The Role of Risk Preferences in Responses to Messaging about COVID-19 Vaccine Take-up

Jennifer S. Trueblood

Department of Psychology, Vanderbilt University

Abigail B. Sussman

Booth School of Business, University of Chicago

Daniel O'Leary

Booth School of Business, University of Chicago

Author Note

Author Biographies:

- Jennifer Trueblood is associate professor of psychology at Vanderbilt University. Her research uses a joint experimental and computational modeling approach to study human judgment, decision-making, and reasoning.
- Abigail B. Sussman is an associate professor at the University of Chicago Booth Booth School of Business. Her research focuses on intersection of psychology and economics, with the aim of improving human welfare.
- Daniel O'Leary is a postdoctoral scholar and the University of Chicago Booth School of Business. His research focuses on how affect, expectations, and socioeconomic status influence decision-making and consumer behavior.

Correspondence may be addressed to Jennifer S. Trueblood, Department of Psychology, Vanderbilt University, Nashville TN 37235, USA; Email: jennifer.s.trueblood@vanderbilt.edu or Abigail Sussman, Booth School of Business, University of Chicago, Chicago, IL 60637 , USA; Email: abigail.sussman@chicagobooth.edu. This work was supported by NSF grant 1846764 and by the True North Communications, Inc. Fund and the Initiative for Global Markets at the University of Chicago Booth School of Business. We thank Abigail Bergman for excellent research assistance.

Abstract

Development of an effective COVID-19 vaccine is widely considered one of the best paths to ending the current health crisis. While the ability to distribute a vaccine in the short-term remains uncertain, the availability of a vaccine alone will not be sufficient to stop disease spread. Instead, policymakers will need to overcome the additional hurdle of rapid widespread adoption. In a large-scale nationally representative survey (N=34,200), the current work identifies monetary risk preferences as a correlate of take-up of an anticipated COVID-19 vaccine. A complementary experiment (N=1,003) leverages this insight to create effective messaging encouraging vaccine take-up. Individual differences in risk-preferences moderate responses to messaging that provides benchmarks for vaccine efficacy (by comparing it to the flu vaccine), while messaging that describes pro-social benefits of vaccination (specifically herd immunity) speeds vaccine take-up irrespective of risk-preferences. Findings suggest that policy-makers should consider risk-preferences when targeting vaccine-related communications.

Keywords: vaccine, individual differences, pro-social behavior, public policy

The Role of Risk Preferences in Responses to Messaging about COVID-19 Vaccine Take-up

Starting in early 2020, the COVID-19 virus wreaked havoc around the world. In addition to the direct impact on physical health, the virus has dramatically curtailed social and economic interactions. One of the best paths to ending the COVID-19 pandemic, or any pandemic, is through the development and distribution of a vaccine. Although there are significant scientific and operational challenges to producing a new vaccine, the availability of a vaccine alone is not sufficient to stop disease spread. Instead, widespread adoption of the vaccine is necessary to achieve “herd immunity" where enough people are immune to the disease that continued spread is unlikely. However, surveys conducted in the second half of 2020, showed that many Americans do not want to take a COVID-19 vaccine (NORC, 2020). This pattern is consistent with reluctance to take vaccines in other contexts (i.e., vaccine hesitancy) (Jarrett et al., 2015; Larson et al., 2014). Even among those reporting a willingness to take a vaccine, important questions arise over how soon after the vaccine is available people will take it. To reach herd immunity through a vaccine and stop the spread of COVID-19 as soon as possible, policymakers will need to find ways to ensure immediate and widespread vaccine take-up in the face of these challenges.

Given the importance of widespread adoption for the efficacy of vaccines in general, behavioral research has aimed to understand and promote vaccine take-up (Betsch et al., 2015; Brewer et al., 2017; Jarrett et al., 2015; Oliver & Berger, 1979). In the context of messaging to increase vaccine take-up, one valuable insight is that highlighting pro-social benefits (e.g., through descriptions of herd immunity) is often more effective than highlighting selfish benefits (Betsch et al., 2017; Betsch et al., 2011; Brockmann, 2017; Shim et al., 2012).

Additionally, a large body of research examines the relationship between perceptions of health risks and benefits of vaccination in decisions to vaccinate (Brewer et al., 2007; Gidengil et al., 2012; Seale et al., 2010). When individuals decide whether to take a vaccine, they have to weigh the possible benefits of the vaccine (e.g., immunity to COVID-19) against the possible harms, including side effects and the physical pain of the shot. When considering a brand-new vaccine, neither risks nor rewards are known with certainty. Further, while vaccines are provided to reduce health risks, individuals hold false beliefs about risks that extend even to established vaccines such as the flu vaccine (Dibonaventura & Chapman, 2008). While turning down a vaccine might be as risky, if not riskier, than taking it, research documenting an omission bias suggests that individuals view negative outcomes resulting from taking vaccines as worse than the same negative outcomes from avoiding it (Dibonaventura & Chapman, 2008; Ritov & Baron, 1990).

