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Optimism Bias and Perceptions of Behavioral Factors for Preventing Severe COVID-19 Complications

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Abstract
We examine the presence of optimism bias in individuals' perceptions of factors associated with preventing severe complications from COVID-19. Consistent with optimism bias, we find for several factors, that engaging in a behavior is associated with viewing it as more influential for preventing illness severity. Specifically, we find that individuals who exercise more, eat healthier, and take dietary supplements rate these behaviors as more important for preventing severe complications from COVID-19.

JEL Classification: I12; D9

Keywords
COVID-19 — optimism bias — perceived-risk

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Introduction

The outbreak of 2019 coronavirus disease (COVID-19) caused by the novel coronavirus known as SARS-CoV-2 (severe acute respiratory syndrome-coronavirus 2) led to a global public health emergency. The initial outbreak began in late 2019 in Wuhan, China and by March 11, 2020 the World Health Organization (WHO) announced its status as a global pandemic.[1] As of October 26, 2022, almost three years into the pandemic, there were 634,021,228 cases and 6,586,568 deaths from COVID-19 worldwide. (Worldometer Staff, 2022).

Since the initial outbreak, many nations put various public protection measures in place such as strict lockdowns, mask mandates, and emphasized adherence to public health guidelines such as hand washing and social distancing to curb the staggering health and economic effects of the crisis (see, e.g., Ozili, 2020 for Africa; Karunathilake, 2021 for Asia; Alifano et al., 2020 for Europe; and Martin et al., 2020 for the US). However, the success of public health measures depends crucially on adherence to such guidelines by the public. Research focused on understanding motivating factors of prevention in previous pandemics have highlighted perceived susceptibility or risk as a major determinant for adoption of prevention behavior (Agüero et al., 2011; Bish & Michie, 2010; Park et al., 2010).

However, a hurdle may exist in the way individuals process information regarding risk. Many psychological influences bias perceptions of risk. For example, *confirmation bias* may influence the public to interpret information in a manner that promotes their existing perceptions of risk (Lord Ross & Lepper, 1979; Plous, 1991). Another example is the *availability heuristic* where individuals judge an outcome to be more likely due to the fact a similar event is easily recalled from memory (Tversky & Kahneman, 1974). Finally, *anticipatory utility* predicts individuals may take costly actions to avoid useful information that would reveal lower future utility (Ganguly & Tasoff, 2017).[2]

The ultimate goal is to understand the psychological processes that determine individuals' perceptions of risk so policymakers can implement successful interventions. Behavioral economics has been effective at analyzing risky health behaviors such as drug addiction, smoking, alcohol consumption, poor diet, physical inactivity, etc. and helping to implement behavior change programs (Bickel et al., 2016). With respect to effective communication on health outcomes, there has been a focus on message framing, specifically, comparing messages framed in terms of gains or losses (Farrell et al., 2001; Ferguson et al., 2005; Detweiler et al., 1999; Schneider et al., 2001).[3]

Here, we study a particularly relevant psychological factor for COVID-19 risks, optimism bias. Optimism bias is the tendency of individuals to underestimate the probability of negative events occurring when compared to one's peers. Its presence may be harmful in the current pandemic where

[1] WHO Director-General's opening remarks at the media briefing on COVID19 - March 2020.

[2] This is in no way an exhaustive list of psychological mechanisms that may affect individuals' perceptions of COVID-19 risk. Other factors include *exponential-growth bias* (Stango & Zinman, 2009), *present bias* (Thaler & Shefrin, 1981), and *limited attention* (Lacetera et al., 2012), to name a few.

[3] There have been other studies aimed at studying effective communication in the presence of psychological factors concerning risk that do not focus on gains and losses. One such example is van der Linden et al. (2015) who found that highlighting consensus among medical scientists increased perceptions of childhood vaccine safety.

individuals exhibiting optimism bias would be less likely to adhere to health guidelines due to their lower perceived risk, which can be detrimental behavior for themselves and others.

