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DISCUSSION PAPER SERIES

IZA DP No. 14905

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Peng Nie
Xi'an Jiaotong University, University of Hohenheim and IZA

Lu Wang
Xi'an Jiaotong University

Davide Dragone
University of Bologna

Haiyang Lu
Southwestern University of Finance and Economics

Alfonso Sousa-Poza
Xi'an Jiaotong University, University of Hohenheim and IZA

Nicolas R. Ziebarth
Cornell University, NBER, ZEW Manheim and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

"The Better You Feel, the Harder You Fall": Health Perception Biases and Mental Health among Chinese Adults during the COVID-19 Pandemic

The health risks of the current COVID-19 pandemic, together with the drastic mitigation measures taken in many affected nations, pose an obvious threat to public mental health. The social science literature has already established a clear link between mental health and sociodemographic as well as economic factors, and a growing number of studies investigate the role of biased risk perceptions. To assess this role in the context of COVID-19, this study first implements survey-based measures of over- and underconfidence in the health self-perceptions among Chinese adults during the pandemic. Then, it analyzes their relation to three mental health outcomes: life satisfaction, happiness, and depression (as measured by the CES–D). We show that the health overconfidence displayed by approximately 30% of the survey respondents is a clear risk factor for mental health problems; it is a statistically significant predictor of depression and low levels of happiness and life satisfaction. We also document that these effects are stronger in regions that experienced higher numbers of confirmed COVID-19 cases and deaths. Recent research has shown that health overconfidence can influence risky behaviors such as smoking and excessive alcohol consumption, which may be particularly detrimental during a pandemic. Our results also offer clear guidelines for the implementation of effective interventions to temper overconfidence, particularly in uncontrollable situations like the COVID-19 pandemic.

JEL Classification: I12, I18, P46

Keywords: health perception bias, overconfidence, underconfidence, mental health, China, COVID-19

Corresponding author:
Alfonso Sousa-Poza
Institute for Health Care & Public Management
University of Hohenheim
70599 Stuttgart
Germany

E-mail: alfonso.sousa-poza@uni-hohenheim.de

“The better you feel, the harder you fall”:

Health perception biases and mental health among Chinese adults during the COVID-19 pandemic

1. Introduction

As of May 15, 2020, the novel coronavirus (COVID-19) was responsible for over 4.5 million confirmed cases and 305 thousand deaths across 213 countries and territories. On that day, China officially counted 84,031 cases and 4,637 deaths.[1] Because of the virus’s contagiousness and lethality, as well as the many policy measures taken by governments worldwide, this COVID-19 pandemic is profoundly influencing all aspects of society (Holmes et al., 2020; Qiu, Chen, & Shi, 2020, Wan 2020), with pervasive negative effects that are likely to continue into the future (Brooks et al., 2020; Chen et al., 2020; Holmes et al., 2020; Xiang et al., 2020). The numerous sources of this strong psychological effect include fear of the infection’s potentially dire consequences, the “cabin fever” associated with quarantine, the uncertain economic consequences of the lockdowns, and the overwhelming flow of negative information on TV and social media. A growing body of literature has thus begun to assess both the extent of the pandemic-induced psychological distress and the sociodemographic and economic characteristics of those most affected (Qiu et al., 2020; Wang et al., 2020). In China, the groups most vulnerable to this psychological distress are the young, the elderly, the well-educated, women, and migrant workers (Qiu et al., 2020).

Despite such growing interest, however, one crucial aspect – shown empirically to affect mental health – has received no scientific attention during the COVID-19 pandemic: the role of biased health perceptions and health overconfidence. In one seminal study of the relation between mental health and “positive illusions” – defined

[1] Yale University, COVID-19 Global Cases Dashboard: https://covid.yale.edu/innovation/mapping/case-maps/global-case-map/

specifically as unrealistically positive self-evaluations, exaggerated perceptions of control and mastery, and unrealistic optimism − Taylor and Brown (1988) demonstrate that the most realistic respondents (i.e., those with the lowest positive illusion scores) have lower self-esteem and mild or severe depression, implying that positive illusions may improve mental health. Pirinsky (2013) similarly shows that extremely confident people tend to be happier than moderately confident individuals, while Murphy, Barlow, and von Hippel (2017) relate intelligence overconfidence to better mental health, and sports overconfidence to higher self-esteem and life satisfaction and less loneliness. Nevertheless, several authors question the generality of this beneficial association between overconfidence and mental health (Colvin & Block, 1994; Colvin, Block, & Funder, 1995; McGraw, Mellers, & Ritov, 2004; Mellers & McGraw, 2001; Murphy et al., 2017; Paulhus, 1998), with McGraw et al. (2004) documenting less outcome enjoyment among recreational basketball players who display overconfidence.