In the present research, we drew on these two literatures - one on vaccine messaging and one on risk preferences and vaccine uptake - to examine the relationships between risk preferences and willingness to take the COVID-19 vaccine. We use one of the most common methods for eliciting risk preferences in psychology, a multiple price list or gamble ladder (Charness et al., 2013). While individual risk preferences are domain specific (Weber et al., 2002), in many cases they also carry over across domains. For example, overall risk preferences tend to vary as a function of individual differences such as gender and personality traits (Harris & Jenkins, 2006; Markiewicz & Weber, 2013; Mishra et al., 2010). Moreover, recent work indicates that risk preferences exhibit characteristics similar to other stable psychological traits and that half the variance in risk preferences is determined by a domain-general risk preference factor (Frey et al., 2017). Thus, important questions regarding the relationship between risk preferences in non-health domains and decisions to vaccinate remain. Interestingly, when considering the relationship between intertemporal preferences and flu vaccine take-up, monetary time preferences are a stronger (although still weak) predictor of take-up than health time preferences (Chapman & Coups, 1999). Building on this insight, the current research asks whether risk preferences in the financial domain predict vaccination decisions.

The current research improves our understanding of the decision-making process surrounding take-up of a COVID-19 vaccine and leverages this understanding to identify messaging that effectively motivates people to vaccinate. In a nationally representative survey of more than 34,000 participants, we first explore several factors, including risk preferences and sociodemographic variables, thought to influence take-up of a COVID-19 vaccine. Our key hypothesis is that willingness to take a COVID-19 vaccine is positively associated with preference for risk. We follow up on results from our survey data with an experiment that examines messaging intended to increase COVID-19 vaccine take-up. We hold information about the risks (i.e., potential side-effects) of taking the vaccine constant but vary communications of rewards. In sum, our aim is to explore (1) the relationship between risk-taking in non-health domains and vaccination decisions, (2) how vaccine messaging affects COVID-19 vaccine uptake, and (3) how heterogeneity in risk preferences influences responses to our messages.

The data and R code to reproduce the results is available on the Open Science Framework at https://osf.io/nkuzp/?view_only=e4d29f1892014a859a18783279363522

Study 1

Study 1 uses data from a cross-sectional survey conducted between June and December 2020 to examine risk preferences and sociodemographic variables as predictors of potential COVID-19 vaccine take-up.

Method

Participants

Participants were recruited using the Lucid platform (see Coppock & McClellan, 2019) as part of an ongoing cross-sectional survey examining beliefs and behaviors related to the COVID-19 pandemic. The Lucid platform was selected because it targets a nationally representative sample. The first wave of the survey was conducted on 3/20/2020. In the initial stages of the pandemic (from 3/20/2020 to 4/21/2020) two waves of data were collected every week. Starting on 4/21/2020, one wave of data was collected per week. Beginning 12/1/2020, one wave of data was collected per month. In wave 16 (launched on 6/2/2020), questions related to COVID-19 vaccine uptake were added to the survey. The current analyses use data from waves 16 to 40 (launched 12/1/2020). Dates for each wave included in this paper are provided in the supplemental materials.

For each wave, we targeted 1,500 to 2,000 participants prior to exclusions and between 1000 to 1500 participants after exclusions. These sample sizes were determined before running the analyses. For the analyses of the COVID-19 vaccine questions, participants were excluded based on the following criteria: (1) education level was not reported and (2) political affiliation was reported as ‘other’. These exclusions were determined in advance and necessary since we include education and political affiliation as control variables in our central analysis. In total, there were 34,200 participants after exclusions, averaging 1,368 participants per wave. An additional 1,006 participants were excluded from the analysis of the 2019 flu vaccine question because they responded “not sure" to this question. Participants ranged in age from 18-99 (*M*=46), 43% were male, and had an average income of between $50,000-$59,999.[1] This study was approved by the Institutional Review Board at a Midwestern university.

Materials and Procedure

After entering the survey and providing consent, participants answered approximately 50 questions. These questions fell into several different categories including: psychological characteristics (e.g., risk preferences), perceptions of COVID-19 (e.g., predictions about future spread), health behaviors (e.g., willingness to take a vaccine), employment and financial impacts (e.g., COVID-related job risk), consumer activity (e.g., charitable giving), and demographics.

