Word Count: 3625

Actual versus Perceived Infection Rates of COVID-19: Impact on Distress, Behavior and Disability

Norman B. Schmidt, Ph.D.[a,*]

Alex D. Martin, B.S. [a]

Nicholas P. Allan, Ph.D.[b, c]

Brittany M. Mathes, M.S. [a]

Kevin G. Saulnier, M.S.[b]

David S. March, Ph.D. [a]

[a] Department of Psychology, Florida State University, Tallahassee, FL

[b] Department of Psychology, Ohio University, Athens OH

[c] VA Center of Excellence for Suicide Prevention, VA Finger Lakes Health Care System

[*]Corresponding author: Department of Psychology, Florida State University, Tallahassee, FL

Email address: schmidt@psy.fsu.edu

Disclosures and conflicts of interest. The authors have no conflicts of interest to declare. Effort on this project for Drs. Allan and Schmidt was partially supported by the National Institutes of Health (NIH) award administered by the National Institute of Mental Health (1R15MH116311-01A1).

Please cite this article as: Schmidt NB, Martin AD, Allan NP, Mathes BM, Saulnier KG, March DS, Actualversus Perceived Infection Rates of COVID-19: Impact on Distress, Behavior and Disability, *Journal ofPsychiatric Research,* https://doi.org/10.1016/j.jpsychires.2021.03.061

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Abstract

Objective: Accurate threat appraisal is central to survival. In the case of the coronavirus pandemic, accurate threat appraisal is difficult due to incomplete medical knowledge as well as complex social factors (e.g., mixed public health messages). The purpose of this study was to evaluate the degree to which individuals accurately perceive COVID-19 infection rates and to explore the role of COVID-19 threat perception on emotional and behavioral responses both cross sectionally and prospectively. Methods: A community sample (*N* = 249) was assessed using online crowdsourcing and followed for one month. COVID-19 threat appraisal was compared with actual COVID-19 infection rates and deaths at the time of data collection in each participant's county and state. It was predicted that actual versus perceived COVID-19 infection rates would only be modestly associated. Relative to actual infection rates, perceived infection rates were hypothesized to be a better predictor of COVID-related behaviors, distress, and impairment. Results: Findings indicated that relative to actual infection, perceived infection was a better predictor of COVID-related outcomes cross sectionally and longitudinally. Interestingly, actual infection rates were negatively related to behaviors cross sectionally (e.g., less stockpiling). Prospectively, these variables interacted to predict avoidance behaviors over time such that the relationship between perceived infection and avoidance was stronger as actual infection increased. Conclusions: These data suggest that perceived COVID-19 infection is significantly associated with COVID-related behaviors, distress and impairment whereas actual infection rates have a less important and perhaps even paradoxical influence on behavioral responses to the pandemic.

Keywords: COVID-19, pandemic, perceived threat, anxiety, distress, disability

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1. Introduction

The COVID-19 pandemic represents one of the most significant global public health issues in decades. In addition to impacting the physical health of millions, the pandemic is a significant psychological stressor due to both the threat of the illness itself and the mitigation strategies used to contain the spread. Early reports regarding COVID-19 indicate that people are reporting significant concern about the pandemic and its consequences (Holmes et al., 2020). Within the U.S., in particular, it is estimated that approximately 65-70% of individuals may be experiencing moderate to severe levels of psychological distress due to the pandemic (Twenge & Joiner, 2020; Hsing et al., 2020; Nelson et al., 2020; Rosen et al., 2020). There have also been noted increases in feelings of hopelessness, sadness, and worthlessness (Twenge & Joiner, 2020), as well as decreases in feelings of social connection (Hsing et al., 2020). Initial studies have also shown that more people are seeking psychiatric care and calling national crisis lines, further supporting the idea that the pandemic is posing a significant threat to mental well-being (Graves, 2020; Levine, 2020; Bharath, 2020; Lakhani, 2020).

Despite clear data suggesting the pandemic is creating increased distress, we still understand very little regarding the underlying mechanisms. One important candidate to consider is COVID-related threat perception. Perception Motivation Theory suggests that a number of different factors are associated with behavioral response to fear-based health communications: the severity of a negative health outcome (such as contracting a virus), the likelihood of that event, and feasibility of preventative measures (Maddux & Rogers, 1983; Rogers, 1973).

Generally speaking, threat perception is critical to our ability to adaptively deal with dangerous situations. That is, one must perceive a threat to initiate processes to protect the individual from harm. Yet, the perception of threat (i.e., how dangerous is this situation) is often not isomorphic with the actual threat. Such *mis*perception has been theorized to occur due to motivated processing that guides perception toward fulfilling basic needs—which in the case of threat is the need for survival (Balcetis & Dunning, 2010; Bruner, 1957).

With regard to COVID-19, a likely distress-inducing perceptual bias may involve one's actual versus perceived current susceptibility to COVID-related danger. That is, there may be a discrepancy between the actual severity of the COVID-19 outbreak in one’s local area or state versus the severity of the outbreak that one perceives. This is analogous in many ways to the perception of the proximity of a threat. When a threat is near in the current environment, quick response is often the key to a successful response. The more proximal the threat, the more motivationally significant a threat is (Muhlberger et al., 2008), and the more people are compelled to act (Pichon et al., 2012). Hence, there is a direct connection between perception and response.

Detecting and avoiding infection is hypothesized to be the responsibility of a behavioral immune system designed to focus on signs of disease-threat (Neuberg et al., 2011; Schaller & Park, 2011). Once a signal has been detected (e.g. a physical cue like a fever, or an external cue like a news story), physical and cognitive responses are marshalled to minimize the likelihood of contacting the pathogen (Neuberg et al., 2011; Schaller & Duncan, 2007). An individual’s disposition is also altered in a disease-avoiding, adaptive fashion. For example, when disease-threat is made salient, people perceive themselves as less extraverted and display increased avoidant motor movements to other people (Mortensen et al., 2010), reducing the likelihood of contacting a pathogen.

Previous work has shown that there are individual differences in perceived vulnerability to disease (Faulkner et al., 2004). It is clear that there are also dramatic individual differences in threat perception relating to COVID-19. As we have noted, many individuals are reporting increased fear and distress (Fitzpatrick et al., 2020; Pfefferbaum & North, 2020) and exaggerated behaviors such as stockpiling (Garbe et al., 2020). On the other hand, many others appear to underestimate COVID-related dangers by failing to follow social distancing guidelines. Such divergent emotional and behavioral responses may be due to discrepant actual versus perceived COVID-19 infection rates. Therefore, the aim of the current paper was to evaluate both actual and perceived COVID-19 infection rates and to determine the degree to which each of these predicts distress, behavior and disability. Using a national community sample (N = 249) that was followed for approximately one month, we evaluated COVID-19 infections and deaths at the county and state level (i.e., actual threat) on the same day (and same week) that we collected measures of perceived infection rates, as well as additional measures of COVID-related worry, behaviors, and disability. Consistent with reports on dramatic differences in compliance with social distancing measures (Pederson & Favero, 2020) and increased lethality among certain groups (e.g., older adults, African Americans; Goldenstaneh et al., 2020), we included relevant demographic factors as covariates of COVID-19 response. We predicted actual and perceived infection rates would only be moderately associated and that perceived versus actual threat would be a better predictor of distress, behavior, and disability cross sectionally as well as longitudinally. We also examined whether perceived and actual threat potentiate one another (interacted) in predicting outcomes.

