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The impact of public health messaging and personal experience on the acceptance of mask wearing during the COVID-19 pandemic☆

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ABSTRACT

Face coverings have been shown to slow the spread of COVID-19, yet their use is not universal and remains controversial in the United States. Designing effective nudges for widespread adoption is important when federal mandates are politically or legally infeasible. We report the results from a survey experiment in which subjects were exposed to one of three video messages from President Trump, and then indicated their preference for wearing a mask. In the first video, the President simply recited the Centers for Disease Control and Prevention (CDC) guidelines. In the second, the President additionally emphasized that wearing a mask is optional. In the third video, the President added that he will not personally wear a mask. We find that exposure to presidential messages can increase the stated likelihood of wearing a mask—particularly among the President's supporters. We also explore experiential effects of COVID-19, and find that people (especially supporters of the President) are more likely to support wearing a mask if they know someone who has tested positive for COVID-19. These results offer guidance to policy makers and practitioners interested in understanding the factors that influence viral risk mitigation strategies.

"I wear a mask. And that mask, it's not to hide who I am, but to create what I am"—Batman

1. Introduction

The COVID-19 pandemic continues to throttle the global economy. The novel coronavirus (SARS-CoV-2) that causes COVID-19 was identified in December 2019, with the first confirmed human-to-human transmission occurring in January 2020. Rapid proliferation led the World Health Organization to declare the outbreak a public health emergency within weeks

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and proclaim it a global pandemic in March 2020. To reduce the virus's spread and slow the growth in COVID-19 cases, governments worldwide recommended or enacted broad-based shutdowns of social and economic activities. The impact on the U.S. economy was immense. Early studies indicate the response led to a job loss of 23.9 million in April 2020 (Cajner et al., 2020), an average decline of $5293 in income for about 50% of households (Coibion et al., 2020), and about a 50% decline in consumer spending (Baker et al., 2020). The economic cost of the pandemic for the first two months exceeded $2 trillion, with nearly 90% of the impact resulting from voluntary actions rather than mandatory shutdowns (Makridis and Hartley, 2020; Goolsbee and Syverson, 2020). Faced with the prospects of an extended pandemic, policymakers considered options to reopen the economy while mitigating the spread of COVID-19 cases.

A promising course of action is the widespread use of public face coverings, or face masks. The case for wearing masks is persuasive. Wearing a mask is not difficult or expensive, and studies provide considerable evidence that wearing a mask disrupts transmission by both symptomatic and asymptomatic individuals (Chu et al., 2020; Eikenberry et al., 2020; Leung et al., 2020). Abaluck et al. (2020) report that mask-wearing during a pandemic translates to significant economic benefits. Despite the health and economic benefits associated with mask-wearing, this simple prescription has faced enough public resistance in the U.S. to undercut the potential gains from widespread voluntary adoption. More coercive policy options are limited as many elected leaders do not favor a federal mask mandate, and even if a national mandate were politically feasible, it is unclear as to whether it is constitutionally legal (Shen, 2020).

One source of public opposition to wearing a mask is psychological reactance—people's reaction to perceived threats to individual freedom of choice (Brehm, 1966). From integrated threat theory (Stephan Walter and Renfro Lausanne, 2002), we can distinguish between realistic and symbolic threats. The virus presents a realistic threat to people's physical health and financial security, while the guidelines and mandates that prescribe behavior, such as mask wearing, pose a symbolic threat to the integrity or validity of a group's belief system. Recent research finds that, among some groups, the symbolic threat of prescribing mask wearing actually undermines the prevalence of mask wearing (Kachanoff et al., 2020).

However, such reactance is malleable and affected by messaging and experience. For messaging, a large literature in political science, sociology and economics has shown that leadership by example can foster cooperation (Frohlich et al., 1971; Hermalin, 1998; Levati et al., 2007), particularly by democratically-elected leaders (Jack and Recalde, 2015). Further, effective leaders often influence people to take particular actions and can sometimes transform their beliefs and preferences (Ahlquist and Levi, 2011). In the context of the current pandemic, studies find that people respond affirmatively to Centers for Disease Control and Prevention (CDC) mask-wearing recommendations and gubernatorial shelter-in-place recommendations (Goldberg et al., 2020; Grossman et al., 2020).

However, the public has received mixed messages from U.S. President Donald Trump, who has expressed inconsistent views on mask-wearing and has generally avoided wearing a face mask in public. During his April 3, 2020, White House press conference, he announced that the CDC recommended that people wear face masks in public, while also emphasizing that doing so was voluntary and that he would not wear one. Some have suggested that inconsistent messaging from the President has led to greater transmission of the virus (e.g., Smith, 2020). Beyond messaging, a related literature offers considerable evidence that experience shapes beliefs and preferences (Leventhal et al., 1992; Shahrabani and Benzion, 2012; Myers et al., 2013; Cassar and Klein, 2017). In the case of influenza, for example, Shahrabani and Benzion (2012) show that experience with influenza significantly affects the perceived benefits of a flu vaccine. By announcing a public health recommendation to wear a mask, while simultaneously stating that he would not do so in the midst of the current pandemic in which experience with the illness is heterogeneously distributed across the country, the President created a unique setting to consider the relative import of messaging and experience on stated resistance to mask-wearing.

This paper reports the findings from a survey experiment designed to examine how individual stated behavior and preferences on mask-wearing and mask mandates are shaped by both President Trump's messages and personal experiences with COVID-19. The design takes advantage of President Trump's mixed messaging in the April CDC press conference, which offers variation in the message while holding the messenger and other confounding factors like temporal variation constant. Respondents were randomly assigned to one of three message treatments derived from the press conference or a no-message control treatment. The respondents in the message treatments watched a video clip from the press conference which varied by treatment. The first treatment showed President Trump announcing the CDC guidelines. The second treatment also included him emphasizing that the guidelines were voluntary, and the third included both his statements that the guidelines were voluntary and that he would not be wearing a mask. To examine experiential effects, we elicited respondents' experience with COVID-19, specifically whether they knew anyone who had died as the result of contracting the virus, or if they knew anyone who had tested positive. We also asked subjects whether they had personally been tested for COVID-19 and the outcome. Using the resulting data, we examine how the message treatments and experience influence subjects' stated preferences for masks and a government mandate to wear masks in public. We investigate possible heterogeneous effects across political factions that capture differences in people's reaction to perceived threats to individual freedom of choice (i.e., reactance).

A number of key insights emerge from the messaging treatments. Averaged across all subjects, we find that exposure to the CDC guidelines increased a person's stated likelihood of wearing a mask by a statistically significant but qualitatively small amount (roughly 3.6 percentage points). However, we also uncover important heterogeneities in the responses to the messaging treatments. Among the President's strongest supporters, exposure to the CDC guidelines alone did not significantly change their stated likelihood of personally wearing a mask. Among this group, exposure to the two treatments that coupled the CDC guidelines with his statement stressing the voluntary nature of wearing a mask tended to be most effective.

Exposure to either of these treatments increased the stated likelihood of wearing a mask by roughly 9 percentage points among this sub group. We also document meaningful treatment effects on people's support for other people wearing masks and support for a government mandate requiring the public use of face masks. For these outcomes, we again document larger treatment effects among the president's most fervent supporters.

From the experiential analysis, testing negative for COVID-19 tends to be associated with increased support for mask wearing and a government mandate requiring the use of face masks in public when social distancing is not possible. Interestingly, unlike testing negative, testing positive tends to have no effect, and in some cases actually reduces support for face masks (for example, among political moderates). We additionally find that knowing someone who tested positive is associated with increased support for mask wearing and a government mandate, and that this effect is again enhanced among the president's supporters. Somewhat surprisingly, people were largely unaffected by knowing someone who died (conditional on knowing someone who tested positive).

Taken jointly, we conclude that both Presidential messaging and personal experience with COVID-19 influenced stated preferences for various mitigation strategies including personal mask use, social use, and a government mandate requiring the use of face masks. These findings offer important implications for both policy makers and practitioners alike. There are significant political and legal challenges to the enforcement of a federal mandate to wear face masks, and as such, behavioral nudges can be used to substitute for policy. In the context of the current pandemic, what should these nudges look like? Our results offer some guidance. Public health campaigns that include messages from the President might be relatively effective among the President's supporters, and emphasizing the recommendations are voluntary may help when psychological reactance is prevalent. Our analyses of experiential effects suggest that knowing someone who has tested positive increases support for mask-wearing and mask mandates. This suggests that effective messaging from elected and public health officials should extend beyond medical facts to make people feel as if they know someone who has tested positive, and perhaps died, as a result. To the extent that people view celebrities, politicians, or cultural icons as acquaintances, messages from celebrities who have contracted COVID-19 might be effective.[1]

Our results also have implications for researchers modeling the spread and dynamics of COVID-19. The common compartmental epidemiological model "does not explicitly include behavioral responses to disease risk" and incorporating such responses, "implies disease transmission rates change as disease risks and private payoffs of alternative behaviors change" (Fenichel et al., 2011). We document two important behavioral responses to the spread of COVID-19. The first is that transmission of the virus increases the probability that a person has social contact with the virus (e.g., knowing someone who has contracted the virus) even if they are able to avoid physical contact (e.g., contracting the virus themselves). We document evidence that this increases risk perceptions and hence support for mask wearing. On the other hand, we also show that political moderates are less likely to wear a mask after testing positive. This points to a potential unintended consequence of mass testing; testing positive possibly sends a message to people who experience only minor symptoms (or who experience a false positive test) that the consequences of contracting COVID-19 are relatively minor. People adapt to these perceptions and reduce their (stated) risk mitigation efforts.

2. Experimental design

To investigate the influence of *messaging* and *personal experience* on individual preferences for mask-wearing behavior and related public health policies, we conducted an online survey experiment that varied messages while collecting respondents' experiences with COVID-19. The survey experiment was designed to address three primary research questions. First, how do changes in messaging influence individual behavior and preferences related to mask wearing? Second, how do different experiences with COVID-19 affect these behaviors and preferences? And third, by stratifying individuals by political orientation, do we observe heterogeneous effects from messaging or experience?

The survey consisted of five sections. (See online supplement for the full survey instrument.) The back button was disabled, so respondents could not change their answers as they proceeded through the survey. After an introduction that elicited informed consent, the survey started with a warm up section that contained two questions asking about the individual's general attitude towards the pandemic and the government's response.

Section two consisted of the message treatments and randomly assigned participants to one of four treatments. A *No Message Baseline* provided a control group, and the three message treatments presented one of three video messages from President Trump. The videos were all from his press conference on April 3, 2020, in which he presented the CDC guidelines on the use of face masks while in public.[2] Participants were instructed to watch the video and to "Please pay careful attention because you will be asked to answer a question regarding this video on the next page." The ability to proceed to the next screen was delayed by the approximate length of the video.