We focus our analysis on several key questions. The full list of questions analyzed in this paper are available in the supplemental materials. To examine willingness to take a COVID-19 vaccine, we asked two questions. In each case, participants considered “a situation in which a vaccine for COVID-19 is free and widely available." The first question presented a vaccine authorized by the FDA through an expedited process: “This vaccine was authorized by the FDA through an expedited authorization process, in other words, a process that took place on a faster timeline than is typical for vaccines." The second question presented a vaccine authorized by a standard authorization process: “This vaccine was approved by the FDA in a standard

[1] The percentage of males in the survey is lower than the national percentage. While Lucid targets a nationally representative sample, it does not guarantee an exact match.

authorization process, in other words, a process that took place on a typical timeline for vaccines". After each vaccine description, participants were asked: "How likely would you be to take this vaccine?" Response options for both questions were on a 5-point scale from 1 = extremely likely to 5 = extremely unlikely. For the analyses, these questions were reverse coded (i.e., higher numbered responses indicate increased likelihood of taking the vaccine).

To examine whether results for the COVID-19 vaccine generalize to other vaccines, we also asked participants if they received the flu vaccine for the 2019-2020 flu season. Response options were “yes", “no", and “not sure". For the analyses, “yes" was coded as 1 and “no" coded as 0.

To measure risk preferences we examined two questions, one question was a gamble ladder asking participants to make choices between risky and safe options and the other question asked participants to report how many lottery tickets they purchased last week (a proxy for real world risk-taking). The gamble ladder consisted of 9 choices between a gamble offering X% chance of $100 and $50 for sure. The chance of winning the gamble ranged from X = 90% to X = 10% in increments of 10%, yielding 9 distinct gambles. For the analyses, the gamble ladder was scored as the proportion of risky choices out of the nine choice sets.

Results

Across all waves, 65.1% of participants stated that they would be extremely or somewhat likely to receive a COVID-19 vaccine under a standard authorization process. This drops to 53.2% of participants when asked about a COVID-19 vaccine under an expedited authorization process. 54.2% of participants reported that they received a flu vaccine during the 2019-2020 flu season, excluding those participants who responded “not sure".

To test the relationship between risk preferences and prospective COVID-19 vaccine take-up, we conducted three OLS linear regressions to predict: (1) vaccine take-up under a standard authorization process, (2) vaccine take-up under an expedited authorization process, and (3) the difference in vaccine take-up under the standard and fast authorization processes. For each model, we included the following predictors: proportion of risky choices on the gamble ladder, number of lottery tickets purchased in the past week, income, age, education, political affiliation, gender, and the month the survey wave was launched. Gender and month were dummy coded with “male" and “June" as the reference groups, respectively. Note that the correlation between the gamble ladder variable and the lottery ticket variable is $r = 0.123$, $p < .001$. While this is significant, the correlation coefficient is low, thus we decided to treat these as two distinct variables. Theoretically, while both variables measure risk-taking, they do so in different ways. The gamble ladder variable is a hypothetical measure of risk preferences while the lottery ticket variable is measure of real-world risky behavior.

We also examined the relationship between risk preferences and reported flu vaccination during the 2019-2020 flu season to see if our hypothesis that vaccine uptake is positively associated with risk-seeking preferences holds for a well-known vaccine, such as the flu vaccine. We conducted a logistic regression with the same predictors as before, with the exception of month, which theoretically should not matter since the question pertained to past behavior.[2]

Results from the four regressions are shown in Table 1. Participants who were more risk-seeking on the gamble ladder were more likely to take the COVID-19 vaccine under standard authorization, under expedited authorization, and were more likely to have received the 2019 flu vaccine. Increased risk aversion was associated with a larger difference in vaccine take-up under standard and expedited authorization processes. The number of lottery tickets purchased last week (a proxy for real world risk taking behavior) was a significant predictor of COVID-19 vaccine take-up under expedited authorization, the difference between standard and expedited authorization processes, and the 2019 flu vaccine, confirming the relationship between risk attitude and prospective vaccine take-up observed using the gamble ladder.

In addition, participants with higher household incomes, who were older, more educated, and reported being Democrats were more willing to take a COVID-19 vaccine under both standard and expedited processes and were more likely to have received the 2019 flu vaccine.

[2] Including month in the model does not meaningfully change results.

Willingness to take a COVID-19 vaccine (under both standard and expedited authorization) varied by month, being the highest in the summer 2020, dropping in the early fall, and rising again in late fall / early winter 2020 (see supplemental materials for details).

Additional analyses are available in the supplemental materials, including a correlation matrix as well as mediation analyses testing whether risk preference mediates the relationship between each demographic variable and vaccine uptake.