2. Method

Data collection involved completion of batteries of self-report questionnaires. These surveys were hosted on the Qualtrics platform. Both waves were recruited from Amazon Mechanical Turk (MTurk) workers; participants had to have an approval rating of at least 95% with a minimum of 100 surveys (Peer et al., 2014). All participants had to be 18 years of age or older and live in the United States to participate. Study procedures were approved by the Institutional Review Board of Florida State University and the study was conducted in accordance with the 1964 Helsinki declaration and its later amendments.

2.1 Participants and Procedures

The sample was comprised of 249 participants recruited from MTurk. Due to emerging evidence that traditional attention check items can be circumvented using automatic or “bot” responding (Pei et al., 2020), a variety of attention check items using both adversarial questioning (i.e., referring to alternative answers in the questions) and deliberate “typos” (i.e., se1ected) were included in the study. Data were reanalyzed excluding participants who failed any attention check item as well as multiple attention check items. Of note, patterns of findings did not change as a consequence of either exclusion criterion. As a result, findings are presented with the total sample. Wave 1 data collection began on 2020-04-13, with modal completion on the same day. The Wave 2 survey was sent to the same participants on 2020-05-14, with modal completion on the same day. We collected data from 249 participants at Wave 1 (*M* age = 38.3 years, *SD* = 11.8; 51.4% male) and 170 participants at Wave 2 (*M* age = 39.7, *SD* = 12.3; 52.4% male). Most participants in this sample identified as White (Wave 1: *n* = 190, 76.3%; Wave 2: *n* = 133, 78.2%), with approximately 13% identifying as Black or African American (Wave 1: *n* = 33, 13.3%; Wave 2: *n* = 20, 11.8%). Within this sample at Wave 1, 49.4% of participants endorsed a four-year college degree (BA, BS) as their highest level of education achieved. Most participants reported an estimated yearly family income of $75,000 or less (62.2%). At Wave 1, the survey took 29.13 minutes to complete on average (SD = 15.25 minutes); At Wave 2, the survey took 43.78 minutes to complete on average (SD = 20.74 minutes) because a longer assessment battery was utilized. Participants were compensated $4.00 per hour for completing the survey.

2.2 Measures

Participants completed a battery of self-report measures that included demographics as well as basic information about COVID-19 exposure and testing. The primary instrument we report on here is the COVID-19 Impact Battery (CIB). The CIB has been validated and consists of three separate measures focused on COVID-related behaviors, worry, and disability (Schmidt et al., *manuscript submitted for publication*). The CIB also tracks other ratings including COVID-19 exposure and perceived COVID-19 infection rates. Below we provide descriptions of the measures as well as reliability estimates.

2.2.1 COVID-19 Impact Battery (CIB).

CIB Behaviors Scale. This 12-item scale measures behavioral responses (e.g., “Hand washing;” “Using hand sanitizer”) to the COVID-19 outbreak. Participants responded to this scale by rating the extent to which they “have engaged in the following behaviors in response to COVID-19” using a five-point scale (from 0 = “Not at all” to 4 = “Very much”). The overall scale can be decomposed to three subscales assessing stockpiling, cleaning, and avoidance behaviors. The overall scale and each subscale have good internal consistency (total scale α = .81 at Wave 1 and .83 at Wave 2).

CIB Worry Scale. This 11-item scale measures worry related to the outbreak of COVID-19. The items on this measure use a five-point scale (from 0 = "Not at all" to 4 = "Very Much"). Participants used this scale to rate each item (e.g., “I worry that I will lose my employment”). The worry scale consists of three subscales assessing worry related to: health, finances, and catastrophic worry (e.g., I worry that if I go into quarantine, I will go crazy) based on the degree to which it has caused distress. The overall scale and each subscale have excellent internal consistency (Total scale α = .89 at Wave 1 and .90 at Wave 2).

CIB Disability Scale. Seven items from the WHODAS II were adapted to measure difficulties resulting from the outbreak of COVID-19 (World Health Organization, 2000). Instructions asked participants to consider difficulties “due to the COVID-19 outbreak” rather than those “due to health conditions.” Item wording reflected the adaptation to the COVID-19 outbreak (e.g., “How much have you been emotionally affected by the COVID-19 outbreak?”). Items ask participants to rate difficulties on a five-point scale from 0 (“None”) to 4 ("Extreme or cannot do"). Participants used this scale to rate the degree of difficulties experienced in the preceding 30 days that are due to the COVID-19 outbreak. In the current study, this scale had excellent internal consistency (α = .85 at both Waves).

2.2.2 Perceived COVID-19 Outbreak Size (PCOS). Ratings of perceived threat were obtained from a single item asking participants “What is the approximate size of the COVID-19 outbreak in your area?” Scores ranged from 0 (No cases) to 7 (Very Large). At Wave 1, ratings for this item were normally distributed with sample endorsement of 12% for “No cases” or “Very small,” 33% for “Small” and “Small to medium,” 40.6% endorsing “Medium” and “Medium to large,” and 14.4% endorsing “Large” or “Very large.” At Wave 2, ratings were 8.2% for “No cases” to “Very small,” 37.1% “Small” and “Small to medium,” 40.6% endorsed “Medium” or “Medium to Large,” and 14.1% reporting “Large” and “Very large.”

2.2.3 Actual COVID-19 Outbreak Size (ACOS). To measure the actual size of the outbreak in the participants’ area, we utilized their reported zip codes that identified which county each participant currently resided in. Then, using data obtained from USA Facts (2020), we recorded—for the day that each participant completed the survey—the number of active cases and COVID-related deaths in survey participants’ counties, then summed them to get the total number of cases per county. Additionally, we used county population numbers to calculate these values per 100,000 people. We similarly calculated state numbers for active cases, deaths, and total cases as well as those numbers per 100,000 people. Due to day-to-day fluctuations in outbreak values, we also calculated a 7-day rolling average for the total number of cases (and total per 100,000), as this may better reflect COVID-19 infection rates relative to a one-day window.

To simplify analyses, we present the county’s 7-day rolling average per 100,000 people to represent ACOS for each participant. County data provide a more proximal index of actual threat than state data and also allow for greater variance across participants. Since active infection and COVID-19 deaths are both meaningful to understanding overall infection rates, we used their combination to compute ACOS. Given the skewed distributions of outbreak data, we log-transformed these variables, which brought them to within acceptable ranges of skewness.

3. Statistical Analysis

Cross sectional analyses were conducted using correlational and regression analyses. A series of stepwise linear regression analyses were conducted in SPSS version 26 with participants’ Wave 2 data to determine the effects of gender, minority status, age, PCOS, ACOS, and the interaction between PCOS and ACOS on COVID-19 behaviors, worries, and disability. In these models, gender, minority status, and age were entered in the first block and PCOS, ACOS were entered in the second block, and the PCOS by ACOS interaction was entered in the third block. If the interaction was not significant, it was not included in the final model. The Benjamini-Hochberg procedure was used to control familywise Type 1 error rate at $\alpha = .05$ for all analyses.

