking. Recall the experiment elicited subjects' ambiguity attitude using Ellsberg task (see Section 2.3). Figure 6 shows vaccination rates over time by ambiguity attitude (i.e., averse, neutral, seeking) separated by treatment. The left panel (a) indicates that, absent ambiguity, averse types are most likely to vaccinate, then neutral, then ambiguity-seeking. As this treatment involves no ambiguity, this ordering is not explained directly from ambiguity attitudes, and could be due to any number of correlated preferences. Once ambiguity is introduced (b, right), however, the differences across types is no longer clear. Thus, the net effect of Ambiguity Treatment is to reduce (increase) vaccination rates by the ambiguity averse (seeking) while behavior of the ambiguity neutral remains the same. This directional shift is entirely consistent with Prediction 3.

Table 4, specification (3) confirms these relations. In the No Ambiguity treatment, ambiguity seeking subjects vaccinate only in 1/3 of all rounds with no difference over each half of the experiment (0.0 pp, $p = 1.000$). Ambiguity averse and neutral types are 27.8 ($p = 0.001$) and 16.2 ($p = 0.015$) percentage points more likely to vaccinate relative to the seeking level, respectively. Neither type meaningfully changes their behavior in the second half of the experiment either (averse, B×D: -5.0 pp, $p = 0.622$; neutral, B×E: 0.0 pp, $p = 0.981$).

Compared to the first half of the No Ambiguity Treatment, ambiguity seeking subjects in the Ambiguity Treatment increase their rate of vaccination by 19.8 pp ($p = 0.018$); ambiguity averse subjects decrease their rate by 10.8 pp ($0.198 + (-0.306) = -0.108$), $p = 0.033$). Ambiguity neutral subjects show no net change ($0.198 + (-0.212) = -0.014$, $p = 0.802$). The three results confirm Prediction 3. By the second half of the experiment, there is no significant difference between treatments for any of the three groups (seeking: $0.198 + (-0.100) = 0.098$, $p = 0.360$; neutral: $0.198 + (-0.212) + (-0.100) + 0.137 = 0.023$, $p = 0.690$; averse: $0.198 + (-0.306) + (-0.100) + 0.142 = -0.066$, $p = 0.228$). The reduction of these effects is (again) consistent with Prediction 2. Taken together, these results point to a common temporal pattern: ambiguity attitudes strongly shape the treatment response in the early rounds, when the side-effect distribution is least known, but these type-specific treatment effects dissipate as subjects gain experience.

The No Ambiguity Treatment is a direct replica of Böhm et al. (2016)'s No Framing treatment, albeit with a different subject population (German vs. US) and era (pre-Covid vs. post-Covid). A key explanatory variable of the former study was a dummy variable indicating proself or prosocial orientation on the Social Value Orientation task (SVO). We use the same task (see Section 2.2) and categorization. Figure 7 shows vaccination rates over each round by SVO type (prosocial vs. proself) in the No Ambiguity Treatment (a, left) and Ambiguity Treatment (b, right). In the absence of ambiguity, proself types are more likely to vaccinate than prosocial, with the latter type decreasing vaccination rates over time. The 60.7% rate of proself vaccination is very close to the Nash equilibrium rate of 58.3%. The ordering of the two groups reverses under the Ambiguity Treatment: prosocial types vaccinate slightly more often than proself. There also is no apparent time trend. Analysis in 4.2 suggests proself types may be more responsive to parameter changes across rounds which may make the classification of their aggregate behavior more nuanced.

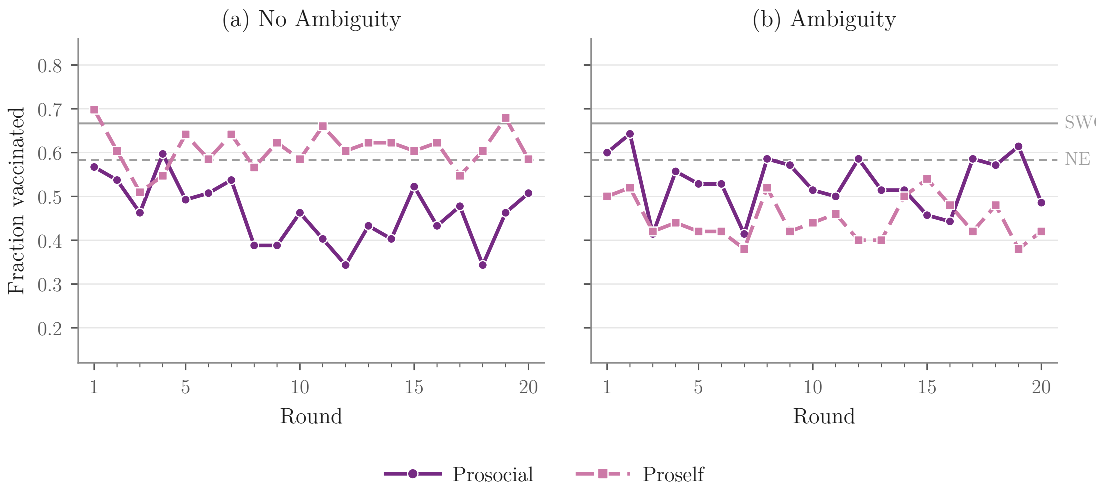


Figure 7: Vaccination rates over time by SVO type, separate panels for each treatment.