Several studies done on COVID-19 suggest that optimism bias is present. One international study from Pascual-Leone et al. (2021) showed that in all countries surveyed people are more concerned about the health of others compared to their own health. Another study done in the UK by Asimakopoulou et al. (2020) showed that a strong optimism bias was present when asked about probabilities related to perceived controllable events. Lastly, a study done by Druică et al. (2020) comparing Romania and Italy, identified optimism bias in both countries and found optimism bias depends on self-reported health status and increases with age. While these studies provide support of the existence of optimism bias during the COVID-19 pandemic, they lack more detailed information regarding the source of the bias.

Our goal is to attempt to measure optimism bias in a real and unique way. Is the reason that people exhibit optimism bias due to them latching onto personal behaviors that make their risk seem lower? In other words, individuals may believe behaviors or actions they take (do not take) are more (less) effective at reducing the risks associated with COVID-19. We examine how exercise, diet, alcohol consumption, smoking, supplement use, and sleep are related to individuals' perceptions of these factors as measures preventing illness severity. It is important to note that this is a different mechanism than people engaging in a particular behavior because they believe it is more preventative. If someone believes exercise is beneficial for preventing serious symptoms of COVID-19, they may be inclined to exercise more, which is not optimism bias. It should also be noted that this is a different mechanism than people engaging in negative behaviors as a result of the pandemic, such as increased amounts of food consumption/addiction, smartphone usage, and video game usage as some research has found (Attanasi et al., 2021; Cherikh et al., 2020).

Method

Survey Design

We conducted an online cross-sectional national U.S. survey between March 5 and March 31, 2021, a little over a year into the COVID-19 pandemic. The final survey sample included data from 602 adults. As shown in Table 1, the sample resembles the U.S. population demographic profile for the majority of characteristics measured.

The survey was comprised of three sections: Part I – Demographics and general health, Part II – Rating risk characteristics for COVID-19 illness severity, and Part III – Rating prevention factors for COVID-19 illness severity.[4] The order in which the survey sections appeared was randomized among participants to ensure no priming of the participants occurring related to question order.

[4]The full survey is available upon request from the authors.

As for Part I, in the demographic portion, respondents were asked to answer questions regarding their age, sex, ethnicity, education level, income level, marital status, citizenship status, political affiliation, and geographic location. The general health portion inquired about each participant's height and weight to determine their body mass index (BMI), average number of days exercised in a week, number of alcoholic drinks consumed in the past week, smoker status, hours of sleep the previous night, diagnosed medical conditions, and dietary supplement usage. Participants were also asked what they ate for dinner the previous night. These meal descriptions were then given a rating score on a 1-3 scale: 1=unhealthy, 2=neutral, 3=healthy. The food pyramid and the Environmental Working Group (EWG) food rating website was used as guidance to score the meals (EWG-Environmental Working Group, 2014). Furthermore, respondents were asked if they had significantly changed their exercise habits, diet, sleep habits, alcohol consumption, smoking habits, or other behaviors; however, they were not asked how these behaviors changed. For example, we do not know if an individual exercised more or less, just if they changed their behavior.

In Part II of the survey, participants were asked to allocate points to various potential risk characteristics they believe increase COVID-19 illness severity such as age, race, gender, and a list of pre-existing medical conditions. In Part III they were asked to allocate points to potential prevention factors they believe reduce COVID-19 illness severity such as diet, exercise, sleep, alcohol consumption, smoker status, use of dietary supplements, and no pre-existing conditions. Participants had to allocate all 100 points in each question and were directed to allocate more points to the factors they believed were most important. To analyze the presence of optimism bias, we focus on responses regarding possible prevention factors for illness severity. Our five behavioral factors of interest include exercise, diet, alcohol consumption, smoking, and dietary supplement use.[5] The allocation of points allows measurement not only of which factors participants deemed important (a ranking of factors), but also allowed a comparison of how important certain factors are in relation to others (the magnitude of differences). In the analyses that follow, we use both the reported number of points allocated to each factor as well as the points scaled relative to the highest rated factor. The scaled points allow for comparisons across individuals; telling us how beneficial a factor is perceived to be relative to the factor the individual deems most important.