Longitudinal predictor analyses were modeled with path analyses. Path analysis was conducted in Mplus version 8.4 (Muthen & Muthen, 2017) to examine the cross-lagged effect of PCOS, ACOS, and the interaction between PCOS and ACOS at Wave 1 on Wave 2 behaviors, worries, and disability. These analyses were conducted controlling for the autoregressive effects of behaviors, worries, and disability as well as gender, minority status, and age. All manifest variables were allowed to covary, resulting in a just-identified model with no fit indices to report.

4. Results

4.1 Preliminary Analyses

No problematic skew or kurtosis values were detected based on values problematic in simulation studies (i.e., skew > 2, kurtosis > 7; Curran et al., 1996) except for the COVID-19 infection rate variable. This variable was log transformed to obtain acceptable skew and kurtosis values, and the log transformed variable was used in all analyses. Preliminary analyses for all regression analyses indicated that there were no threats or violations of normality, multicollinearity, or homoscedasticity.

4.2 Descriptive Statistics and Correlations

Descriptive statistics and bivariate correlations for all self-report and demographic variables are contained in Table 1. Of note, ACOS in most areas significantly increased from

Wave 1 to Wave 2 (see Table 2). However, paired-samples t-tests indicated there were no statistically significant differences in the means of responses to self-report measures between the two waves of data collection (ps > .076), suggesting high stability of scores (or low sensitivity to change). Participants that did not complete the follow-up were significantly younger and endorsed more stockpiling behaviors at Wave 1 (ps < .05). Therefore, age was used as a covariate in relevant analyses.

4.3 Participant Estimation of Outbreak Size

To determine whether participants were accurate in estimating the size of the COVID-19 outbreak cross sectionally, Pearson correlations were run using PCOS and ACOS, where ACOS was the log-transformed county 7-day rolling average values per 100,000 people. As can be seen in (Table 1), these correlations were significant and in the large effect range (.36 at Wave 1 and .40 at Wave 2), per Funder & Ozer (2019). Similar analyses using state infection, deaths, and total cases versus county ACOS values revealed only moderate correlations at Wave 1 ($.27 \leq r$s $\leq .30$) and Wave 2 ($.26 \leq r$s $\leq .33$), suggesting that individuals may be better at estimating local versus statewide infection rates.

4.4 Cross Sectional (Wave 2) PCOS and ACOS Prediction of COVID-19 Behaviors, Worries, and Disability

Across all cross-sectional Wave 2 models, the interaction term between PCOS and ACOS was not a significant predictor and was dropped from the analyses (see Table 3). Model results are reported after applying a Benjamini-Hochberg correction to the final model. PCOS was positively related to overall COVID-19 behaviors ($\beta = .41$, $p < .001$) and was the only significant predictor in the final model. Separate models were estimated for each CIB behavior subscale, as the stockpiling and avoidance subscales were not significantly correlated. See Figures 1-5 for visual portrayals of regression effects. Gender was significantly related to stockpiling (β = -.27, p < .001), such that men reported greater levels of stockpiling than did women. PCOS was also significantly, positively related to stockpiling (β = .49, p < .001). PCOS was the only significant predictor of cleaning (β = .30, p = .001). There were no significant predictors of avoidance.

No demographic variable was uniquely related to COVID-19 worries. However, PCOS was significantly, positively related to COVID-19 worries (β = .41, p < .001), and ACOS was significantly, negatively related to COVID-19 worries (β = -.24, p = .006). Regarding COVID-19 disability, PCOS was significantly, positively associated with COVID-19 disability (β = .31, p < .001), and ACOS was significantly, negatively associated with COVID-19 disability (β = -.20, p = .02).

Additional analyses were conducted to assess whether this was a true effect or a statistical artifact as a result of including PCOS in the regression model. For worry and disability, specifically, the negative direction of their relationship with ACOS was present in their zero-order correlations (-.04 and -.06, respectively). However, the strength of the relationship between ACOS and worry was notably weaker prior to including PCOS in the final regression model (β = -.05, p = .58), and the same goes for the relationship between ACOS and disability (β = -.07, p = .81).

4.5 Prospective PCOS and ACOS Prediction of COVID-19 Behaviors, Worries, and Disability at Wave 2

A total of three path analytic models were estimated to examine the impact of PCOS and ACOS on 1) specific COVID-19 behaviors, 2) COVID-19 worries, and 3) COVID-19 disability. The path analytic results for Wave 1 variables predicting specific behaviors at Wave 2 can be found in the top panel of Table 4. There was a significant PCOS by ACOS interaction predicting avoidance; however, the PCOS by ACOS interaction was not significantly related to stockpiling or cleaning. Therefore, the final COVID-19 behaviors model was estimated without the interaction term predicting stockpiling or cleaning. After accounting for Wave 1 COVID-19 behaviors, PCOS significantly predicted increased stockpiling at Wave 2 ($\beta = .17$, $p = .01$). Regarding avoidance, there was a significant PCOS by ACOS interaction ($\beta = .74$, $p = .01$), such that the relation between PCOS and avoidance was stronger as ACOS increased (see Figure 6).

The path analytic results for PCOS and ACOS predicting Wave 2 COVID-19 worries can be found in the middle panel of Table 4. In this model, the interaction between PCOS and ACOS was not significantly related to Wave 2 COVID-19 worries; therefore, the final model was estimated without the interaction term. In this model, being African American predicted lower COVID-19 worries at Wave 2 ($\beta = -.12$, $p = .01$). There were no other significant predictors of Wave 2 COVID-19 worries beyond Wave 1 COVID-19 worries.

The path analytic results for PCOS and ACOS predicting Wave 2 COVID-19 disability can be found in the bottom panel of Table 4. In the COVID-19 disability model, the interaction term was nonsignificant; therefore, the final model did not include this term. In this model (Table 4) there were no significant predictors of Wave 2 COVID-19 disability other than Wave 1 COVID-19 disability.

5. Discussion

The primary goal of this study was to evaluate the relationship between perceived and actual COVID-19 infection rates, and to determine whether each differentially influenced COVID-related emotional and behavioral responses. Findings relating to actual and perceived COVID-19 threat generally supported our expectations. As anticipated, actual and perceived COVID-19 infection were significantly associated with each other. This suggests that most people are generally aware of the level of COVID-19 infection in their local area as well as their state. Yet the strength of this relationship suggests there is a fair amount of discrepancy as well. Overall accuracy numbers suggest that the various daily reports relating to COVID-19 infection rates delivered by medical, administration, and media outlets, are not being accurately distilled by individuals as they appraise their current situations. Perhaps this is due to sometimes conflicting information that is produced by these various sources, the somewhat unpredictable nature of COVID-19 infection rates, or a lack of attention (or access) to viable sources of information. Further work is needed to clarify this important discrepancy.

