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BRIEF REPORT

Stress, Intertemporal Choice, and Mitigation Behavior During the COVID-19 Pandemic

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Delayed gratification is an important focus of research, given its potential relationship to forms of behavior, such as savings, susceptibility to addiction, and pro-social behaviors. The COVID-19 pandemic may be one of the most consequential recent examples of this phenomenon, with people's willingness to delay gratification affecting their willingness to socially distance themselves. COVID-19 also provides a naturalistic context by which to evaluate the ecological validity of delayed gratification. This article outlines four large-scale online experiments (total $N = 12,906$) where we ask participants to perform Money Earlier or Later (MEL) decisions (e.g., \$5 today vs. \$10 tomorrow) and to also report stress measures and pandemic mitigation behaviors. We found that stress increases impulsivity and that less stressed and more patient individuals socially distanced more throughout the pandemic. These results help resolve longstanding theoretical debates in the MEL literature as well as provide policymakers with scientific evidence that can help inform response strategies in the future.

Public Significance Statement
The COVID-19 pandemic was one of the most consequential global events in recent history. Containing the virus required mass coordination of human behavior, and thus psychological research of choice mechanisms can help inform policymakers to develop effective response strategies in the future. Our paper develops a link between the psychological concept of delayed gratification with the choice to socially distance, finding that stress increases impulsivity and that less stressed and more patient individuals socially distanced more throughout the pandemic.

Keywords: delayed gratification, intertemporal choice, delay discounting, stress, COVID-19

Supplemental materials: https://doi.org/10.1037/xge0001417.supp

Delayed gratification is an important focus of research, given its potential relationship to forms of behavior, such as savings, susceptibility to addiction, and pro-social behaviors (Funder et al., 1983; Mischel, 1974). While there has been substantial debate about the validity of experimental paradigms that have been used to study delayed gratification (e.g., Mischel et al., 1989), and the interpretation of their results (Benjamin et al., 2020; Cohen et al., 2020), it is clear that humans are often capable of sacrificing

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The study's data will be released through the Open Science Foundation upon publication. This study was not preregistered.

The study's data can be publicly accessed through the Open Science Foundation at https://osf.io/grf9p/. A preprint of this paper was posted on PsyArxiv at https://psyarxiv.com/ureqg/.

Mayank Agrawal contributed equally to formal analysis, software, and visualization. Thomas L. Griffiths contributed equally to resources, Mayank Agrawal, Joshua C. Peterson, Jonathan D. Cohen, and Thomas L. Griffiths contributed equally to conceptualization, funding acquisition, writing–review and editing. Mayank Agrawal, Jonathan D. Cohen, and Thomas L. Griffiths contributed to investigation and writing–original draft equally. Mayank Agrawal and Thomas L. Griffiths contributed equally to methodology. Mayank Agrawal and Joshua C. Peterson contributed equally to validation and data curation. Jonathan D. Cohen and Thomas L. Griffiths contributed equally to project administration and supervision.

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immediate rewards for greater long-term benefits, and that this proclivity can be predictive of other real-world behaviors. Behavioral scientists refer to this form of decision-making as an intertemporal choice (ITC; Samuelson, 1937; Ainslie, 1975; Laibson, 1997; Frederick et al., 2002), and have studied it using tasks in which people must decide between receiving a smaller, sooner outcome versus a larger, later outcome (e.g., $ 5 today vs. $ 10 tomorrow). A consistent finding is that an individual's choices in such paradigms can be predictive of behaviors such as alcohol consumption (Vuchinich & Simpson, 1998), drug use (Kirby et al., 1999), grades (Kirby et al., 2005), texting while driving (Hayashi et al., 2015), and smoking (Ohmura et al., 2005).