Table 4, specification (4) provides complementary regression results. Indeed, in the No Ambiguity Treatment, proself types are 10.6 percentage points more likely to vaccinate in the first half of the experiment ($p = 0.074$) and 18.2 percentage points more likely in the second half ($0.106 + 0.076 = 0.182$, $p = 0.016$). The greater second half effect is driven by the prosocial types who decrease their rate of vaccination by 6.1 percentage points ($p = 0.000$); the proself types do not meaningfully change ($-0.061 + 0.076 = +0.015$; $p = 0.638$).

Ambiguity affects proself types more than prosocials. Proself types comparatively reduce their rates of vaccination 15.2 percentage points ($0.042 + (-0.194) = -0.152$, $p = 0.000$) in the first half of the experiment and 16.7 percentage points in the second half (-0.167, $p = 0.014$). Prosocials increase their rate by 4.2 (0.042, $p = 0.234$) and 9.5 ($0.042 + 0.053 = 0.095$, $p = 0.046$) percentage points relative to prosocials in the no ambiguity treatment, in the first and second halves, respectively. The statistically meaningful second term is due to the reduction among prosocials in the No Ambiguity Treatment mentioned earlier; there is little change in vaccination rates among prosocials in the Ambiguity Treatment (53.6% vs. 52.7%; $-0.061 + 0.053 = -0.009$, $p = 0.747$.)

Specification (5) combines the explanatory variables of specifications (3) and (4), namely social value orientation and ambiguity attitudes. The ordering of the Ambiguity Treatment's effect by ambiguity attitude persists after accounting for SVO type. Among proself subjects in the first ten rounds, seeking types increase by 9.6 percentage points ($0.254 + (-0.159) = 0.096$, $p = 0.294$), neutral types decrease by 10.8 percentage points ($0.254 + (-0.204) + (-0.159) = -0.108$, $p = 0.105$), and averse types decrease by 19.4 percentage points ($0.254 + (-0.290) + (-0.159) = -0.194$, $p = 0.001$). Interestingly, the Ambiguity Treatment positively affects prosocial types 15.9 pp more than proself, an effect not explained by the distribution of ambiguity attitudes ($p = 0.016$). These findings are consistent with prior work showing that vaccination decisions depend on how individuals respond to others' behavior and motivations (Böhm et al., 2019).

4.2 Response to Past Outcomes

We next examine how subjects respond to observed parameters from the previous round. To begin, the number of other players in the group who vaccinate directly determines a player's payoff from remaining unvaccinated. Specifically, low (high) vaccination rates suggest the individual benefit for vaccination will be higher (lower) (see Figure 2). Figure 8 plots the fraction of subjects who vaccinate as a function of the number of others who vaccinated in the previous round, separately for prosocial and proself types in each treatment. Background shading indicates the strategic regions defined by the No Ambiguity best-response benchmark: "vaccinate" when others ≤ 6 and "don't vaccinate" when others ≥ 7. As the response of other players is not uniformly distributed, gray bars show the observed frequency of how often each subject observed that specific other player total. In general, for both SVO types subjects reduce their rate of vaccination when they observe more of other subjects vaccinating.

Going further, we focus on the past round parameters in our analysis, specifically, (i) a binary variable of past period's best response region and the incidence of adverse reactions to the (ii) disease and (iii) vaccine. Böhm et al. (2016) analyzes the same three variables and finds among these latter two categories, subjects are more responsive to side effects than adverse disease outcomes, a result consistent with the omission bias (Spranca et al., 1991; Ritov and Baron, 1999; Kahneman and Tversky, 1982). This pattern is also consistent with prior evidence showing that omission bias affects vaccination decisions, as individuals tend to evaluate vaccine side effects more negatively than comparable disease outcomes (Asch et al., 1994). We examine this question in our data in both the No Ambiguity and Ambiguity Treatments. We note that a differential response to side effects in the Ambiguity Treatment could also be consistent with belief updating and not necessarily evidence of an omission bias. Under this interpretation, the response to side effects should be strongest early in the Ambiguity Treatment, when individual realizations provide more information about the unknown distribution, and weaken as experience accumulates.

As we have identified several types of subjects and these three variables differ within subject, we choose to analyze data from within-subject variation which allows removal of subject-type interaction terms. This approach is more tractable as we are limited by a maximum of 20 regressors. Specifically, we use subject fixed effects to isolate this within-subject variation, progressively adding interactions with time-

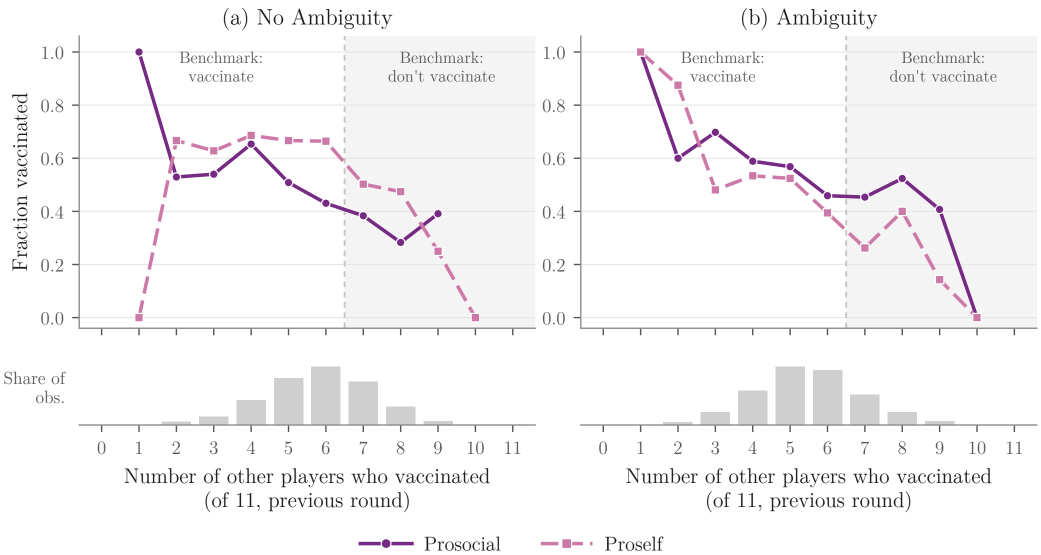


Figure 8: Strategic response by SVO type. Left: No Ambiguity. Right: Ambiguity. Shading: best-response regions. Bars: distribution of observations.