Study 2

Deciding to take a vaccine is inherently a risky choice under uncertainty. Individuals have to trade-off the possible risks (i.e., side-effects) with the possible rewards (i.e., immunity for self and herd immunity that protects everyone). Results from Study 1 showed that financial risk preferences predict vaccine take-up, illustrating the importance of thinking about vaccines in terms of risky decision-making. Study 2 builds on this by leveraging insights from psychology and neuroscience that show risk-taking can be influenced by focusing attention on specific pieces of information or by facilitating relative comparisons during the decision process (Glimcher & Fehr, 2013). In this study, we examine (1) how messaging influences stated time to receive a COVID-19 vaccine, (2) how messaging influences risk perceptions of the vaccine, and (3) how heterogeneity in general risk preferences influences responses to our messaging manipulations. In this study, we hold information about the side-effects constant and vary communication about the rewards. We examine two types of messages. One message provides relevant efficacy benchmarks by describing the COVID-19 vaccine as being more effective than the flu vaccine. We hypothesized that this message would reduce the perceived risk of the COVID-19 vaccine by facilitating a favorable relative comparison to a known vaccine. The other message emphasizes the social benefit of taking the vaccine, by providing information about the necessary coverage rate of vaccination to achieve herd immunity. We hypothesized that this message would reduce the perceived risk of the COVID-19 vaccine by focusing attention on the rewards of vaccination for both self and others.

Table 1

Coefficients of OLS linear regression models of stated COVID-19 vaccine uptake for standard approval process, expedited approval process, and the difference between standard and expedited processes. Logistic regression results for receiving the flu vaccine during the 2019-2020 flu season.

	Dependent variable:			
	Standard Authorization	Expedited Authorization	Difference	2019 Flu Vaccine
	OLS	*OLS*	*OLS*	*logistic*
	(1)	(2)	(3)	(4)
Risky Choices	0.021^{***}	0.048^{***}	-0.027^{***}	0.052^{***}
	(0.014,0.028)	(0.041,0.055)	(-0.032,-0.022)	(0.040,0.063)
Num Lottery Tickets	0.004	0.029^{***}	-0.025^{***}	0.037^{***}
	(-0.003,0.010)	(0.022,0.036)	(-0.030,-0.021)	(0.027,0.048)
Income	0.046^{***}	0.044^{***}	0.002	0.064^{***}
	(0.042,0.050)	(0.040,0.048)	(-0.001,0.005)	(0.057,0.071)
Age	0.007^{***}	0.002^{***}	0.005^{***}	0.018^{***}
	(0.006,0.008)	(0.001,0.003)	(0.005,0.006)	(0.017,0.019)
Education	0.084^{***}	0.066^{***}	0.018^{***}	0.074^{***}
	(0.076,0.092)	(0.058,0.074)	(0.012,0.024)	(0.061,0.087)
Political Affiliation	0.124^{***}	0.061^{***}	0.063^{***}	0.076^{***}
	(0.115,0.132)	(0.052,0.069)	(0.057,0.070)	(0.062,0.090)
Female-Male	-0.270^{***}	-0.378^{***}	0.108^{***}	0.002
	(-0.298,-0.242)	(-0.407,-0.349)	(0.087,0.129)	(-0.045,0.049)
July-June	0.027	0.007	0.020	
	(-0.018,0.071)	(-0.039,0.054)	(-0.015,0.054)	
Aug-June	-0.145^{***}	-0.198^{***}	0.053^{**}	
	(-0.189,-0.101)	(-0.244,-0.152)	(0.019,0.086)	
Sept-June	-0.221^{***}	-0.348^{***}	0.127^{***}	
	(-0.263,-0.179)	(-0.392,-0.304)	(0.095,0.160)	
Oct-June	-0.233^{***}	-0.337^{***}	0.104^{***}	
	(-0.276,-0.190)	(-0.382,-0.291)	(0.071,0.137)	
Nov-June	-0.173^{***}	-0.187^{***}	0.014	
	(-0.227,-0.119)	(-0.244,-0.130)	(-0.027,0.056)	
Dec-June	-0.164^{***}	-0.101^{**}	-0.063^{*}	
	(-0.236,-0.092)	(-0.176,-0.026)	(-0.118,-0.008)	
Constant	2.584^{***}	2.713^{***}	-0.128^{***}	-1.855^{***}
	(2.515,2.654)	(2.640,2.786)	(-0.182,-0.075)	(-1.967,-1.742)
Observations	34,200	34,200	34,200	33,194
R^2	0.101	0.091	0.035	
Adjusted R^2	0.101	0.091	0.035	
Log Likelihood				-21,950.120
Akaike Inf. Crit.				43,916.250
Residual Std. Error (df = 34186)	1.254	1.313	0.960	
F Statistic (df = 13; 34186)	295.575^{***}	264.722^{***}	96.305^{***}	

Note: Regression coefficients are unstandardized $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Method

Participants

Participants were recruited using Amazon Mechanical Turk on July 8, 2020. We targeted 1,000 participants and 1,003 participants completed the experiment. Sample size was determined before running the study, and we did not analyze data until all data had been collected. Participants ranged in age from 18-77 (M=38), 56% were male, with an average income of between \$50,000-\$59,999. This study was approved by the Institutional Review Board at a Midwestern university.

