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Risk Perceptions and Health Behaviors as COVID-19 Emerged in the United States: Results from a Probability-based Nationally Representative Sample

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Abstract

Understanding psychosocial correlates of engaging in health-protective behaviors during an infectious disease outbreak can inform targeted intervention strategies. We surveyed a national probability-based sample of 6,514 Americans, with three separate, consecutive representative cohorts between 3/18/2020–4/18/2020, as the U.S. COVID-19 epidemic began. Americans adopted many health protective behaviors (e.g., hand hygiene, social distancing) early, performing them, on average, "most of the time," with frequency increasing over time. In covariate-adjusted models, self-reported female gender (β=.16, p<.001), older age (β=.13, p <.001), more COVID-related secondary stressors (β=.17, p<.001), and greater perceptions of the risks of catching (β=.07, p=.001) and dying (β=.09, p<.001) from Coronavirus were associated with greater frequency of social-distancing behaviors. Wearing face masks and/or gloves was positively associated with female gender (β=.07, p<.001), older age (β=.14, p<.001), Black (β=.14, p<.001) and Hispanic (β=.07, p=.002) ethnicity, personal-COVID-19 exposure (β=.06, p<.001), reporting secondary stressors (β=.11, p<.001), and higher perceived risk of dying from Coronavirus (β=.13, p<.001). Participants in cohorts 2 and 3 (compared to cohort 1) wore face masks and gloves and engaged in social distancing more frequently. Overall, early in the U.S. COVID-19 outbreak, despite the novelty and uncertainty, Americans were responsive to guidelines, adopting them early and following them frequently.

Keywords

COVID-19; risk perceptions; health behaviors; social distancing

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Prior to vaccine availability, control of the COVID-19 pandemic relied entirely on non-pharmacological interventions. Severe government interventions and individual-level behavior changes contained the COVID-19 epidemic in China (Maier & Brockmann, 2020) and social-distancing policies initially "flattened the curve" in the United States (Matrajt & Leung, 2020). After early confusion in messaging, reflecting incomplete evidence regarding their efficacy (National Academies of Sciences, Engineering, and Medicine, 2020b), face masks emerged as a major control measure. By April-May 2020, most U.S. states had mandates requiring face coverings for employees or the general public (Lyu & Wehby, 2020).

The COVID-19 pandemic has provided a tragic "natural experiment," revealing how the public responds to novel contagions, which many experts expect to increase in frequency (Tollefson, 2020) and scope (Fernández et al., 2021). Although the details of outbreaks vary, all require behavioral interventions, administered in the context of complex interactions among disease threats; medical resources for prevention and treatment; and social, political and economic reactions (Fischhoff et al., 2006). The success of those interventions will depend on three set of processes: direct experiences (i.e., disease, quarantine), secondary stressors (e.g., job loss, isolation, caregiving), and psychological responses (e.g., risk perceptions, attitudes).

Collective events, such as the COVID-19 pandemic, provide opportunities to assess the robustness of relationships observed in experimental settings, as well as their interaction, when it is impossible to control most factors, while experimentally manipulating focal ones. Here, we examine these three sets of processes (direct experiences, secondary stressors, psychological responses), which have rarely been studied together, as they relate to protective behaviors during the COVID-19 pandemic. Our observations are from surveys of nationally representative U.S. samples, conducted in three consecutive 10-day periods, during the early stages of the pandemic (mid-March to early April, 2020).

At that time, the science was rapidly evolving, with contentious and conflicting interpretations of the data (Kreps & Kriner, 2020). While modeling uncertainty is an essential part of the scientific process (Uusitalo et al., 2015), it can erode trust in experts (Kreps & Kriner, 2020) unless lay audiences have managed to extract the implications for their practical decision-making needs (Fischhoff & Davis, 2014). Such uncertainty can amplify the role of episodic exposures in shaping stress responses (Peters et al., 2017), risk perceptions (Lichtenstein et al., 1978), and contingent health protective behaviors (Dryhurst et al., 2020). The interactions between cognition and stress have long been studied for acute collective traumas (e.g., earthquakes, mass violence) (Silver et al., 2020; Silver & Garfin, 2016), including infectious disease outbreaks (Wu et al., 2009). Indeed, it is the initial cognitive appraisal of an external event that initiates the stress response (Folkman & Lazarus, 1984), particularly for extreme events (Olff, Langeland, & Gersons, 2005) such as COVID-19. However, it has rarely been possible to observe those cognitive appraisals, stress responses, and contingent behaviors concurrently, as they unfold and interact. Here, we report observations using measures drawn from each of these fields, extending the research in each, as well as their integration.

Risk Perceptions

At the start of the pandemic in the U.S., communications about the pandemic were confused, partly reflecting the state of scientific knowledge, partly reflecting the lack of coordinated, tested messaging (NASEM, 2017, 2020a, 2021). Particularly rare were the authoritative, quantitative risk estimates that people need for informed decision making (Fischhoff, 2013; Schwartz & Woloshin, 2013). As a result, people were largely on their own, needing to sort through conflicting, ambiguous, and potentially inaccurate claims, regarding the size of the risks and the effectiveness of protective behaviors. A long tradition in cognitive psychology (Gentner & Steven, 1983) studies how people create and use mental models to interpret novel events (e.g., COVID-19), drawing on past experiences (e.g., SARS, avian flu, Ebola, seasonal influenza) (Bruine de Bruin & Bostrom, 2013; Morgan et al., 2001), education, and informal exposures (e.g., social media, news reports). Sometimes, these mental models appear to serve people well; sometimes, people need help. For example, a study using a sample of Amazon MTurk workers found that explaining the concept of exponential growth of COVID-19 disease incidence afforded people more accurate assessments of the efficacy of behavioral protections (Lammers et al., 2020). That result echoed those from many other studies demonstrating the difficulty people have extrapolating non-linear processes (Cohen & Hansel, 1956; Shaklee & Fischhoff, 1990; Sterman, 2011).

Stress and coping research predicts that these mental models both affect and reflect direct experiences of a threat (e.g., knowing someone who has becomes seriously ill with COVID-19), shaping perceptions of both susceptibility, to having adverse events happen (c.f., Blum, Poulin, & Silver, 2014), and severity, if they do. Indeed, risk perceptions play critical roles in many theories of health protective behavior, including the Health Belief Model, Protection Motivation Theory, the Theory of Reasoned Action, and the Extended Parallel Process Model (Breakwell, 2018; Brewer et al., 2007). A meta-analysis suggested large effects of risk perceptions on adoption of health protective behaviors, the perceived likelihood of contracting a disease and, to a lesser extent, its expected severity (Brewer et al., 2007). For example, women of childbearing age and living in high-risk areas, with more accurate perceptions of the teratogenic risks of Zika, were more likely to take preventative action (Patel et al., 2019). Egyptian healthcare workers who knew more about COVID-19 had more positive attitudes toward disease prevention and mitigation efforts (Wahed et al., 2020). In another domain, van der Linden (2015) summarized evidence showing the role of risk perceptions in responses to climate change, in studies prompted by several theories.

A cross-sectional study of Americans (N=6,884), conducted during the early phase of COVID-19 (March 10- March 31, 2020), found that individuals who perceived higher risk were more likely to report performing health protective behaviors, with both perceptions and behaviors increasing during the period (Bruine de Bruin & Bennett, 2020). Toward the end of the 2014–2015 Ebola crisis, we found that Americans had relatively accurate perceptions of the risk and the effectiveness of protective behaviors, despite confusing initial official communications and risk management (Fischhoff et al., 2018), as is common with emerging public health crises (Carey et al., 2020; Oyeyemi et al., 2014). Whether the general public should wear face masks was one such source of confusion in the early days of COVID-19, and afterward (Lyu & Wehby, 2020; World Health Organization, 2020). Allington and colleagues (2020) found that such inconsistent messaging reduced willingness to perform health protective behaviors. Here, we ask how Americans perceived the risk of COVID-19 in the pandemic's early days and how those perceptions related to their experiences, stress, attitudes, and self-reported behaviors.