Stress has been hypothesized as one variable that affects ITC behavior, with greater stress being proposed to lead to more impulsive behavior (Haushofer & Fehr, 2014). However, the evidence for this has largely been mixed (Delaney et al., 2014; Haushofer et al., 2013; Kimura et al., 2013; Lempert et al., 2012; Riis-Vestergaard et al., 2018) and the specific paradigms have often been restricted to artificial laboratory settings. In the study reported here, we took the opportunity to evaluate whether a natural stressor, the COVID-19 pandemic (Byrne et al., 2021; Carstensen et al., 2020), modulated ITC decisions. Furthermore, we hypothesized that mitigation behavior (i.e., the extent of social distancing and mask use) during the pandemic might also reflect a form of ITC: quicker and more aggressive adoption of mitigation behaviors, though expensive in the short-term, is more likely to lead to better long-term prospects (i.e., reduced exposure to the virus). Motivated by these considerations, we conducted four large-scale experiments over the course of the COVID-19 pandemic, in which we collected participants' responses to Money Earlier or Later (MEL) decisions (Frederick et al., 2002; Marzilli Ericson et al., 2015) as well as self-report indicators of stress and mitigation.

Method

Participants

Four large-scale experiments were conducted via Amazon's Mechanical Turk with the recruitment of participants in the United States via CloudResearch (Litman et al., 2017) on March 26, 2020 ($N = 3, 335$); April 15, 2020 ($N = 3, 195$); June 30, 2020 ($N = 3, 216$); and November 2, 2020 ($N = 3, 160$). Each of these samples included participants from all 50 states and the District of Columbia, with ages varying from 18 to 89 (see the online supplemental material for detailed demographic analyses and information regarding participant overlap). The experiments were conducted until every unique MEL problem specification (defined below) received 20 responses. Participants were required to have received at least a 95% approval rate on a minimum of 100 tasks. Once a participant completed one experiment, they were emailed at the start of subsequent experiments to encourage repeated measures at different time points throughout the pandemic. The online supplemental material outlines two control experiments validating the experimental paradigm and the use of this crowdsourcing service.

This study was approved by the Institutional Review Board at Princeton University. All participants provided informed consent and were compensated $ 2.50 for each experiment.

Materials and Procedure

Participants made choices in 200 MEL scenarios. Following the format of Marzilli Ericson et al. (2015), participants were randomly placed into one of the five framing conditions defined below:

1. **Absolute Difference, Delay Framing:**
   $5 today versus $5 plus an additional $5 in 4 weeks
2. **Relative Difference, Delay Framing:**
   $5 today versus $5 plus an additional 100% in 4 weeks
3. **Standard Money Earlier or Later (MEL) Format:**
   $5 today versus $10 in 4 weeks
4. **Absolute Difference, Speedup Framing:**
   $10 in 4 weeks versus $10 minus $5 today
5. **Relative Difference, Speedup Framing:**
   $10 in 4 weeks versus $10 minus 50% today

One hundred and ninety-five unique decisions were then sampled from the problem parameters:

1. **Absolute Value Difference:**
   $ 0.10, $ 0.50, $ 1.00, $ 2.00, $ 5.00, $ 10.00, $ 25.00, $ 50.00, $ 100.00, $ 500.00, $ 1, 000.00
2. **Relative Value Difference:**
   1%, 5%, 10%, 25%, 50%, 100%, 200%, 300%
3. **Start Time:**
   today, 1 day, 2 days, 4 days, 7 days, 14 days, 21 days, 50 days
4. **Time Difference:**
   1 day, 2 days, 4 days, 7 days, 14 days, 21 days, 50 days

For example, if the absolute value difference was $ 5.00, the relative value difference 100%, the start time 2 days, the time difference 7 days, and the framing condition standard MEL format, then the participant was asked to choose between $5 in 2 days and $10 in 9 days. Responses across the five framing conditions collapsed prior to analyses.

An additional five dilemmas were included in which the sooner reward was larger and the later reward was smaller. These served as attention checks, in which failure was defined as choosing the smaller, later option, and were added to the original 195 dilemmas for a total of 200 dilemmas. For any given dataset, participants were excluded from subsequent analyses if they (a) failed any of the five attention checks; (b) always chose the larger, later option; or (c) always chose the smaller, sooner option.