Materials and Procedure

At the start of the experiment, all participants completed the gamble ladder from Study 1, involving 9 choices between a gamble offering X% chance of \$100 and \$50 for sure where X ranged from 90% to 10% in increments of 10%.

Next, participants were randomly assigned to one of three treatment groups or a control condition. In the control condition, participants were provided information about the vaccine approval process, side effects, and efficacy (full text is available in the supplement). Participants in the treatment groups read the same information as participants in the control condition, but also read one of the following pieces of additional information: (1) details about relevant efficacy benchmarks (i.e., benchmark condition), (2) information about the necessary coverage rate of vaccination to achieve herd immunity (i.e., coverage condition), or (3) both the details about efficacy benchmarks and coverage rate (i.e., benchmark + coverage condition). Specifically, the benchmark group read the following information in addition to the information from the control condition:

> Based on the clinical trial results, the FDA estimates that the COVID-19 vaccine will be about 70% effective in preventing the disease, consistent with success benchmarks set by the World Health Organization. This efficacy rate would also compare favorably to the flu vaccine, which has ranged from 19% to 60% since 2010.

The coverage group read the following information in addition to the information from the control condition:

> Experts estimate that 85% of people in the US would need to be vaccinated in order to reach herd immunity, where enough people are immune to the disease to make its spread unlikely. The sooner people receive the vaccine, the sooner the US would reach herd immunity. Waiting to receive the vaccine for just a few months will delay herd immunity and lead to more deaths.

The coverage rate of 85% was selected based on the rate of other known vaccines (Vally, 2019). The true coverage rate to achieve herd immunity for COVID-19 will depend on a range of factors. Participants in the benchmark + coverage condition read both of the passages above in addition to the control information.

There were two key dependent variables (DVs) in this study. The first measured stated time to receive the vaccine after it becomes available: “Which option below best describes when you be willing to take this vaccine?" with response options on an 11-point scale from 1 = “Immediately (as soon as the vaccine was available)", 2 = “After the vaccine has been available for about 1 month", ..., 10 = “After the vaccine has been available for 9 months or longer", and 11 = “I would never want to take the vaccine". The second DV asked participants to consider when they would want others to take the vaccine: “ Which option below best describes when you would want others to take this vaccine?" using the same 11-point scale. The dependent variables in the current study measured the stated time to receive a vaccine rather than measuring likelihood of taking the vaccine. We selected this outcome both because it provides a more nuanced measure of people’s vaccine preferences and because of its importance in minimizing damage caused by COVID-19. Even if all or most people were to take the vaccine eventually, speeding up this process remains of critical importance. Any delay in vaccine take-up meaningfully adds to case counts and deaths, in addition to mental health and financial concerns.

Next, participants answered three questions about their perceptions of risk and effectiveness of the vaccine, which were hypothesized mediators of the effect of treatment on stated vaccine wait time: (1) “How risky do you believe taking this vaccine would be for your health?", (2) “If you took this vaccine, how much do you think that your taking this vaccine would reduce your risk of getting COVID-19?", and (3) “If you took this vaccine, how much do you think that your taking this vaccine would reduce other people’s risk of getting COVID-19?". These questions used a 5-point response scale from 1 = “Not at all" to 5 = “Extremely".

Results

No participants were excluded from these analyses. First, we examined the effect of condition on stated vaccine wait time for oneself using OLS linear regression with sum (i.e., deviation) coding. This coding scheme compares the mean of the DV for a given level of the IV to the overall mean of the DV over all the levels, similar to an ANOVA. Thus, it detects whether each condition is different from the remaining conditions. As shown in Table 2 and illustrated in the left panel of Figure 1, the coverage condition significantly reduced one’s wait time as compared to the other three conditions ($b = -0.416$, $t = -2.21$, $p = 0.0276$, 95%CI = (-.785, -0.046)). The other conditions were not significantly different. The same results were found for the DV asking about vaccine wait time for others, see Table 3.

Table 2
OLS linear regression results for vaccine wait time for self by treatment.