Based on previous research using a similar methodology, we selected demographic indicators that were likely covariates of COVID-19 risk perceptions, namely age, gender, income, and education (Fischhoff et al., 2018). We added other covariates based on early results from concurrent research, finding that these perceptions were related to race, education, income, and age (Bruine de Bruin & Bennett, 2020). As a final covariate, we added personal exposure, reflecting its known, complex role in shaping risk perceptions, sometimes accurately, sometimes not (Lichtenstein et al., 1978; Tversky & Kahneman, 1973). A global survey, concurrent with our own, found that personal experience (yes/no) with a suspected or confirmed case of Coronavirus predicted increased risk perception (Dryhurst et al., 2020), potentially a valid inference. Research on natural disasters has also found that prior exposure to events increases the likelihood of engaging in mitigation behaviors (Coulston & Deeny, 2010).

Exposure to COVID-19-related Stressors

With collective traumas, such as terrorism (Garfin et al., 2015), earthquakes (Garfin et al., 2014), hurricanes (Kessler et al., 2012), and other disasters (Silver & Garfin, 2016), psychological responses have been associated with both the type (e.g., financial loss, loss of a loved one) and the amount of event-related exposures. Here, we ask whether these same predictors inform the mental models that inform cognitive and behavioral responses to COVID-19 – an invisible, contagious, deadly health threat. How are risk perceptions, stress, and protective behaviors associated with personal exposure to pandemic-related health effects (e.g., death of a loved one or close other), community impacts (e.g., closed schools and businesses), and secondary stressors (e.g., waiting in line to buy basic needs, difficulty accessing healthcare)? These exposures likely trigger the appraisal of a threat in terms of susceptibility and severity. Yet, while interrelationships are likely, evidence is needed regarding their power and variation.

Information regarding the role of risk perceptions, stress, and appraisals in promoting health protective behaviors is critical for public health officials who must evaluate the feasibility of voluntary policies that require public understanding and adoption. A recent Cochrane Collaboration systematic review of 67 randomized control trials of self-protective behavior interventions for infectious disease found an ambiguous picture (Jefferson et al., 2011). A commentary with head of the Collaboration as its lead author noted the difficulty of clarifying that picture without assessing the psychological processes involved individuals' personal adoption decisions (Soares-Weiser et al., 2020). Here, we assess the personal experiences (i.e., stressors, exposures), risk perceptions, and attitudes that prior research would expect to be determinative.

We also examine demographic indicators that are potential covariates. Some are expected covariates of risk perceptions, based on research in other domains (Breakwell, 2018). For example, a study of an MTurk sample of U.S. residents (*N*=1,080), conducted shortly after our own, found more self-reported health protective behaviors during COVID-19 among respondents who were females, older, and more educated, as well as among Blacks and Asian Americans (Li et al., 2020). We also consider geographic location, given the great regional variability at the time of the survey, with its concentration of disease in the Northeastern U.S. (particularly, the New York City area) (Messner & Payson, 2020; Rosenberg et al., 2020). Although health behavior theories would expect greater risk perceptions, leading to more protective behaviors in such regions, a quota sampling study in China did not find regional variability (Duan et al., 2020).

The Present Study

While survey research has proliferated during the COVID-19 pandemic, relatively few studies have used probability-based national samples. Rather, the literature has been defined by studies using convenience and non-probability volunteer samples, assessed at a single time, regarding a limited set of issues (see Holman et al., 2020, for a discussion and critique). These samples often use “snowball sampling” or opt-in techniques whose inherent biases can limit their generalizability and policy relevance (Heckathorn, 2007; Pierce et al., 2020). We, fortunately, had access to a nationally representative sample and were able to administer a suite of measures, representing two research traditions (i.e., decision science, stress and coping) whose interrelationships have drawn only limited study in the past. Moreover, we were able to examine these perceptions, experiences, and behaviors as they evolved during the early phase of the COVID-19 outbreak in the U.S., a time of extreme scientific ambiguity. We measured perceptions of risk for both *susceptibility*, to contracting the novel Coronavirus, and *severity*, should that happen. We examined their relationship to potential determinants (demographics, experiences, stressors) and consequences (health protective behaviors).

We conducted our survey in three waves from mid-March to mid-April, 2020, a period of potentially great change over a short period of time, as much of the U.S. was shut down and intensely focused on the disease. The timing is important for interpreting these results, given the concurrent rise in what the World Health Organization called an “infodemic” of misinformation (Zarocostas, 2020), whose promulgators included prominent public figures (Brennen et al., 2020). In mid-February 2020, a convenience sample (*N*=718) found that, while most Americans perceived little risk, they still knew the Centers for Disease Control and Prevention (CDC) recommendations for infection prevention measures (including handwashing and avoiding close contact with others) (McFadden et al., 2020). By May 2020, a substantial minority of Americans opposed social-distancing and mask-wearing policies (Czeisler et al., 2020). Our results provide constructive replication of other methodologically rigorous surveys conducted at this time (Bruine de Bruin & Bennett, 2020; Lyu & Wehby, 2020), critical given the reproducibility crisis in science (Aarts et al., 2015; Ioannidis, 2005, 2007; Tackett et al., 2017)

Method

Data Collection and Sample

The survey was administered to a subsample of NORC's AmeriSpeak Panel, a probability-based, representative panel of 35,000 U.S. households, recruited by random door-to-door interviewing. AmeriSpeak panelists are then selected, using random sampling techniques, to participate in individual studies or surveys. Participants are compensated for their participation via internet access or other compensation (e.g., points that can be exchanged for merchandise). AmeriSpeak attains response rates for individual surveys nearly three times higher than any other probability panel in the U.S. (Dennis, 2020). Unlike many Internet panels, to which people with Internet access can opt in, no one can volunteer for the AmeriSpeak panel. This facilitates enhanced demographic representativeness of the population and allows for population-based inferences.

NORC drew our sample from the AmeriSpeak panel using sample stratification (based on random sampling techniques) to assure representativeness with respect to age, gender, education, and race/ethnicity. A 20-minute web-based survey was fielded to three consecutive probability-based, nationally representative cohorts of 3,713 panelists for 10 days each between March 18 and April 18, 2020 (Holman et al., 2020). A sequential cohort design was used to document the progression of COVID-19-related exposures and psychological and behavioral responses to the pandemic during the very early phase of the outbreak in the United States. Participants received notice that the survey was available for a designated period and completed the survey online anonymously. Respondents received points equivalent to $4, which can be redeemed for various goods, for survey completion. After data cleaning (see Holman et al., 2020), N=6,514 (n=2,122, n=2,234, n=2,158 for the three cohorts) comprised the final sample for analysis (58.5% completion rate). In all three cohorts, ~85% percent of respondents completed the survey within 3 days of its fielding, using smartphones (54%), computers (44%), or tablets (2%). Participants provided informed consent when they joined the NORC panel and were informed that their identities would remain confidential. The research was reviewed and approved by the University of California, Irvine Institutional Review Board for Human Subjects Research.

The survey was designed to test a variety of hypotheses related to decision making and psychological responses to COVID-19. Given the unprecedented nature of the event and extreme time pressure to field the survey, we focused on exploratory and descriptive analyses for hypotheses central to our respective research literatures. As such, we did not preregister the study. Our analysis plan, as described below, sought to reduce the risk of capitalization on chance patterns. Given our sample size (N=6,514), we are powered to detect extremely small effects f^2=.0075. We conservatively estimated β=.95, α=.001, with 20 potential predictors of a linear multiple regression analysis.