Then, to collect stress measures among our population, we asked participants variants of the principal question of the annual Stress in America survey conducted by the American Psychological Association (American Psychological Association, 2007):

> On a scale of 1–10 where 1 means you have "little or no stress" and 10 means you have "a great deal of stress," how would you rate your current level of stress about
>
> 1. the health of yourself and your friends/family?
> 2. the finances of yourself and your friends/family?
> 3. the upcoming U.S. presidential election?

The election question was only asked in the November dataset.

Second, to assess mitigation behavior, we asked:

Which best describes how your behavior has changed as a result of the coronavirus precautions? (single choice)

- No change
- Social distancing (e.g., maintaining 6 feet of distance), but otherwise no change
- Self-quarantined except for buying essentials (food, supplies, etc.)
- Completely self-quarantined (relying on delivery)

We collected mask-use data in the last two datasets:

Which best describes your use of masks? (Single choice)

- Always, when outside home
- When close to people or inside buildings
- Only inside high-risk environments (such as hospitals)
- Never

Last, to gauge predictions about increases in infections, we asked:

The current number of confirmed coronavirus (COVID-19) infections in the United States is approximately X, XXX as of today. What would you estimate this number to be:

Tomorrow ______________________
One week from now ______________________
One month from now ______________________

The estimated number of confirmed coronavirus infections in the United States was provided by the Johns Hopkins Coronavirus Resource Center.[1] These prediction data have not been analyzed.

Computational Analyses

Discount rates were inferred using the SciPy (Virtanen et al., 2020) brute optimize functionality. The algorithm first computes a grid search over the parameter space and then finishes with a (default) downhill simplex algorithm. Discounting models were optimized to maximize log-likelihood, and hence area under the receiver operating characteristics curve (AUC). Table 7 in the online supplemental material reports the average AUCs across models.

Linear and (ordered) logistic regression analyses were done using the *brms* package (Bürkner, 2017), which relies on a Stan (Carpenter et al., 2017) backend. Default noninformative priors were used in the linear regression analyses. For the (ordered) logistic regression analyses, default priors were used when predicting the extent of social distancing. Predicting mask use had convergence issues with default priors, and we thus added three standard priors: $\mathcal{N}(0, 1)$ for coefficients, Student's $t(3, 0, 1)$ for the standard deviation, and an LKJ(3) for the correlation matrix.

Transparency and Openness

The raw choice and survey data from all four studies can be accessed through the Open Science Framework at https://osf.io/grf9p/ (Agrawal et al., 2023). This study was not preregistered due to the immediate need to begin data collection and the lack of clarity at that point concerning the duration of the pandemic. All survey materials are reproduced verbatim in the "Materials and Procedure" section.

Results

Individual Measures

Delay discounting (Ainslie, 1975; Frederick et al., 2002; Laibson, 1997; Samuelson, 1937) is the canonical framework to model decision-making in MEL paradigms. Here, the value $v(\cdot)$ of option o with reward r and time delay t is formalized as

$$v(o) = r \cdot f(t) \tag{1}$$

where $f(t)$ represents the discount factor. A hyperbolic function (e.g., Ainslie, 1975) is used to define the discount factor

$$f(t) = \frac{1}{1 + \delta t} \tag{2}$$

Larger discount rates (i.e., value of δ) are a preference for the smaller, sooner reward and thus indicate greater impulsivity. Once $v(o_1)$ and $v(o_2)$ are computed, the participant selects o_1 as their choice c with probability

$$P(c = o_1 | v_{o_1}, v_{o_2}, \tau) = \frac{1}{1 + e^{-\tau(v_{o_2} - v_{o_1})}} \tag{3}$$

Parameters δ and τ can be fit with respect to each participant or once across an entire dataset.[2] For our purposes, we fit discount rates for each individual's set of decisions. Discount rates were then log-transformed for all analyses in order to normalize the variable. We also excluded the outer 5% (i.e., include those between the 2.5th and 97.5th percentiles) as a safeguard against any outliers.