invariant subject characteristics:

$$V_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{Z}_{i,t-1} + \boldsymbol{\gamma}'\left(\mathbf{D}_i \times \mathbf{Z}_{i,t-1}\right) + \boldsymbol{\delta}'\left(\mathbf{D}_i \times B_t \times \mathbf{Z}_{i,t-1}\right) + \varepsilon_{it}, \tag{2}$$

where α_i is a subject fixed effect, $\mathbf{Z}_{i,t-1} = (F_{i,t-1}, G_{i,t-1}, H_{i,t-1})'$ collects lagged strategic variables: F indicates whether others' vaccination in round $t-1$ was at or above the Nash equilibrium level ($N \geq 7$ of 11 others), G indicates whether the subject experienced a vaccine side effect, and H indicates whether the subject experienced disease. $\mathbf{D}_i$ contains time-invariant subject characteristics — the ambiguity treatment indicator (A) and the proself SVO indicator (C) — whose main effects are absorbed by α_i but whose interactions with the time-varying $\mathbf{Z}_{i,t-1}$ are identified. B_t is the second-half indicator. Standard errors are clustered at the session level.

Table 5 examines how subjects respond to past outcomes. Across all specifications, experiencing a vaccine side effect reduces subsequent vaccination (e.g., -0.075, $p = 0.001$), while experiencing the disease increases it (e.g., 0.052, $p = 0.019$). The response to side effects is larger in magnitude and more robust across specifications,

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Chooses to Vaccinate				
Above NE, $t-1$ (F)	-0.025*	-0.024	0.008	0.011	-0.029
	(0.014)	(0.018)	(0.022)	(0.026)	(0.020)
Side effect, $t-1$ (G)	-0.075***	-0.067***	-0.056**	-0.043*	-0.068**
	(0.018)	(0.021)	(0.023)	(0.024)	(0.032)
Disease, $t-1$ (H)	0.052**	0.037	0.029	0.017	0.053
	(0.020)	(0.027)	(0.023)	(0.029)	(0.041)
A × F		-0.002		-0.007	0.026
		(0.030)		(0.027)	(0.043)
A × G		-0.016		-0.022	-0.066
		(0.035)		(0.035)	(0.049)
A × H		0.028		0.023	-0.016
		(0.039)		(0.039)	(0.063)
C × F			-0.077**	-0.078**	
			(0.034)	(0.034)	
C × G			-0.049	-0.052	
			(0.040)	(0.039)	
C × H			0.052	0.050	
			(0.045)	(0.046)	
Second half (B)					-0.021
					(0.015)
A × B					0.006
					(0.027)
B × F					0.006
					(0.023)
B × G					0.002
					(0.053)
B × H					-0.027
					(0.046)
A × B × F					-0.049
					(0.051)
A × B × G					0.094
					(0.062)
A × B × H					0.083
					(0.070)
Constant	0.518***	0.518***	0.518***	0.518***	0.527***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Observations	4560	4560	4560	4560	4560
Subjects	240	240	240	240	240
Sessions	20	20	20	20	20
R^2 (within)	0.009	0.009	0.012	0.013	0.011

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Fixed effects regressions of strategic response to past play. Treatment (A) and SVO (C) main effects are absorbed by subject fixed effects; their interactions with F, G, H are identified from within-subject variation.

which is suggestive of omission bias, although the two effects are not statistically distinguishable.

There is also meaningful heterogeneity across subject types. Proself individuals respond strongly to all three lagged variables, namely strategic conditions, side effects, and disease, while prosocial individuals primarily respond to side effects. This pattern is consistent with proself individuals being more sensitive to strategic incentives, whereas prosocial individuals exhibit more stable behavior.

Turning to treatment-specific estimates, the response to side effects is relatively stable over time in the No Ambiguity Treatment (about -0.066 to -0.068 across halves). In the Ambiguity Treatment, the corresponding point estimate is larger in magnitude in the early rounds (about -0.134, $p = 0.002$) and becomes smaller in the later rounds. By comparison, the response to disease is generally smaller and less precisely estimated, though it becomes stronger in the later rounds under Ambiguity (about 0.093, $p = 0.004$).

In the No Ambiguity treatment, experiencing a vaccine side effect consistently reduces subsequent vaccination, while experiencing the disease increases it, although the latter effect is imprecisely estimated. Although the two coefficients are not statistically distinguishable, the stronger and more robust response to side effects is suggestive of omission bias.

Under ambiguity, the point estimate of the response to side effects is largest in magnitude in the early rounds and weakens later, while the response to disease remains relatively muted. This pattern is consistent with belief updating about the initially unknown side-effect distribution. Early side-effect realizations are potentially more informative about that distribution, which could account for the larger behavioral response in early rounds. In this sense, the larger early response to side effects under ambiguity may reflect belief updating rather than omission bias alone. However, the relevant interaction estimates are imprecise, so we view this evidence as suggestive rather than a direct test of learning.