Measures

Demographics.—Participants' demographics (including age, race/ethnicity, education, gender, income, geographic region of residence) were collected by NORC upon enrollment in the AmeriSpeak panel and are annually updated.

Perceptions of Risk (Probability Response Mode).—Eight questions assessed judgments of personal and population susceptibility and severity for COVID-19, as well as other causes, for comparison purposes. Participants were asked to report probabilities of events as a percent chance (from 0–100%) by providing a number between 0 and 100. *Susceptibility* was assessed as the percent chance that: 1) you will get the ordinary (seasonal) flu in the next 3 months; 2) you will become seriously ill from any cause other than Coronavirus in the next 3 months; 3) you will get sick with Coronavirus in the next 3 months; 4) an average American will get sick with Coronavirus in the next 3 months; and 5) a "vulnerable American" (e.g., a person over 60 or someone with serious health conditions) will get sick with Coronavirus in the next 3 months. *Severity* was assessed as the percent chance from 0–100% that: 1) you will die if you get sick with Coronavirus; 2) the average American will die if they get sick with Coronavirus; and 3) a vulnerable American will die if they get sick with Coronavirus.

Similar questions have been used in prior research on infectious disease outbreaks (Bruine De Bruin et al., 2006; Fischhoff et al., 2018). Predictive, concurrent, and construct validity has been established in longitudinal research, demonstrating that even adolescents can provide probability judgments of future life events that are appropriately correlated with their risk factors (Fischhoff et al., 2000), and biased in ways expected from studies of how they see their world (de Bruin et al., 2007; Fischhoff et al., 2010)

Attitudes.—Participants reported their perceptions of three aspects of the science related to the pandemic on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*): 1) Scientists have a very good understanding of Coronavirus; 2) Scientists will have a vaccine that prevents Coronavirus within a year; and 3) Scientists will have a treatment that cures Coronavirus within a year. Similar measures were used to assess responses to the 2014 Ebola outbreak (Fischhoff et al., 2018).

Knowledge.—Participants reported their beliefs regarding three key facts regarding COVID-19 on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*): 1) Coronavirus is more contagious than the flu; 2) Coronavirus is more deadly than the flu; and 3) It is important for everyone to take precautions to prevent the spread of the Coronavirus, even if they are not in a high-risk group (e.g., elderly, chronically ill). Similar measures were used to assess responses to the 2014 Ebola outbreak (Fischhoff et al., 2018).

Support for Public Policies.—Participants reported support for four Coronavirus-related policies on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*): 1) Officials should provide Americans with honest, accurate information about the situation (even if that information worries people); 2) We should invest more in general capabilities, like better public health services; 3) If people are quarantined because of exposure to Coronavirus, they should get help with the costs, such as lost wages; and 4) We should have been better prepared for Coronavirus. Similar measures were used to assess responses to the 2014 Ebola outbreak (Fischhoff et al., 2018).

Health Protective Behaviors.—Participants reported their frequency of engaging in eight health protective behaviors in response to the Coronavirus outbreak on a Likert-type scale from 1 (*never*) to 5 (*all the time*): 1) I wash my hands and/or use hand sanitizer more often; 2) I wear a face mask and/or gloves in public; 3) I avoid people who may be infected with the coronavirus; 4) I avoid public places; 5) I avoid public transportation (e.g., buses, subways, Uber, Lyft); 6) I cancel or reschedule travel plans (e.g., air, train); and 7) I isolated myself at home for several days or more. Items 3–7 were averaged to make a composite measure of "social distancing" (alpha=.77).

COVID-19-Related Exposure and Secondary Stressors.—Degree of exposure to the COVID-19 outbreak was ascertained using a checklist (Holman et al., 2020). Ten items assessed (direct or indirect) personal exposure (e.g., I/someone close to me was diagnosed with coronavirus). Six items assessed community exposure (e.g., my community has been instructed to "shelter in place"). Seven items assessed secondary stressors, including lost job, inability to obtain healthcare, or waited in long lines for basic necessities. Responses to each subset of items were averaged to create composite scores for personal exposures, community exposures, and secondary stressors, respectively. The personal exposure item was dichotomized (0=no direct or indirect exposure; 1=at least one indirect or direct exposure), given that less than 25% of the sample reported one or more of these exposures and less than 3% reported 2 or more.

Analytic Strategy

Statistical analyses were conducted using Stata 16.1 (StataCorp, College Station, TX). Unless otherwise indicated, data were weighted to adjust for probability of selection into the AmeriSpeak panel and for differences between the sample and U.S. Census benchmarks. This weighting procedure ensures that we can make population estimates and draw conclusions accordingly, despite any non-response during the fielding period. To account for missing data, unless noted, inferential statistics were estimated by multiple imputation using the chained equations (MICE) method. A total of 30 imputations was used. (The appropriate number of imputations was checked for each analysis using the "how_many_imputations" command in Stata; no analyses required more than 27 imputations.)

Descriptive statistics were calculated for perceptions of risk, health protective behaviors, attitudes, knowledge, and support for public policies, including covariances between key study variables. Between-cohort differences were calculated for each variable. Probability responses of 50 can represent epistemic uncertainty (e.g., "it's a 50–50 chance"), rather than a true 50% probability estimate, especially with unfamiliar and negative events (Fischhoff & Bruin de Bruin, 1999). As a result, we show the frequency of such responses, along with an estimate of how many are "excess 50s," calculated using the averaging method, which compares the observed frequency with that expected based on responses in the adjacent bins (40–49 and 60–69), a method found to produce estimates similar to those that fit a beta function to the distribution after removing the 50s.

We conducted the following analyses, in turn: (a) Risk perception was analyzed as a dependent variable, using ordinary least squares (OLS) regression. Predictors were demographics (gender, age, income, education, and race/ethnicity), region of residence, survey cohort, and COVID-19 exposure and stressors. (b) Two health protective behaviors (social distancing; face mask and/or glove wearing) were analyzed with ordinary least squares (OLS) regression analyses using the same predictors along with risk perception. (A third health protective behavior, hand hygiene, was reported so often that we did not include it, given ceiling effects.) In all cases, independent variables were added in a hierarchical entry strategy, with the following conceptually meaningful blocks, first adding preexisting individual-level factors, second adding the exposures that inform mental models of risk, and third adding the risk perceptions. More specifically, we blocked (a) demographics (gender, age, income, education, race/ethnicity, region of residence) and survey cohort; (b) COVID-19 exposures (personal exposure, community exposure, secondary stressors), and (c) perceptions of personal risk, for susceptibility and severity.

We then conducted OLS regression analyses predicting attitudes (toward science and public policy) and knowledge (of COVID-19), using the same hierarchical entry strategy. For readability, only the final multivariate models are presented in the main text tables. Finally, we examined how these attitudes and knowledge measures predict health protective behaviors. To that end, we conducted OLS regression analyses with a) social distancing and b) face mask and/or glove wearing as the dependent variables. The independent variables were: 1) demographics (gender, age, income, education, race/ethnicity, region of residence) and cohort, 2) exposure (personal exposure, community exposure, secondary stressors), and 3) attitudes and knowledge.

Given the epistemic uncertainty potentially reflected in the high proportion of 50 responses to the risk perception questions, we conducted the analyses in two ways to assess the robustness of findings. First, analyses were conducted by treating all “50” responses as missing values, re-imputing the data, and replicating all analyses. Second, all risk judgments were dichotomized at the median into low/high (0, 1) and then entered into analyses as dichotomous variables; for analyses where risk judgments were the outcome, logistic analyses were conducted in place of OLS regression. The pattern of results remained consistent throughout these iterations; these analyses are included as Supplementary Material (Tables S3–S9).