The top panel of Figure 1 reports the results of discount rates and stress measures in our four collected datasets. Discount rates oscillated between higher and lower values, whereas the stress measures steadily decreased except for a small uptick in November (immediately prior to the 2020 U.S. election). The middle and bottom panels of Figure 1 report the mitigation behavior of participants. Most participants were self-isolating (i.e., not leaving their home except for purchasing essentials) during the beginning stages, and shifted toward resuming normal activities with social distancing in the later months. Mask use (which was only collected for the last two datasets) was consistently high, with participants increasing use in the last dataset.

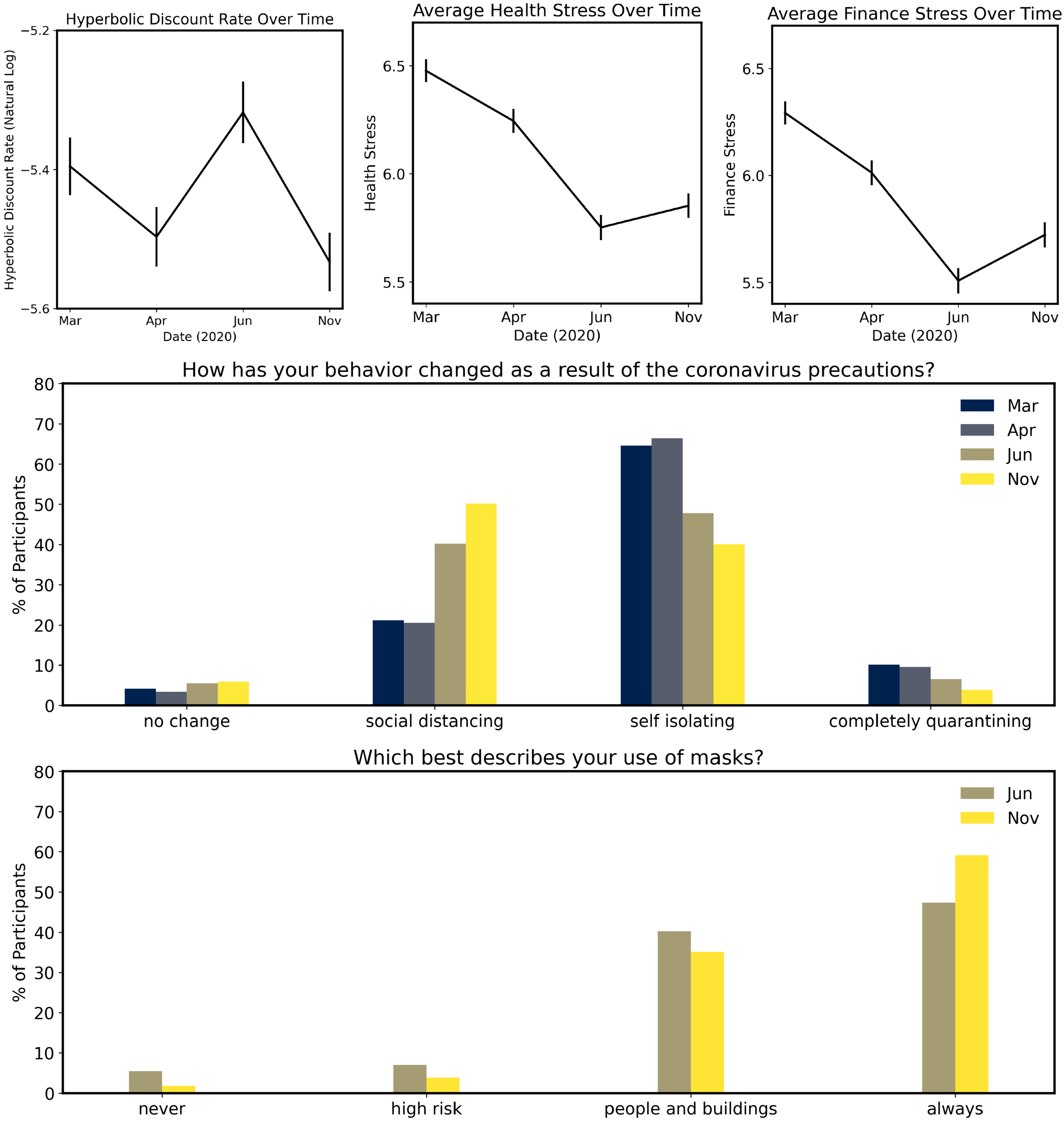
Correlations Between Measures

Next, we evaluated the extent to which discount rates correlated with self-reported stress measures. The top panel of Figure 2 shows the average (log-transformed) discount rate for each level of stress measure. A hierarchical Bayesian linear regression model specifying individuals as random effects revealed a significant positive relationship between the discount rates and health stress ($\beta = 0.02$, 95% confidence interval [CI] [0.00, 0.04]), and

[1] https://coronavirus.jhu.edu/.

[2] Alternate delay discounting models in the literature include exponential (Samuelson, 1937) and quasi-hyperbolic discounting (Laibson, 1997). Following the recent standard in the ITC literature (e.g., Hardisty et al., 2011), we focus on the hyperbolic discount rates.