	Estimate (b)	Std. Error	Standardized (β)	t value	Pr(>|t|)
(Intercept)	3.9534	0.1088	0.0000	36.33	0.0000
Coverage	-0.4155	0.1884	-0.0850	-2.21	0.0276
Benchmarks	0.2133	0.1882	0.0437	1.13	0.2572
Benchmarks + Coverage	0.0427	0.1882	0.0087	0.23	0.8206

Note: $F(3,999) = 1.728$, $R^2 = 0.005$, Adjusted $R^2 = 0.002$

Next, we examined possible mediators of the effect of the coverage treatment on vaccine wait time for one’s self. We used binary coding where the coverage condition = 1 and the other three conditions = 0. We tested three mediators: vaccine risk (“How risky do you believe taking this vaccine would be for your health?"), vaccine effectiveness for self (“how much do you think that your taking this vaccine would reduce your risk of getting COVID-19?"), and vaccine

Table 3

OLS linear regression results for vaccine wait time for other by treatment.

	Estimate (b)	Std. Error	Standardized (β)	t value	Pr(>|t|)
(Intercept)	3.1807	0.0964	0.0000	33.01	0.0000
Coverage	-0.4437	0.1668	-0.1024	-2.66	0.0080
Benchmarks	0.1923	0.1666	0.0444	1.15	0.2487
Benchmarks + Coverage	0.0732	0.1666	0.0169	0.44	0.6603

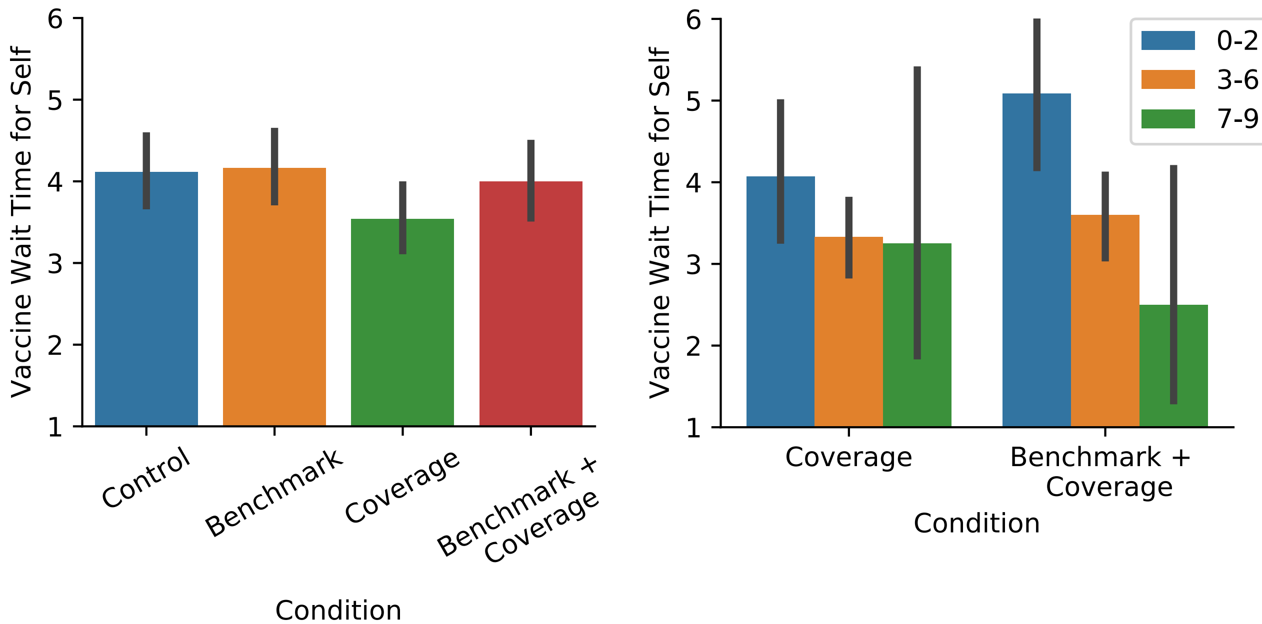
Note: $F(3,999) = 2.432$, $R^2 = 0.007$, Adjusted $R^2 = 0.004$

effectiveness for others (“how much do you think that your taking this vaccine would reduce other people’s risk of getting COVID-19?").

Results showed that the effect of the coverage condition on vaccine wait time was fully mediated by a reduction in risk perceptions about the vaccine and increased belief that taking the vaccine would reduce other’s chances of getting COVID-19, see Figure 2. For the vaccine risk mediator, the regression coefficient between treatment and vaccine risk was significant (b = -0.19, p = .017), implying participants in the coverage condition thought that the vaccine was less risky for their health than participants in the other conditions. The regression coefficient between vaccine risk and vaccine wait time was significant (b = 0.88, p < .001), implying that people who believed the vaccine was risky for their health would wait longer to receive it. The indirect effect was (-0.19)(0.88) = -.17, which was significant (z = -2.33, p = .020). For the mediator related to people’s beliefs about the vaccine effectiveness for others, the regression coefficient between treatment and effectiveness for others was significant (b = 0.15, p = .037), implying participants in the coverage condition thought that taking the vaccine would reduce other people’s chances of getting COVID-19 as compared to participants in the other conditions. The regression coefficient between effectiveness for others and vaccine wait time was significant (b = -0.69, p < .001), implying that people who believed taking the vaccine would reduce other’s risk of getting COVID-19 would take the vaccine sooner. The indirect effect was (0.15)(-0.69) = -.11, which was significant (z = -1.96, p = .050). Importantly, the direct effect of the coverage condition on the DV was no longer significant (b = -0.22, p = 0.279), thus full mediation was achieved. Note that the regression coefficient between vaccine effectiveness for self and treatment was not significant