Due to the large number of tests included in these analyses, only those $p<.01$ and $p<.001$ are highlighted in the results. Of note, a Bonferroni correction at 31 tests at $\alpha=.05$ yields a Bonferroni corrected value of $\alpha=.002$, for the most conservative interpretation.

Data and associated syntax file are available on the Open Science Framework.

Results

The final weighted sample (N=6,514) was 48.1% male, ranged from 18 to 97 yrs old (M=47.50 yrs; SD=17.44), and was 63.6% white (non-Hispanic), 11.8% Black (non-Hispanic), 16.0% Hispanic, and 8.7% Other ethnicities. About one-third of the weighted sample (33.6%) had earned a bachelor’s degree or higher; the median annual income was between $40,000-$49,999. Approximately two-thirds (66.0%) lived in an urban area, 12.9% in a town, 10.6% in a rural area, and 10.4% in suburbs. In the full sample, 37.7% lived in the South, 24.1% in the West, 21.0% in the Midwest, and 17.3% in the Northeast region of the U.S. (See Holman et al., 2020, for weighted sample demographics compared to February 2020 U.S. Current Population Survey benchmarks.) Table 1 reports correlations between key study variables. As reported elsewhere (Holman et al., 2020), 23.4% of the sample reported at least one personal exposure to COVID-19. Participants reported a mean of 4.88 (range: 0–6; SD=1.54) community-related exposures and a mean of 1.36 (range: 0–7; SD=1.21) secondary stressors. There were significant correlations between all of the perceived risk measures (variables 1–8), including the Coronavirus-specific risk perception items (3–8) and support for public policies (14–16). The three measures of confidence in science (11–13) were related to one another, but not to risk perceptions; these relationships persisted in multivariate models (see below). We consider correlations with self-reported health behaviors (9,10) more systematically below.

Risk Probability Estimates.

Table 2 reports responses to the risk perception questions, pooled across the three cohorts. There were no significant differences in the mean probabilities for any of the susceptibility questions, across the cohorts. However, there was a significant increase in perceptions of severity (rising between cohorts 1 and 3 from 13.7% to 19.8%, 14.6% to 19.0% and 32.5% to 40.0%, for the three risks included in the table, respectively; $ps<.001$). Across cohorts, participants perceived a greater chance of getting sick from Coronavirus in the next 3 months (21.9%) than of getting seasonal flu (16.8%) or another serious illness (12.1%). They saw themselves as less likely than the average American to get sick with Coronavirus (21.9% v. 35.1%), but equally likely to die, if they got sick (16.7% vs. 16.9%). They perceived vulnerable Americans as more likely to get sick (43.0%) and to die (36.2%), perhaps reflecting media attention to individuals in long-term care facilities. These means are skewed upwards in cases where most 50% responses are Excess 50%, suggesting epistemic uncertainty, where participants were uncertain what to say.

Table 3 presents multivariate demographic predictors of probability estimates of susceptibility and severity. Respondents who were female and those who had lower incomes reported seeing greater risk. Older individuals saw themselves as less susceptible to getting sick, but more likely to suffer severe consequences if they did. Blacks saw themselves as less susceptible than whites. Blacks and Hispanics reported higher severity estimates for the average American, but not for themselves. There were no educational or regional differences when using the most stringent Bonferroni correction. Participants who reported more personal exposures and secondary stressors perceived themselves as more susceptible, but no more likely to experience severe effects. Those who reported more community exposures saw average and vulnerable Americans as more susceptible, but not themselves.

Health Protective Behaviors.

As seen in Table 4, self-reported practice of all health protective behaviors increased significantly over the three cohorts, except for handwashing, which began near the scale maximum (=5). The order of these behaviors was similar over time. By cohort 3, the mean for each behavior, except “wear a face mask and/or gloves” was close to or above “most of the time.” (=4)

A regression model found that self-reported distancing behavior was more likely for female and older participants, and for those in the later cohorts. However, it was unrelated to income, education, region or ethnicity (Table 5, Model 1). Those relations remained when the analysis added the three exposure variables, with the additional finding that social distancing was significantly higher for individuals reporting secondary stressors and, to a lesser extent, community exposure (Model 2). Those relations remained when judgments of personal risk of Coronavirus susceptibility and severity were included in the model; both were significant predictors (Model 3).

Analogous models (Table 6) found greater self-reported mask and/or glove use among participants who were female, older, in later cohorts, and who reported secondary stressors or greater personal severity – but not among those who reported greater personal susceptibility. Black, Hispanic, and participants in the Northeast reported greater mask and/or glove use (but not greater social distancing). As with social distancing, neither income nor education predicted face mask and/or glove use.

Attitudes and Knowledge.

Table 7 summarizes responses to the attitude and knowledge questions. The strongest endorsements were for "It is important that everyone take precautions to prevent the spread of Coronavirus" and "Officials should share honest, accurate information about the situation (even if that information worries people)." There was also strong support for investing "in general capabilities, like better public health services"; "financially helping people who are quarantined or lost wages"; and "having been better prepared for Coronavirus." Confidence in science was near the middle of the scale. There was general, but not universal, understanding that Coronavirus is more contagious and more deadly than the flu, increasing over the three cohorts.

Table 8 reports multivariate predictors of attitudes and knowledge about the Coronavirus. Looking for general patterns in this complex set of relationships, we find that (a) confidence in scientific knowledge (questions 1–3) has few strong predictors; (b) public health measures (questions 4–7) are more strongly endorsed by Blacks and people who report community, but not personal, exposure or secondary stressors; (c) understanding of Coronavirus transmissibility and severity (questions 8–9) is greater among older respondents and those who see greater community risk and report greater secondary stress; and (d) support for collective action (question 10) increases with age and perceived community risk, while decreasing over time. While attitudes were associated with neither social distancing nor mask wearing, knowledge was associated with engaging in more of these health protective behaviors. More specifically, frequency of health protective behaviors was associated with the belief that coronavirus is more contagious than the flu (β=.11, b=.11, 95% CI, .07, .15, p <.001), that coronavirus is more deadly than the flu (β=.09, b=.08, 95% CI, .04, .12, p <.001), and that it is important that everyone take precautions to prevent the spread of Coronavirus (β=.13, b=.17, 95% CI, .11, .22, p <.001). Knowledge that Coronavirus was more contagious than the flu was associated with greater mask wearing (β=.08 b=.11, 95% CI, .06, .17, p <.001). See Table S9 for full results.

Discussion

We present data from a large, nationally representative, probability-based sample of Americans assessed in the early phase of the COVID-19 pandemic in the United States. We drew key concepts, hypotheses, and measures from research on decision making and on stress and coping, to examine individuals' risk perceptions, attitudes, and self-reported protective behaviors at the time, as well as how they were related to one another, demographic variables, personal and community exposure, and secondary stressors.

Americans' perceptions of catching Coronavirus (susceptibility) remained relatively stable over the 30 days of the fielding period, while their perceptions of dying from the virus (severity) increased (Table 2). This pattern could reflect growing understanding of the impact of social distancing policies (Courtemanche et al., 2020; McGrail et al., 2020) and of disease severity, reflected in increasing mortality rates, during that period (Rivera et al., 2020). As in our previous study of Ebola risks, using a similar methodology, people may be able to extract a message from a relatively consistent societal response, even when initial risk management actions and communications are confused (Fischhoff et al., 2018).