In the *CDC Treatment*, respondents watched a 29-s video of President Trump reading the CDC guidelines:

> *"Also, the CDC is announcing additional steps Americans can take to defend against the transmission of the virus. From recent studies we know that the transmission from individuals without symptoms is playing a more significant role in the*

[1] The marketing literature on para-social relationships suggests that repeated exposure to a celebrity causes people to feel a high level of intimacy with a celebrity and to perceive them as a "surrogate friend" (Chung and Cho, 2017).

[2] The video is available at: https://www.c-span.org/video/?c4865960/white-house-announces-cdc-facemask-guidelines

spread of the virus than previously understood. So you don't seem to have symptoms and it still gets transferred. In light of these studies the CDC is advising the use of non-medical, cloth face covering."

The *Voluntary Treatment* included the above message from the *CDC Treatment*, plus the following additional statement (the underlined text identifies words emphasized by President Trump):

"[Message from CDC Treatment]" + "as an additional voluntary public health measure. So it's voluntary, you don't have to do it. They suggest it for a period of time, but this is voluntary."

Finally, the *Refusal Treatment* added President Trump's statement that he will not be wearing a mask:

"[Message from Voluntary Treatment]" + "I don't think I'm gonna be doing it."

Before moving on, a few things should be highlighted about the treatments. The three video messages are additive—the voluntary message included the CDC message and the refusal message included the *Voluntary* and *CDC* messages. Also, the videos were unedited: The Refusal treatment being an unedited statement from President Trump, which was trimmed to create the *Voluntary* and *CDC Guidelines* treatments. After watching the video, we asked respondents about their perception of the degree to which the video encouraged the use of face masks (on a 5-point Likert scale). This allows us to test whether respondents' actual interpretation of the video messages corresponded with the intention of the experimental design.

The last three sections were identical for all four treatments. Section three elicited stated behavior and preferences on mask-wearing. We asked all respondents about: (i) the likelihood they will wear a mask in public in the near future when social distancing is difficult to maintain, (ii) the extent to which they agree that others should wear a mask to help prevent transmission, and (iii) the extent to which they support a government mandate that requires people to wear a mask in public settings when social distancing is difficult to maintain. Comparisons of this data across messaging treatments allow us to address the first research question about whether behaviors and preferences are influenced by messaging.

Section four asked all respondents about their experiences with COVID-19. We consider three levels of social distance—personal, direct relationship, and indirect relationship. Specifically, in relation to COVID-19, respondents indicated whether they had been tested and, if so, whether the results were negative or positive (or awaiting results). For direct relationship, respondents also indicated whether they knew of someone who had tested positive or died. For indirect relationship, respondents indicated whether they knew someone who knew someone that had tested positive or died. Responses to these questions are used to consider how respondents' stated behaviors and preferences were shaped by their experience with the virus.

Section five concluded the survey with demographic questions that collected information about political leaning, level of support for President Trump, race, ethnicity, US state of residence, age, gender, education and income. The socioeconomic characteristics provide opportunities to condition estimated treatment effects on these individual characteristics. In addition, considering the political polarization of mask-wearing, we are also interested in understanding any heterogeneous effects from messaging and experience across individual political leanings and support for the president. (See Table 1 for a list of the variable names and descriptions.)

The survey experiment was conducted online on Thursday, June 25, 2020 at 10:00AM (Pacific Daylight Time). The sample of respondents was recruited using Amazon Mechanical Turk (MTurk). MTurk is an online labor market that offers access to over 500,000 different workers from almost 200 countries, with most located in the United States (Paolacci and Chandler, 2014; Hitlin, 2016). With the increasing use of MTurk in social science and behavioral research (Mason and Suri, 2012; Berinsky et al., 2012; Cherry et al., 2017; Jacquemet et al., 2021), studies have examined the reliability of the online platform. Many studies have tested the robustness of MTurk and findings indicate that results using MTurk are consistent with traditional experiments (Chesney et al., 2009; Horton et al., 2011; Hergueux and Jacquemet, 2015; Arechar et al., 2017; Almaatouq et al., 2020). Research also finds that MTurk is more representative of the U.S. population than in-person convenience samples (Paolacci et al., 2010; Berinsky et al., 2012; Buhrmester et al., 2018).

For recruitment, we posted the following advertisement on MTurk: "Participate in a survey about COVID-19. The survey should take about 5 min, and you will be paid fifty cents for completing it." We restricted survey participation to those residing in the United States who were at least 18 years of age. The survey was completed by 3014 respondents. To identify suspicious data, the survey included an attention (or effort) check. We asked participants their state of residence. After they submitted a response, we asked their zip code. We dropped any individual whose zip code did not match the state of residency. This left 2813 subjects in our sample.

3. Analysis

Our analysis is motivated by the seminal work of Rosenstock (1966, 1974) which helped develop and formalize the Health Belief Model (HBM). As discussed by Stretcher and Rosenstock (1997), this model was originally used to explain low participation rates in programs designed to detect and prevent diseases (such large-scale screenings for tuberculosis). The model was subsequently extended by Kirscht (1974) and Becker and Maiman (1980) to model behavioral responses to symptoms and diagnoses, respectively. The HBM has been "one of the most widely used psychosocial approaches to explaining health-related behavior" and predicts that "individuals will take action to ward off, to screen for, or to control ill-health conditions if they regard themselves as susceptible to the condition; if they believe it to have potentially serious consequences; if they

Table 1
Variable definitions.

Subject Demographics	
Rich	= 1 if income > $50,000 per year.
College	= 1 for subjects that have earned at least a four-year college degree.
Health Cond	= 1 for subjects who have a complicating health condition (or care for someone with such a condition)
Male	= 1 for Male subjects.
Mature	= 1 for subjects sixty years and older.
Hispanic	= 1 for Spanish, Hispanic, or Latino subjects.
Black	= 1 for Black, or African American subjects.
White	= 1 for White subjects.
Asian	= 1 for Asian subjects.
Political Preferences	
Trump	5 point Likert scale, higher numbers indicate stronger support from President Trump.
Trump> 3	= 1 for subjects who “strongly approve” or “approve” of President Trump’s performance.
Trump< 3	= 1 for subjects who “strongly disapprove” or “disapprove” of President Trump’s performance.
Views about COVID-19	
Gov. Reaction	7 point Likert scale, = 1 if subject thinks federal government reaction is “Extreme Underreaction”
Concern	5 point Likert scale, = 1 if subject is “None at all” concerned with COVID-19.
Mask Self	5 point Likert scale, higher numbers indicate a subject is more likely to wear a mask in public.
Mask Self Support	= 1 for subjects who “Definitely” or “Probably” will wear a mask when attending a social event in the near future.
Mask Others	7 point Likert scale, higher numbers indicate a subject is more supportive of other people wearing a mask.
Mask Others Support	= 1 for subjects who “Strongly agree”, “Agree”, or “Somewhat agree” that others should wear masks.
Mandate	5 point Likert scale, higher numbers indicate a greater level of support for a government mandate to wear masks in public.
Mandate Support	= 1 for subjects who “Strongly support” or “Support” a government mandate to wear masks.
Experience with COVID-19	
Known pos. test	= 1 for subjects who know someone (or known someone who knows someone) who has Tested positive for COVID-19.
Known death	= 1 for subjects who knew someone (or knows someone who knew someone) who has died from COVID-19.
Tested	= 1 for subjects who have previously either Tested positive or negative for COVID-19
Tested pos.	= 1 for subjects who have previously Tested positive for COVID-19.
Survey Behaviors	
Treatment Review	5 point Likert scale, higher numbers indicate a subject thought a video treatment discouraged the use of face masks.
Treatment Time	Number of seconds a subject spent watching the treatment video.
Duration (sec.)	Number of seconds a subject spent answering the entire survey.

Note: See Appendix B for the survey instrument.

believe that a course of action available to them would be beneficial in reducing either their susceptibility to, or the severity of, the condition; and if they believe that the anticipated barriers to (or costs of) taking the action are out-weighed by its benefits” (Stretcher and Rosenstock, 1997).

More precisely, the key variables of the HBM model include perceptions of one’s susceptibility, the severity of the illness, benefits of various actions that can be taken to reduce the threat of illness, and any barriers to action (i.e., mitigation costs). The basic structure of the model can be conceptualized as a benefit-cost framework in which people weigh expected, or perceived, benefits of a mitigating action against the cost(s) of those actions and provides the theoretical underpinnings of our experimental design.

We hypothesize that Presidential messaging largely influences perceptions of the benefits of mitigating actions, i.e., the effectiveness of wearing a face covering when social distancing is not allowed. Because people tend to trust government more when their party controls the executive branch of government (Keele, 2005), we expect to find that exposure to the CDC guidelines is relatively effective at raising support for face masks among the President’s supporters. Relatedly, reactance theory suggests that people often resist what they perceive to be forceful demands (Brehm, 1966; Brehm and Brehm, 2013). To the extent that some people perceive CDC recommendations as a requirement to wear a mask, highlighting that wearing a mask is voluntary might be effective, especially among people on the political right (the President’s supporters). Because people often follow the views of their self-proclaimed leaders Lenz (2013)[3], we expect to find that supporters of the president are less likely to support wearing face masks if they are exposed to the Refusal treatment in which the President states he will not wear a mask himself.

To the extent that experience with COVID-19 influences perceptions of risk and the benefits of action, the HBM model predicts that experience should influence the use of face masks and support for other people wearing masks. We hypothesize that knowing someone who has tested positive for COVID-19 increases a person’s perception of their own susceptibility. Similarly, we hypothesize that knowing someone who died as the result of contracting the novel coronavirus increases perceptions of illness severity. Both of these effects should increase the perceived benefits of mitigating efforts like wearing a mask in public.

[3] Lenz (2013) writes that, “This tendency to follow is particularly evident among voters who learn politicians’ positions between panel interviews...When supporters of a Republican president learn, for instance, that the Republic Party is on the ideological right, they shift their own reported ideology to the right. Instead of leading on policy, in case after case, citizens follow.” (p. 18).