In terms of the relationship between actual versus perceived infection rates and emotional/behavioral responses, findings supported the unique importance of perceived over actual COVID-19 threat. The directionality of perceived COVID-19 threat, as anticipated, is consistent with a bias toward increased danger. As such, COVID-19 threat perception would appear to generally motivate increased stockpiling and cleaning, which should be more adaptive for survival (Balcetis & Dunning, 2010; Bruner, 1957), but perhaps also lead to increased psychological distress and impairment. Like well-established work showing that anxiety can facilitate performance to a point after which performance suffers (Broadhurst, 1957; Duffy, 1957), there may also be a Goldilocks zone for infection related anxiety. Too little and one is more likely to contact a carrier, but too much can be debilitating, which itself has survival implications.

We found that in general actual COVID-19 infection rates were relatively poorly associated with COVID-related emotional distress and behaviors. Surprisingly, however, some analyses indicate that actual infection rates are *negatively* associated with COVID-related worry and disability. As such, greater actual infection rates are associated with *lower* levels of a presumably adaptive response. Upon further investigation, the direction of this relationship was found to be true, but the strength of the relationship was increased after accounting for PCOS. Though further research is needed to clarify this finding, this paradox of decreased adaptive response to increased infection rates may be due to psychological adjustments or coping that have occurred among those in highly affected areas. These surveys were administered at a moment when many areas had been experiencing significant COVID-19 infection rates for some time. Individuals in these areas may feel as though they have "weathered the storm" and emerged relatively unscathed. Similarly, it may be that in less affected areas, there is greater anticipation of the unpredictable negative impacts of COVID-19 infection once it manifests itself in their local area.

There are a number of limitations to be considered with the current report. First, we necessarily relied on online data sources for the acquisition of study participants. Although use of online crowdsourcing mechanisms is increasingly common and the procedures are generally well-accepted (Thomas & Clifford, 2017; Sheehan, 2017), there are some concerns about these procedures including the contamination of data from automated or "bot" responses and the representativeness of such samples (Pei et al., 2020). To mitigate some of these concerns, we utilized reliability checks, which are commonly recommended for these data sources (Peet et al., 2014; Pei et al., 2020). While online data collection will likely become increasingly utilized in light of COVID-19, concerns about representativeness of these samples is still warranted. An additional limitation was the reliance on self-report measures. Online interviews or even behavioral measures should be considered in future work. Attrition was also higher than desirable at our one-month follow-up. This level of attrition seems comparable to other studies using MTurk samples (Bunge et al., 2018; Cunningham et al., 2019). Moreover, Wave 2 completers were generally comparable to noncompleters in terms of Wave 1 demographics as well as the key COVID-19 variables that were studied here. Finally, the proposed direction of the investigated relationship (i.e., PCOS predicting distress, impairment, and behaviors) may not reflect the true nature of these variables. It is possible that alternate models with the opposite direction (e.g., distress predicting greater perceived COVID-related threat) are more accurate representations of these variables. With the current data, causality is more difficult to assess and poses a limitation to the conclusions that can be drawn, but future studies should look to compare models across multiple waves of data with different directions of these relationships.

Despite these limitations, the current study presents an intriguing set of findings that have relevance to public health responses about the COVID-19 pandemic. First, previous work has suggested that COVID-19 is creating increased mental health issues (Twenge & Joiner, 2020; Hsing et al., 2020; Nelson et al., 2020; Rosen et al., 2020). While other studies have investigated similar models (e.g., Mækelæ et al., 2020), the current study is the first—to our knowledge—to highlight the role of perceived COVID-19 threat *over* that of *actual* COVID-19 infection in contributing to this increased distress. These findings indicate that managing perceived infection rates could have a powerful impact on mental health sequelae. Other work has identified other viable intervention targets as well. In one such study, anticipatory regret mediated the relationship between Protective Motivation Theory scores and frequency of health behaviors (Kowalski & Black, 2021), and another showed that motivated helplessness was significantly related to COVID-19 infection distress (Lifshin, Mikulincer, & Kretchner, 2020). Second, this study suggests a considerable number of individuals would benefit from learning to more accurately assess actual infection rates. Greater accuracy is likely to produce a commensurate behavioral and emotional response to the pandemic. As such, our findings indicate that perceived

COVID-19 threat is a viable target for intervention efforts designed to alleviate pandemic related mental health responses.

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Table 1. Correlations and Descriptive Statistics of Study Variables across Waves 1 and 2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. W1 PCOS	--																		
2. W1 Stockpiling	.23*	--																	
3. W1 Cleaning	.17*	.42*	--																
4. W1 Avoidance	-.01	-.11	.32*	--															
5. W1 Total Behaviors	.20*	.69*	.84*	.52*	--														
6. W1 Worries	.25*	.44*	.24*	-.03	.34*	--													
7. W1 Impairment	.30*	.55*	.26*	-.15*	.36*	.65*	--												
8. W1 ACOS	.36*	.02	-.03	-.12	-.06	.02	.08	--											
9. W2 PCOS	.73*	.26*	.18*	-.03	.22*	.24*	.27*	.42*	--										
10. W2 Stockpiling	.29*	.78*	.36*	-.12	.55*	.38*	.51*	.06	.38*	--									
11. W2 Cleaning	.16*	.45*	.77*	.23*	.71*	.25*	.28*	.00	.21*	.50*	--								
12. W2 Avoidance	.00	-.13	.23*	.68*	.32*	.01	-.17*	-.07	-.02	-.05	.29*	--							
13. W2 Total Behaviors	.23*	.58*	.64*	.31*	.75*	.33*	.34*	.01	.29*	.76*	.85*	.50*	--						
14. W2 Worries	.22*	.41*	.14	-.14	.23*	.75*	.62*	.08	.31*	.50*	.28*	-.09	.37*	--					
15. W2 Impairment	.20*	.45*	.11	-.15	.24*	.52*	.69*	.06	.25*	.48*	.18*	-.22*	.26*	.69*	--				
16. W2 ACOS	.41*	.06	-.01	-.05	.01	.00	.12	.91*	.40*	.06	.00	-.06	.01	.04	.04	--			
17. Gender	.00	-.26*	.01	.17*	-.07	-.06	-.11	-.12	.05	-.21*	.04	.14	-.04	-.07	-.07	-.13	--		
18. Minority Status	.15*	.16*	.10	.06	.16*	.13*	.09	.18*	.04	.02	.02	.00	.02	.00	.01	.23*	.01	--	
19. Age	-.15*	-.23*	-.10	.14*	-.11	-.09	-.27*	-.17*	-.16*	-.12	.04	.21*	.04	-.08	-.21*	-.06*	.09	-.27*	--
M	4.65	6.69	10.14	13.29	20.11	18.43	10.09	2.62	4.76	6.01	9.91	13.41	29.33	17.61	9.19	3.07	.48	.23	38.30
SD	1.69	4.49	3.94	3.57	8.27	10.08	6.29	1.01	1.58	4.57	3.91	3.29	8.42	10.14	6.04	1.06	.50	.42	11.80

Note. N = 249 at Wave 1. N = 170 at Wave 2. There were no significant differences in means from Wave 1 to Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size.W1 = Wave 1. W2 = Wave 2. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

$^{*}p < .05$

Table 2. Actual COVID Outbreak Size Data based on Participant Zip Codes

Outbreak Measurements	Wave 1 (N = 246) Mean (SD)	Wave 2 (N = 170) Mean (SD)
County Active per 100k people	194.1 (293.4)	483.5 (593.8)
County Deaths per 100k people	7.6 (15.8)	32.2 (50.9)
County Total Cases per 100k people	201.8 (308.0)	515.7 (640.8)
State Active per 100k people	209.6 (266.9)	501.4 (499.2)
State Deaths per 100k people	8.8 (13.6)	32.8 (41.0)
State Total Cases per 100k people	218.4 (280.3)	534.2 (539.6)

Note: Wave 2 values are statistically significantly greater than Wave 1 values across all levels at a .001 alpha-level. Also, all distributions prior to log-transformation were significantly positively skewed (skew values >1), and all log-transformed distributions are within acceptable limits of skewness.