Our sample's severity estimates might be compared with the estimated adjusted case fatality in China available at the time, which had a mean of 1.38% and a maximum of 13.4% in the most vulnerable group (i.e., those over 80) (Verity et al., 2020). By that standard, the individuals in our study slightly, but not strikingly, overestimated their personal COVID-19 mortality risk. However, they substantially overestimated it for the average American and a vulnerable American. We cannot tell to what extent the difference in results reflected differences in methodology or sample. Thus, our findings suggest that people had relatively accurate risk perceptions, despite the intense and sometimes sensational media coverage (Garfin et al., 2020), and the elevated risk perceptions sometimes found with novel threats (Chakraborty, 2020). We note that our probability-based sampling design allowed inclusion of individuals not typically included in other research (Medin et al., 2017), which may help explain differences in findings. For example, a concurrent experimental study found that members of a convenience (MTurk) sample overestimated their own risk (and that of younger people), while underestimating the risk to older individuals (Abel et al., 2021).

In our study, risk perceptions were also related to actual risk factors in orderly ways. Perceptions of personal susceptibility were higher for participants who reported more personal exposures and more COVID-19-related secondary stressors in their lives, two factors plausibly related to actual susceptibility. However, neither was related to perceived disease severity, which may be less related to these experiences, as it has been with some other hazards (Brewer et al., 2007). Older individuals perceived relatively less susceptibility risk, and relatively more severity risk, consistent with actual risk for these individuals, who tend to be less exposed, but more fragile (Centers for Disease Control and Prevention, 2020). Bruine de Bruin and Bennett (2020) similarly report greater perceived risks among older respondents. Compared to the average American, participants saw themselves as facing a lower probability of getting the disease, but the same conditional probability of severe illness – consistent with the optimism bias often found with seemingly controllable events (Klein & Helweg-Larsen, 2002). Risk perceptions were unrelated to individuals' education, suggesting the everyone had gotten the same message, as found in China as well (Duan et al., 2020). Risk perceptions were also unrelated to where people lived, indicating that the New York area's then-current hot-spot status did not lead respondents to believe that the disease would be confined there.

According to individuals' self-reports (Table 4), there was near-universal hand washing or hand sanitizer use; very high levels of avoiding people who may be infected with the Coronavirus and avoiding public transportation; and high levels of avoiding public places, cancelling or rescheduling travel plans, and isolating at home. Each behavior increased over the month spanned by the three cohorts, except handwashing (which was already high). Wearing face masks and/or gloves started very low, but reached the scale midpoint by the third cohort. This is in alignment with classic theories of health protective behavior, such as Protection Motivation Theory (Prentice-Dunn & Rogers, 1986; Weinstein, 1993), which posits that people take action when a threat is judged to be high risk (both susceptibility and severity), self- and response-efficacy is high, and adaptive response costs are low (Floyd et al., 2000). Handwashing, a very low response cost, was high throughout the duration of our assessments. People engaged more frequently in social distancing and face mask wearing, which bear a substantially higher response cost, over time, coinciding with increases in perceptions of risk.

As seen in Tables 5 and 6, both social distancing and face mask and/or glove wearing were more common among women and older people, consistent with previous research in other domains (Finucane et al., 2010) and other studies of COVID-19 (Alsan et al., 2020). Both behaviors were also more common among individuals who reported greater personal exposure, secondary stressors, and severity risk. Social distancing, but not mask and/or glove wearing, was related to perceived severity risks. Mask and/or glove wearing, but not social distancing, was higher for Blacks, Hispanics, and participants in the Northeast – a differential response that, as with other threats (van der Linden, 2015), may reflect social norms, as neither behavior was related to education or income.

As seen in Table 7, participants expressed strong support for public health policies, including honest information sharing, even of bad news; investing in public health services; and financially supporting people whose lives were disrupted by the pandemic. Overall support appears consistent with respondents' accurate beliefs that Coronavirus is more contagious and more deadly than the flu, a risk perception that was, in turn, greater for older respondents and those who reported greater community exposure and secondary stress. Support for public health measures was stronger among Blacks and people who reported community exposures (but not personal exposure or secondary stressors). Respondents in all groups acknowledged the limits to science providing complete solutions for the pandemic.

Thus, shortly after the White House declared the COVID-19 outbreak a national emergency in the U.S. (March 13, 2020), members of this representative sample of Americans had generally accurate understanding of the disease, with beliefs, behaviors, and attitudes that were sensitive to their personal circumstances and to one another. Over the month of the three cohorts, understanding seemed to grow and behaviors solidify. Group differences paralleled those seen in other domains, including greater sensitivity to risks among women and older individuals, and greater support for public health policies among Blacks. Males had somewhat more confidence in science (Finucane et al., 2010). College-educated individuals had lower expectations for an effective vaccine or treatment, perhaps reflecting knowledge of the generally slow process of bringing drugs to market (Wouters et al., 2020).

Thus, even before nationwide stay-at-home orders (Gupta et al., 2020), many individuals were able to extract essential knowledge, despite the great scientific uncertainty and confusing communications. That pattern is reason for optimism, regarding highly motivated individuals' ability to make reasonable inference regarding an evolving, uncertain risk. The malleability of these responses also suggests their vulnerability to ineffective or malevolent communication, as seen in the growing polarization of beliefs, attitudes, and behaviors in the ensuing period (e.g., Calvillo et al., 2020; Oster et al., 2020), and associated health, social, and economic toll. Which pattern prevails will depend on the availability of coordinated, authoritative communications, informed by psychological research on risk communication, as recommended by the U.S. National Academies (NASEM, 2017, 2020a, 2021) and other bodies.

Our findings contrast with the less optimistic picture seen with public responses to other threats (e.g., climate change). Speculatively, we attribute it to the distinct role played by scientists in the COVID-19 pandemic, with frequent media appearances, explaining potentially unintuitive dynamic processes, like flattening the curve and exponential growth, to a public with intense desire to understand (and often little to do but that). The group differences in risk perceptions, attitudes, and behaviors, as related to personal experiences and stressors, are further evidence of the complexity of these processes and the value of multifaceted assessment (Dryhurst et al., 2020; van der Linden, 2015).

Strengths and Limitations

Our large, nationally-representative, probability-based sample offers generalizability not possible with studies using small or convenience samples (Pierce et al., 2020). One limitation is that, although we collected data among three representative cohorts, in order to examine responses over time, each sample included different individuals, preventing longitudinal analyses (while avoiding priming participants). Health protective behaviors were ascertained through self-reports and were not corroborated observationally. We did not include political ideology in these analyses, although later research on COVID-19 suggests it can play an important role in health protective behaviors (Calvillo et al., 2020). Given the large sample, even small effects can be statistically significant. For that reason, and the many tests we performed, we have used p<.001 as our threshold for textual comments, while providing fuller details in the tables. We note that that even relatively small increases in protective behaviors can have meaningful population effects (Courtemanche et al., 2020; Poletti et al., 2012; Soares-Weiser et al., 2020).

As medical interventions (e.g., vaccines) arrive, controlling the COVID-19 pandemic (or future ones) will depend on the public's willingness to adopt protective behaviors and accept public policies that are disruptive in the short-run, in return for longer-terms benefits, including protecting the healthcare system and reducing disease spread to vulnerable populations. Thus, there is an urgent need for trusted, comprehensible communications. Our results show relative success in that task, early in the pandemic. Such findings can inform communications during the next phase of the COVID-19 pandemic as well as in response to future hazards (e.g., infectious disease outbreaks, preparation for natural disasters). The United States, along with other countries that are currently struggling with such challenges, could try to repeat these earlier experiences, drawing on the best available communication science.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Public Significance Statement:

During the early phase of the COVID-19 pandemic in the U.S., data from three nationally-representative probability samples indicated that Americans appeared to understand the risk, adopted recommended health protective behaviors early, and followed them frequently–with higher rates among female, older, Black and Hispanic respondents, and those reporting greater risk perceptions, exposures, and secondary stressors.