Table 2
Summary statistics: Means by treatment and support for President Trump

	Control	T1	T2	T3	Control		No COVID Exp		
					Trump=5	Trump=1	Pooled	Trump=5	Trump=1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subject Demographics									
Rich	0.542	0.531	0.558	0.556					
College	0.715	0.689	0.678	0.684					
Health Cond	0.483	0.497	0.502	0.500					
Male	0.548	0.583	0.542	0.554					
Mature	0.072	0.081	0.074	0.079					
Hispanic	0.178	0.172	0.174	0.176					
Black	0.135	0.133	0.129	0.149					
White	0.751	0.746	0.755	0.734					
Asian	0.078	0.088	0.082	0.077					
Political Preferences									
Trump	2.784	2.821	2.768	2.661					
Trump>3	0.434	0.418	0.416	0.374					
Trump<3	0.449	0.444	0.463	0.480					
Views about COVID-19									
Gov. Reaction	3.725	3.661	3.575	3.553					
Concern	3.365	3.428	3.439	3.539					
Mask Self	4.309	4.439	4.411	4.477					
Mask Self Support	0.821	0.863	0.859	0.879	0.738	0.925	0.798	0.519	0.931
Mask Others	6.098	6.252	6.227	6.275					
Mask Others Support	0.877	0.916	0.911	0.918	0.757	0.952	0.843	0.539	0.962
Mandate	4.045	4.117	4.053	4.155					
Mandate Support	0.766	0.787	0.765	0.806	0.644	0.913	0.691	0.392	0.893
Experience with COVID-19									
Known Pos. Test	0.618	0.616	0.608	0.639					
Known death	0.314	0.259	0.282	0.275					
Tested	0.138	0.126	0.110	0.123					
Tested Pos.	0.042	0.030	0.033	0.028					
Survey Behaviors									
Treatment Review	–	1.856	2.452	2.726					
Treatment Time	–	72.115	70.329	89.575					
Duration (s)	243.523	330.763	330.049	327.010					
N	728	698	690	697	107	253	939	102	377

Note: See Table 1 above for variable definitions. T1, T2, and T3 refer to the three messaging treatments. T1 refers to the CDC Treatment, in which President Trump recites CDC recommendations regarding the use of face masks or cloth face coverings. T2 refers to the Voluntary Treatment, in which President Trump additionally emphasizes the voluntary nature of wearing a mask. T3 refers to the Refusal Treatment, in which President Trump additionally emphasizes that he will not wear a mask. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). No COVID Exp is the percent of people from each sample who have not tested positive or negative and do not know anyone (or know anyone who knows anyone) who has tested positive or died of COVID-19.

Turning to one's personal experience with COVID-19, we consider testing negative to be a kind of "false alarm" in which there are lasting effects of momentarily believing one has possibly contracted COVID-19. While the literature on false alarms and risk perceptions offers mixed conclusions, Whitmer et al. (2017) argue that "Experience with false alarms may be an influential component in one's mental representation of emergencies that guides risk perception and decision-making in emergency situations" (p. 1419). They go on to show that people who have experienced false "weather crisis" alarms are more likely to perceive such events as dangerous.[4] Following the work of Shahrabani and Benzion (2012), we expect to find that testing positive for COVID-19 reduces perceptions of illness severity—and therefore reduces the perceived benefits of mitigation. The sub-group of our sample who had previously tested positive also survived, at least up until the point they participated in our survey experiment. As such, this group experienced relatively minor (non-fatal) symptoms. Considering that people often substitute their own personal experience for aggregated data Fagerlin et al. (2005), people who recovered from COVID-19 may perceive COVID-19 to be less severe than people who never contracted the disease.

3.1. Treatment effects

Tables 1 and 2 present variable definitions along with summary statistics and sample sizes for each treatment.[5] We use these data to estimate treatment effects on three binary outcomes. The first measures a person's stated willingness to wear a

[4] Alternatively, others have argued that false alarms may cause a "cry wolf" effect whereby such events reduce perceptions of risk and mitigating behavior (e.g., Simmons and Sutter, 2009; Mackie, 2013). While this effect seems plausible in some contexts, we do not think it is applies to negative tests for COVID-19 as such an event is unlikely to be re-occurring for most people.

[5] Appendix Table A1, shows that treatment assignment was uncorrelated with observed subject characteristics with one exception. By chance, subjects in the third treatment were more likely to say they are "concerned" with the pandemic. As such, treatment effect are conditioned on observed subject heterogeneity.

mask[6] and is unity for people who say they "definitely" or "probably" will wear a mask if they were to attend a social event in the near future and zero otherwise. Similarly, the second outcome is unity for people who say they "strongly support" or "support" other people wearing masks. The third outcome indicates a person's level of support for a government mandate and is unity for those who say they "strongly support" or "support" a hypothetical mandate to wear masks in public. We estimate effects of treatment using a series of linear regressions of the basic following form:[7]

$$y_i = \alpha + \beta_1 Treated_i + \beta_2 T2_i + \beta_3 T3_i + \gamma X_i + \epsilon_i, \tag{1}$$

where y_i is subject i's stated preference for one of the three outcomes discussed above. Treatment indicator *Treated* is equal to unity for subjects in any one of the three messaging treatments. Indicators *T2* and *T3* are equal to unity for subjects in the *Voluntary* and *Refusal* treatments, respectively. Subjects who were not exposed to a video made up the baseline, or Control group, which is captured by the constant α. We condition the estimates on individual characteristics (X_i), specifically whether a person indicated they, or someone in their care has a health condition that increases their risk associated with COVID-19, a person's age, level of education, gender, race, stated level of concern with COVID-19, perception of whether the government response was an "over" or "under" reaction, and experience with COVID-19, including whether a person has tested positive or negative, whether a person knows someone who has tested positive, and whether a person knows someone who has died of COVID-19. Since the videos are nested (i.e., those in the $Voluntary$ and $Refusal$ treatments also saw the *CDC Guidelines* video), we decompose the effects into (1) the baseline effect of watching the *CDC Guidelines* video (which all subjects, other than the Control group, viewed), and (2) the additional effect of the *Voluntary* (*T2*) or *Refusal* (*T3*) treatment relative to the *CDC Guideline*. Modeled this way, β_1 is interpreted as the effect of exposure to the CDC guidelines on the likelihood of wearing a mask (or supporting mask use or government mandate), and β_2 and β_3 are the additional effects of being in either the Voluntary or the Refusal treatment, relative to the *CDC Guidelines* treatment (*Treated*). The cumulative effect of the *Voluntary* treatment (relative to the no-video control group) is therefore given by $\beta_1 + \beta_2$, and the cumulative effect of the *Refusal* treatment is $\beta_1 + \beta_3$. All regressions feature robust standard errors (though significant heteroskedasticity does not appear prevalent in our data).

For each of the three outcomes, we report results using the full sample of data and then re-estimate after limiting the sample in various ways. More specifically, the variable "Trump" ranges from one to five, where 1 indicates a person is strongly unsupportive of the President and five indicates a person in strongly supportive of the President. We estimate treatment effects conditioned on an individual's level of support for the president by limiting the sample accordingly. We also report results for males and females separately to test whether gender influenced treatment effects.

3.2. Experiential effects

The survey included questions about people's social proximity to—or experience with—COVID-19. We specifically asked each subject if they had been tested, and if the result was positive, negative or still pending. We also asked if subjects knew someone (or know someone who knew someone) who had tested positive or died as the result of contracting COVID-19. We use these data to explore how experience with COVID-19 influenced the outcome variables discussed above (namely, their stated likelihood of wearing a mask, their support for others to wear masks, and their stated support for a government mandate). We estimate experiential and treatment effects separately because each requires a (slightly) different set of controls. Whereas it is important to control for a person's stated level of concern with COVID-19 when estimating treatment effects (see footnote 5), concern is likely endogenous to experience. Because people with greater experience might be more likely to be both supportive of facemask use and more concerned with the disease, conditioning the effect of experience on level of concern could bias the estimated effect of experience towards zero. As with the estimation of treatment effects, we estimate experiential effects using variants of the following linear OLS estimator:[8]

$$y_i = \alpha + \beta_1 Known\ Pos\ Test_i + \beta_2 Known\ Death_i + \beta_3 Tested_i + \beta_4 Tested\ Pos_i + \gamma X_i + \epsilon_i, \tag{2}$$

where *Known Pos Test* is unity for subjects who knew someone (or knew someone who knew someone) who had tested positive, regardless of whether that person survived. *Known Death* is unity for subjects who knew someone (or knew someone who knew someone) who tested positive and also died from COVID-19. As such, *Known Death* is a subset of *Known Pos Test* as anyone who definitively died of COVID-19 must have, at some point, tested positive.[9] *Tested Pos* is unity for subjects who had personally tested positive, and *Tested* is unity for subjects who tested either positive or negative. Unlike the video treatments, experience with COVID-19 might not be randomly distributed across the subject pool. For example, people who were worried about the risk of COVID-19 may be more likely to wear a mask, and also more likely to have been tested. This raises

[6] We specifically asked subjects, "This week, suppose you will need to attend a public setting where social distancing is difficult to maintain. What is the likelihood that you will wear mask or other mouth and nose covering?"

[7] Given the three outcomes are binary, we also estimate all of the baseline average treatment effects using a Probit estimator. These results are provided in Table 2 in the appendix and complement those obtained using a linear estimator.

[8] As with the estimation of treatment effects, for robustness we also estimate average experiential effects using a Probit estimator given that each of the four outcomes are binary. These results are provided in Table A3 in the appendix.

[9] 9.5% of subjects who said they know someone who died of COVID-19 did not say they know someone who tested positive. We assume that such responses are made by mistake and require that anyone who knows someone who died of COVID-19 must also know someone who tested positive.

Table 3
Treatment effects: review.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Treated	0.427***	0.528***	0.566***	0.780***	0.571***	0.762***	0.444***	0.412***
	(0.0519)	(0.160)	(0.0856)	(0.0845)	(0.145)	(0.0986)	(0.0656)	(0.0800)
T2	−0.240***	−0.218***	−0.0500*	−0.421***	−0.0208	−0.448***	−0.193***	−0.296***
	(0.0226)	(0.0613)	(0.0293)	(0.0357)	(0.0425)	(0.0421)	(0.0304)	(0.0340)
T3	−0.339***	−0.334***	−0.172***	−0.482***	−0.249***	−0.505***	−0.292***	−0.398***
	(0.0227)	(0.0622)	(0.0324)	(0.0347)	(0.0576)	(0.0409)	(0.0305)	(0.0349)
Treated+T2	0.187***	0.310*	0.516***	0.358***	0.550***	0.314***	0.251	0.115
	(0.0533)	(0.164)	(0.0864)	(0.0866)	(0.142)	(0.103)	(0.0683)	(0.0815)
Treated+T3	0.0874*	0.194	0.394***	0.298***	0.322**	0.257**	0.152	0.0132
	(0.0531)	(0.166)	(0.0896)	(0.0855)	(0.151)	(0.101)	(0.0671)	(0.0822)
R^2	0.708	0.747	0.831	0.576	0.863	0.568	0.717	0.702
N	2085	280	840	965	300	696	1167	918

Note: The dependent variable is binary and equal to unity for subjects who say the video message “strongly encouraged” or “somewhat encouraged” the use of face masks. Subjects in the Control group are not included as this group was not exposed to any video treatment. *Treated* indicates a subject was exposed to any one of the three video treatments. T2 indicates a subject was exposed to the Voluntary treatment. T3 indicates a subject was exposed to the Refusal treatment. Thus, T2 and T3 are the additional effects of these treatments relative to the CDC Guidelines treatment (which is captured by the *Treated* coefficient). The constant term has been suppressed to ease interpretation. Treatment effects are conditioned on observed subject heterogeneity including race, education, income, age, gender, experience with COVID-19, health conditions, and stated level of concern regarding COVID-19. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Robust standard errors in parentheses. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

the concern of omitted variable bias, something we address in a couple of ways. First, we condition experiential effects on age, income, education, gender, race, and the presence of any complicating health conditions.[10] Second, we exploit the fact that, while the decision to be tested may not be random, the outcome of the test is more likely left to chance.[11] Similarly, whether a person knows someone who has tested positive for the virus may be endogenous, but whether a person survives after testing positive is plausibly exogenous. Given all of this, we broadly interpret β_1 as the effect of knowing someone who tested positive, and β_2 as the additional causal effect of knowing someone who not only tested positive but also died (as opposed to knowing someone who tested positive and survived). To explore the effects of individual personal experience with COVID, β_3 captures the effect of the survey respondent being tested for COVID (regardless of outcome), and β_4 as the additional causal effect of testing positive as opposed to negative. As with the estimation of treatment effects, experiential effects are estimated using the full sample of data, and also sub-samples which reveals heterogeneous experiential effects. All specifications again feature robust standard errors.