Table 3. Hierarchical Linear Regression of Wave 2 PCOS and ACOS predicting COVID-19 related Behaviors, Worries, and Disability at Wave 2

DV: Safety Behaviors Scale	*B* (SE)	β	*t*	*p*	R^2	ΔR^2
Stockpiling						
Gender	-2.43 (.67)	-.27	-3.61	<.001	.07*	
Minority Status	1.38 (1.00)	.10	1.38	.17		
Age	-.01 (.03)	-.03	-.41	.68		
PCOS	1.40 (.23)	.49	6.01	<.001		.19***
ACOS	-1.43 (.63)	-.18	-2.27	.03ns		
Cleaning						
Gender	-.10 (.62)	-.01	-.16	.87	.01	
Minority Status	.80 (.92)	.07	.87	.39		
Age	.03 (.03)	.10	1.24	.22		
PCOS	.72 (.22)	.30	3.36	.001		.08**
ACOS	-.23 (.58)	-.04	-.40	.69		
Avoidance						
Gender	.66 (.57)	.10	1.17	.25	.07*	
Minority Status	-.79 (.84)	-.08	-.94	.35		
Age	.06 (.02)	.20	2.39	.02ns		
PCOS	.05 (.20)	.02	.26	.80		.001
ACOS	.11 (.53)	.02	.20	.84		
DV: Worry Scale	*B* (SE)	β	*t*	*p*	R^2	ΔR^2
Gender	-2.28 (1.62)	-.11	-1.41	.16	.01	
Minority Status	.99 (2.41)	.03	.41	.68		
Age	-.02 (.07)	-.02	-.26	.80		
PCOS	2.66 (.56)	.41	4.74	<.001		.14***
ACOS	-4.25 (1.52)	-.24	-2.80	.006		
DV: Disability Scale	*B* (SE)	β	*t*	*p*	R^2	ΔR^2
Gender	-1.01 (.98)	-.08	-1.03	.30	.06*	
Minority Status	1.08 (1.45)	.06	.74	.46		
Age	-.08 (.04)	-.16	-1.99	.05		
PCOS	1.21 (.34)	.31	3.57	<.001		.08**
ACOS	-.2.11 (.91)	-.20	-2.31	.02		

Note: PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American. * $p < .05$; ** $p < .01$; *** $p < .001$. ns Indicates nonsignificant parameter estimates after applying a Benjamini-Hochberg correction.

Table 4. Path Analytic Models of Wave 1 PCOS and ACOS Predicting Behaviors, Worries, and Disability Surrounding COVID-19 at Wave 2

	W2 Stockpiling			W2 Cleaning			W2 Avoidance		
	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*
W1 Stockpiling	.73	.05	< .001	.18	.06	.002	-.04	.06	.52
W1 Cleaning	.03	.05	.59	.70	.05	< .001	.08	.06	.16
W1 Avoidance	-.05	.05	.31	.02	.05	.63	.63	.08	< .001
Gender	-.04	.06	.47	.06	.05	.22	.01	.05	.84
Minority Status	-.08	.05	.09	-.09	.05	.07	.03	.05	.54
Age	.06	.05	.23	.09	.05	.08	.11	.05	.02[ns]
PCOS	.17	.06	.01	.00	.06	.98	-.44	.20	.03[ns]
ACOS	-.01	.06	.88	.07	.05	.17	-.41	.19	.03[ns]
PCOS x ACOS	--	--	--	--	--	--	.74	.29	.01

	W2 Worry		
	β	*SE*	*p*
W1 Worry	.74	.04	< .001
Gender	-.02	.05	.74
Minority Status	-.12	.05	.01
Age	-.03	.05	.56
PCOS	.08	.06	.15
ACOS	.05	.06	.43

	W2 Disability		
	β	*SE*	*p*
W1 Disability	.68	.06	< .001
Gender	.03	.06	.56
Minority Status	-.08	.05	.13
Age	-.04	.05	.41
PCOS	.05	.06	.37
ACOS	-.02	.07	.80

Note: PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size.
Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.
[ns]Indicates nonsignificant parameter estimates after applying a Benjamini-Hochberg correction.

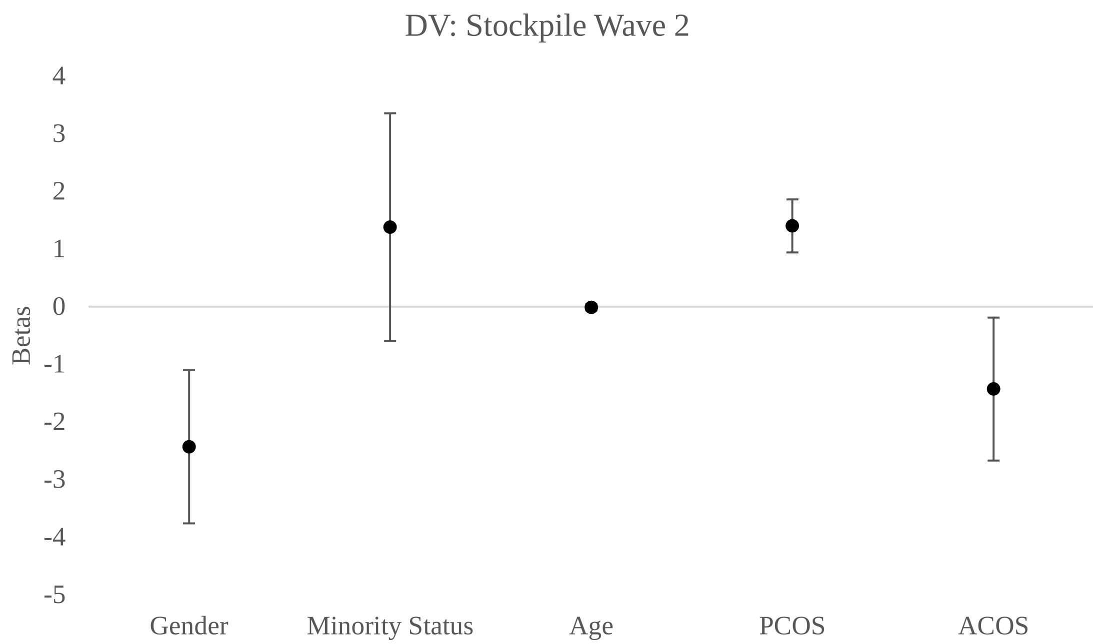

Figure 1. Regression Effects and 95% Confidence Intervals Predicting Stockpiling at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