To test this generality, this study is the first to examine the association between biased health perceptions and mental health in China during the COVID-19 outbreak. The dataset used − the Social Attitudes and Psychological Health in the COVID-19 Pandemic survey administered in early March 2020 − is particularly relevant because, although the National Health Commission (NHC) issued guidelines in January 2020 for emergency psychological crisis interventions for those affected by COVID-19, this population's mental health needs were poorly met (Duan & Zhu, 2020; Xiang et al., 2020). Moreover, by early March, China had been experiencing this epidemic for around 3 months and had had various response tactics in place for many weeks, including quarantine, social distancing, city lockdowns, and community containment, thereby potentially accentuating the mental health problems (Wu & McGoogan, 2020). Although China has now managed to mostly control COVID-19 nationwide, and has opened up business, factory operations, and schools in an effort to revive the economy, other countries are still struggling to contain the spread. Our findings may thus provide important insights for nations fighting the mental health risks associated with the COVID-19 pandemic.

Our contribution to the literature is threefold: first, after drawing on the growing psychological and economic literature to construct an individual measure of health perception biases, we develop a conceptual framework that illustrates how these biases can affect mental health. Second, we conduct both parametric and nonparametric assessments of the empirical association between biased health perceptions and mental health, which, given the thin and inconsistent evidence of this link in the otherwise rich psychological and economic research on overconfidence, may well be the first attempt to model and empirically test this relation. Lastly, by addressing both positive (happiness and life satisfaction) and negative (depression) aspects of mental health, we are able to produce a nuanced picture of the connection between health perception biases and mental health.

The remainder of the paper is structured as follows: Section 2 outlines our proposed theoretical framework of how health perception biases affect individuals' mental health. Section 3 describes the data and methods, and Section 4 reports the results. Section 5 concludes the paper by reviewing the main findings and outlining their primary implications for policy.

2. Theoretical framework

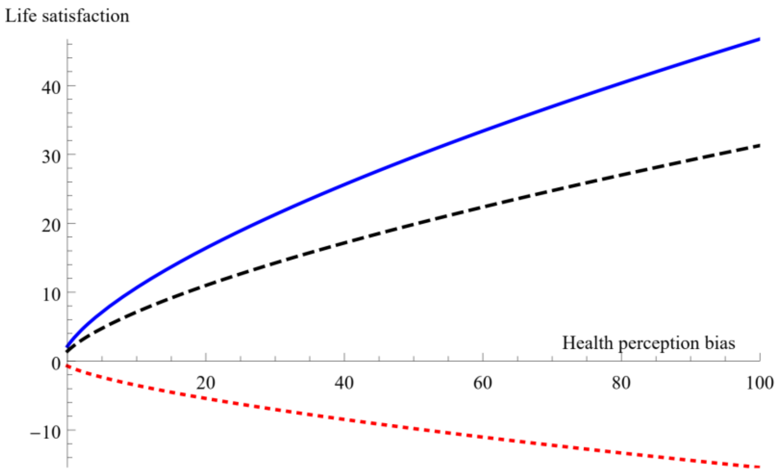
A rich body of psychological, economic, and sociological research documents the link between frequent positive experiences, emotions, happiness and life satisfaction (Haller & Hadler 2006, Shaw & Taplin 2007, Dolan et al. 2008, Dolan 2014). Although the literature identifies many determinants of psychological well-being − ranging from the fulfillment of basic needs to the existence of satisfactory relationships and self-fulfillment (Maslow, 1943, Frey & Stutzer 2002) − good physical and mental health play a major role, with perceptions of better health typically associated with higher life satisfaction and personal utility (Grossman, 1972, Dolan & Kahneman 2008). This better health status invokes two channels: first, it provides satisfaction per se; and second, it enables individuals to enjoy life activities more fully.