4.3 Ambiguity Attitude and COVID-19 Vaccination

Our experiment took place in 2022, roughly two years after the advent of COVID-19 and one year after the first availability of the corresponding vaccine. Though our experiment intentionally did not frame the I-Vax game in terms of vaccination, at the end of the experiment we collected three vaccination-related measures. Specifically, we inquired about subjects' attitudes toward vaccination in general, their attitudes toward COVID-19 vaccination, and whether they had been vaccinated for COVID-19 (see Section 2.4). At the time, no governmental or institutional regulations required subjects to receive a vaccine. The decision was voluntary.

We look to examine whether any data we have, especially ambiguity attitudes, might be predictive of the decision to take the COVID-19 vaccine. We interpret subject responses to the two other survey questions as mediators of this decision. We develop a structural equation model (SEM) in kind, having ambiguity attitudes and prosociality affect COVID-19 vaccination both directly and indirectly through standardized vaccination attitude and COVID-19 attitude mediators. Figure 9 provides the path diagram of this model. Formally the three-equation system is:

$$\tilde{A}_i^{\text{vacc}} = \gamma_0 + \gamma_1 D_i + \gamma_2 E_i + \gamma_3 C_i + \mathbf{W}_i' \boldsymbol{\delta} + \eta_i \tag{3}$$

$$\tilde{A}_i^{\text{covid}} = \theta_0 + \theta_1 D_i + \theta_2 E_i + \theta_3 C_i + \mathbf{W}_i' \boldsymbol{\phi} + \nu_i \tag{4}$$

$$Y_i^{\text{covid}} = \beta_0 + \beta_1 \tilde{A}_i^{\text{vacc}} + \beta_2 \tilde{A}_i^{\text{covid}} + \beta_3 D_i + \beta_4 E_i + \beta_5 C_i + \mathbf{W}_i' \boldsymbol{\psi} + \epsilon_i \tag{5}$$

As the responses are on different scales, we standardize both vaccine and covid attitudes, producing $\tilde{A}_i^{\text{vacc}}$ and $\tilde{A}_i^{\text{covid}}$ as mediators. The main dependent variable Y_i^{covid} is a binary outcome for having received the COVID-19 vaccine. Terms D_i and E_i are indicators for ambiguity averse and ambiguity seeking (reference: neutral), C_i is a proself indicator, and $\mathbf{W}_i$ collects control variables from demographics (sex, age, economics major) and experimental data, specifically a standardized count of the total times a subject chooses to vaccinate in 20 rounds of the experiment.

	(1) Full sample	(2) Early sessions (3/10–4/20)	(3) Late sessions (6/28–9/21)
Eq 1: Vaccination attitude (std.)			
Ambig. averse	-0.105	-0.365*	0.089
	(0.137)	(0.188)	(0.238)
Ambig. seeking	-0.082	-0.444	0.320
	(0.211)	(0.283)	(0.316)
Proself (SVO)	-0.231*	-0.300*	-0.177
	(0.133)	(0.169)	(0.207)
Vacc. count (std.)	0.012	0.065	0.003
	(0.063)	(0.091)	(0.093)
Female	0.063	0.327**	-0.189
	(0.129)	(0.164)	(0.206)
Age	0.033**	0.045**	0.032
	(0.015)	(0.020)	(0.020)
Econ major	-0.024	0.075	-0.032
	(0.166)	(0.188)	(0.347)
Constant	-0.566	-0.759*	-0.578
	(0.347)	(0.418)	(0.506)
Eq 2: COVID-19 attitude (std.)			
Ambig. averse	-0.122	-0.451**	0.127
	(0.136)	(0.177)	(0.228)
Ambig. seeking	-0.119	-0.427	0.216
	(0.211)	(0.270)	(0.335)
Proself (SVO)	-0.099	-0.230	0.040
	(0.127)	(0.160)	(0.197)
Vacc. count (std.)	0.119*	0.236***	0.055
	(0.064)	(0.089)	(0.089)
Female	0.286**	0.556***	0.041
	(0.129)	(0.162)	(0.206)
Age	0.029**	0.033	0.036*
	(0.014)	(0.023)	(0.019)
Econ major	-0.206	-0.150	-0.052
	(0.182)	(0.221)	(0.293)
Constant	-0.602*	-0.612	-0.843*
	(0.333)	(0.493)	(0.483)
Eq 3: COVID-19 vaccinated			
Vacc. attitude (std.)	0.029	-0.044	0.076*
	(0.031)	(0.047)	(0.041)
COVID att. (std.)	0.192***	0.259***	0.151***
	(0.034)	(0.050)	(0.045)
Ambig. averse	0.015	0.039	-0.009
	(0.037)	(0.050)	(0.063)
Ambig. seeking	-0.037	-0.020	-0.073
	(0.056)	(0.071)	(0.084)
Proself (SVO)	-0.003	-0.016	0.019
	(0.035)	(0.048)	(0.050)
Vacc. count (std.)	-0.013	-0.031	-0.007
	(0.017)	(0.027)	(0.022)
Female	0.021	0.024	0.002
	(0.036)	(0.045)	(0.059)
Age	0.001	-0.000	0.002
	(0.003)	(0.007)	(0.003)
Econ major	0.075	0.096	0.068
	(0.052)	(0.068)	(0.079)
Constant	0.814***	0.837***	0.819***
	(0.081)	(0.145)	(0.114)
Observations	240	132	108

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Full results from mediation analysis on full sample, early sessions (Spring 2022), and late sessions (Fall 2022).