Statistical Methods

Our initial analysis for each factor is a simple descriptive analysis, which we present graphically. For the rating and scaled rating, we present averages at the various levels of the corresponding behavior. We also examine the probabilities of rating a factor as the most or least preventative. For these

[5]We also conduct the statistical analyses on sleep; however, due to self-reported hours of sleep the previous night being a very noisy measure, we omit the analysis here. The analyses are available from the authors.

Variables	Survey Data	U.S. Population Data
Female Population	50.17%	50.5%
Male Population	49.67%	49.5%
Population age 18-34	25.42%	29.5%
Population age 35-54	49.17%	32.7%
Population age 54-64	9.14%	16.8%
Population age 65+	16.28%	21.1%
Asian or Asian American	4.15%	5.9%
Black or African American	11.46%	13.4%
Hispanic/Latino	7.48%	18.5%
White	74.25%	76.3%
No H.S. diploma	1.83%	9%
H.S. diploma or GED	28.57%	27.7%
Some college no degree	22.26%	15.2%
Associante's degree	10.8%	10.6%
Bachelor's degree	23.59%	23.4%
Master's degree	9.3%	10.5%
Doctorate degree	2.49%	2.1%
Professional degree (JD, MD)	1.16%	1.5%
Income $0-$49,999	49.2%	37.1%
Income $50,000-$99,999	36.2%	28.8%
Income $100,000+	14.6%	34.1%
Married - Male	51.2%	49%
Married - Female	49.3%	46.3%
Single - Male	48.8%	51%
Single - Female	50.7%	53.6%
Not a U.S. Citizen	2.16%	6.63%
Republican	31.89%	29%
Democrat	38.7%	33%
Independent	24.25%	34%
Other or No Political Affiliation	5.15%	4%
Urban/City	26.08%	27%
Suburban	51.16%	52%
Rural	22.43%	21%

Sources: Bucholtz, 2020; Gramlich, 2020; US Census Bureau, 2020.

Table 1. Comparison of Survey Sample and U.S. Population Demographics

probabilities, we present proportions of the respondents giving a factor the highest or lowest rating. However, differences in beliefs about prevention may not be due to optimism bias, but rather from individuals changing their behavior to engage in activities they believe are more preventative. Therefore, we present the graphical evidence for those who have changed the relevant behavior during the pandemic and those who have not separately.

While the graphs are illustrations of associations, we cannot tell if the associations are simply noise; this is especially true for binary actions. Therefore, we analyze each factor with regression methods. Due to the inability to compare raw ratings across individuals, we focus our regression analyses on scaled ratings.[6] In the Online Appendix, we also use Tobit estimation, since scaled ratings are bound between zero and one. Furthermore, we examine the probabilities of giving the highest and lowest rating via logistic regression. All of our estimations include whether or not the individual changed the underlying behavior during the pandemic and the following covariates sex, age, race, BMI, education, income, marital status, children, and political preference.

Results

Descriptive statistics are presented in Table 2 for ratings and behavior data. On average, diet is the most highly rated factor for preventing serious complications from COVID-19, followed by exercise. Interestingly, alcohol consumption is the lowest rated factor. In fact, 58% of respondents rated it as the least important factor. Similar proportions of individuals changed their exercise, diet, supplement use, and sleep habits;

[6] In the Online Appendix, we also conduct our regression analyses on the sample of individuals who did not change their behavior during the pandemic.

however, fewer people reported changing their drinking and smoking behavior. In terms of behaviors, the average number of days of exercise per week is 3.2. The proportions of individuals who ate a healthy or neutral final meal the previous day are approximately equal, and roughly double the proportion eating an unhealthy meal. 31% of survey respondents reported smoking, and 53% regularly took supplements.

Exercise

We begin by analyzing perceptions of exercise and exercise frequency. We present graphical results in Figure 1. Individuals who exercise more days per week believe that exercise is more effective at preventing serious complications from COVID-19. A similar pattern is evident when considering any behavioral change in exercise during the pandemic. From our graphical results in Figure 2, those who exercise more are more likely to rate exercise as effective overall and relative to their perceived most effective factor, are more likely to rate exercise as the most preventative factor, and are less likely to rate exercise as the least important factor. This holds regardless of whether there was or there was not a behavioral change in exercise during the pandemic.