Arni et al. (2020) show that not only objective health but also *perceived* health can be a significant determinant of individual behavior. Applied to the context of this paper, those who overestimate their health would experience a higher life satisfaction. Moreover, everything else equal, those who overestimate their health would enjoy life activities more. While Arni et al. (2020) focus on the consequence for risky health behaviors, when considering psychological outcomes, the interdependence between health (be it objective or perceived) and enjoyable activities could amplify the effect that social activities have on perceived health. Unfortunately, the amplifying effect can also operate in the opposite direction. It is conceivable, for instance, that forced engagement in social distancing and abstinence from enjoyable activities may negatively impact perceived health, thereby reducing happiness and well-being.

This latter conjecture is consistent with the psychological evidence that isolation and quarantine, by preventing engagement in many social activities, often have negative impacts on mental health and life satisfaction. For example, subjects quarantined because of exposure to SARS showed a higher prevalence of depression, stress, low mood, irritability, insomnia, and post-traumatic stress symptoms (Brooks et al., 2020). This evidence is consistent with the assumption that isolation, increased fear of infection, and limitations on individual freedom generally reduce subjective well-being and mental health because of the interdependence between perceived health and the level of enjoyment from daily activities. Nevertheless, the evidence on pre-quarantine predictors of negative mental health effects is mixed, with many questions still unanswered (Brooks et al., 2020), including whether younger individuals are more resilient to the fear of infection but less resilient to social isolation and quarantine.

Given that perceived health and utility from life activities affect each other, it is likely that the higher the initial sense of well-being, the larger its decrease from social isolation. In particular, if high levels of well-being are linked to individuals' overconfidence in their own health, then the more positive the health bias, the larger the probable decrease in well-being. Empirically, this assumption implies that the more individuals overestimate their health, the lower their levels of life satisfaction and happiness and the greater their levels of depression. Hence, as Figure 1 illustrates, although life satisfaction rises with overconfidence, any negative shock can induce a particularly strong reduction in life satisfaction among individuals who overestimate their health.

Figure 1 Health perception bias and life satisfaction.



Note: The solid (dashed) line represents utility before (after) the negative shock, while the dotted line represents the drop in life satisfaction. The figure considers the case of a person in the first percentile of the health distribution.

3. Data and methods

3.1 Study design and sample

The Internet-based Social Attitudes and Psychological Health in COVID-19 Pandemic survey was administered on March 6-12, 2020, to a population of adults 16 years and older, residing in 31 provinces, municipalities, or autonomous regions of China. Conducted in accordance with STROBE (STrengthening the Reporting of OBservational studies in Epidemiology), this cross-sectional study recruited its respondents by circulating the survey weblink and QR code to academic staff and students residing in various geographical locations and asking them to use their social networks to extend the link to individuals residing in the 31 target areas. In addition to recording demographic and socioeconomic characteristics, the survey collected data on COVID-19-related psychological responses, social attitudes, self-assessed health (SAH), and mental health measures (life satisfaction, happiness, and depression). Of the 1,952 responses collected (1,930 from individuals 16−65 years old), 100 had to be dropped because of missing data, leaving a final sample of 1,830 respondents.

3.2 Mental health measures

Our measures of life satisfaction and happiness are based on responses to two questions: "Overall, how satisfied are you with your life?" and "Overall, how happy are you?", measured on a 10-point Likert scale from 1 = very unsatisfied/very unhappy to 10 = very satisfied/very happy. Because life satisfaction refers to thoughts and feelings about life, while happiness is a mental health measure capturing the emotional quality of everyday experience (Kahneman & Deaton, 2010), these two domains serve as a long-term and short-term measure of mental health, respectively (Pénard, Poussing, & Suire, 2013).