4. Results

4.1. Treatment effects

Before discussing treatment effects on stated preferences and behavior, we first explore how people perceived each of the three videos, and whether they perceived differences in the underlying message (Table 3). To do this, we define the outcome variable in Eq. (1) as unity for those subjects who said the video they watched either “strongly encouraged” or “encouraged” the use of facemasks. For this analysis, we drop all subjects in the Control group as they were not exposed to any of the video messages. We also suppress the constant term to ease interpretation. The first column of Table 3 pools the data across all subjects in the three messaging treatments. Conditional on subject characteristics, respondents viewed the *CDC Guidelines* treatment as the most encouraging of wearing face masks, followed by the *Voluntary* treatment, and then the *Refusal* treatment. In the *CDC Guidelines* treatment, 42.7% of respondents ($Treated = 0.427$, p=0.000) stated that the video somewhat or strongly encouraged mask use. Those who were in the *Voluntary* treatment were 24.0 percentage points ($T2 = -0.240$, p=0.000) less likely than those in the *CDC Guidelines* treatment to say the video encouraged mask use. Combining these effects ($Treated + T2 = 0.427 - 0.240 = 0.187$, p=0.000), Table 3 shows that 18.7% of respondents in the *Voluntary* treatment stated that the video encouraged mask use (conditional on subject characteristics). The marginal effect

[10] We do not condition on subject's stated concern with the pandemic, or their stated beliefs about government reaction, because these outcomes are likely endogenous to experience with COVID-19. For example, someone who knows someone who has died as the result of contracting the virus may be more concerned with the pandemic as a result.

[11] However, one may be concerned that people who are more likely to support the use of face masks are also more likely to be tested when experiencing only minor symptoms. This potentially creates a negative relationship between support for face masks and positive test results (conditional on being tested). For example, there is evidence that positive test rates are higher in some sparsely populated, conservative states like Wyoming and South Dakota (Johns Hopkins Coronavirus Resource Center). For robustness, we therefore estimate a variant of Eq. (2) that conditions experience on state fixed effects. These results are provided in Table 4 in the appendix and are similar to our baseline set of results.

Table 4
Treatment effects: mask self support.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Treated	0.0360**	0.0361	0.0356	0.0127	0.0487	0.0280	0.0399	0.0337
	(0.0176)	(0.0609)	(0.0299)	(0.0204)	(0.0495)	(0.0200)	(0.0246)	(0.0250)
T2	−0.00694	−0.0468	0.00990	0.000766	0.0368	−0.0181	0.00767	−0.0256
	(0.0169)	(0.0586)	(0.0286)	(0.0195)	(0.0433)	(0.0187)	(0.0231)	(0.0250)
T3	0.000479	−0.0656	−0.00725	0.0416**	0.0409	0.0113	0.0247	−0.0256
	(0.0164)	(0.0617)	(0.0295)	(0.0165)	(0.0472)	(0.0156)	(0.0220)	(0.0249)
Constant	0.697***	0.870***	0.536***	0.913***	0.304**	0.942***	0.678***	0.723***
	(0.0336)	(0.128)	(0.0745)	(0.0407)	(0.129)	(0.0451)	(0.0444)	(0.0499)
Treated+T2	0.0291	−0.0107	0.0456	0.0135	0.0855*	0.00991	0.0475*	0.00814
	(0.0178)	(0.0652)	(0.0295)	(0.0205)	(0.0452)	(0.0214)	(0.0253)	(0.0248)
Treated+T3	0.0365**	−0.0295	0.0284	0.0544***	0.0895*	0.0393**	0.0646***	0.00814
	(0.0173)	(0.0653)	(0.0307)	(0.0176)	(0.0502)	(0.0184)	(0.0242)	(0.0247)
R^2	0.171	0.122	0.224	0.140	0.332	0.111	0.163	0.191
N	2813	365	1156	1292	407	949	1566	1247

Note: The dependent variable is binary and equal to unity for subjects who say they are "very likely" or "likely" to wear a mask when attending a social event in the near future during which social distancing is not possible. *Treated* indicates a subject was exposed to any one of the three video treatments. T2 indicates a subject was exposed to the Voluntary treatment. T3 indicates a subject was exposed to the Refusal treatment. Thus, T2 and T3 are the additional effects of these treatments relative to the CDC Guidelines treatment (which is captured by the *Treated* coefficient). Treatment effects are conditioned on observed subject heterogeneity including race, education, income, age, gender, experience with COVID-19, health conditions, and stated level of concern regarding COVID-19. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Robust standard errors in parentheses. *** $p \le 0.01$, ** $p \le 0.05$, * $p \le 0.10$.

of the *Refusal* treatment, relative to the *CDC Guidelines*, was a 33.9 percentage point reduction ($T3 = -0.339$, p=0.000), which means that 8.74% ($Treated + T3 = 0.0874$, p=0.100) of respondents in the *Refusal* treatment viewed the video as encouraging face mask use.

Interestingly, these results are enhanced among people who oppose (Trump < 3) or strongly oppose (Trump = 1) the president. This group perceived the *CDC Guidelines* to be (qualitatively) more supportive of wearing masks—and viewed the *Refusal* and *Voluntary* treatments as less (qualitatively) supportive of wearing face masks—than those who do not support the President. Of course, the perception of messaging may not translate to stated behavioral changes, but these results nonetheless provide evidence that people were attentive to the video messages and interpreted them differently from one another.

Turning to our main analyses, we start by exploring the effect of treatment on the stated likelihood of personally wearing a mask. Table 2 provides unconditional means across the three treatments and control group. The variable Mask Self Support is the binary variable measuring support for personal mask use. The percent of people in the Control group who say they are "very likely" or "likely" to wear a mask in the near future is 82.1%. Across the three treatments, this number ranges from 85.9% to 87.9%.

Table 4 presents the results using Eq. (1) to estimate the stated likelihood of personally wearing a mask. The first column reports treatment effects pooling across all subjects. The Constant (0.697, p=0.000) indicates that, after conditioning on observed subject heterogeneity, 69.7% of individuals in the Control group report that they are likely or very likely to wear a mask in the near future. Exposure to the *CDC Guidelines* treatment increased the stated likelihood of wearing a mask by roughly 0.036 ($p = 0.041$). Note that the average response among subjects in the control group was 0.821 (see the first column of Table 2). We therefore estimate that exposure to the *CDC Guidelines* treatment increased the stated likelihood of personally wearing a mask by 0.036/0.821 = 4.4%.

Restricting the sample to people who strongly support the President (Trump=5), the *Treated* coefficient increases to 0.0487, but is not statistically significant (p=0.32). To some extent this reflects the resulting reduction in sample size (of the 2813 subjects, 407 report that they "strongly support" the President). The individual coefficients for the *Voluntary* and *Refusal* messages are also not significant, indicating that these statements had no additional effect relative to the *CDC guidelines*. However, the cumulative effects of the *Voluntary* and *Refusal* treatments are positive (0.0855 and 0.0895, respectively) and significantly different from the *No Message Baseline*. With an average response among the control group of 0.738 (see the fifth column of Table 2), the effect of the *Refusal* treatment for strong Trump supporters was a 0.089/0.738 = 12% increase in the stated likelihood of wearing a mask. Restricting the sample to people who support or strongly support the president (Trump>3) yields consonant, albeit reduced and statistically insignificant effects. For people who do not support the President, exposure to the *CDC Guidelines* and the *Voluntary* treatments both had negligible effects. However, there is some evidence that exposure to the *Refusal* treatment increased the stated likelihood of wearing a mask even among this sub group. Restricting the sample by gender, we find a positive and statistically significant effects for the *Voluntary* and *Refusal* treatments among males, but not females. This may partially reflect the fact that males are more likely than females to

Table 5
Treatment effects: mask others support.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Treated	0.0331**	0.0685	0.0397	0.00445	0.0481	0.0190	0.0248	0.0444**
	(0.0145)	(0.0501)	(0.0250)	(0.0159)	(0.0438)	(0.0159)	(0.0197)	(0.0216)
T2	−0.00616	−0.0686	0.00175	0.00786	0.0650	0.0148	−0.00360	−0.0119
	(0.0138)	(0.0475)	(0.0239)	(0.0151)	(0.0396)	(0.0121)	(0.0191)	(0.0203)
T3	−0.0112	−0.0734	−0.0188	0.0108	−0.00254	0.00280	0.0124	−0.0399*
	(0.0136)	(0.0463)	(0.0254)	(0.0143)	(0.0506)	(0.0127)	(0.0182)	(0.0211)
Constant	0.698***	0.677***	0.494***	0.945***	0.206	0.980***	0.725***	0.672***
	(0.0279)	(0.100)	(0.0660)	(0.0313)	(0.127)	(0.0313)	(0.0347)	(0.0445)
Treated+T2	0.0269*	−0.0000210	0.0414*	0.0123	0.113***	0.0338**	0.0212	0.0325
	(0.0147)	(0.0569)	(0.0253)	(0.0150)	(0.0404)	(0.0139)	(0.0206)	(0.0212)
Treated+T3	0.0219	−0.00485	0.0209	0.0153	0.0456	0.0218	0.0373*	0.00457
	(0.0145)	(0.0512)	(0.0264)	(0.0142)	(0.0515)	(0.0142)	(0.0196)	(0.0216)
R^2	0.174	0.137	0.241	0.148	0.347	0.129	0.156	0.203
N	2813	365	1156	1292	407	949	1566	1247

Note: The dependent variable is binary and equal to unity for subjects who say they "Strongly Agree", "Agree", or "Somewhat Agree" that others should wear masks in public. *Treated* indicates a subject was exposed to any one of the three video treatments. T2 indicates a subject was exposed to the Voluntary treatment. T3 indicates a subject was exposed to the Refusal treatment. Thus, T2 and T3 are the additional effects of these treatments relative to the CDC Guidelines treatment (which is captured by the *Treated* coefficient). Treatment effects are conditioned on observed subject heterogeneity including race, education, income, age, gender, experience with COVID-19, health conditions, and stated level of concern regarding COVID-19. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Robust standard errors in parentheses. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

experience psychological reactance (Waller et al., 2007) and hence the voluntary message is relatively effective among this group (and recall the voluntary message is included in both the *Voluntary* and *Refusal* treatments).