Figure 1
Measures Throughout the COVID-19 Pandemic

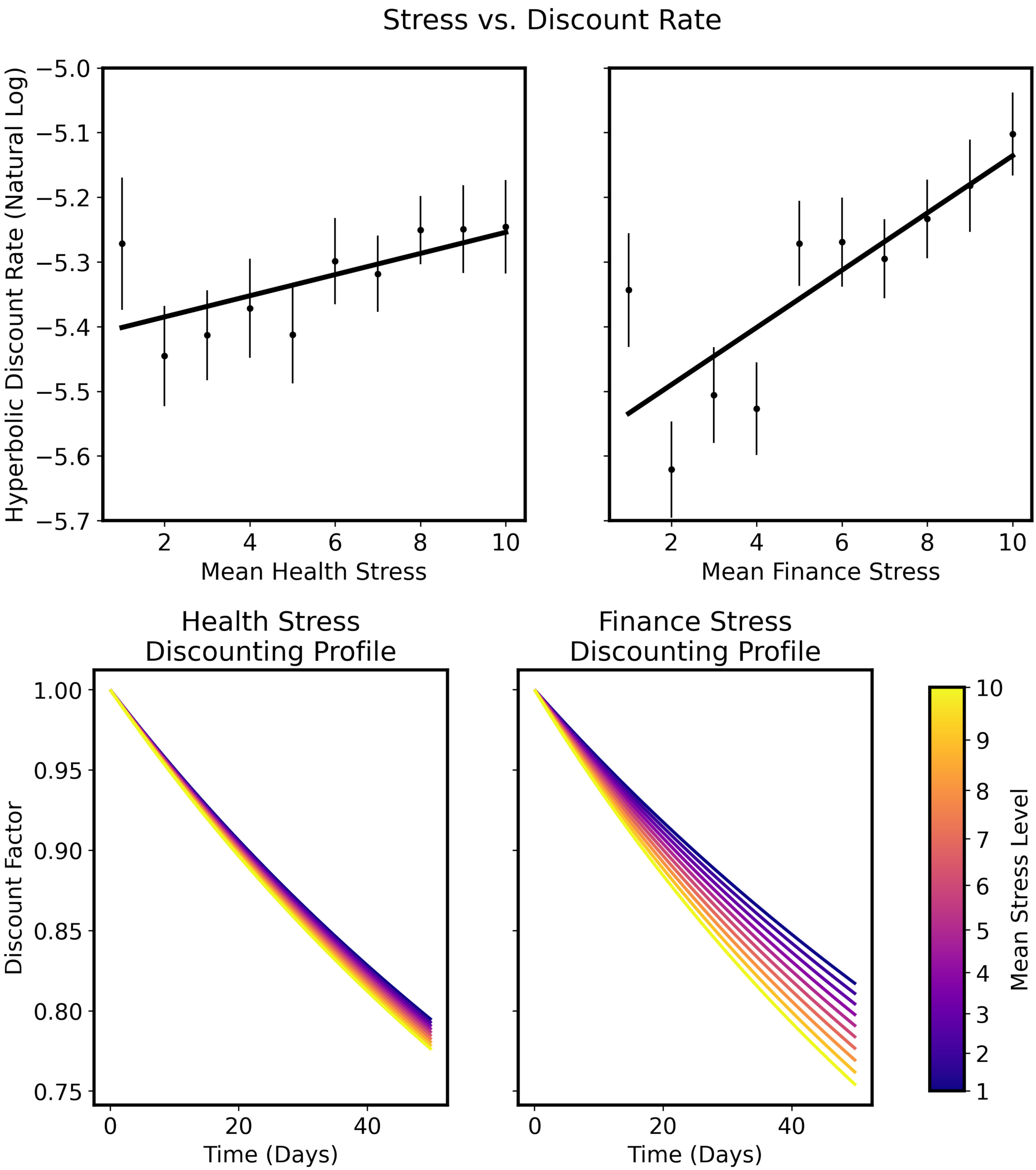


Note. (Top) Average discount rate, health, and financial stress measures over time. (Bottom) Distribution of mitigation behaviors over time. See the online article for the color version of this figure.

between discount rates and financial stress (β = 0.04, [0.03, 0.06]). Thus, we find that higher impulsivity is indeed associated with greater stress, aligning with previous work suggesting that stress can modulate ITC behavior (e.g., Haushofer & Fehr, 2014). This effect size, seemingly small but significant with a sufficiently large sample, may help account for the disparate findings in the literature relating stress with discount rates (Delaney et al., 2014; Haushofer et al., 2013; Haushofer & Fehr, 2014;

Figure 2

(Top) Average Discount Rates for Each Response Level of Stress. (Bottom) Average Hyperbolic Discount Profiles for Each Response Level of Stress



Note. See the online article for the color version of this figure.

Kimura et al., 2013; Lempert et al., 2012; Riis-Vestergaard et al., 2018).[3]

To most accurately interpret the effect size, Figure 2 plots the individual discount curves (i.e., Equation 2) for the mean discount rate at each level of stress. These curves allow us to predict how ITC decision-making is expected to change as a function of stress level. Consider the option of choosing between $ 100 today versus $ 110 in 20 days. Those with the highest health stress are predicted to choose the larger, later option 42% of the time, whereas the least stressed individuals are predicted to choose it 71% of the time. Individuals with the highest financial stress are predicted to choose the larger, later option 18% of the time, whereas the least stressed are predicted at 88%. (These predictions assume the value of τ from Equation 3 is 1.0, which was the median across the dataset).