Our depression measure is based on the Center for Epidemiologic Studies Depression (CES-D) questionnaire (Radloff, 1977), which employs a scale ranging from 9 to 45, with higher scores indicating a higher likelihood of depression. These final scores are derived from the summed scores for each of the following 9 items: (i) loss of appetite, (ii) upset, (iii) hopelessness in the future, (iv) meaningless life, (v) poor sleep, (vi) inability to concentrate, (vii) sadness, (viii) scare, and (ix) difficulty doing anything. Each item asks respondents how often they have experienced the specific depression-associated condition in the preceding week, with responses coded as 1= not at all, 2 = very little, 3 = occasionally, 4 = often, and 5 = always. One advantage of the CES-D questionnaire is that the unintrusiveness of its probes and their relation to everyday feelings makes it easy for respondents to answer, making this survey-based instrument better than other clinical tools at detecting depression symptoms (Hsieh & Qin, 2018). This methodology may also alleviate the underreporting common in data collection from the mentally ill (Bharadwaj, Pai, & Suziedelyte, 2017).

3.3 Measuring relative health bias

Following Arni et al. (2020), we define relative health perception biases as the difference between the subjectively perceived ($\widetilde{r_i}$) and the objectively measured rank (r_i) in the population health distribution. To measure individual relative health perception bias $R_i = \widetilde{r_i} - r_i$, we measure $\widetilde{r_i}$ by the following question: "Imagine a randomly chosen group of 100 people the same age as you; how many would be in better health than you?"[2] After first using the raw untransformed response b_i to this question to compute $\widetilde{r_i} = 100 - b_i$, we calculate r_i, by adopting SAH to infer both individual health H_i and the population health distribution *f(H)*. After each respondent self-categorizes into one of the five SAH groups (1 = very unhealthy, 2 = unhealthy, 3 = OK, 4 = healthy, and 5 = very healthy), we assign every respondent to an upper cumulative distribution function (CDF) threshold of the category chosen in the SAH distribution. For example, if 10% of all respondents self-categorize into the highest category of "very healthy," we assign $r_{i,SAH}$ = 90 to all respondents in the second highest category "healthy" and so on down the line.

The concept of "overconfidence," examined extensively in the psychology literature (e.g., Fischhoff, Lichtenstein, & Slovic, 1977; Kahneman & Lovallo, 1993; Kahneman & Tversky, 1982; Moore & Schatz, 2017), is commonly defined in three distinct ways: overestimation, overplacement, and overprecision (Moore & Healy, 2008; Moore & Schatz, 2017). Whereas the first implies a belief in having more ability, higher performance, or greater control than is the reality (Moore & Healy, 2008; Moore & Schatz, 2017), the second refers to an exaggerated belief of being better than others (the so-called better-than-average effect). The third, overprecision, indicates that the individual is overly certain of knowing the truth (Moore & Schatz, 2017). Hence, whereas the first and the third classifications represent absolute overconfidence measures (Chen & Schildberg-Hörisch, 2018), the second corresponds to relative overconfidence (Benoît & Dubra, 2011; Benoît, Dubra, & Moore, 2015; Burks,

[2] This survey question has been successfully tested in other contexts (see, e.g., Friehe & Pannenberg, 2019; Tiefenbeck et al., 2016).

Carpenter, Goette, & Rustichini, 2013). In our case, because we define a relative health perception bias as the difference between the subjectively perceived and the objectively measured rank in the population health distribution (as first proposed by Arni et al., 2020), we use the term "overconfidence" in the sense of overplacement.

3.4 Sociodemographic characteristics

In our empirical analysis, we control for several sociodemographic and economic characteristics; namely, age, gender, religion, education, marital status, trust, self-reported household economic status, community-level quarantine, living in a rural area, and different regions. We capture the possible nonlinearity in the age and well-being relation (Blanchflower & Oswald, 2008) by controlling for both age and age squared. The gender variable and religion dummy are both binary, being equal to 1 if the respondent is male or specifies a religious affiliation, and 0 otherwise. Educational level, coded initially on a 4-point scale of 1 = primary school or below, 2 = secondary school, 3 = vocational school, and 4 = university or higher, is converted into a dummy variable with primary school (or below) as the reference. Likewise, marital status, originally coded as 1 = married, 2 = single, and 3 = other, is collapsed into a dummy with single as the reference. Because trust is an important predictor of well-being (see, e.g. Bartolini, Mikucka, & Sarracino, 2017), we proxy it by agreement with the claim that "In general, most people can be trusted" measured on a 5-point Likert scale from 1 = fully disagree to 5 = fully agree. We similarly measure household economic status based on how respondents rank their "household situation right now" on a 5-point Likert scale from 1 = poorest to 5 = richest. However, because very few respondents report the highest category, we combine this latter with the second highest, using the poorest category as the reference group. In addition, because mental health risks are more likely in a household suffering from a shortage of food or water, we include an additional binary dummy (1 = yes, 0 = no) that captures this condition. Likewise, because quarantine measures and its associated "cabin fever" may lead to mental health problems (Brooks et al., 2020; Holmes et al., 2020), we construct a community-level quarantine variable equal to 1 if the community or village of residence is quarantined, and 0 otherwise. To this, we also add a rural dummy (1 = rural, 0 = urban) and a regional dummy (1 = east, 2 = central, 3 = north, and 4 = northeast) with east as the reference.