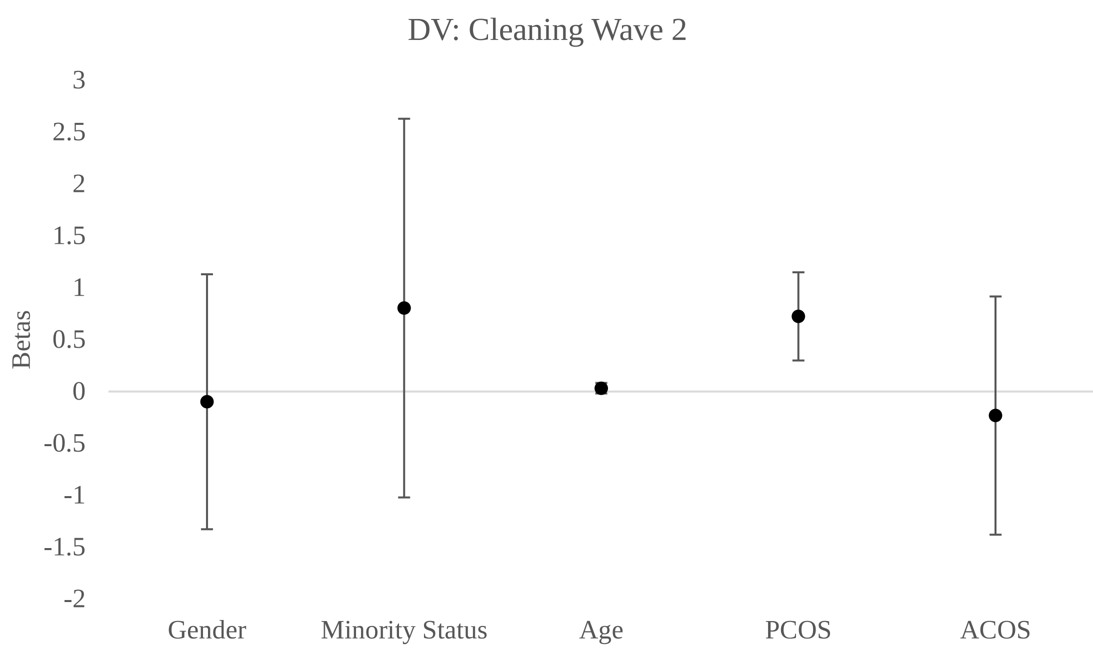

Figure 2. Regression Effects and 95% Confidence Intervals Predicting Cleaning at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

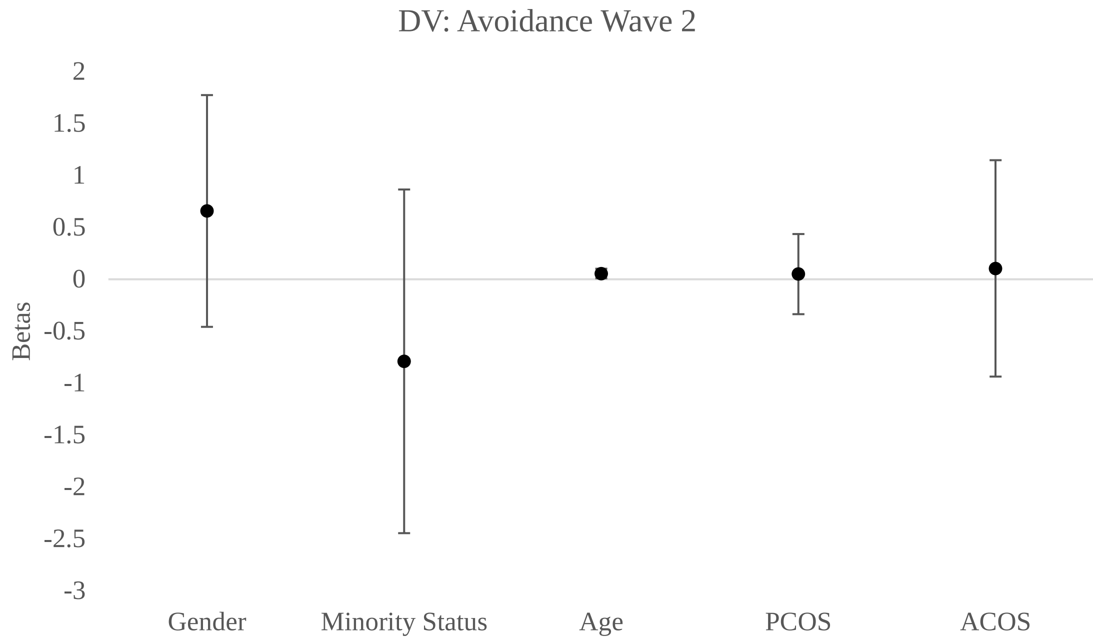

Figure 3. Regression Effects and 95% Confidence Intervals Predicting Avoidance at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

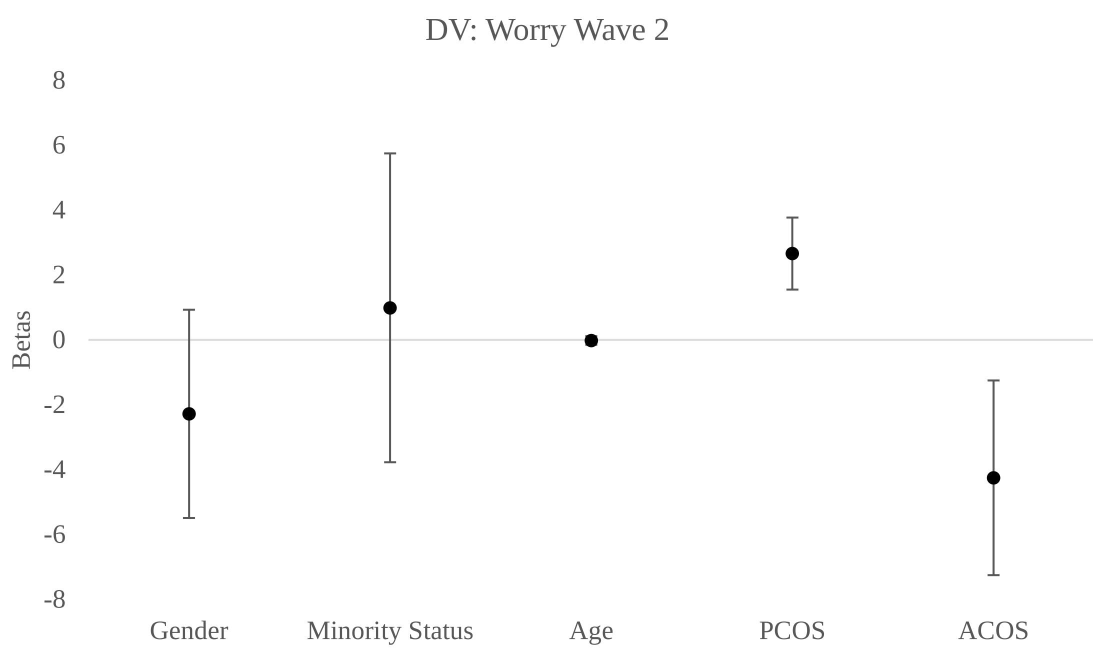

Figure 4. Regression Effects and 95% Confidence Intervals Predicting Worry at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