Figure 1

Left panel: Mean vaccine wait time for four conditions in Study 2. Right panel: Mean vaccine wait time for the coverage and benchmark + coverage conditions split by risk preferences based on the number of risky choices out of 9 gambles (blue = 0-2 risky choices, orange = 3-6 risky choices, and green = 7-9 risky choices). Risky choices are binned for illustrative purposes only. Error bars in both panels show the 95% confidence interval.

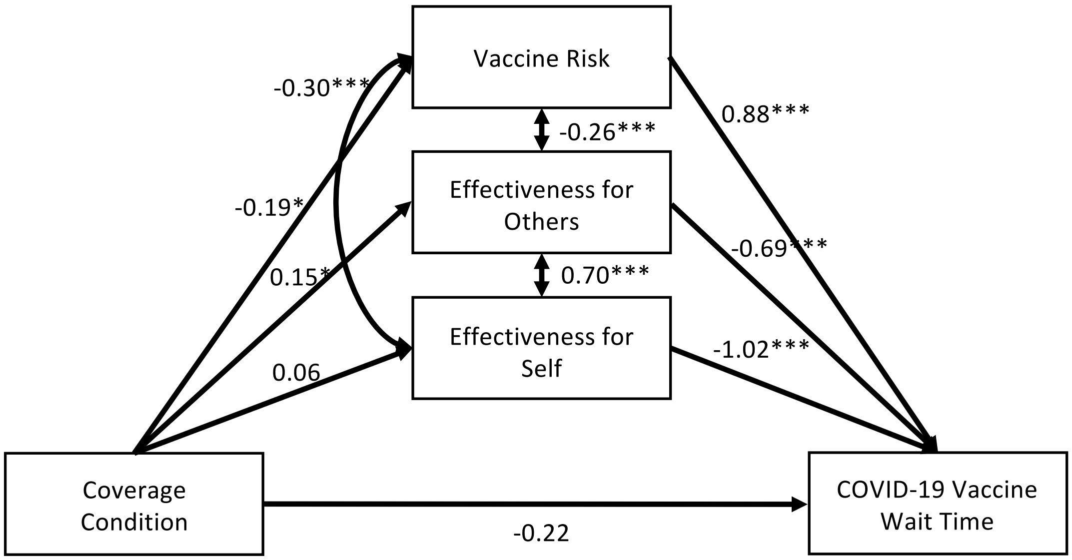


(b = 0.06, p = .398), thus the indirect effect, (0.06)(-1.02) = -0.06, was not significant (z = -0.84, p = .400). Full details of this analysis are in the supplemental materials.

Results so far show that information about the vaccination coverage rate needed to achieve herd immunity is effective in reducing people's wait time to receive a vaccine. Interestingly, when the coverage rate information is combined with the benchmark information, we do not observe a reduction in wait time. To further understand why coverage alone is effective, we examined the role of risk preferences, as measured by the gamble ladder, on stated vaccine wait times for one's self in the coverage condition and the benchmark + coverage condition. For this analysis, we conducted an OLS linear regression to predict vaccine wait time for one's self based on (1) risk preference, (2) condition (either coverage or benchmark + coverage), and (3) their interaction. A full analysis of all conditions is available in the supplemental materials.

Figure 2

*Mediation model and parameter estimates for Study 2. Parallel mediation using the mediating effect of vaccine risk, vaccine effectiveness for others, and vaccine effectiveness for self in the relationship between messaging condition and wait time to receive a COVID-19 vaccine. Coefficients are unstandardized. *p <0.05; **p < 0.01, ***p <0.001*



In this analysis, we use dummy (i.e., treatment) coding, where the reference level was the coverage condition. Results (see Table 4) showed a significant interaction between risk preference and condition (b = -3.30, t = -2.065, p = 0.0395, 95% CI = (-6.432, -0.167)). In the coverage condition, there was no effect of risk preference on vaccine wait time (b = -0.78, t = -0.71, p = 0.479). This means risk averse individuals reported similar wait times as risk seeking individuals in the coverage condition. However, in the benchmark + coverage condition, the effect of risk preference on vaccine wait time was negative (specifically, -0.78 + -3.30 = -4.08), implying risk seeking participants reported shorter wait times than risk averse participants, as illustrated in the right panel of Figure 1. Taken together, these results suggest that risk preference plays an important role in the effectiveness of the different messages. When the benchmark information is added to coverage information, risk averse people report increased wait times. One possible explanation is that benchmarking the COVID-19 vaccine against other vaccines highlights the general risk of vaccines, negating any positive effects of the coverage rate information.