3.5 Empirical strategy

3.5.1 Relative health bias and mental health: parametric model

Our OLS estimation employs the following model:

$$MH_i = \beta_0 + \beta_1 R_i^+ + \beta_2 R_i^- + X_i\beta_3 + \varepsilon_i \quad (1)$$

where MH_i represents individual i's mental health score and R_i stands for health perception bias measure. Specifically, we replace the continuous R_i variable with two separate measures, $R_i^+\{R_i \mid R_i \in (0;100)\}$, truncated from below, and $\{R_i \mid R_i \in (-100;0)\}$, truncated from above, denoting the degree of health overconfidence and underconfidence, respectively. X_i is a vector of individual and household sociodemographic factors, and ε_i is the error term.

To test whether our results differ by the severity of the COVID-19 pandemic, we create two dummy variables that capture highly affected and less affected areas using official data from the Chinese Center for Disease Control and Prevention website from April 18, 2020 (http://2019ncov.chinacdc.cn/2019-nCoV/). Specifically, the dummy for highly affected areas is 1 if the provincially confirmed cases (deaths) are above the average of confirmed cases (deaths) nationwide, and 0 otherwise.

After merging the information on confirmed cases and deaths with our survey data, we add an interaction between our health perception bias measure and the high-impact dummy to the model:

$$MH_i = \alpha_0 + \alpha_1 R_i^+ + \alpha_2 HI_i + \alpha_3 R_i^+ * HI_i + \alpha_4 R_i^- + X_i\alpha_5 + \vartheta_i \quad (2)$$

where HI_i represents the high-impact dummy (i.e., a highly affected area) for confirmed COVID-19 cases or deaths, with α_1 and α_3 as the key parameters of interest in assessing the effect of overconfidence on mental health and the possible attenuating or enhancing effect of living in a highly affected area. All other variables are defined as above with ϑ_i as the error term.

3.5.2 Relative health bias and PWB: Nonparametric model

When assumptions such as normality do not hold, parametric estimates may be inefficient, making nonparametric approaches a more appropriate choice. In particular, these latter, rather than giving simple point estimates, yield a fuller picture of mental health responses along the entire distribution of relative health perception biases (DiNardo & Tobias, 2001). This analysis thus applies kernel-weighted local polynomial smoothing (Cox, 2015) to the following univariate nonparametric model:

$$MH_i = m(R_i^+) + \varepsilon_i,\ \varepsilon_i \sim iid(0, \sigma_\varepsilon^2) \qquad (3)$$

where $m(R_i^+)$ is an unknown functional form of health overconfidence.

4. Results

4.1 Descriptive statistics

As Table 1 shows, the mean values of life satisfaction and happiness are 7.63 (SD=1.78) and 7.27 (SD=1.94), respectively, with an average depression score of 16.4. The mean age in the sample is around 31, with females accounting for approximately 63%. Whereas only slightly over 9 percent of respondents reported household shortages of food or water, 92 percent were residing in communities or villages under quarantine. Most noteworthy, the majority of respondents perceived themselves as healthy or very healthy (see Figure A1) even though on the last day of our online survey (March 12, 2020), China reported 13,526 confirmed cases and 3,176 deaths at the national level (NHC, 2020).