Table 5 uses a similar framework as Table 4 to provide the estimated treatment effects on stated support for other people wearing masks. The pooled results (provided in the first column) show that exposure to the *CDC guidelines* in any of the three message treatments increased support for mask wearing by others (by 0.033). Here, the average response among the control group was 0.877 implying a treatment effect of 0.033/0.877 = 3.7%. We continue to find enhanced effects among the President's strongest supporters. Restricting the sample to people who "strongly support the President" (Trump=5) exposure to the *Voluntary* treatment had the largest effect, increasing support by 0.113, or 0.113/0.757 = 15%[12]. In contrast, for people who are strongly unsupportive of the president (Trump=1), all three treatment effects are much smaller (though the *Voluntary* treatment had a positive, statistically significant effect on this group). For example, among people who are strongly unsupportive of the President, the *Voluntary* treatment increased support by just 0.033, or 0.033/0.952 = 3.4%.

Finally, Table 6 shows that, pooled across all subjects, none of the videos had a statistically significant effect on a person's stated support for a government mandate. However, by restricting the sample to the President's supporters we again document significant effects of the *CDC Guidelines* and *Voluntary* treatments. Among this group, we document the largest effect (0.085) for the *CDC Guidelines* treatment. This constitutes a large percentage change in support for a mandate (0.085/0.644 = 13.2%).

4.2. Experiential effects

Estimated experiential effects are given in Tables 7–9. Pooling the data, column 1 of Table 7 shows that people who knew someone who had tested positive (and survived) were significantly (*Known Pos Test* = 0.069; p=0.000) more likely to say they would wear a mask in the future than those who did not know someone who had tested positive. Because the average response among people without any experience with COVID-19 is 0.798 (see column 7 of Table 2), this implies the stated likelihood of wearing a mask is 0.069/0.798 = 8.6% greater among people who knew someone who had contracted the virus. Surprisingly, knowing someone who died (*Known Death*) has no additional effect on the likelihood of wearing a mask, and this is true across all sub-groups examined in Table 7. It is important to note, however, that this result is conditioned on whether a person knows someone who has previously tested positive. Interestingly, the coefficient on Test is qualitatively small (0.018) and not statistically significant (p-value = 0.399) while that on *Tested Pos* is negative (−0.082) and statistically significant (p-value = 0.063). Considered jointly, the effect of testing positive is 0.018−0.082 = −0.064, but is not statistically different from zero (p-value = 0.115). These results are largely consistent with the findings of Shahrabani and Benzion (2012) who show that the perceived benefits of an influenza vaccine are smaller among people who previously had contracted the virus. The authors of that study hypothesize that perhaps, "people who had a mild case of the illness may

[12] While the effect of the *Voluntary* treatment is qualitatively larger than that of the other two, it is not statistically different. We therefore fail to reject the null hypothesis that the President's strongest supporters responded differently to the three treatments.

Table 6
Treatment effects: mandate support.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Treated	0.0113	−0.0123	0.0468	−0.0203	0.0849*	0.000181	0.0235	−0.00583
	(0.0194)	(0.0673)	(0.0328)	(0.0224)	(0.0482)	(0.0230)	(0.0261)	(0.0290)
T2	−0.0242	−0.0799	−0.0153	−0.0171	−0.00489	0.00951	−0.0203	−0.0270
	(0.0197)	(0.0692)	(0.0330)	(0.0234)	(0.0486)	(0.0220)	(0.0261)	(0.0305)
T3	−0.00170	0.0345	−0.0290	0.0156	−0.0526	0.00625	−0.00531	0.00785
	(0.0192)	(0.0622)	(0.0329)	(0.0219)	(0.0528)	(0.0218)	(0.0255)	(0.0293)
Constant	0.563***	0.128	0.403***	0.855***	0.183	0.967***	0.571***	0.581***
	(0.0373)	(0.150)	(0.0795)	(0.0489)	(0.125)	(0.0536)	(0.0480)	(0.0586)
Treated+T2	−0.0129	−0.0922	0.0315	−0.0374*	0.0800*	0.00969	0.00318	−0.0329
	(0.0195)	(0.0744)	(0.0329)	(0.0222)	(0.0487)	(0.0219)	(0.0270)	(0.0286)
Treated+T3	0.00962	0.0222	0.0179	−0.00464	0.0323	0.00643	0.0182	0.00201
	(0.0191)	(0.0667)	(0.0330)	(0.0207)	(0.0535)	(0.0215)	(0.0264)	(0.0277)
R^2	0.241	0.205	0.258	0.217	0.410	0.193	0.226	0.267
N	2813	365	1156	1292	407	949	1566	1247

Note: The dependent variable is binary and equal to unity for subjects who say they "Strongly support" or "Support" a govenment mandate to wear masks in public. *Treated* indicates a subject was exposed to any one of the three video treatments. T2 indicates a subject was exposed to the Voluntary treatment. T3 indicates a subject was exposed to the Refusal treatment. Thus, T2 and T3 are the additional effects of these treatments relative to the CDC Guidelines treatment (which is captured by the *Treated* coefficient). Treatment effects are conditioned on observed subject heterogeneity including race, education, income, age, gender, experience with COVID-19, health conditions, and stated level of concern regarding COVID-19. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Robust standard errors in parentheses. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table 7
Experiential effects: mask self support.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Known Death	0.000615	0.0780	−0.00456	−0.0302*	−0.00607	−0.0124	−0.0123	0.0163
	(0.0153)	(0.0588)	(0.0251)	(0.0167)	(0.0388)	(0.0165)	(0.0221)	(0.0209)
Known Pos Test	0.0695***	−0.0491	0.162***	0.0437***	0.225***	0.0333**	0.0561***	0.0837***
	(0.0161)	(0.0536)	(0.0312)	(0.0155)	(0.0562)	(0.0162)	(0.0216)	(0.0238)
Pos Test	−0.0825*	−0.320**	−0.0329	−0.219	−0.0399	−0.170	−0.0970*	−0.0740
	(0.0444)	(0.152)	(0.0423)	(0.194)	(0.0551)	(0.218)	(0.0577)	(0.0681)
Test	0.0183	0.00326	0.0892***	−0.0300	0.138***	−0.0293	0.0306	0.0102
	(0.0217)	(0.0729)	(0.0308)	(0.0331)	(0.0483)	(0.0387)	(0.0288)	(0.0325)
Health Cond	0.0413***	0.000994	0.0638**	0.0124	0.0934**	0.00198	0.0446**	0.0378*
	(0.0134)	(0.0470)	(0.0251)	(0.0140)	(0.0438)	(0.0142)	(0.0186)	(0.0194)
Age	0.000404	0.0182	−0.00832	0.0120**	−0.00335	0.0105**	−0.00400	0.00468
	(0.00505)	(0.0171)	(0.00973)	(0.00465)	(0.0150)	(0.00515)	(0.00735)	(0.00678)
Rich	0.0176	−0.0444	0.00844	0.0366**	−0.0134	0.0311**	0.0226	0.0113
	(0.0134)	(0.0444)	(0.0229)	(0.0146)	(0.0368)	(0.0144)	(0.0186)	(0.0195)
College	0.0464***	0.0413	0.129***	0.00799	0.158***	0.00116	0.0327	0.0639***
	(0.0155)	(0.0495)	(0.0331)	(0.0152)	(0.0551)	(0.0151)	(0.0218)	(0.0221)
Male	−0.0146	−0.0400	−0.00655	−0.00598	−0.0269	0.0137		
	(0.0133)	(0.0459)	(0.0233)	(0.0139)	(0.0368)	(0.0140)		
White	−0.0869***	−0.0747	−0.0678	−0.0738***	−0.0290	−0.0607***	−0.0740***	−0.0983***
	(0.0176)	(0.0558)	(0.0486)	(0.0147)	(0.0926)	(0.0133)	(0.0257)	(0.0234)
Black	0.00328	0.0538	−0.00331	−0.0161	0.0411	−0.0338	0.00457	0.00793
	(0.0205)	(0.0785)	(0.0510)	(0.0183)	(0.0923)	(0.0215)	(0.0294)	(0.0282)
Hisp	−0.0262	−0.0741	0.0137	−0.0390	0.00765	−0.0453	0.00534	−0.0732**
	(0.0179)	(0.0662)	(0.0241)	(0.0292)	(0.0368)	(0.0313)	(0.0220)	(0.0300)
Constant	0.826***	0.810***	0.619***	0.909***	0.502***	0.927***	0.826***	0.807***
	(0.0261)	(0.0942)	(0.0657)	(0.0244)	(0.117)	(0.0249)	(0.0347)	(0.0347)
Known(Death+Pos Test)	0.0701***	0.0289	0.157***	0.0135	0.219***	0.0210	0.0438*	0.100***
	(0.0166)	(0.0564)	(0.0314)	(0.0178)	(0.0521)	(0.0174)	(0.0230)	(0.0239)
Test + Pos Test	−0.0642	−0.317**	0.0562	−0.249	0.0978**	−0.199	−0.0664	−0.0638
	(0.0408)	(0.140)	(0.0353)	(0.191)	(0.0441)	(0.214)	(0.0533)	(0.0614)
R^2	0.0353	0.0442	0.110	0.0388	0.208	0.0326	0.0277	0.0523
N	2813	365	1156	1292	407	949	1566	1247

Note: The dependent variable is binary and equal to unity for subjects who say they are "very likely" or "likely" to wear a mask when attending a social event in the near future at which social distancing is not feasible. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Known Death and Known Pos Test are unity for people who know someone, or know someone who knows someone who has died from, or tested positive for, COVID-19, respectively. Pos Test is unity for people who have tested positive for COVID-19 and Test is unity for people who have either tested positive or negative for COVID-19. See Table 1 for descriptions of covariates. Robust standard errors in parentheses. *** p $\leq$0.01, ** p $\leq$0.05, * p $\leq$0.10.