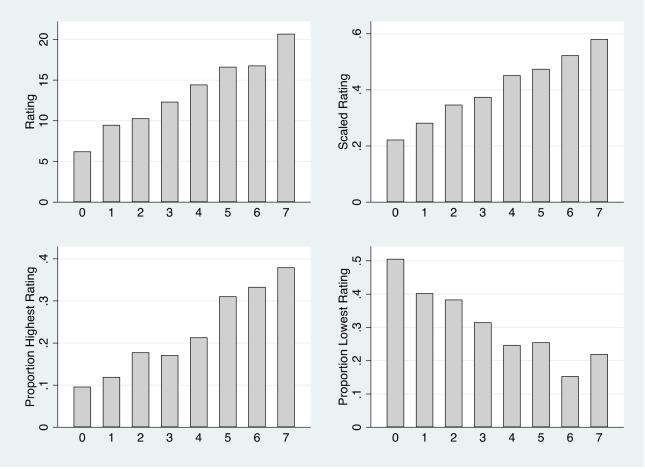

Figure 1. Results for Exercise

To further examine the connection between exercise frequency and perceptions of risk, we present results from our regression analyses for the scaled rating. Scaled rating results are presented in column (1) of Table 3.

Even while controlling for our full set of covariates, there is a statistically significant relationship between exercise frequency and perception of importance as a preventative factor. The standardized coefficient is 0.236, suggesting a one-standard deviation increase in exercise frequency is associated with a 0.236 standard deviation increase in the scaled rating. Tobit results and logistic results for the probabilities of rating exercise as the most and least preventative factor, presented in the Online Appendix, are consistent with our OLS results. Additionally, since days of exercise per week

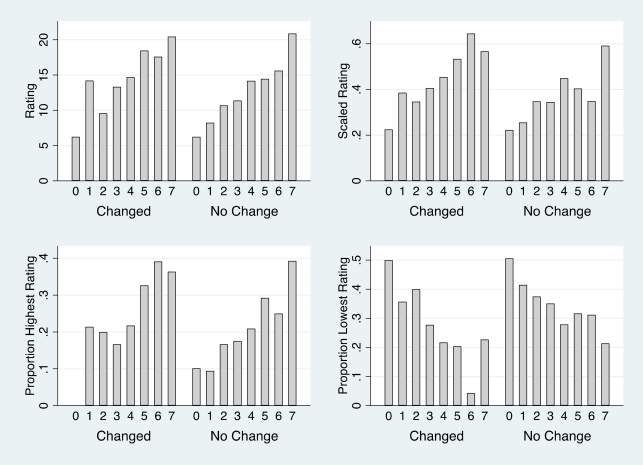

Figure 2. Results for Exercise by Behavioral Change during the Pandemic

is limited between zero and seven, we present results using a set of binary variables, rather than treating it as continuous, in the Online Appendix. The results are consistent with our previous conclusions: the more frequent a person exercises the more preventative they believe it is.

Diet

The second factor we analyze is diet. We have a noisy measure of diet since our measure is based on a single meal and classified into only one of three categories. However, the quality of the previous nights' dinner may still contain useful information on a person's overall diet. Our graphical results are shown in Figure 3 and 4. There appears to be a relationship between quality of meal and rating for diet as a preventative factor. Those who ate a healthy meal rate diet as more important than either the neutral or unhealthy group. Furthermore, the neutral group rates diet higher than the unhealthy group. This pattern holds true when examining the probabilities of rating diet as the most and least important factor. When the data are stratified based on whether or not the respondent changed their diet during the pandemic, the results remain the same.

Next, we present our regression results for diet, contained in column (2) of Table 3. There is only a marginally significant difference in scaled rating between the unhealthy and neutral groups. There is, however, a significant difference between the healthy group and the unhealthy group, but no difference between the neutral and healthy groups. The difference between healthy and unhealthy groups is equivalent to a 0.252 standard deviation change in scaled rating. Furthermore, Tobit and logistic regressions, presented in the Online Appendix, are consistent with these conclusions. Considering all the analyses for diet, we conclude that there is a relationship between quality of last meal and rating of diet as a preventative factor. Those who ate a healthier meal rated diet as more important for preventing serious complications from COVID-19.