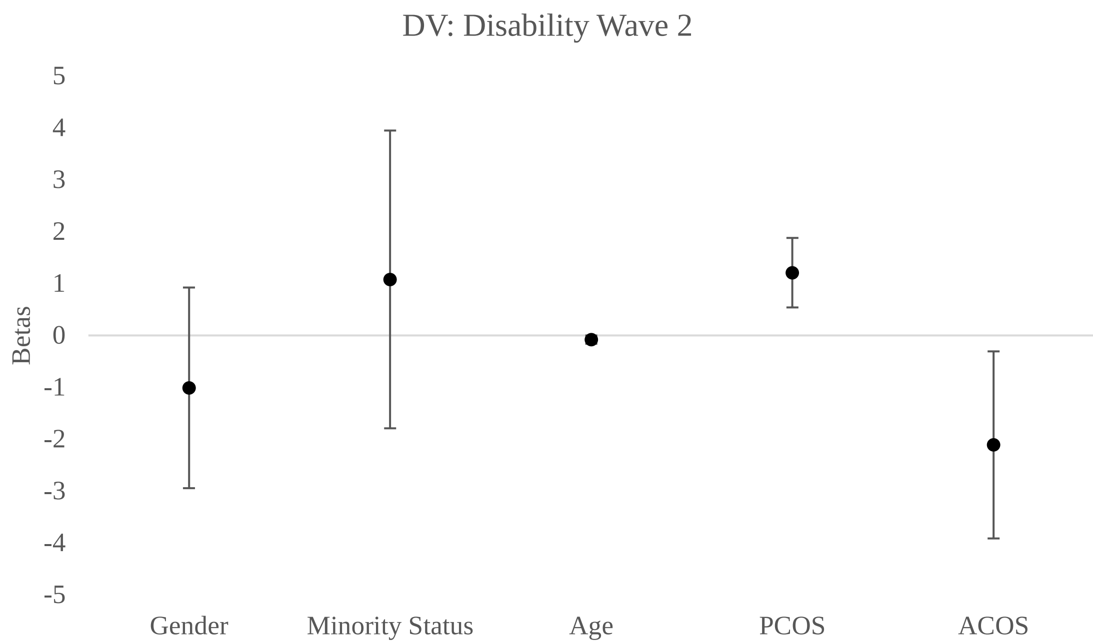

Figure 5. Regression Effects and 95% Confidence Intervals Predicting Disability at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

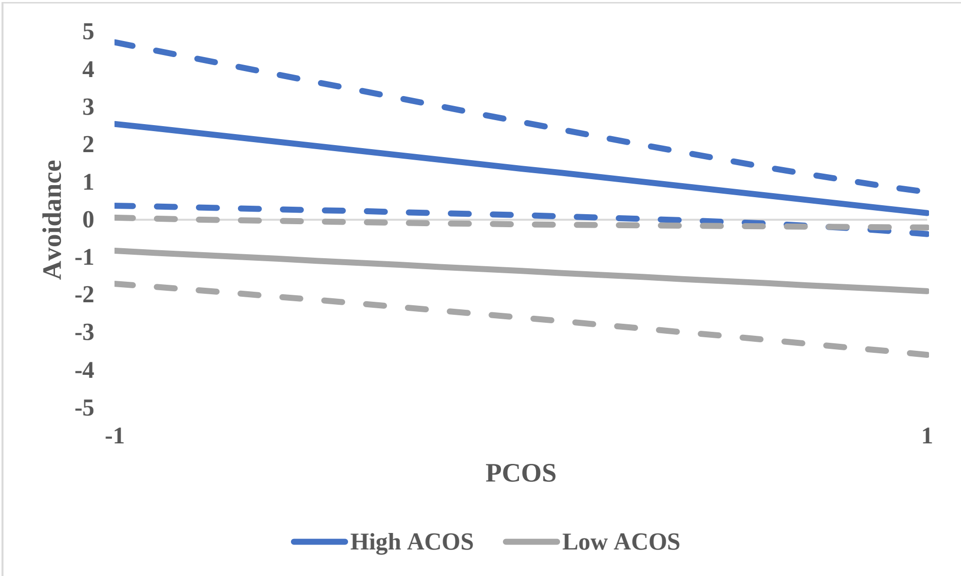

Figure 6. Perceived COVID Outbreak Size by Actual Outbreak Size Interaction Predicting Avoidance behaviors. PCOS and avoidance were mean centered prior to being entered in the model. PCOS = Perceived COVID Outbreak Size. High ACOS = High, low Actual COVID-19 Outbreak Size are +/- 1 standard deviation around the mean.

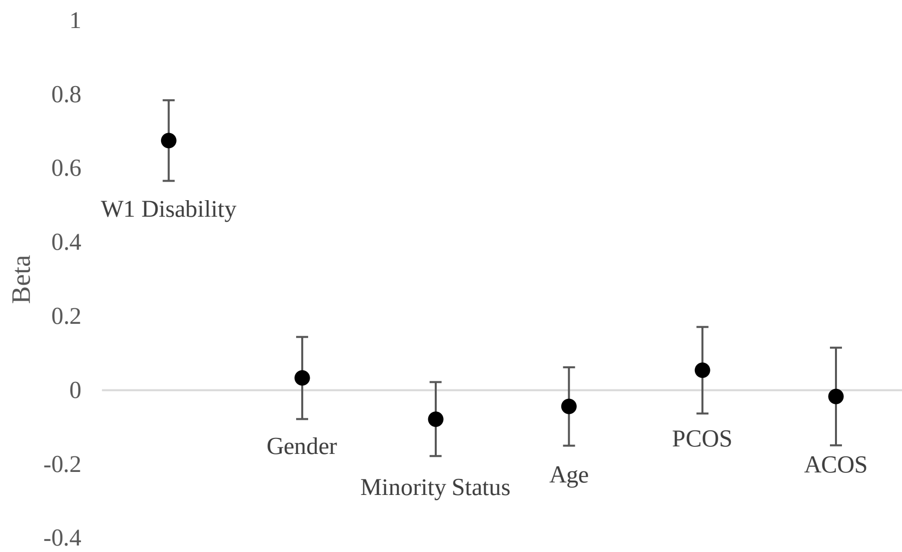

Figure 7. Standardized Path Analytic Effects and 95% Confidence Intervals Predicting Disability at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size. W1 = Wave 1. W2 = Wave 2. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