Table 8
Experiential effects: mask others support.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Known Death	−0.0209*	−0.0328	−0.0308	−0.00909	−0.0205	−0.0123	−0.0260	−0.0147
	(0.0116)	(0.0482)	(0.0194)	(0.0114)	(0.0351)	(0.0117)	(0.0161)	(0.0169)
Known Pos Test	0.0808***	0.0420	0.160***	0.0422***	0.217***	0.0202*	0.0760***	0.0874***
	(0.0131)	(0.0405)	(0.0267)	(0.0124)	(0.0521)	(0.0112)	(0.0170)	(0.0202)
Pos Test	−0.0534*	−0.241*	−0.0230	0.0512*	−0.0847**	0.00548	−0.0660*	−0.0425
	(0.0305)	(0.127)	(0.0281)	(0.0276)	(0.0408)	(0.0166)	(0.0397)	(0.0465)
Test	0.0422***	0.0869**	0.0877***	−0.00109	0.170***	0.0201***	0.0547***	0.0283
	(0.0148)	(0.0404)	(0.0226)	(0.0223)	(0.0362)	(0.00612)	(0.0183)	(0.0247)
Health Cond	0.0447***	−0.0510	0.0639***	0.0386***	0.0966**	0.0223**	0.0390***	0.0538***
	(0.0110)	(0.0377)	(0.0213)	(0.0105)	(0.0413)	(0.0102)	(0.0147)	(0.0166)
Age	0.000173	0.00973	0.00523	0.00124	0.00565	0.00383	−0.00214	0.00294
	(0.00401)	(0.0118)	(0.00800)	(0.00385)	(0.0145)	(0.00445)	(0.00557)	(0.00578)
Rich	0.0250**	0.0526	0.0107	0.0229**	−0.0376	0.0230**	0.0277*	0.0223
	(0.0112)	(0.0370)	(0.0194)	(0.0115)	(0.0340)	(0.0110)	(0.0154)	(0.0166)
College	0.0464***	0.0967**	0.131***	−0.00240	0.185***	−0.00401	0.0295	0.0664***
	(0.0137)	(0.0434)	(0.0308)	(0.0113)	(0.0560)	(0.0104)	(0.0189)	(0.0198)
Male	−0.000211	0.00331	−0.00480	0.00805	−0.0393	0.0160		
	(0.0110)	(0.0377)	(0.0198)	(0.0110)	(0.0341)	(0.0100)		
White	−0.0502***	−0.0451	−0.0311	−0.0329**	−0.00277	−0.0281***	−0.0362	−0.0640***
	(0.0151)	(0.0445)	(0.0440)	(0.0128)	(0.0811)	(0.0101)	(0.0222)	(0.0199)
Black	−0.00129	−0.125	0.00816	0.0157	0.0613	0.00747	−0.00703	0.0114
	(0.0175)	(0.0768)	(0.0451)	(0.0121)	(0.0781)	(0.00808)	(0.0258)	(0.0225)
Hisp	−0.00350	−0.0937	0.0352*	−0.000928	0.0389	−0.0234	0.00893	−0.0176
	(0.0138)	(0.0574)	(0.0191)	(0.0196)	(0.0322)	(0.0233)	(0.0171)	(0.0231)
Constant	0.828***	0.795***	0.603***	0.921***	0.459***	0.946***	0.839***	0.808***
	(0.0221)	(0.0800)	(0.0578)	(0.0201)	(0.110)	(0.0196)	(0.0277)	(0.0331)
Known(Death+Pos Test)	0.0599***	0.00913	0.129***	0.0331**	0.197***	0.00784	0.0500***	0.0728***
	(0.0141)	(0.0493)	(0.0273)	(0.0131)	(0.0486)	(0.0124)	(0.0187)	(0.0213)
Test + Pos Test	−0.0113	−0.154	0.0647***	0.0501***	0.0856**	0.0256	−0.0112	−0.0142
	(0.0284)	(0.124)	(0.0237)	(0.0178)	(0.0380)	(0.0169)	(0.0379)	(0.0410)
R^2	0.0444	0.0719	0.134	0.0331	0.246	0.0273	0.0361	0.0606
N	2813	365	1156	1292	407	949	1566	1247

Note: The dependent variable is binary and equal to unity for subjects who say they "Strongly agree", "Agree", or "Somewhat agree" that others should wear masks in public. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Known Death and Known Pos Test are unity for people who know someone, or know someone who knows someone who has died from, or tested positive for, COVID-19, respectively. Pos Test is unity for people who have tested positive for COVID-19 and Test is unity for people who have either tested positive or negative for COVID-19. See Table 1 for descriptions of covariates. Robust standard errors in parentheses. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

not perceive the vaccine as necessary." Further, the influence of knowing someone who has tested positive is consistent with previous work that report information from experience has greater impacts on behavior than observed information (Nisbett and Ross, 1980).[13]

Restricting the data to the President's supporters (Trump> 3) and his strongest supporters (Trump= 5), the estimated experiential effects are enhanced. For example, among the President's most fervent supports (Trump= 5), the stated likelihood of wearing a mask was 0.225 greater among people who knew someone who had tested positive (a 0.225/0.519 = 43% increase). Conversely, among people who strongly opposed the President, this effect was just 0.0333/0.931 = 3.5%. Further, among the President's supporters, testing negative increased the stated likelihood of wearing a mask (but this may reflect that people who are worried about contracting the virus are both more likely to wear a mask, and more likely to be tested). Among this group, the effect of testing positive (the sum of *Tested Pos* and *Tested*) is positive (0.098) and statistically significant (p-value = 0.027). In fact, the negative effect of testing positive is entirely driven by moderates, or people who do not support the President. In fact, among people who neither support or oppose the President (Trump = 3), the effect of testing positive is negative (−0.317) and significant (p-value = 0.024).

Table 8 gives experiential effects on the stated preference for other people to wear masks. The results are broadly in line with those for personal mask use. For example, people who know someone who tested positive (and survived) are more likely to support others wearing a mask (*Known Pos Test* is positive across all sub samples). We again find that there is no additional effect of knowing someone who died after testing positive. These effects are again amplified among people who strongly support the president. Somewhat surprisingly, pooling the data we find that testing positive has no effect

[13] Simonsohn et al. (2008) conduct three experiments that disentangle the influence of experienced information and observed information. Results show that experienced information has a greater impact on behavior than observed information and that this finding was due to people placing greater weight on experience rather than attending less to observation. Relatedly, prior work shows that simple reinforcement from past observed actions of others is a better predictor of behavior than belief-based learning (e.g., Wilcox and Rutstrom, 2009; Camerer et al., 2005).

Table 9
Experiential effects: mandate support.

	All	Trump=3	Trump>3	Trump<3	Trump=5	Trump=1	Male	Female
Known Death	−0.0121	−0.0203	−0.0319	−0.00819	0.0455	−0.0105	−0.0191	−0.00742
	(0.0183)	(0.0674)	(0.0298)	(0.0193)	(0.0460)	(0.0194)	(0.0250)	(0.0271)
Known Pos Test	0.106***	0.0607	0.189***	0.0747***	0.190***	0.0546***	0.102***	0.117***
	(0.0188)	(0.0588)	(0.0340)	(0.0200)	(0.0604)	(0.0199)	(0.0251)	(0.0282)
Pos Test	−0.0290	−0.0557	0.0224	−0.263	−0.0829	0.0259	−0.0000149	−0.0753
	(0.0430)	(0.138)	(0.0475)	(0.200)	(0.0647)	(0.0417)	(0.0499)	(0.0770)
Test	0.0657***	0.113	0.133***	0.0411	0.210***	0.0425*	0.0896***	0.0342
	(0.0244)	(0.0845)	(0.0356)	(0.0288)	(0.0457)	(0.0241)	(0.0310)	(0.0398)
Health Cond	0.0553***	−0.0917*	0.0685**	0.0575***	0.147***	0.0268	0.0478**	0.0674***
	(0.0159)	(0.0528)	(0.0281)	(0.0168)	(0.0493)	(0.0165)	(0.0215)	(0.0236)
Age	−0.00279	0.0612***	−0.0295***	0.0107*	−0.0474***	0.0117*	−0.000143	−0.00479
	(0.00583)	(0.0202)	(0.0102)	(0.00576)	(0.0167)	(0.00622)	(0.00812)	(0.00833)
Rich	0.0200	0.0114	0.0000548	0.0206	−0.0295	0.0121	−0.00726	0.0525**
	(0.0158)	(0.0513)	(0.0255)	(0.0183)	(0.0391)	(0.0185)	(0.0211)	(0.0238)
College	0.0426**	0.122**	0.108***	0.0117	0.0983*	0.00625	0.0202	0.0697***
	(0.0179)	(0.0579)	(0.0347)	(0.0185)	(0.0540)	(0.0183)	(0.0244)	(0.0266)
Male	0.00747	0.0283	0.0233	0.0165	−0.00454	0.0313*		
	(0.0154)	(0.0524)	(0.0257)	(0.0172)	(0.0400)	(0.0170)		
White	−0.142***	−0.157**	−0.141***	−0.0944***	−0.114	−0.0863***	−0.116***	−0.166***
	(0.0202)	(0.0668)	(0.0498)	(0.0183)	(0.0779)	(0.0142)	(0.0293)	(0.0276)
Black	−0.0454*	−0.0747	−0.0504	−0.0467*	0.00204	−0.0598**	−0.0294	−0.0553
	(0.0250)	(0.0975)	(0.0535)	(0.0272)	(0.0784)	(0.0272)	(0.0348)	(0.0364)
Hisp	0.0122	−0.0323	0.0843***	0.00541	0.129***	0.00549	0.0144	0.0158
	(0.0197)	(0.0688)	(0.0271)	(0.0300)	(0.0381)	(0.0289)	(0.0249)	(0.0323)
Constant	0.759***	0.450***	0.621***	0.834***	0.592***	0.887***	0.770***	0.739***
	(0.0302)	(0.110)	(0.0672)	(0.0315)	(0.112)	(0.0294)	(0.0386)	(0.0439)
Known(Death+Pos Test)	0.0942***	0.0404	0.157***	0.0665***	0.235***	0.0441**	0.0826***	0.109***
	(0.0197)	(0.0665)	(0.0346)	(0.0210)	(0.0551)	(0.0208)	(0.0266)	(0.0294)
Test + Pos Test	0.0366	0.0568	0.155***	−0.222	0.127**	0.0684*	0.0896**	−0.0411
	(0.0380)	(0.120)	(0.0387)	(0.198)	(0.0602)	(0.0356)	(0.0432)	(0.0689)
R^2	0.0499	0.0629	0.147	0.0445	0.284	0.0341	0.0428	0.0675
N	2813	365	1156	1292	407	949	1566	1247

Note: The dependent variable is binary and equal to unity for subjects who say they "Strongly support" or "Support" a government mandate to wear masks in public. Trump varies from 1 (strongly unsupportive of President Trump) to 5 (strongly supportive of President Trump). Known Death and Known Pos Test are unity for people who know someone, or know someone who knows someone who has died from, or tested positive for, COVID-19, respectively. Pos Test is unity for people who have tested positive for COVID-19 and Test is unity for people who have either tested positive or negative for COVID-19. See Table 1 for descriptions of covariates. Robust standard errors in parentheses. *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

on a person's stated support for social mask use. In fact, there is evidence that, among moderates testing positive reduces support for other people wearing masks, but this result lacks statistical significance (p-value = 0.21).

Table 9 gives the results for support for a government mandate, which are mostly in line with the findings for the other outcomes. People who know someone who has tested positive are typically more likely to support a government mandate to wear masks in public. While this is true among all groups, it is especially true among the President's supporters. In fact, for the president's strongest supporters, knowing someone that tested positive for COVID-19 and died as a result increases support for a government mandate by 0.235, or roughly 0.235/0.392 = 60% (p-value = 0.000).