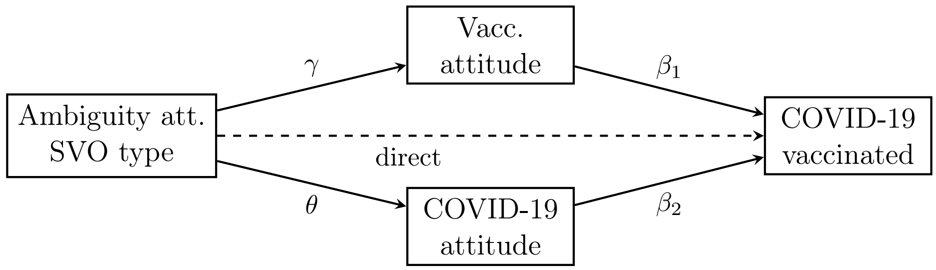


Figure 9: Path diagram for the mediation SEM. Solid arrows represent indirect paths through the two attitude mediators; the dashed arrow represents the direct effect.

Indirect Effect	Estimate	Std. Err.	z	p
Full sample (N=240)				
Averse → Vacc Att → COVID Vacc	-0.0031	0.0056	-0.55	0.585
Averse → COVID Att → COVID Vacc	-0.0234	0.0254	-0.92	0.358
Averse Total Indirect	-0.0264	0.0289	-0.91	0.360
Early sessions (3/10–4/20, N=132)				
Averse → Vacc Att → COVID Vacc	0.0160	0.0185	0.87	0.386
Averse → COVID Att → COVID Vacc	-0.1170	0.0478	-2.45	0.014
Averse Total Indirect	-0.1010	0.0406	-2.49	0.013
Late sessions (6/28–9/21, N=108)				
Averse → Vacc Att → COVID Vacc	0.0068	0.0174	0.39	0.698
Averse → COVID Att → COVID Vacc	0.0192	0.0360	0.53	0.595
Averse Total Indirect	0.0259	0.0480	0.54	0.589

Table 7: Indirect effects of ambiguity aversion on COVID-19 vaccination through attitude mediators.

Table 6, Column (1) reports the SEM path coefficients for the entire sample. We see from the third panel that only one's attitude toward COVID-19 vaccination is strongly associated with individual vaccination status. More variables are associated with the mediators. In particular, proselfs are more negative toward vaccination in general. Older individuals are more positive toward both vaccination in general and COVID-19 vaccination. Those identifying as female are also more positive toward COVID-19 vaccination. Interestingly, the number of times a subject vaccinates in the experiment is positively correlated with attitudes toward COVID-19 vaccination. However, whether through direct or indirect channels, we see little evidence that ambiguity attitudes are associated with the decision to be vaccinated for COVID-19 in the full sample.

However, this paper considers how ambiguity attitudes are related to vaccination hesitancy rather than outright avoidance. And further, as our experimental results have shown, the effects of ambiguity tend to dissipate over time as more information about the ambiguous distribution is revealed. To this end, we expect any association between ambiguity attitudes and COVID-19 vaccination to be stronger in earlier periods. Our sample contains a natural break: between April 20 and June 28 no experiments were run and roughly half the data falls on either side of this interval.

Table 6, Column (2) and Column (3) run our model exclusively on these early and late periods, respectively. In the early sessions, ambiguity aversion is significantly negatively associated with both vaccination attitude and COVID-19 attitude. Female subjects are more positive on both general vaccination and COVID-19 vaccination. The number of vaccine decisions in the experiment is more strongly positively associated with COVID attitude. In the late sessions, there is little evidence of significant associations, although age is positively associated with COVID-19 attitude. Vaccine attitude in general is positively associated with the decision to vaccinate. COVID-19 attitude is strongly associated with the decision to vaccinate.

We specifically examine the indirect association between ambiguity aversion and the decision to vaccinate in the early sample. Through the channel of COVID-19 attitudes, ambiguity aversion is associated with a lower likelihood of COVID-19 vaccination. There is no corresponding effect in the late sample. We view these results as exploratory and not necessarily indicative of causal relationships.

5 Conclusion

This paper posits that ambiguity attitudes may play a role in the prevalence of vaccine hesitancy. As vaccines naturally lag the diseases they are intended to prevent, the distribution of side effects of the vaccine will be more uncertain than the distribution of bad disease outcomes. The greater ambiguity may cause ambiguity averse individuals to forestall their decision to vaccinate until after more uncertainty about side effects is resolved.

Using a previously developed experimental design to model vaccination decisions, we introduce ambiguity into this I-Vax game. Compared to a treatment with no ambiguity, subjects are less likely to vaccinate under ambiguity and the effect is concentrated in the first half of the experiment. Classifying subjects' ambiguity attitudes in an entirely separate Ellsberg task, we find this effect is driven by ambiguity averse subjects. True to their type, ambiguity seeking subjects *increase* their vaccination rates under the Ambiguity Treatment, ambiguity neutral subjects do not change their rate. Together, these results suggest that ambiguity primarily affects vaccination decisions while the side-effect distribution is poorly known: responses initially track independently elicited ambiguity attitudes, but these type-specific differences fade with experience.

While our data is from an experimental game that removes any terminology related to vaccination, we try to see if our results can have some predictive power outside the lab. We elicit all subjects attitudes about vaccines in general, their attitude toward COVID-19 vaccination, and whether they had been vaccinated for COVID-19. Looking over our entire sample, we see little effect except for the positive relation between COVID-19 attitude and COVID-19 vaccination. However, as our data come from 2022 where uncertainty of the COVID-19 vaccination was still being resolved, we separate our data from the Spring and late Summer and Fall. Looking at the early period, we find that ambiguity aversion has a negative indirect effect on COVID-19 vaccination. While we are cautiously skeptical of this result, it does give credence to the general principles of this paper.