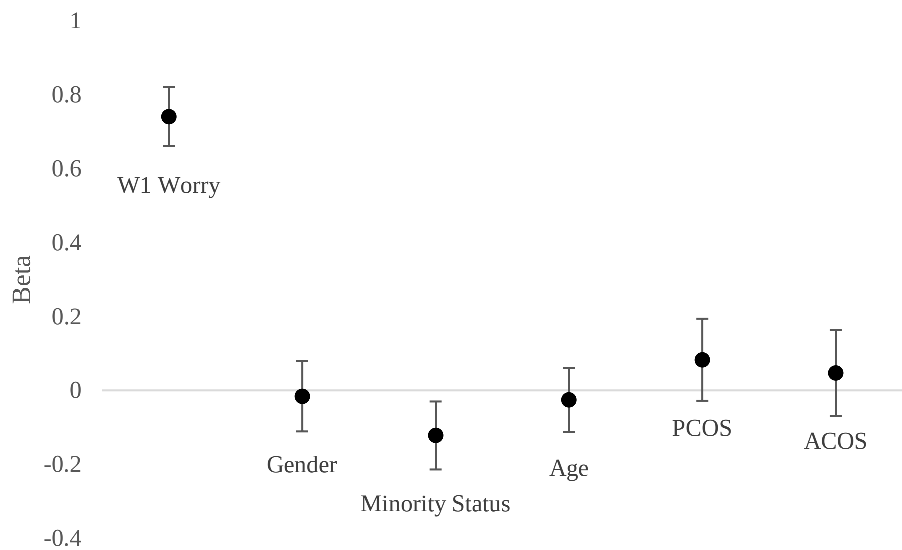

Figure 8. Standardized Path Analytic Effects and 95% Confidence Intervals Predicting Worry at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size.W1 = Wave 1. W2 = Wave 2. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

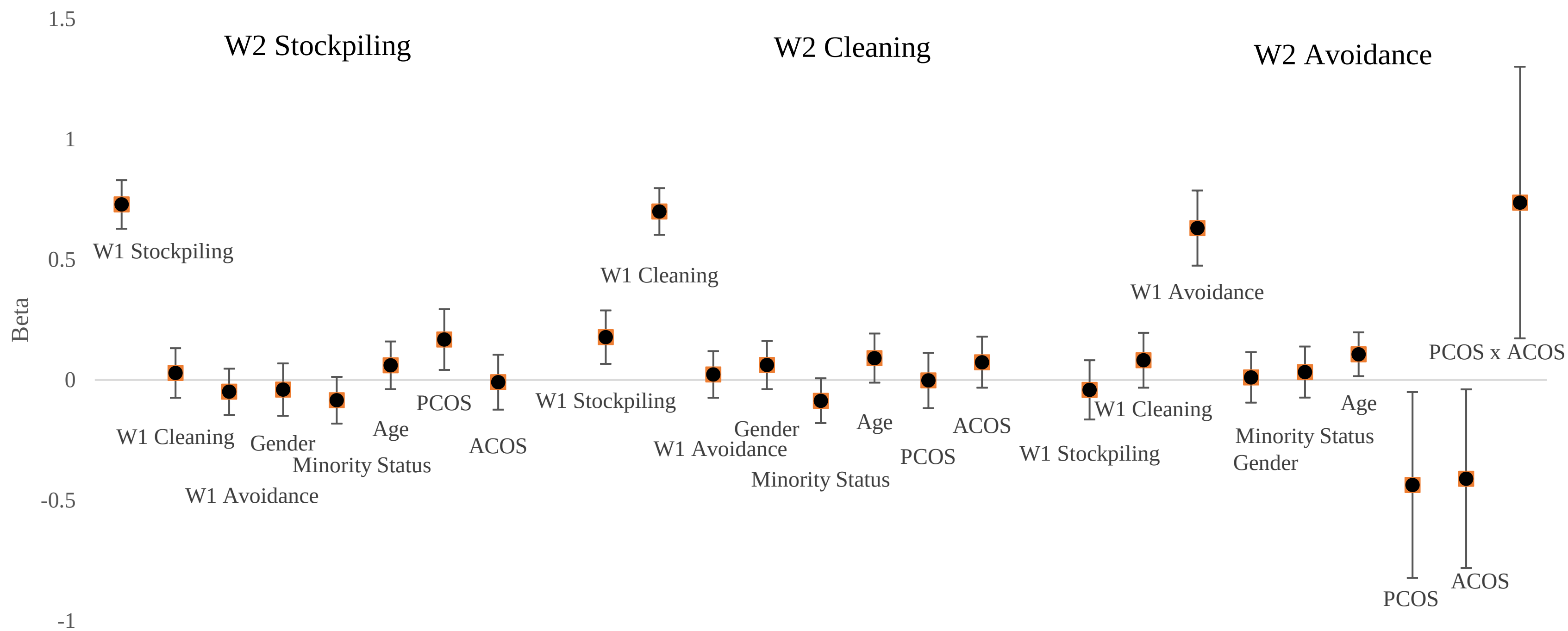

Figure 9. Standardized Path Analytic Effects and 95% Confidence Intervals Predicting Specific Behaviors at Wave 2. PCOS = Perceived COVID Outbreak Size. ACOS = Actual COVID Outbreak Size.W1 = Wave 1. W2 = Wave 2. Gender dummy coded so 1 = Female. Minority Status dummy coded so 1 = African American.

Appendices

Appendix Table 1.
CIB Behaviors Scale

Question: To what extent have you engaged in the following behaviors in response to COVID-19?	Not at all 0	1	2	3	Very Much 4
1. Stockpiling food and water					
2. Stockpiling cleaning supplies					
3. Stockpiling protective gear (e.g., masks, gloves)					
4. Stockpiling non-essential items (e.g., toilet paper)					
5. Using hand sanitizer					
6. Disinfecting home					
7. Disinfecting items like grocery carts before use					
8. Disinfecting packages/mail					
9. Avoided small group gatherings					
10. Avoided hospitals/clinics					
11. Avoided taxis or ride-sharing (e.g., Uber, Lyft)					
12. Avoided travelling					

*Note*s. Items 1-4 comprise the Stockpiling subscale; items 5-8 comprise the Cleaning subscale; items 9-12 comprise the Avoidance subscale.

Appendix Table 2.
CIB Worry Scale

Item	Not at all 0	1	2	3	Very Much 4
1. I worry I will be unable to provide for my family during this time of COVID-19					
2. I worry that I will lose my employment					
3. I worry that my family will not have enough food					
4. I worry that I will get sick and be unable to take care of my family					
5. I worry that I am not going to get the medical attention I need					
6. I worry that my family members will not receive adequate help during this time					
7. I worry that I will not have enough money or access to resources to survive this time					
8. I worry that if I go into quarantine, I will go crazy					
9. I am worried I will not be able to handle being in quarantine					
10. I worry that I am going to contract COVID-19					
11. I am worried I will lose friends due to social distancing					

Notes. Items 1-3 and 7 comprise the Financial Worries subscale; items 4-6 and 10 comprise the Health Worries subscale; items 8-9 and 11 comprise the Catastrophizing subscale.

Appendix Table 3.
CIB Disability Scale

Think back over the past 30 days and answer these questions, thinking about how much difficulty you had doing the following activities.	Not at all 0	Mild 1	Moderate 2	Severe 3	Extreme or cannot do 4
1. Taking care of household responsibilities?					
2. Joining in community activities (for example, festivities, religious or other activities) in the same way as anyone else can?					
3. How much have you been emotionally affected by the COVID-19 outbreak?					
4. Concentrating on doing something for ten minutes?					
5. Dealing with people you do not know?					
6. Maintaining a friendship?					
7. Your day to day work?					

Notes. No subscales; sum all items to get total score.