Turning to the covariates, we find that people who have a health condition (or care for someone with a health condition) that increases their risk of COVID-19 ("Health Cond") are more likely to support the use of face masks. People with at least a four-year college degree report greater support for face masks and a mandate. Interestingly, we find that age is not associated with stated behaviors or preferences, but note that the effect of age is conditioned on the presence of complicating health conditions. This result is somewhat at odds with Haischer et al. (2020) who find that older people and females are (unconditionally) more likely to wear masks than other people. We also find that White people are relatively less likely to support the use of face masks. Exploring heterogeneous effects, we see that the effects of having a college degree or pre-existing health condition are especially pronounced among the President's supporters. In fact, conditional on not supporting the president, stated preferences and behaviors are uncorrelated with education and health status. Interestingly, we also find that being White reduces stated support for masks, but only among people who do not support the president.

5. Discussion

Our previous analyses uncovered significant effects of Presidential messaging and of experience with COVID-19. Here we discuss the importance of these findings and their practical and qualitative relevance to practitioners and policy makers.

Starting with the treatment effects, our key finding is that exposure to the CDC guidelines significantly increased the stated likelihood of wearing a mask. We roughly interpret these results as the effect of treatment on the percent of people choosing to wear a mask, but are these large, economically meaningful effects? To the extent that stated behavior proportionally translates to real behavioral changes, our results suggest that exposure to treatment increases the percent of people wearing masks. According to existing literature (Chu et al., 2020; Eikenberry et al., 2020; Leung et al., 2020), this is likely to have a significant effect on the rate of transmission, measured as R_0 (the average number of people who are infected from a single infected person in a population with no prior exposure). More specifically, according to Tian et al. (2020), wearing masks reduces R_0 by a factor of $(1 - ep_m)^2$, where e measures the effectiveness of face coverings in trapping viral particles and p_m is the percent of a population that wears a mask. Estimates of the reproductive number for COVID-19 range between 1.4 and 6.49, with a mean of 3.28 (Liu et al., 2020). Following Howard et al. (2020), assuming masks are moderately effective (e=0.50), if mask-wearing were to increase from zero to 50% this would cause the R_0 to fall from an initial value of 3.28 to 1.84. If instead mask use were at 53.6% (a 3.6 percentage point increase, equal to the effect of exposure to the *CDC Guidelines* treatment), the resulting R_0 would fall to 1.75. It is also important to recall that treatment effects are larger among the President's supporters (more than 40% of our sample). Among this population, we estimate that exposure to either the *Voluntary* or *Refusal* treatments increases mask use by roughly 9 percentage points. For reference, if 59% of the population wore masks, the R_0 would fall to just 1.63. Turning to the experiential effects, recall that, pooling across all subjects, knowing someone who tested positive increases the stated likelihood of wearing a mask by roughly 7 percentage points. This effect is similar in size to treatment effects for the president's supporters discussed above. Among the president's supporters, however, knowing someone who tested positive increases the likelihood of wearing a mask by roughly 22 percentage points. Starting from a baseline of 50% mask use (with an R_0 of 1.84), a 22 percentage point increase in mask use would cause the R_0 to drop to just 1.34.

Another key result is that testing negative is associated with higher support for mitigation efforts, but testing positive tends to have the opposite effect (particularly among political moderates, or people who do not support the President). One, somewhat speculative interpretation of this result is that people who have recovered from the virus believe they have antibodies that will protect them in the future. Though, it is also possible that survivors adjust their perceptions of the deadliness of the virus—after all, everyone in our survey who previously tested positive had, by June 25, 2020 (the date of the survey), survived. But supposing people prefer other people not to contract the virus, those with reduced risk perceptions should reasonably have reduced preferences for other people wearing masks as well. And yet, this is not what we find. Rather, the results indicate that testing positive reduces preferences for personal mask use, but has no significant effect on preferences for social use. Taken jointly, all of this is suggestive that people who have tested positive believe, perhaps incorrectly so, that they have protective antibodies.

Reducing mitigating effort in response to believing one is carrying antibodies is potentially problematic for a couple of reasons. The first is that it is possible that people can contract the virus twice. While the duration of acquired immunity to COVID-19 is uncertain, an analysis of the "four seasonal human coronaviruses" which may "reveal common characteristics applicable to all human coronaviruses" suggests an "alarmingly" short duration of protective immunity (Edridge et al., 2020). It is further possible for people who have previously tested positive to spread the disease even if they do not have any visible symptoms (Jabir et al., 2020). The second reason is the possibility of false positive test results. In this case, people may reduce mitigation efforts while falsely believing they have immunity. And the frequency of false positive tests may be significant, which is why Ramdas et al. (2020) recommends repetitive testing. Related to this, according to Arevalo-Rodriguez et al. (2020), the probability of experiencing a false negative test is estimated to range between 2% and 54%.

In this context, widespread testing may have an unintended consequence. Namely, people who have tested positive are less likely to mitigate risky behavior and choose not to wear a mask or face covering. The significance of this finding depends on people's prevailing, status-quo behavioral choices. Suppose for example that without any testing everyone wore masks and that masks are sufficiently effective to stop the spread of the novel coronavirus. In this case, widespread testing that results in fewer masks being worn may actually increase the spread of the illness. This idea is related to that of Philipson and Posner (1994) who analyze the effects of testing for sexually transmitted diseases. They find that "if the pretesting status quo is safe sex, testing [for sexually transmitted diseases] is likely to increase the incidence of the STD if only one partner tests". The key insight is that a person who tests negative may be more likely to engage in unprotected sexual activities in the future, and hence are more likely to become infected. This is not to say that widespread testing is a bad idea. But it is to say that unintended consequences may exist, and understanding these consequences can help to inform optimal health and public policy. For example, positive test results could be supplemented with messages that encourage patients to continue to wear face masks, and that warn against the dangers of reducing mitigating efforts even after receiving a positive test result.

6. Conclusion

There is evidence that the use of face coverings helps to slow the spread of the novel coronavirus that causes COVID-19 (e.g., Chu et al., 2020), and yet, their use in the United States is not universal and remains controversial. Who is reluctant to wearing a face mask and why? What can be done to change people's willingness to wear a mask? We explore these questions using an online survey experiment of roughly three thousand people. We test whether messages from President Trump influence stated behavior, and explore how experience with—or social distance from—COVID-19 effects peoples' (i) stated likelihood of wearing a mask, (ii) stated support for widespread face mask use, and (iii) stated support for a government mandate to require face coverings when social distancing is not feasible. We collect a variety of socio-economic data, including political preferences, allowing us to explore heterogeneity in both the effects of treatment and experience.

A number of important insights emerge from the data. First, Whites and people without a college degree, as well as those without a pre-existing condition are less likely to support the widespread use of face coverings or a government mandate to wear masks. Second, we find that listening to the President recite the CDC guidelines regarding the use of face coverings significantly increases stated support for masks, especially among the president's supporters. Among the president's most fervent supporters, there is evidence that coupling the CDC message with one that reinforces the voluntary nature of wearing a mask is most effective. Third, people who know someone who has tested positive for the virus are more likely to support the use of face coverings, and a government mandate and we again document enhanced effects among the president's supporters. Fourth, personally testing negative is associated with increased support for mask use, while the average effect of testing positive is mostly insignificant. Among political moderates who may be more responsive to experiences and new information, testing positive tends to reduce support for mask use.

These results are of importance to policy makers and practitioners alike. A marketing campaign featuring the president reciting the CDC guidelines may be a fruitful strategy to increase support for face coverings among his supporters (a group of people who are less likely to wear masks than other groups). Further, making people feel as though they know someone who has tested positive for COVID-19 may also be an effective strategy.

Practitioners modeling the spread of COVID-19 should consider that mitigating efforts are endogenous to the spread of the disease. As more people contract COVID-19, average social distance from the virus declines and this increases mitigating efforts. However, testing people for COVID-19 is a double-edged sword. People who test positive know to social distance and this slows the spread of the disease. However, after testing positive, survivors reduce mitigating efforts and this increases the rate of transmission. This is problematic as false positives may cause people to reduce mitigating efforts when they have not yet been exposed to the virus. This suggests that, perhaps, positive test results should be coupled with a message that highlights that the severity of symptoms varies across groups of people and people who test positive should continue to wear face coverings in the future. However, this conjecture remains speculative until additional research is carried out.

Declaration of Competing Interest

None.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2021.04.006
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References

Arevalo-Rodriguez, I., Buitrago-Garcia, D., Simancas-Racines, D., Zambrano-Achig, P., del Campo, R., Ciapponi, A., Sued, O., Martinez-Garcia, L., Rutjes, A., & Low, N., et al. (2020). False-Negative Results of Initial RT-PCR Assays for Covid-19: A Systematic Review. MedRxiv.

Abaluck, J., Chevalier, J. A., Christakis, N. A., Forman, H. P., Kaplan, E. H., Ko, A., & Vermund, S. H. (2020). The Case for Universal Cloth Mask Adoption and Policies to Increase Supply of Medical Masks for Health Workers. Available at SSRN 3567438.

Ahlquist, J.S., Levi, M., 2011. Leadership: what it means, what it does, and what we want to know about it. Annu. Rev. Polit. Sci. 14, 1–24.

Almaatouq, A., Noriega-Campero, A., Alotaibi, A., Krafft, P., Moussaid, M., Pentland, A., 2020. Adaptive social networks promote the wisdom of crowds. Proc. Natl. Acad. Sci. 117 (21), 11379–11386.

Arechar, A.A., Kraft-Todd, G.T., Rand, D.G., 2017. Turking overtime: how participant characteristics and behavior vary over time and day on Amazon mechanical turk. J. Econ. Sci. Assoc. 3 (1), 1–11.

Baker, S.R., Farrokhnia, R.A., Meyer, S., Pagel, M., Yannelis, C., 2020. How Does Household Spending Respond to an Epidemic? Consumption During the 2020 Covid-19 Pandemic. Technical report. National Bureau of Economic Research.

Becker, M.H., Maiman, L.A., 1980. Strategies for enhancing patient compliance. J. Commun. Health 6, 113–135.

Berinsky, A.J., Huber, G.A., Lenz, G.S., 2012. Evaluating online labor markets for experimental research: Amazon.com's mechanical turk. Polit. Anal. 20 (3), 351–368.

Brehm, J. W. (1966). A Theory of Psychological Reactance.

Brehm, S.S., Brehm, J.W., 2013. Psychological Reactance: A Theory of Freedom and Control. Academic Press.

Buhrmester, M.D., Talaifar, S., Gosling, S.D., 2018. An evaluation of Amazon's mechanical turk, its rapid rise, and its effective use. Perspect. Psychol. Sci. 13 (2), 149–154.

Cajner, T., Crane, L.D., Decker, R.A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., Yildirmaz, A., 2020. The US Labor Market During the Beginning of the Pandemic Recession. Technical report. National Bureau of Economic Research.

Camerer, C., Loewenstein, G., Prelec, D., 2005. Neuroeconomics: how neuroscience can inform economics. J. Econ. Lit. 43 (1), 9–64.

Cassar, L., & Klein, A. (2017). A Matter of Perspective: How Experience Shapes Preferences for Redistribution.