Table 4

OLS linear regression results for vaccine wait time by treatment and risky choices

	Estimate (b)	Std. Error	Standardized (β)	t value	Pr(>|t|)
(Intercept)	3.8239	0.4574	0.0000	8.36	0.0000
Risky Choices	-0.7766	1.0961	-0.0430	-0.71	0.4790
Benchmarks + Coverage	1.6981	0.6669	0.2466	2.55	0.0112
Risky Choices:Benchmarks + Coverage	-3.2996	1.5982	-0.2187	-2.06	0.0395

Note: $F(3,499) = 5.020$, $R^2 = 0.029$, Adjusted $R^2 = 0.023$

General Discussion

While creating a novel vaccine is a challenge for epidemiologists and virologists, ensuring take-up of the vaccine is a challenge for behavioral scientists. Policymakers have typically been aware of differences in the likelihood of vaccine take-up as a function of basic demographic and health differences, such as race, income, and virus-risk. The current work introduces risk-preferences as an additional relevant factor. While vaccines are provided to minimize health risks, our findings suggest that risk perceptions remain a barrier to take-up. Specifically, those who are risk-averse in financial domains may be least willing to take both novel (e.g., COVID-19) and established (e.g., flu) vaccines in the absence of effective messaging. Importantly, our findings also identify risk-preferences as a moderator of the effectiveness of identical messaging on vaccine take-up. Together, our findings highlight the importance of understanding that individuals are likely to view even established vaccines as risky. They suggest that messaging campaigns aimed at increasing awareness or accessibility may not be as effective as those that simultaneously aim to minimize risk perception.

In our messaging experiment, we found that emphasizing the social benefits of taking a COVID-19 vaccine decreases people's wait time to receive the vaccine. This effect was mediated by vaccine risk and vaccine effectiveness for others. While the mediating role of vaccine effectiveness for others seems reasonable in this context, it is less clear why pro-social messaging would influence perceptions of vaccine risk. We hypothesize that this occurs because the messaging focuses attention on the vaccine's rewards (immunity for self and others), resulting in increased weight on these rewards during decision-making. However, it is possible that pro-social messaging impacts people's risk perceptions through other avenues. While there has been extensive research on prosociality and risk-taking separately, less research has examined their relationship. Related research in cognitive neuroscience and developmental science has shown that the neural circuitry that underlies risk-taking also contributes to pro-social behaviors (Telzer, 2016), suggesting an interesting connection between these behaviors.

Our experiment also included benchmark conditions which provided participants with sufficient context to interpret efficacy statistics, by comparison to vaccines targeted at the seasonal flu. We hypothesized that participants might consider 70% efficacy for a new vaccine to be low and therefore created this messaging as an attempt to increase the perceived rewards associated with a realistic efficacy statistic in describing a potential COVID-19 vaccine. To our surprise, the presence of this context actually reduced willingness to take the vaccine, driven by reluctance among generally risk-averse individuals. It is possible that mentioning another vaccine (i.e., the flu vaccine) highlighted the general risks of vaccines to participants. Alternatively, participants may believe the flu vaccine is less effective than other vaccines, making the stated efficacy of the COVID-19 vaccine appear low. We note that we cannot tease apart whether the effect of benchmarking came from general vaccine risk or flu specific vaccine risk. Further, it is possible that benchmarking led participants in the benchmark + coverage condition to interpret the coverage statement differently. These complexities should be examined in future work. Regardless, this finding provides support for the importance of risk-preferences in communications. It is also consistent with recent research showing that the impact of messaging related to COVID-19 (i.e., social distancing) depends on audience characteristics (Luttrell & Petty, 2020).

Given the high stakes of the COVID-19 vaccine roll-out, discussion of a potential vaccine has taken center stage in many public outlets. In the context of this global pandemic, which person or agency controls the messaging around the vaccine? Surely, some messaging will be coming from individuals, through personal networks and social media. This messaging will be very difficult to control. Importantly, messaging will also be coming from federal government agencies such as the CDC and FDA, state and local governments, and community organizations. This messaging should be coordinated and leverage scientific knowledge to speed vaccination efforts. The insights in this paper highlight the importance of carefully constructed vaccine communications, where seemingly useful information can have unintended consequences.

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