Variables	Exercise	Diet	Alcohol	Smoking	Supplements	Sleep
Rating	12.89	19.10	5.813	11.77	8.675	11.27
	(13.75)	(19.84)	(9.277)	(13.99)	(13.19)	(13.18)
Scaled Rating	0.394	0.515	0.203	0.351	0.271	0.354
	(0.380)	(0.405)	(0.304)	(0.377)	(0.338)	(0.367)
Pr (Highest Rating)	0.211	0.347	0.0815	0.191	0.120	0.173
Pr (Lowest Rating)	0.321	0.233	0.582	0.399	0.481	0.358
Changed Behavior	0.393	0.315	0.231	0.126	0.316	0.313
Exercise	3.210					
	(2.100)					
Neutral Meal		0.392				
Healthy Meal		0.397				
Drinks per Week			1.895			
			(1.245)			
Smoker				0.311		
Supplements					0.526	
Hours of Sleep						6.784
						(1.740)
Observations	601	600	601	601	601	601

Note: Means reported with standart deviations in parentheses for continuous variables. Proportions presented for binary variables.

Table 2. Descriptive Statistics

Alcohol Consumption

Our third factor is alcohol consumption. Specifically, respondents were asked to rate the effectiveness of reduced alcohol consumption of preventing serious complications. As a result, if optimism bias were at play, we would expect those who consume more alcohol per week to respond with lower ratings. Our graphical results are presented in Figure 5 and 6. From the graphs there does not seem to be a consistent relationship between alcohol consumption and ratings. This is especially true when examining the proportions of respondents who rated reduced alcohol consumption as either the most or least important factor. Similarly, when the sample is divided based on those who changed their drinking habits during the pandemic, a similar conclusion is made, there is no easily discernable relationship between alcohol consumption and beliefs about its importance in determining severity.

Our regression results for alcohol consumption are contained in column (3) of Table 3. Treating alcohol consumption as continuous, there are no statistically significant differences in ratings depending on alcohol consumption. Furthermore, the effect size, measured using the OLS standardized coefficient, is very small; a one-standard deviation change in alcohol consumption is associated with a less than 0.01standard deviation change in ratings. Since alcohol consumption is measured in drinks per week and is categorized into five categories, we present results using binary variables for the categories in the Online Appendix. All coefficients for the binary variables are estimated to be close to zero, are not statistically significant, and there is no relationship between effect size and amount of alcohol consumption.

Smoking

Our fourth factor is smoking. Respondents indicated their beliefs about the importance of being a nonsmoker for preventing serious complications. Thus, optimism bias would manifest itself as nonsmokers providing higher ratings than smokers. Figure 7 and 8 represent our results graphically. It appears as though nonsmokers rate being a nonsmoker as more important, based on raw and scaled ratings. Nonsmokers seem to also be more (less) likely to rate being a nonsmoker as the most (least) important factor. Furthermore, when focusing on those who did not change their behavior during the pandemic, the results appear to be consistent with optimism bias.

Consistent with our graphical analysis, our results, presented in column (4) of Table 3, have the sign predicted by optimism bias. Being a nonsmoker is positively related with rating of being a nonsmoker as a preventative factor, which

Variables	**Exercise**	**Diet**	**Alcohol**	**Smoking**	**Supplements**	**Sleep**
Exercise Frequency	0.0428***					
	(0.00802)					
	[0.236]					
Neutral Meal		0.0743*				
		(0.0445)				
		[0.184]				
Healthy Meal		0.102**				
		(0.0450)				
		[0.236]				
Drinks per Week			-0.00183			
			(0.0119)			
			[-0.00748]			
Nonsmoker				0.0136		
				(0.0401)		
				[0.0362]		
Supplements					0.0790***	
					(0.0283)	
					[0.234]	
Hours of Sleep						-0.00375
						(0.00970)
						[-0.0178]
Changed Behavior	0.0723**	0.0769**	0.0697**	0.0281	0.0191	0.0616*
	(0.0345)	(0.0363)	(0.0332)	(0.0543)	(0.0320)	(0.0344)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.313**	0.695***	0.556***	0.474***	0.343**	0.362**
	(0.156)	(0.195)	(0.135)	(0.167)	(0.170)	(0.162)
Observations	601	600	601	601	601	601
R-squared	0.150	0.071	0.098	0.063	0.077	0.090