Finally, we evaluated the extent to which stress measures and discounting model parameters predict mitigation behavior throughout the pandemic. The idea here is that, if social distancing and/or mask use reflects a delayed gratification decision, we should see lower discounting (less impulsive) individuals take more aggressive precautionary measures. Mitigation behaviors were categorical and likely to be unevenly spaced, and thus we modeled responses with a Bayesian ordered logistic regression model (e.g., Liddell & Kruschke, 2018). First, we linearly mapped the independent variables of interest onto a one-dimensional infinite latent space and then split this space into intervals that defined the (ordered) categorical responses. We let the intervals be modulated by random effects based on the time of collection in order to allow for changing mitigation norms over time while maintaining the qualitative analysis of interest. Individuals were also modeled as random effects.

Table 1 reports model results when using the variables of interest (discount rate, inverse temperature, health stress, and financial stress) to predict mitigation behavior.[4] We find that discount rate and health stress jointly predict the extent of social distancing. A lower discount rate (less impulsivity) predicts more aggressive mitigation behavior, while greater health stress predicts more aggressive mitigation behavior. (This relationship between impulsivity and mitigation behavior makes sense under the interpretation that more aggressive mitigation behaviors are more costly in the short-term, but more valuable in the long run). These effects of our predictors are especially intriguing since we previously demonstrated in Figure 2 that they are positively correlated. One conjecture that may help elucidate these findings is that (health) stress is a high-variance construct that directly affects mitigation behavior, whereas discount rates are a lower-variance construct that has a broader impact on an individual's behavior. Another possible interpretation is that the relationship between stress and social distancing is affected by an individual's "trait"-based impulsivity. Our paper focused mainly on the influence of "state"-based ITC-making, but a large debate in the literature aims to discern to what extent these decisions are "state"-based versus "trait"-based (Augustine & Larsen, 2011; Lempert et al., 2012; Odum, 2011). Future work can combine hierarchical modeling with mediation analyses to shed light on some of these interpretations.