Table 1.

Covariance matrix of key study variables (N=6,514)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1																							
2	**.47**	1																					
3	**.35**	**.43**	1																				
4	**.19**	**.37**	**.37**	1																			
5	**.23**	**.27**	**.53**	**.24**	1																		
6	**.19**	**.29**	**.25**	**.43**	**.50**	1																	
7	**.22**	**.21**	**.42**	**.18**	**.75**	**.44**	1																
8	**.17**	**.20**	**.30**	**.41**	**.44**	**.57**	**.58**	1															
9	.05	**.08**	.04	**.20**	**.07**	**.21**	.06*	**.15**	1														
10	.03	**.06**	**.12**	**.16**	**.14**	**.13**	**.14**	**.15**	**.30**	1													
11	−.02	−.02	−.06*	−.03	−.04	−.02	−.04	−.05*	.05*	.01	1												
12	.02	−.02	**−.09**	−.03	−.04	−.02	−.04	−.03	.02	−.03	**.40**	1											
13	.03	−.02	**−.13**	−.05*	**−.08**	.02	−.05*	−.03	.03	−.03	**.33**	**.66**	1										
14	.02	.00	**.08**	.05*	.07*	−.05	**.10**	.06*	−.05	**.13**	**.09**	**.12**	.05*	1									
15	.05*	.04	**.13**	**.09**	**.16**	**.11**	**.22**	**.17**	**.10**	**.23**	**.08**	.01	−.03	**.32**	1								
16	.05*	.03	**.10**	**.07**	**.15**	**.10**	**.21**	**.16**	.06*	**.19**	**.08**	.03	.01	**.28**	**.55**	1							
17	.05*	**.06**	**.16**	**.11**	**.18**	**.13**	**.21**	**.16**	**.13**	**.25**	.02	**−.07**	**−.08**	**.26**	**.57**	**.46**	1						
18	−.01	.01	**.16**	**.12**	**.16**	**.09**	**.14**	**.14**	**.17**	**.31**	.00	−.05*	**−.07**	**.12**	**.23**	**.18**	**.25**	1					
19	.00	.03	**.15**	**.16**	**.14**	**.13**	**.13**	**.14**	**.17**	**.30**	.03	−.05*	**−.08**	**.12**	**.28**	**.20**	**.29**	**.61**	1				
20	.03	.02	**.12**	**.08**	**.15**	.06*	**.16**	**.15**	**.07**	**.29**	.02	.00	−.05	**.28**	**.28**	**.26**	**.28**	**.41**	**.36**	1			
21	.05	.06*	**.17**	.04	**.09**	.01	**.08**	.04	**.10**	.03	.00	**−.07**	−.06*	−.03	.03	.01	.05*	.04	.03	−.04	1		
22	.04	.02	**.10**	.06*	**.11**	−.01	**.12**	**.09**	.02	**.14**	−.01	.01	**−.06**	**.31**	**.18**	**.20**	**.17**	**.13**	**.07**	.23	.00	1	
23	**.10**	**.08**	**.16**	−.01	**.11**	.03	**.12**	**.10**	**.10**	**.19**	−.03	−.05*	−.05*	−.03	**.09**	**.08**	**.12**	**.08**	.06*	.05*	**.16**	**.16**	1

*$p<.01$, **$p<.001$ in bold**.

1. % chance you will get the ordinary (seasonal) flu in the next 3 months
2. % chance you will become seriously ill from any cause other than Coronavirus in the next 3 months

3. % chance you will get sick with Coronavirus in the next 3 months
4. % chance you will die if you get sick with Coronavirus
5. % chance average American will get sick with Coronavirus in the next 3 months
6. % chance average American will die if they get sick with Coronavirus
7. % chance vulnerable American will get sick with Coronavirus in the next 3 months
8. % chance vulnerable American will die if they get sick with Coronavirus
9. Wearing a facemask and/or gloves
10. Composite social distancing
11. Scientists have a very good understanding of Coronavirus.
12. Scientists will have a vaccine that prevents Coronavirus within a year.
13. Scientists will have a treatment that cures Coronavirus within a year.
14. Officials should provide Americans with honest, accurate information about the situation (even if that information worries people).
15. We should invest more in general capabilities, like better public health services.
16. If people are quarantined because of exposure to Coronavirus, they should get help with the costs, such as lost wages.
17. We should have been better prepared for Coronavirus.
18. Coronavirus is more contagious than the flu.
19. Coronavirus is more deadly than the flu.
20. It is important for everyone to take precautions to prevent the spread of the Coronavirus, even if they are not in a high-risk group (e.g., elderly, chronically ill).
21. Personal exposure (e.g., I/someone close to me was diagnosed with coronavirus)
22. Community exposure (e.g., my community has been instructed to “shelter in place”).
23. Secondary stressors (e.g., job loss, inability to obtain healthcare)

Table 2.

American's perception of risk of sickness and death related to coronavirus in March-April, 2020 (N=6,514)

	Combined (Cohorts 1–3) N=6,514						
	M	**SD**	**Median**	**0%**	**50%**	**100%**	**Excess 50%**
What is the % chance….							
Susceptibility							
1…you will get the ordinary (seasonal) flu in the next 3 months?	16.8	20.7	10	27.3%	11.2%	1.2%	10.4%
2.…you will become seriously ill from any cause other than Coronavirus in the next 3 months?	12.1	17.4	5	32.6%	7.8%	0.4%	7.2%
3…you will get sick with Coronavirus in the next 3 months?	21.9	22.4	10	22.2%	18.6%	0.4%	17.1%
4…the average American will get sick with Coronavirus in the next 3 months?	35.1	25.6	30	6.9%	21.7%	2.1%	16.9%
5….a vulnerable American will get sick with Coronavirus in the next 3 months?	43.0	27.4	50	4.2%	20.5%	3.0%	14.1%
Severity							
6…you will die if you get sick with Coronavirus in the next 3 months?	16.7	24.7	5	31.1%	10.9%	1.5%	10.1%
7…the average American will die if they get sick with Coronavirus?	16.9	20.5	10	7.8%	11.1%	8.5%	9.9%
8…a vulnerable American will die if they get sick with Coronavirus?	36.2	29.5	30	4.4%	15.3%	3.0%	11.3%

Table 3.