Note: Robust standard errors in parentheses.Standarized coefficients in square brackets. For binary variables standarized coefficients are for a discrete change in the variable. Covariates include sex, age, race, BMI, education, income, marital status, children, and political preference. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3. Descriptive Statistics

is consistent with our other analyses in the Online Appendix. However, our regression results also show that these apparent differences are not statistically distinguishable from zero. Similarly to alcohol consumption, not only is the relationship between smoking and perceived importance of smoking behavior statistically insignificant, the OLS point estimate is also very small, being a nonsmoker is associated with a change of only 0.0362 standard deviations in scaled rating. Therefore, while all of the estimated coefficients have the signs consistent with optimism bias, we conclude optimism bias is not affecting perceptions of COVID-19 risk associated with smoking.

Supplements

The fifth factor analyzed is dietary supplements. We present graphs for the perceived effectiveness of supplements at preventing serious complications for those who report regular supplement use and those who do not in Figure 9 and 10. Optimism bias would cause those who regularly take supplements to provide higher ratings of supplements as a preventative factor. The graphs show the supplement group provides higher ratings, and scaled ratings, on average. They are also more (less) likely to rate supplement use as the most (least) important factor. The observed graphical pattern also holds for the group of individuals who did not change their diet during the pandemic. Respondents were not directly asked about changing their behavior regarding supplement use during the pandemic; however, they were asked about changes to their

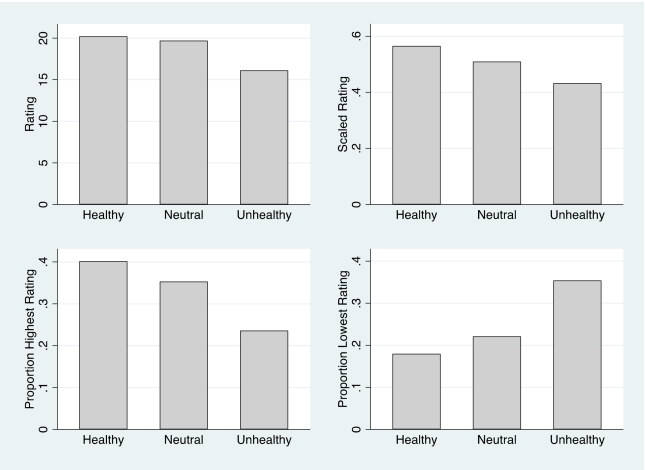

Figure 3. Results for Diet and Last Meal

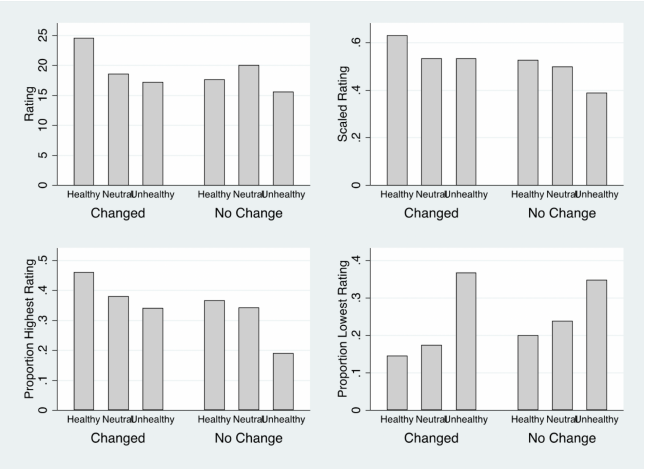

Figure 4. Results for Diet and Last Meal by Behavioral Change during the Pandemic