Furthermore, we note that while health stress and financial stress independently predict mask use, only the effect of health stress remains statistically significant when put in a joint model. Discount rates did not significantly predict mask use, even when used as the sole predictor. While our experimental results cannot certainly demonstrate why, one conjecture is that mask use is largely affected by politics (e.g., Byrne et al., 2021; Xu & Cheng, 2021).

Tables 8–11 in the online supplemental material report the same analyses as Table 1, but for each individual dataset. Effect sizes remained similar, but CIs were wider, presumably due to the decreased sample size.

Discussion

The relationship between stress and ITC has been a longstanding question in the literature on human decision-making with mixed results (Delaney et al., 2014; Haushofer et al., 2013; Haushofer & Fehr, 2014; Kimura et al., 2013; Lempert et al., 2012; Riis-Vestergaard et al., 2018). We leveraged a natural stressor (the COVID-19 pandemic) and large-scale experiments to uncover a small but significant positive relationship between log-transformed discount rates and perceptions of health and financial stress. We used example MEL dilemmas to illustrate the magnitude of this effect, demonstrating how each increase in stress level affects the aggregate response and thus how extreme stress can have a meaningful effect on the extent to which people discount future rewards when making financial decisions.

Exploring our research question during a pandemic also provided an opportunity to contribute to the existing body of work suggesting that ITC behavior can be predictive of real-world behaviors (Byrne et al., 2021; Hayashi et al., 2015; Kirby et al., 1999, 2005; Ohmura et al., 2005; Vuchinich & Simpson, 1998). We found that the degree of social distancing, but not mask use, was statistically significantly correlated with discount rates in financial decision-making. This result may be of interest to public health officials as they try to plan responses for similar situations in the future. In particular, the stresses associated with a pandemic might be expected to attenuate future-oriented thinking, leading people to make decisions that favor short-term payoffs. Planning for such shifts in decision-making will result in more effective modeling and interventions.

Our experimental paradigm was not designed to identify the mechanistic relationship between stress, on the one hand, and health and/or financial impulsivity on the other hand. For example, higher stress may globally increase both health and financial impulsivity, or it might be the case that a (health) stressor may require the participant to allocate resources away from (financial) decisions that would correspondingly be measured with increased (financial) impulsivity. A more fine-grained, mechanistically designed study is needed to comment on this distinction. Such a study might control participants' stress levels and manipulate them in both directions and measure the corresponding effect on impulsivity. To determine the extent to which participants actively trade-off between health and financial concerns, a study could create a metric of this allocation and then determine how the metric changes with different stressors.

[3] We also found positive, but not statistically significant, relationships between the inverse temperature τ and health stress ($\beta = 0.02$, 95% CI [− 0.00, 0.05]), and between inverse temperature and financial stress ($\beta = 0.01$, [− 0.01, 0.04]). The closer the inverse temperature is to zero, the more stochastic the participant is.

[4] To get a sense of model fit, we report the leave-one-out (LOO) cross-validation score. The numbers are only meant to be compared relatively, where a lower number indicates a better model fit.