Our research has revealed a novel relationship between vaccination hesitancy, a major concern in public health, and ambiguity aversion. We are optimistic this research may point to the relevance of ambiguity attitudes in everyday decision making.

The results suggest that simply providing information about side effects, which could reduce ambiguity, may effectively decrease vaccination hesitancy. We encourage future studies to consider the practical implications of these findings as well as how they might interact with individual ambiguity attitudes.

References

Asch, D. A., Baron, J., Hershey, J. C., Kunreuther, H., Meszaros, J., Ritov, I., and Spranca, M. (1994). Omission bias and pertussis vaccination. *Medical Decision Making*, 14(2):118–123.

Attema, A. E., Bleichrodt, H., and L'Haridon, O. (2018). Ambiguity preferences for health. *Health Economics*, 27:1699–1716.

Baillon, A., Huang, Z., Selim, A., and Wakker, P. P. (2018). Measuring ambiguity attitudes for all (natural) events. *Econometrica*, 86(5):1839–1858.

Betsch, C. and Böhm, R. (2016). Partial compulsory vaccination can backfire: Evidence from behavioral experiments. *European Journal of Public Health*, 26(3):378–381.

Betsch, C., Böhm, R., and Korn, L. (2017). Using behavioral insights to increase vaccination policy effectiveness. *Nature Human Behaviour*, 1:0056.

Blaisdell, L. L., Gutheil, C., Hootsmans, N. A. M., and Han, P. K. (2015). Unknown risks: Parental hesitation about vaccination. *Medical Decision Making*, 36.

Böhm, R., Betsch, C., and Korn, L. (2019). The impact of responsibility for vaccination on intentions to vaccinate: Experimental evidence. *Journal of Behavioral Medicine*, 42(2):217–229.

Böhm, R., Betschb, C., and KornbaSchool, L. (2016). Selfish-rational non-vaccination: Experimental evidence from an interactive vaccination game. *Journal of Economic Behavior and Organization*, (131):183–195.

Brown, A. L., Guo, H., and Je, H. (2026). Preferences for the resolution of risk and ambiguity. *Journal of Economic Theory*, page 106151.

Courbage, C. and Peter, R. (2021). On the effect of uncertainty on personal vaccination decisions. *Health Economics*, 30:2937–2942.

Dubé, E., Laberge, C., Guay, M., Bramadat, P., Roy, R., and Bettinger, J. (2013). Vaccine hesitancy: an overview. *Human Vaccines and Immunotherapeutics*, 9(8):1763–1773.

Dubé, E., Vivion, M., and MacDonald, N. E. (2015). Vaccine hesitancy, vaccine refusal and the anti-vaccine movement: influence, impact and implications. *Expert Rev Vaccines*, 14(1):99–117.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 75(4):643–669.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10:171–178.

Gillman, A. S., Scharnetzki, L., Boyd, P., Ferrer, R. A., Klein, W. M. P., and Han, P. K. J. (2022). Perceptions and tolerance of uncertainty: Relationship to trust in covid-19 health information and vaccine hesitancy. *Journal of Behavioral Medicine*, 46(1-2):40–53.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association*, 1(1):114–125.

Han, P. K., Zikmund-Fisher, B., Duarte, C. W., Knaus, M., Black, A., Scherer, A. M., and Fagerlin, A. (2018). Communication of scientific uncertainty about a novel pandemic health threat: Ambiguity aversion and its mechanisms. *Journal of Health Communication*, 23:435–444.

Jacobson, R. M., Sauver, J. L. S., and Finney Rutten, L. J. (2015). Vaccine hesitancy. *Mayo Clinic Proceedings*, 90:1562–1568.

Kahneman, D. and Tversky, A. (1982). The psychology of preferences. *Scientific american*, 246(1):160–173.

Khubchandani, J., Sharma, S., Price, J. H., Wiblishauser, Michael J Sharma, M., and Webb, F. J. (2021). Covid-19 vaccination hesitancy in the united states: A rapid national assessment. *Journal of Community Health*, 46:270–277.

Klibanoff, P., Marinacci, M., and Mukerji, S. (2005). A smooth model of decision making under ambiguity. *Econometrica*, 73(6):1849–1892.

Murphy, R. O., Ackermann, K. A., and Handgraaf, M. J. (2011). Measuring social value orientation. *Judgment and Decision Making*, 6(8):771–781.

Ritov, I. and Baron, J. (1999). Protected values and omission bias. *Organizational behavior and human decision processes*, 79(2):79–94.

Sallam, M. (2021). Covid-19 vaccine hesitancy worldwide: A concise systematic review of vaccine acceptance rates. *Vaccines*, 9(2):160.

Simonovic, N., Gesser-Edelsburg, A., and Taber, J. M. (2025). Testing psychological correlates of ambiguity aversion in the context of covid-19 vaccination: Evidence for motivated reasoning and the appraisal-tendency framework. *Behavioral Medicine*, 51(4):332–346.

Spranca, M., Minsk, E., and Baron, J. (1991). Omission and commission in judgment and choice. *Journal of experimental social psychology*, 27(1):76–105.

Trautmann, S. T. and van de Kuilen, G. (2015). Ambiguity attitudes. In Keren, G. and Wu, G., editors, *The Wiley Blackwell Handbook of Judgment and Decision Making*, pages 89–116. John Wiley & Sons.

Troiano, G. and Nardi, A. (2021). Vaccine hesitancy in the era of covid-19. *Public Health*, 194:245–251.

World Health Organization (2014). Report of the sage working group on vaccine hesitancy. Technical report, World Health Organization.