Cherry, T.L., Mc Evoy, D.M., Saelen, H., 2017. Conditional cooperation and cultural worldviews. Econ. Lett. 158, 51–53.

Chesney, T., Chuah, S., Hoffmann, R.-H., 2009. Virtual world experimentation: an exploratory study. J. Econ. Behav. Organ. 72 (1), 618–635.

Chu, D.K., Akl, E.A., Duda, S., Solo, K., Yaacoub, S., Schuänemann, H.J., El-harakeh, A., Bognanni, A., Lotfi, T., Loeb, M., et al., 2020. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and Covid-19: a systematic review and meta-analysis. Lancet 395 (10242), 1973–1987. doi:10.1016/S0140-6736(20)31142-9.

Chung, S., Cho, H., 2017. Fostering parasocial relationships with celebrities on social media: implications for celebrity endorsement. Psychol. Mark. 34 (4), 481–495.

Coibion, O., Gorodnichenko, Y., Weber, M., 2020. The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending. National Bureau of Economic Research.

Edridge, A. W., Kaczorowska, J. M., Hoste, A. C., Bakker, M., Klein, M., Jebbink, M. F., Matser, A., Kinsella, C., Rueda, P., & Prins, M., et al. (2020). Coronavirus Protective Immunity is Short-Lasting. MedRxiv.

Eikenberry, S.E., Mancuso, M., Iboi, E., Phan, T., Eikenberry, K., Kuang, Y., Kostelich, E., Gumel, A.B., 2020. To mask or not to mask: modeling the potential for face mask use by the general public to curtail the Covid-19 pandemic. Infect. Dis. Model. 5, 293–308. doi:10.1016/j.idm.2020.04.001.

Fagerlin, A., Wange, C., Ubel, P.A., 2005. Reducing the influence of anecdotal reasoning on people's health care decisions: is a picture worth a thousand statistics? Med. Decis. Mak. 25 (4), 398–405.

Fenichel, E.P., Castillo-Chavez, C., Ceddia, M.G., Chowell, G., Parra, P.A.G., Hickling, G.J., Holloway, G., Horan, R., Morin, B., Perrings, C., et al., 2011. Adaptive human behavior in epidemiological models. Proc. Natl. Acad. Sci. 108 (15), 6306–6311.

Frohlich, N., Oppenheimer, J.A., Young, O.R., 1971. Political leadership. In: Gans, J.S. (Ed.), The Economic Consequences of R=1: Towards a Workable Behavioural Epidemiological Model of Pandemic. National Bureau of Economic Research. Working Paper Series, (w27632). 2020.

Goldberg, M., Gustafson, A., Maibach, E., Ballew, M. T., Bergquist, P., Kotcher, J., Marlon, J. R., Rosenthal, S., & Leiserowitz, A. (2020). Mask-Wearing Increases After a Government Recommendation: A Natural Experiment in the US During the Covid-19 Pandemic.

Goolsbee, A., Syverson, C., 2020. Fear, Lockdown, and Diversion: Comparing Drivers of Pandemic Economic Decline 2020. Technical report. National Bureau of Economic Research.

Grossman, G., Kim, S., Rexer, J., & Thirumurthy, H. (2020). Political Partisanship Influences Behavioral Responses to Governors' Recommendations for Covid-19 Prevention in the United States. In Available at SSRN 3578695.

Haischer, M. H., Beilfuss, R., Hart, M. R., Opielinski, L., Wrucke, D., Zirgaitis, G., Uhrich, T. D., & Hunter, S. K. (2020). Who is Wearing a Mask? Gender-, Age-, and Location-Related Differences During the Covid-19 Pandemic. MedRxiv.

Hergueux, J., Jacquemet, N., 2015. Social preferences in the online laboratory: a randomized experiment. Exp. Econ. 18 (2), 251–283.

Hermalin, B.E., 1998. Toward an economic theory of leadership: leading by example. Am. Econ. Rev. 1188–1206.

Hitlin, P., 2016. Research in the Crowdsourcing Age, A Case Study: How Scholars, Companies and Workers are Using Mechanical Turk, a "Gig Economy" Platform, for Tasks Computers Can't Handle. Pew Research Center.

Horton, J.J., Rand, D.G., Zeckhauser, R.J., 2011. The online laboratory: conducting experiments in a real labor market. Exp. Econ. 14 (3), 399–425.

Howard, J., Huang, A., Li, Z., Tufekci, Z., Zdimal, V., van derWesthuizen, H. M., von Delft, A., Price, A., Fridman, L., & Tang, L. H., et al. (2020). Face Masks Against Covid-19: An Evidence Review.

Jabir, P., Goothy, S.S.K., Goothy, S., Madhusudhan, U., Singh, R., Choudhary, A., Potey, G., Chakraborty, H., Mahadhik, V., 2020. Coronavirus disease reinfection in discharged patients: an update. Infection 201, 1150–1152.

Jack, B.K., Recalde, M.P., 2015. Leadership and the voluntary provision of public goods: field evidence from Bolivia. J. Publ. Econ. 122, 80–93.

Jacquemet, N., James, A., Luchini, S., Murphy, J.J., Shogren, J.F., 2021. Do truth-telling oaths improve honesty in crowd-working? PloS One 16 (1), e0244958.

Kachanoff, F., Bigman, Y., Kapsaskis, K., & Gray, K. (2020). Measuring two Distinct Psychological Threats of Covid-19 and Their Unique Impacts on Wellbeing and Adherence to Public Health Behaviors.

Keele, L., 2005. The authorities really do matter: party control and trust in government. J. Polit. 67, 3–873.

Kirscht, J., 1974. The Health Belief Model and Illness Behavior. Health Educ. Monogr. 2 (4), 387–408. doi:10.1177/109019817400200406.

Lenz, G., 2013. Follow the Leader?: How Voters Respond to Politician's Policies and Performance. University of Chicago Press.

Leung, N.H., Chu, D.K., Shiu, E.Y., Chan, K.-H., Mc Devitt, J.J., Hau, B.J., Yen, H.-L., Li, Y., Ip, D.K., Peiris, J.M., et al., 2020. Respiratory virus shedding in exhaled breath and efficacy of face masks. Nat. Med. 26 (5), 676–680.

Levati, M.V., Sutter, M., Van der Heijden, E., 2007. Leading by example in a public goods experiment with heterogeneity and incomplete information. J. Conflict Resol. 51 (5), 793–818.

Leventhal, H., Diefenbach, M., Leventhal, E.A., 1992. Illness cognition: using common sense to understand treatment adherence and affect cognition interactions. Cognit. Therapy Res. 16 (2), 143–163.

Liu, Y., Gayle, A.A., Wilder-Smith, A., Rockloäv, J., 2020. The reproductive number of Covid-19 is higher compared to sars coronavirus. J. Travel Med. 27 (2). doi:10.1093/jtm/taaa021.

Mackie, B., 2013. Warning Fatigue: Insights From the Australian Bushfire Context. University of Canterbury, Canterbury, New Zealand Unpublished Doctoral Dissertation.

Makridis, C., Hartley, J., 2020. The Cost of Covid-19: A Rough Estimate of the 2020 US GDP Impact. Special Edition Policy Brief

Mason, W., Suri, S., 2012. Conducting behavioral research on Amazon's mechanical turk. Behav. Res. Methods 44 (1), 1–23.

Myers, T.A., Maibach, E.W., Roser-Renouf, C., Akerlof, K., Leiserowitz, A.A., 2013. The relationship between personal experience and belief in the reality of global warming. Nat. Clim. Change 3 (4), 343–347.

Nisbett, R.E., Ross, L., 1980. Human Inference. Prentice-Hall, Inc., Englewood Cliffs, NJ..

Paolacci, G., Chandler, J., 2014. Inside the turk: understanding mechanical turk as a participant pool. Curr. Direct. Psychol. Sci. 23 (3), 184–188.

Paolacci, G., Chandler, J., Ipeirotis, P.G., 2010. Running experiments on amazon mechanical turk. Judg. Decis. Mak. 5 (5), 411–419.

Philipson, T., Posner, R.A., 1994. Public spending on aids education: an economic analysis. J. Law Econ. 37 (1), 17–38.

Ramdas, K., Darzi, A., Jain, S., 2020. "Test, re-test, re-test": using inaccurate tests to greatly increase the accuracy of Covid-19 testing. Nat. Med. 1–2.

Rosenstock, I.M., 1966. Why people use health services. Milbank Memo. Fund Q. 44 (94), 127..

Rosenstock, I.M., 1974. Historical origins of the health belief model. Health Educ. Monogr. 2, 328–335.

Shahrabani, S., Benzion, U., 2012. How experience shapes health beliefs: the case of influenza vaccination. Health Educ. Behav. 39 (5), 612–619.

Shen, W. (2020). Could the President or Congress Enact a Nationwide Mask Mandate?Available at: https://crsreports.congress.gov/product/pdf/LSB/LSB10530#::text=Pursuant%20to%20the%20princip.

Simmons, K.M., Sutter, D., 2009. False alarms, tornado warnings, and tornado casualties. Weather Clim. Soc. 1, 1–38.

Simonsohn, U., Karlsson, N., Loewenstein, G., Ariely, D., 2008. The tree of experience in the forest of information: overweighing experience relative to observed information. Games Econ. Behav. 62, 263–286.

Smith, S. (2020). Unmasked: How Trump's Mixed Messaging on Face-Coverings Hurt U.S. Coronavirus Response. Available https://www.nbcnews.com/politics/donaldtrump/calendar-confusion-february-august-trump-s-mixed-messages-masks-n1236088.

Stephan Walter, G., Renfro Lausanne, C., 2002. The role of threats in intergroup relations. In: D. Mackie & E. R. Smith (Eds.), From prejudice to intergroup emotions. New York: Psychology Press, pp. 191–208.

Tian, L., Li, X., Qi, F., Tang, Q.-Y., Tang, V., Liu, J., Li, Z., Cheng, X., Li, X., & Shi, Y., et al. (2020). Calibrated Intervention and Containment of the Covid-19 Pandemic. arXiv preprint arXiv:2003.07353

Stretcher, V.J., Rosenstock, I.M., 1997. The health belief model. In: Andrew Baum (Ed.). Cambridge handbook of psychology, health and medicine. Cambridge University Press, UK, pp. 113–117.

Waller, K.M., Buboltz, W.C., Loveland, J.M., 2007. Psychological reactance: examination across age, ethnicity, and gender. Am. J. Psychol. 15–24.

Whitmer, D.E., Schroeder, B.L., Bailey, S.K., Sims, V.K., 2017. Reconsidering the "conventional wisdom" of the relationship between false alarms and risk beliefs. Proc. Hum. Fact. Ergonom. Soc. Annu. Meet. 61, 1–1419.

Wilcox, N., Rutstrom, E., 2009. Stated-beliefs versus inferred beliefs: a methodological inquiry and experimental test. Games Econ. Behav. 67 (2), 616–632.