Table 1
Different Model Fits for Predicting Mitigation Behavior

Variables	Social distancing			Mask use		
	Coefficient	95% CI	LOO	Coefficient	95% CI	LOO
Discount rate	− 0.04	[− 0.08, − 0.01]	14,562	0.05	[− 0.01, 0.11]	7,056
Inverse temperature	− 0.00	[− 0.02, 0.01]	14,569	0.00	[− 0.04, 0.04]	7,048
Health stress	0.30	[0.27, 0.34]	14,125	0.42	[0.35, 0.49]	6,824
Financial stress	0.14	[0.11, 0.17]	14,481	0.18	[0.12, 0.24]	7,004
Discount rate	− 0.05	[− 0.09, − 0.02]	14,122	0.03	[− 0.04, 0.09]	6,824
Health stress	0.31	[0.27, 0.34]		0.42	[0.35, 0.49]	
Inverse temperature	− 0.01	[− 0.03, 0.01]	14,141	− 0.02	[− 0.06, 0.02]	6,800
Health stress	0.30	[0.27, 0.34]		0.43	[0.36, 0.51]	
Discount rate	− 0.05	[− 0.09, − 0.02]	14,478	0.04	[− 0.03, 0.10]	7,001
Financial stress	0.15	[0.12, 0.17]		0.18	[0.12, 0.24]	
Inverse temperature	− 0.01	[− 0.03, 0.01]	14,484	− 0.01	[− 0.05, 0.03]	6,981
Financial stress	0.14	[0.11, 0.17]		0.19	[0.13, 0.25]	
Health stress	0.30	[0.26, 0.33]	14,126	0.46	[0.38, 0.55]	6,782
Financial stress	0.01	[− 0.02, 0.04]		− 0.06	[− 0.12, 0.01]	
Discount rate	− 0.06	[− 0.09, − 0.02]	14,128	0.03	[− 0.03, 0.09]	6,800
Health stress	0.30	[0.26, 0.33]		0.46	[0.38, 0.55]	
Financial stress	0.01	[− 0.02, 0.04]		− 0.06	[− 0.12, 0.01]	
Inverse temperature	− 0.01	[− 0.03, 0.01]	14,124	− 0.02	[− 0.06, 0.02]	6,758
Health stress	0.30	[0.26, 0.33]		0.48	[0.39, 0.58]	
Financial stress	0.01	[− 0.02, 0.04]		− 0.06	[− 0.12, 0.01]	

Note. CI = confidence interval; LOO = leave-one-out.

Furthermore, while the premise of this article is that social distancing and/or mask use reflect a delayed gratification choice, it is possible that the opposite is true: that is, increasing infection probability early in order to develop long-term immunity.[5] We believe this is unlikely to be true of the wider population given public messaging on COVID-19 mitigation strategies and evidence of the highly adverse effects of infection with the initial variants of the virus, coupled with concerns about the long-term health effects. That said, our paradigm cannot distinguish between these two interpretations, and we believe it is an important distinction to investigate further, especially because there may be specific groups in the population that did use this logic. Eliciting responses for people's decision to socially distance and/or use masks, and then separately analyzing the two different approaches may help find a stronger relationship between delayed gratification and mitigation behavior.

Having collected data at multiple points during the pandemic also creates the opportunity to relate the psychological variables we measured to broader social and economic trends. For example, personal savings increased early in the pandemic (Cox et al., 2020)—a measure that is affected by factors such as the inability to spend money in a variety of traditional ways, but is also likely to be related to ITC (Landsberger, 1971). Teasing apart the influences of personal and situational factors influencing these trends is an important direction for future work.

We hope these results further motivate interest in discount rates as an important psychological variable to study. It was not surprising that financial stress had a stronger correlation with discount rates than health stress. But, the fact that the discount rate maintained a statistically significant influence when put in a joint model predicting social distancing behavior suggests that the metric encodes unique information that is not captured in the stress measures. These results are consistent with the idea that there may be a psychological factor underlying ITC decision-making that has a broader impact on behavior (e.g., Becker et al., 2012; Benjamin et al., 2020; Coile et al., 2002; Golsteyn et al., 2014; Viscusi & Moore, 1989).

Constraints on Generality

Our study was interested in how the U.S. population responded to the COVID-19 pandemic. We thus collected four online large-scale samples that were generally representative of the U.S. population. With the constraint that our participants must be adults, our sample closely tracked the U.S. Census (see the online supplemental material). We are not sure to what extent our data (ITC, mitigation behavior, and stress levels) generalizes to participants in other countries, but we conjecture the statistical relationships between the data variables will generalize in directionality.

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[5] We thank multiple reviewers for raising this interpretation.

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