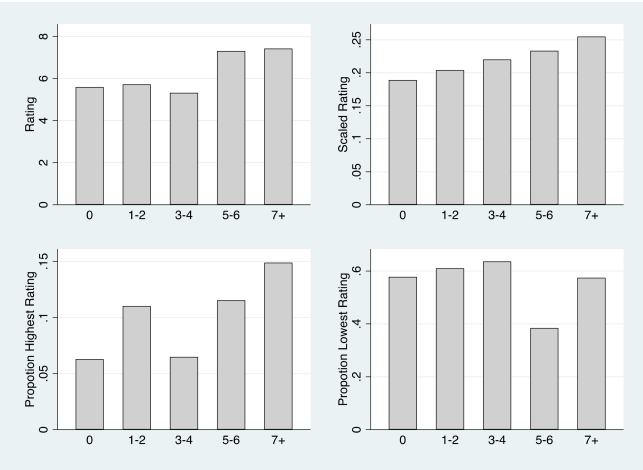

Figure 5. Results for Alcohol Consumption

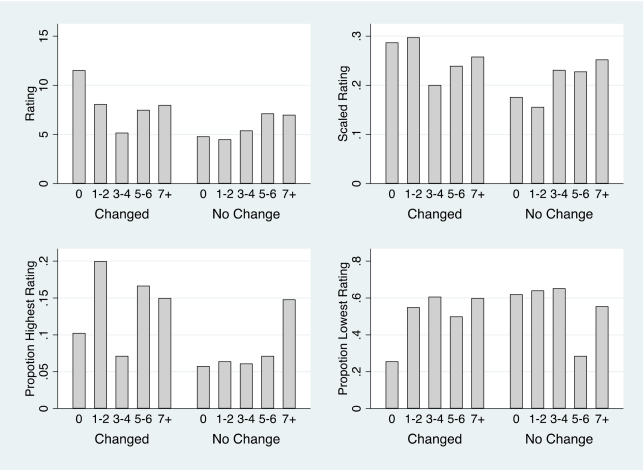

Figure 6. Results for Alcohol Consumption by Behavioral Change during the Pandemic

diet. As a result, we use dietary change as the measure of behavioral change for supplement use.

In our regression results, contained in column (5) of Table 3, we see the difference in beliefs is also statistically significant. The effect size, using OLS, is 0.234, or taking supplements regularly is associated with an increase in scaled rating of 0.234 standard deviations. Also, our Tobit and logistic estimations, in the Online Appendix, yield similar conclusions.

Conclusion

Understanding how individuals perceive their risks regarding COVID-19 is essential for policymakers in order to implement effective public health measures and guarantee public adherence (see, e.g., Alifano et al., 2020; Baddeley, 2020). However, individuals must have accurate perceptions of risk, and optimism bias may produce a situation where individuals systematically misperceive their risks to be lower.

We examine a possible source of this misperception, the tendency of individuals to believe their pre-existing behaviors are more beneficial for reducing illness severity risk. We found that people who exercise more perceive exercise as a more important factor for preventing severe complications from COVID-19. Furthermore, those who exercise more are more (less) likely to perceive exercise as the most (least) important factor for preventing severe complications. We find similar relationships for diet and supplement use. However, we do not find a relationship between pre-existing behavior and beliefs for alcohol consumption, smoking, and sleep.

One potential drawback of our results is our measures of behavior are self-reported. We tried to reduce measurement error by using questions that are easy for individuals