Demographics and COVID-19 exposure as predictors of perceptions of risk about Coronavirus in March-April, 2020 (N=6,514)

	Susceptibility					Severity		
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Female gender	0.004	0.04	0.05*	**0.14**	**0.16**	**0.08**	**0.14**	**0.12**
Age	**-0.09**	−0.01	**-0.13**	**-0.13**	**-0.14**	**0.21**	0.02	−0.06*
Income	−0.02	−0.06*	0.003	−0.04	−0.06*	**-0.09**	−0.06*	−0.07*
Education								
High school graduate	0.05	0.004	0.04	0.06	0.11	0.02	−0.01	0.08
Some college	0.03	−0.03	0.04	0.05	0.11	0.02	−0.06	0.06
BA or above	−0.01	−0.06	0.07	0.04	0.07	−0.03	−0.16*	0.01
Ethnicity								
Black	−0.02	−0.01	**-0.10**	−0.01	0.005	−0.03	**0.11**	0.01
Other/2+ races	0.005	0.01	−0.03	−0.01	0.005	0.02	0.03	0.02
Hispanic	0.05	0.03	−0.04	0.03	0.05	0.02	**0.11**	0.07*
Region								
Midwest	0.07*	0.03	0.001	−0.01	0.03	0.02	−0.01	0.05
South	−0.02	0.01	−0.07	−0.06	−0.01	0.01	0.03	0.07*
West	0.02	−0.03	−0.08*	−0.07*	−0.02	−0.01	−0.04	0.03
Cohort								
3/29–4/7	−0.02	0.01	−0.02	0.005	−0.01	0.06*	0.06*	0.04
4/8–4/18	−0.04	−0.02	−0.06*	−0.06*	−0.05	**0.10**	**0.09**	**0.09**
COVID-19 exposure								
Personal	0.02	0.06*	**0.13**	0.06*	0.05*	0.06*	0.003	0.02
Community	0.04	0.02	0.07*	**0.13**	**0.15**	0.01	0.02	**0.11**
Secondary stressors	0.06	0.06*	**0.10**	0.04	0.04	**0.05**	0.02	0.05
R^2(Adjusted R^2)	.03(.03)	.03(.02)	.09(.08)	.08(.08)	.10(.09)	.06(.06)	.10(.10)	.07(.07)

Estimates reflect median beta coefficients.

* *p*<.01; ***p*<.001 in bold**.

Men, less than high school education, white ethnicity, Northeast, and cohort 1 (3/18–3/28) are the reference groups.

1. % chance you will get the ordinary (seasonal) flu in the next 3 months
2. % chance you will become seriously ill from any cause other than Coronavirus in the next 3 months
3. % chance you will get sick with Coronavirus in the next 3 months
4. % chance average American will get sick with Coronavirus in the next 3 months
5. % chance vulnerable American will get sick with Coronavirus in the next 3 months
6. % chance you will die if you get sick with Coronavirus
7. % chance average American will die if they get sick with Coronavirus
8. % chance vulnerable American will die if they get sick with Coronavirus

Table 4.

Americans' performance of COVID-19-related health protective behaviors in March-April, 2020 (N=6,514)

	Combined (Cohorts 1–3)		Cohort 1 (3/18–3/28/20)		Cohort 2 (3/29–4/7/20)		Cohort 3 (4/8–4/18/20)		Between group differences (Omnibus test from linear regression analyses)
	N=6,514		N=2,042		N=2,234		N=2,158		
Variable	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	
Wash my hands or use hand sanitizer more often	4.51	0.75	4.50	0.73	4.49	0.79	4.52	0.74	$F(2, 6485.0)=0.17$, $p=.840$
Wear a face mask and/or gloves	2.31	1.44	1.75	1.18	2.15	1.37	3.01	1.49	$F(2, 6480.7)= 248.01$, $p<.001$
Avoid people who may be infected with the coronavirus	4.24	1.17	4.07	1.25	4.33	1.11	4.31	1.13	$F(2, 6458.0)= 13.40$, $p<.001$
Avoid public places	3.70	1.03	3.52	1.07	3.78	1.00	3.80	1.00	$F(2, 6490.0)= 25.83$, $p<.001$
Avoid public transportation	4.24	1.39	4.01	1.53	4.35	1.31	4.36	1.31	$F(2, 6418.0)=17.08$, $p<.001$
Cancel or reschedule travel plans	3.80	1.57	3.60	1.61	3.91	1.53	3.91	1.55	$F(2, 6400.0)=14.04$, $p<.001$
Isolate yourself at home	3.78	1.29	3.48	1.37	3.91	1.22	3.96	1.21	$F(2, 6461)=46.88$, $p<.001$

Notes: data weighted by cohort for cohort-level descriptive statistics and for full sample in combined estimates.

Full contrasts between cohorts are presented in Supplemental Tables S1 and S2.

Table 5.

Demographics, COVID-19 exposure, and COVID-19 risk perceptions as predictors of social distancing behaviors in March-April, 2020 (N=6,514)

	Model 1					Model 2					Model 3				
Variable	**Beta**	**b**	**95% CI**		***p***	**Beta**	**b**	**95% CI**		***p***	**Beta**	**b**	**95% CI**		***p***
Female gender	**.18**	**.37**	**.30**	**.45**	**<.001**	**.17**	**.35**	**.28**	**.43**	**<.001**	**.16**	**.33**	**.26**	**.41**	**<.001**
Age	**.09**	**.01**	**.00**	**.01**	**<.001**	**.14**	**.01**	**.01**	**.01**	**<.001**	**.13**	**.01**	**.01**	**.01**	**<.001**
Income	.03	.02	.00	.04	.057	.02	.01	−.01	.03	.239	.03	.02	−.004	.04	.106
Education															
High school graduate	−.07	−.16	−.36	.04	.124	−.07	−.15	−.36	.05	.141	−.07	−.16	−.37	.04	.119
Some college	−.06	−.14	−.33	.05	.140	−.09	−.19	−.38	.00	.046	−.09	−.20	−.40	−.01	.037
BA or above	.02	.05	−.13	.24	.571	−.02	−.03	−.22	.16	.746	−.02	−.04	−.23	.16	.715
Ethnicity															
Black	.03	.09	−.05	.23	.196	.03	.10	−.03	.23	.143	.04	.13	−.01	.26	.061
Other/2+ races	.04	.13	.001	.26	.047	.03	.12	−.01	.24	.063	.03	.12	−.01	.24	.068
Hispanic	.05	.13	.01	.25	.030	.03	.09	−.03	.22	.136	.03	.10	−.03	.22	.119
Region															
Midwest	−.06	−.14	−.25	−.04	.008	−.05	−.12	−.22	−.02	.023	−.05	−.12	−.23	−.02	.017
South	−.07	−.14	−.24	−.04	.009	−.05	−.11	−.21	−.01	.037	−.05	−.10	−.20	.00	.054
West	−.03	−.08	−.19	.03	.142	−.03	−.08	−.19	.03	.147	−.03	−.06	−.17	.04	.242
Cohort															
3/29–4/7	**.15**	**.32**	**.23**	**.41**	**<.001**	**.13**	**.27**	**.19**	**.36**	**<.001**	**.12**	**.27**	**.18**	**.35**	**<.001**
4/8–4/18	**.16**	**.34**	**.26**	**.43**	**<.001**	**.13**	**.28**	**.19**	**.36**	**<.001**	**.12**	**.27**	**.18**	**.35**	**<.001**
COVID-19 exposure															
Personal						.02	.04	−.04	.12	.323	.004	.01	−.07	.09	.836
Community						.06	.04	.01	.07	.008	.06	.04	.01	.07	.017
Secondary stressors						**.18**	**.16**	**.12**	**.19**	**<.001**	**.17**	**.15**	**.11**	**.18**	**<.001**
Personal risk of contracting coronavirus (susceptibility)											.07	.003	.001	.005	.001
Personal risk of coronavirus death (severity)											**.09**	**.004**	**.002**	**.01**	**<.001**
Model statistics	F(14, 6491.8)=17.71, p<.001; R^2=.08; Adj. R^2=.08					F(17, 6487.2)=20.75, p<.001; R^2=.12; Adj. R^2=.11					F(19, 6478.5)=22.09, p<.001; R^2=.13; Adj. R^2=.13				

Table 6.