A Experimental Materials

A.1 Experimental Instructions

The instructions are presented jointly for the two treatments. Where the instructions differed, the treatment-specific passages are presented separately for the No Ambiguity Treatment and the Ambiguity Treatment. For clarity, these treatment-specific passages are enclosed in boxes; the boxes were not part of the original instructions. Each subject received the common instructions and the treatment-specific passages corresponding to their assigned treatment.

Part I

General Information

We would like to welcome you to this experiment. It is very important that you read the following explanations carefully. If you have any questions, please raise your hand. We will then come to you and answer them.

In this experiment you can earn money. The exact amount depends on your decisions and on the decisions of the other participants. **Your total earnings from the experiment comprise two independent parts: Decision task A and decision task B.**

During the experiment, points will be used to calculate your income. At the end of the experiment, the total score earned by you during the experiment will be converted into dollars as follows: **100 points = \$0.50**. At the end of the experiment, your earnings from decision task A and decision task B will be reported and paid in cash.

You cannot communicate with other participants during the experiment. Disregarding this rule will disqualify you from the experiment and from all payments. All decisions will be made anonymously. This implies that none of the other participants will at any time know the identity of the other participants and their decisions. Payments will also be made anonymously. That implies that none of the participants will gain knowledge of the amount earned by any of the other participants.

Decision Task A

In this task there is an **allocator** and a **recipient**. For this purpose, you will be randomly assigned to another participant. You will make decisions from the perspective of the allocator. The allocator decides on the allocation of points between him-/herself and the recipient. At the end of the experiment it will be decided randomly whether you are in the role of the allocator or recipient.

In this example, you (as an allocator) would receive 50 points, while the other person (as a recipient) would receive 40 points. Thus, the decision of the allocator influences the points received by both the allocator and the recipient. There are no right or wrong allocations.

In total, there are **6 allocation decisions**. Exactly **one allocation decision of the allocator will be selected randomly and becomes payoff-relevant** for the allocator and the recipient.

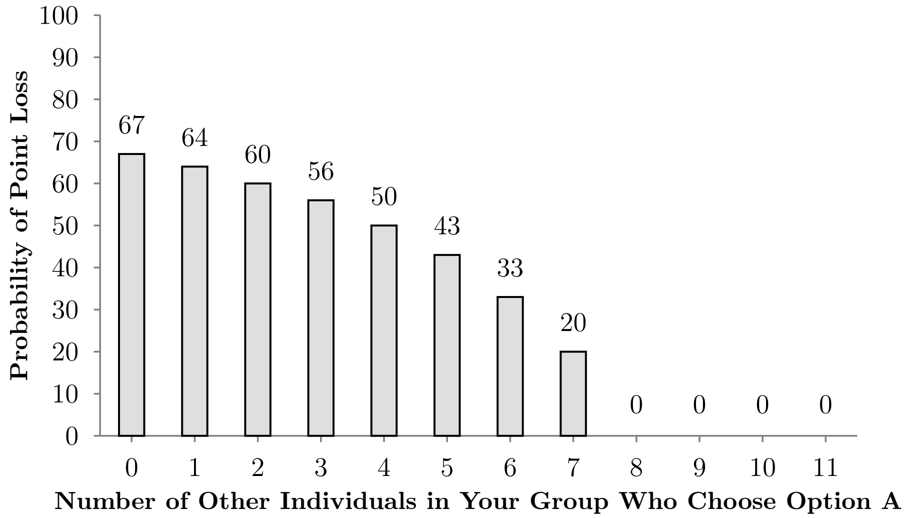
Part II

Decision Task B

Course of the Decision Task. You are part of a group which is composed of 12 participants.

The decision task consists of **20 rounds**. In each round you will make a decision. At the beginning of each round, each participant is equipped with **100 points**. You can decide either **option A** or **against option A**. In both options, there is a probability of losing points. In the following you will be informed of the exact rules for the decision task and the impact of your decision.

Decision Against Option A. In each round, each person who chooses against option A might suffer a point loss. The probability of point loss depends on the number of other people in your group who choose option A. **The greater the number of people who choose option A, the lower the probability of point loss is for people who choose against option A** (see figure below).



In the case of point loss, you will lose points as follows: In 5 of 10 cases you will lose 35 points, in 4 of 10 cases you will lose 60 points, and in 1 of 10 case you will lose 85 points. This implies that **in the case of losing points you will lose on average 50 points, with loss of a few points being more likely than loss of many points.**

Decision for Option A. If you choose option A, **the probability of point loss is fixed, which is 30%**. Also, you will lose **5 points as fixed costs, independent of the occurrence of point loss**.

No Ambiguity Treatment

Conditional on a point loss, you lose 21 points in 5 of 10 cases, 36 points in 4 of 10 cases, and 51 points in 1 of 10 cases. Thus, conditional on losing points, the average loss is 30 points, with a smaller loss being more likely than a larger loss.

Ambiguity Treatment

In the case of point loss, you will lose points as follows: In x of 10 cases you will lose 20 points, in y of 10 cases you will lose 30 points, and in z of 10 cases you will lose 55 points. Unlike the decision against option A, the values of x, y, and z are unknown. (You only know $x + y + z = 10$.) The only restriction is $z < 5$, implying that the probability of losing 55 points is less than 50%. Other than this, you don't have any information about x, y, and z. This implies that **in the case of point loss, you don't know the probability of losing 20 or 30 or 55 points, so you cannot calculate the average of the point loss. The only thing you know is you might lose 20 or 30 or 55 points with unknown probability.**

Information at the end of each round. After all group members have made their decisions, all members will receive the following information:

Your personal decision
Number of other individuals in your group who have chosen option A
Resulting probability of point loss for group members who chose against option A
Your loss of points
Your earnings in the current round (remaining points)

Examples.