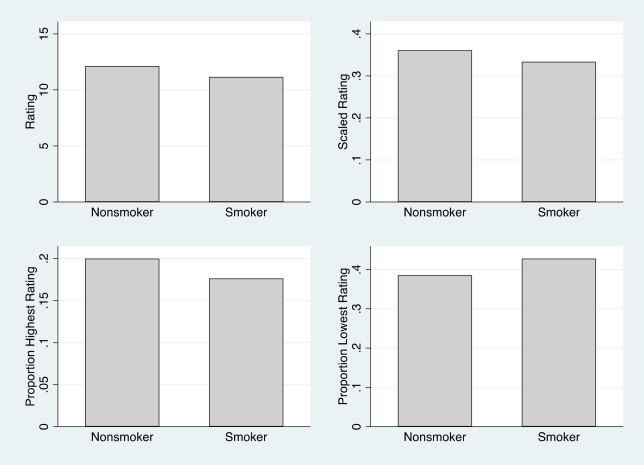

Figure 7. Results for Smoking

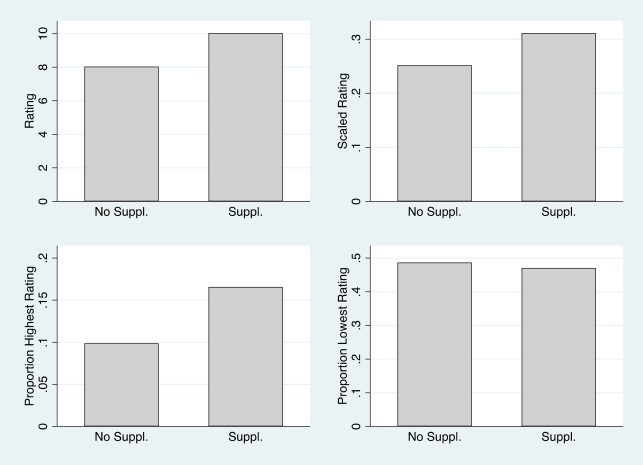

Figure 9. Results for Dietary Supplements

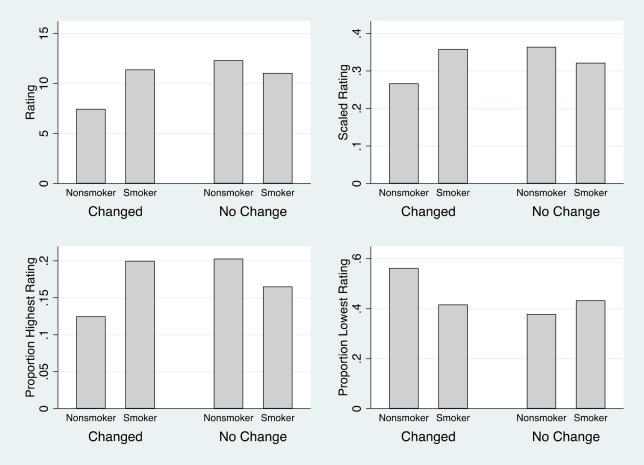

Figure 8. Results for Smoking by Behavioral Change during the Pandemic

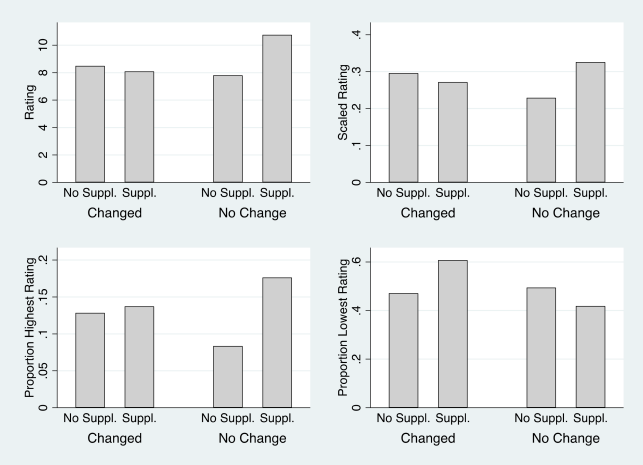

Figure 10. Results for Dietary Supplements by Behavioral Change during the Pandemic

to accurately answer. For example, we use the respondents' final meals from the previous night, rather than a self-reported measure for diet healthfulness. Another potential drawback is the issue of reverse causality. It could be the case that beliefs are affecting behaviors (reaction theory) and not the other way around (projection theory). To address this we show, graphically, the beliefs for those who have not significantly changed the underlying behavior during the pandemic. In the Online Appendix, we present our regression results for the group who did not change their behavior during the pandemic. Focusing on this group does not alter any of our results. Thus, we believe there is indeed an effect of pre-existing behavior on beliefs, specifically, optimism bias is important when considering individuals' perceptions of the risk of serious COVID-19 complications. However, it is still possible we are capturing the effect of other beliefs on behavior. Future research should pursue the issue of effective public health communication in the presence of optimism bias. Another important avenue for future research is the effect of optimism bias on adherence to public health measures.

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