Demographics, COVID-19 exposure, and COVID-19 risk perceptions as predictors of wearing face masks and/or gloves in March-April, 2020 (N=6,514)

	Model 1					Model 2					Model 3				
Variable	**Beta**	**b**	**95% CI**		***p***	**Beta**	**b**	**95% CI**		***p***	**Beta**	**b**	**95% CI**		***p***
Female gender	**.07**	**.22**	**.12**	**.32**	**<.001**	**.08**	**.23**	**.13**	**.33**	**<.001**	**.07**	**.20**	**.10**	**.29**	**<.001**
Age	**.11**	**.01**	**.01**	**.01**	**<.001**	**.17**	**.01**	**.01**	**.02**	**<.001**	**.14**	**.01**	**.01**	**.01**	**<.001**
Income	−.02	−.02	−.05	.01	.187	−.03	−.02	−.05	.01	.127	−.01	−.01	−.04	.02	.404
Education															
High school graduate	−.04	−.14	−.42	.15	.350	−.03	−.10	−.39	.18	.471	−.04	−.11	−.39	.16	.425
Some college	−.06	−.20	−.47	.07	.138	−.06	−.19	−.46	.08	.161	−.06	−.20	−.47	.06	.138
BA or above	−.08	−.25	−.53	.02	.073	−.09	−.26	−.54	.01	.056	−.08	−.25	−.52	.01	.063
Ethnicity															
Black	**.14**	**.65**	**.46**	**.84**	**<.001**	**.13**	**.60**	**.41**	**.78**	**<.001**	**.14**	**.61**	**.43**	**.80**	**<.001**
Other/2+ races	.05	.25	.08	.43	.004	.04	.22	.05	.39	.010	.04	.20	.04	.37	.017
Hispanic	.08	.34	.16	.51	**<.001**	.07	.28	.11	.45	.001	.07	.27	.10	.44	.002
Region															
Midwest	−.10	−.35	−.50	−.20	**<.001**	**−.09**	**−.32**	**−.47**	**−.18**	**<.001**	**−.09**	**−.33**	**−.48**	**−.19**	**<.001**
South	−.08	−.22	−.37	−.08	.003	−.07	−.20	−.35	−.05	.008	−.07	−.20	−.35	−.06	.006
West	−.01	−.05	−.20	.10	.538	−.01	−.04	−.19	.11	.576	−.01	−.04	−.19	.11	.625
Cohort															
3/29–4/7	**.14**	**.43**	**.32**	**.53**	**<.001**	**.13**	**.40**	**.30**	**.51**	**<.001**	**.13**	**.38**	**.27**	**.49**	**<.001**
4/8–4/18	**.41**	**1.26**	**1.14**	**1.37**	**<.001**	**.40**	**1.22**	**1.10**	**1.33**	**<.001**	**.38**	**1.18**	**1.06**	**1.29**	**<.001**
COVID-19 exposure															
Personal						**.07**	**.24**	**.13**	**.35**	**<.001**	**.06**	**.21**	**.10**	**.32**	**<.001**
Community						−.04	−.04	−.08	−.003	.034	−.05	−.04	−.08	−.01	.023
Secondary stressors						**.11**	**.13**	**.09**	**.18**	**<.001**	**.11**	**.13**	**.08**	**.17**	**<.001**
Personal risk of contracting coronavirus (susceptibility)											.0002	.000	−.002	.002	.956
Personal risk of coronavirus death (severity)											**.13**	**.01**	**.01**	**.01**	**<.001**
Model statistics	$F(14, 6493)=52.11$, $p<.001$; $R^2=.18$; Adj. $R^2=.18$					$F(17, 6488.7)=53.66$, $p<.001$; $R^2=.20$; Adj. $R^2=.20$					$F(19, 6479.1)=54.47$, $p<.001$; $R^2=.21$; Adj. $R^2=.21$				

Table 7.

American’s attitudes and knowledge about COVID-19 in March-April, 2020 (N=6,514)

	Combined (Cohorts 1–3)	
	N=6,514	
Attitude & Knowledge Items	**M**	**SD**
Attitudes		
Scientists have a very good understanding of Coronavirus.	3.13	1.08
Scientists will have a vaccine that prevents Coronavirus within a year.	3.34	1.03
Scientists will have a treatment that cures Coronavirus within a year.	3.13	1.06
Officials should provide Americans with honest, accurate information about the situation (even if that information worries people).	4.54	0.82
We should invest more in general capabilities, like better public health services.	4.19	0.90
If people are quarantined because of exposure to Coronavirus, they should get help with the costs, such as lost wages.	4.28	0.90
We should have been better prepared for Coronavirus.	4.15	1.03
Knowledge		
Coronavirus is more contagious than the flu.	3.92	1.07
Coronavirus is more deadly than the flu.	3.73	1.16
It is important that everyone take precautions to prevent the spread of Coronavirus, even if they are not in a high-risk group (e.g., elderly, chronically ill).	4.59	0.80

Table 8.

Demographics and COVID-19 exposure as predictors of attitudes and knowledge about COVID-19 in March-April, 2020 (N=6,514)

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Female gender	**−.06**	−.03	**−.06**	.002	.06*	**.11**	.04	.05*	.01	.07*
Age	**.07**	.06*	.06*	**.12**	−.004	−.02	−.01	**.13**	**.15**	**.11**
Income	−.01	.04	.002	−.01	−.06*	**−.07**	−.07*	.03	.002	.02
Education										
High school graduate	−.04	−.03	−.04	.06	−.02	.03	.0001	−.13*	−.09	−.0002
Some college	−.03	−.09	−.11*	.09	−.02	.01	−.01	−.13*	−.13*	−.03
BA or above	−.002	−.13*	**−.19**	**.18**	.08	.03	.08	−.05	−.02	.04
Ethnicity										
Black	.02	−.002	.04	−.04	**.11**	**.10**	**.13**	.04*	.07*	−.01
Other/2+ races	.0005	.01	.04	.004	.05	.03	**.08**	.03*	.03	.03
Hispanic	.05	.04	.07*	−.003	**.07**	.05	.07*	.04	.02	.03
Region										
Midwest	.02	.004	.004	.02	−.01	−.05	−.05	−.04	−.03	−.01
South	.02	−.01	.003	−.02	−.01	−.03	−.08*	−.05	−.04	−.01
West	.03	−.01	−.002	−.004	−.01	−.04	−.04	**−.08**	−.03	−.02
Cohort										
3/29–4/7	.05*	.02	.02	.004	−.01	−.06*	.02	.05	**.11**	−.02
4/8–4/18	.01	−.02	−.01	−.03	−.07*	**−.12**	.01	.03	**.07**	**−.09**
COVID-19 exposure										
Personal	.01	−.05	−.04	−.02	.02	.02	.04	.04	.03	−.03
Community	−.002	.02	−.03	**.29**	**.18**	**.23**	**.19**	**.09**	.04	**.23**
Secondary stressors	−.02	−.03	−.02	−.04	.04	.03	.05	**.08**	**.08**	.05*
R^2(Adjusted R^2)	.02(.01)	.02(.02)	.04(.04)	.16(.15)	.06(.06)	.08(.08)	.07(.07)	.06(.06)	.06(.05)	.10(.09)

Estimates reflect beta coefficients.

* p<.01; ***p*<.001 bold**.

Men, less than high school education, white ethnicity, Northeast, and cohort 1 (3/18–3/28) are the reference groups.

1. Scientists have a very good understanding of Coronavirus.
2. Scientists will have a vaccine that prevents Coronavirus within a year.
3. Scientists will have a treatment that cures Coronavirus within a year.
4. Officials should provide Americans with honest, accurate information about the situation (even if that information worries people).
5. We should invest more in general capabilities, like better public health services.
6. If people are quarantined because of exposure to Coronavirus, they should get help with the costs, such as lost wages.
7. We should have been better prepared for Coronavirus.
8. Coronavirus is more contagious than the flu.
9. Coronavirus is more deadly than the flu.
10. It is important for everyone to take precautions to prevent the spread of the Coronavirus, even if they are not in a high-risk group (e.g., elderly, chronically ill).