No Ambiguity Treatment

Example 1.

Two other group members have chosen option A. If you choose against option A, the probability of point loss is 60% (see figure) and on average you will lose 50 points.

If you choose option A, you lose 5 points as fixed costs and lose an average of 30 additional points with probability 30%. Your expected loss is therefore $5 + 0.30 \times 30 = 14$, and your expected round income is $100 - 14 = 86$ points. If you choose against option A, your expected loss of points is $0.60 \times 50 = 30$, and your expected round income is $100 - 30 = 70$ points.

Example 2.

Seven other group members have chosen option A. If you choose against option A, the probability of point loss is 20% (see figure) and on average you will lose 50 points.

If you choose option A, your expected loss remains $5 + 0.30 \times 30 = 14$, and your expected round income remains $100 - 14 = 86$ points. If you choose against option A, your expected loss is $0.20 \times 50 = 10$, and your expected round income is $100 - 10 = 90$ points.

Ambiguity Treatment

Example 1.

Two other group members have chosen option A. If you choose against option A, the probability of point loss is 60% (see figure) and on average you will lose 50 points.

In the case of choosing option A, you will lose 5 points as fixed costs and might suffer point loss with a probability of 30%. In the case of point loss, the specific distribution is not known. So you cannot calculate the average of point loss in this case. This implies: Your expected loss of points will be $0.60 \times 50 = 30$ in the case of choosing against option A and $5 + 0.30 \times$ unknown value in the case of choosing option A. You only know that the unknown value could be 20 or 30 or 55. If you choose against option A, your expected round income will be $100 - 30 = 70$ points. If you choose option A, your expected round income is subjective based on your expectation of the unknown value.

Example 2.

Seven other group members have chosen option A. If you choose against option A, the probability of point loss is 20% (see figure) and on average you will lose 50 points.

In the case of choosing option A, you will lose 5 points as fixed costs and might suffer point loss with a probability of 30%. In the case of point loss, the specific distribution is not known. So you cannot calculate the average of point loss in this case. This implies: Your expected loss of points will be $0.20 \times 50 = 10$ in the case of choosing against option A and $5 + 0.30 \times$ unknown value in the case of choosing option A. You only know that the unknown value could be 20 or 30 or 55. If you choose against option A, your expected round income will be $100 - 10 = 90$ points. If you choose option A, your expected round income is subjective based on your expectation of the unknown value.

Round income. If you choose against option A:

$$\begin{aligned}\text{Round income} = \text{points} \\ &- \text{possibly occurring costs due to point loss.}\end{aligned}$$

If you choose option A:

$$\begin{aligned}\text{Round income} = \text{points} - \text{fixed costs} \\ &- \text{possibly occurring costs due to point loss.}\end{aligned}$$

At the end of the decision task, the earnings from the 20 rounds will be totaled.

A.2 Comprehension Questions

Before the 20-round decision task began, participants completed a computerized comprehension check. They were required to answer all questions correctly before proceeding.

If you decide against Option A:

Statement	Response	
I will never suffer a loss.	☐ False	☐ True
I will definitely suffer a loss.	☐ False	☐ True
The likelihood of loss depends on the number of other people who have chosen Option A.	☐ False	☐ True
The probability that a loss will occur is fixed and independent of whether other people have chosen Option A.	☐ False	☐ True

If you choose Option A:

Statement	Response	
I will never suffer a loss (excluding fixed costs).	☐ False	☐ True
I will definitely suffer a loss (excluding fixed costs).	☐ False	☐ True
The likelihood of loss depends on the number of other people who have chosen Option A.	☐ False	☐ True
The probability that a loss will occur is fixed and independent of whether other people have chosen Option A.	☐ False	☐ True

A.3 Post-Experiment Questionnaire

After completing the experimental tasks, subjects completed a post-experiment questionnaire. The questions and response options were as follows:

Question shown to participants	Response options
By and large, I am ...	Slider from 1 (completely against vaccination) to 100 (completely for vaccination)
What is your attitude towards the COVID-19 vaccination?	1 (very negative) to 5 (very positive)
Did you get vaccinated for COVID-19?	Yes / No
How old are you?	Numeric response
What is your gender?	Male / Female
Which subject do you study?	Open-text response

A.4 Choice Sets in the SVO Task

The table below reports the allocation alternatives implemented in the six SVO items. The table summarizes the computerized choice sets and was not displayed to subjects in this tabular form. Each row represents one SVO item, with each ordered pair indicating (points to self, points to other).

Item	1	2	3	4	5	6	7	8	9
1	(85,85)	(85,76)	(85,68)	(85,59)	(85,50)	(85,41)	(85,33)	(85,24)	(85,15)
2	(85,15)	(87,19)	(89,24)	(91,28)	(93,33)	(94,37)	(96,41)	(98,46)	(100,50)
3	(50,100)	(54,98)	(59,96)	(63,94)	(68,93)	(72,91)	(76,89)	(81,87)	(85,85)
4	(50,100)	(54,89)	(59,79)	(63,68)	(68,58)	(72,47)	(76,36)	(81,26)	(85,15)
5	(100,50)	(94,56)	(88,63)	(81,69)	(75,75)	(69,81)	(63,88)	(56,94)	(50,100)
6	(100,50)	(98,54)	(96,59)	(94,63)	(93,68)	(91,72)	(89,76)	(87,81)	(85,85)

Table A.1: Allocation alternatives in the six SVO items.