Table 1 Descriptive statistics

Variable	N	Mean	SD	Min	Max
Relative health bias SAH, R_i	1830	-11.206	33.32	-99	98
R_i>0, SAH	1830	8.563	15.848	0	98
R_i<0, SAH	1830	19.769	22.811	0	99
Mental health measures					
Depression	1828	16.358	7.434	9	45
Happiness	1830	7.625	1.771	1	10
Life satisfaction	1830	7.266	1.935	1	10
Gender (1 = male; 0 = female)	1830	0.372	0.484	0	1
Age	1830	30.530	9.245	16	65
Education					
Primary school or below	1830	0.009	0.093	0	1
Secondary school	1830	0.052	0.222	0	1
Vocational school	1830	0.092	0.289	0	1
University or higher	1830	0.848	0.360	0	1
Religion (1 = yes; 0 = no)	1830	0.082	0.274	0	1
Marital status					
Married	1830	0.430	0.495	0	1
Single	1830	0.555	0.497	0	1
Other	1830	0.015	0.123	0	1
Household shortage of food or water	1830	0.090	0.286	0	1
Community-level quarantine	1830	0.923	0.266	0	1
Trust					
1 = fully disagree	1830	0.022	0.146	0	1
2	1830	0.080	0.272	0	1
3	1830	0.402	0.490	0	1
4	1830	0.451	0.498	0	1
5 = fully agree	1830	0.045	0.207	0	1
Household economic status					
Poorest	1830	0.023	0.150	0	1
Poorer	1830	0.143	0.350	0	1
Middle	1830	0.788	0.409	0	1
Richer/richest	1830	0.046	0.209	0	1
Rural	1830	0.375	0.484	0	1
Region					
East	1830	0.353	0.478	0	1
Center	1830	0.208	0.406	0	1
West	1830	0.368	0.482	0	1
Northeast	1830	0.071	0.257	0	1

Source: The 2020 Social Attitudes and Psychological Health during the COVID-19 Pandemic survey.

4.2 Relative health bias and SAH

Figure 1 shows the untransformed distribution of b_i which indicates the number of respondents that believe to be in *better* health than they are. It is worth emphasizing that the mass of the distribution lies between 10 and 30, very similar to what Arni et al. (2020) find for a representative German survey. In other words, a significant share of respondents believes that between 10 to 30 out of 100 people are in better health ($b_i \in (10, 30)$) suggesting that they rank themselves in the 70th to 90th percentile of the population health distribution ($\tilde{r}_i \in (70, 90)$). This result clearly indicates the existence of health perception biases among the Chinese population.

Figure 1 Perceived Population Share in Better Health (b_i)

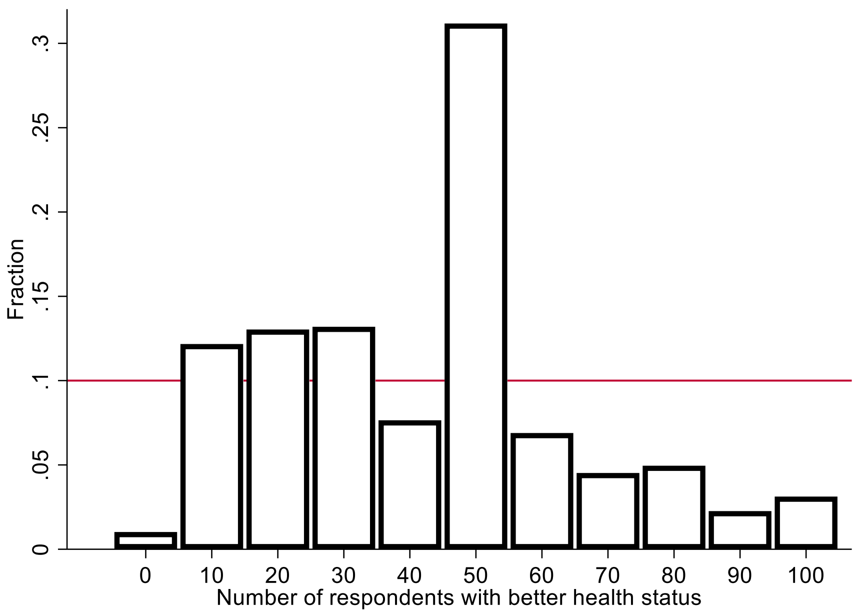


Figure 2 plots the entire distribution of $R_i = \tilde{r}_i - r_i$, where $\tilde{r}_i = 100 - b_i$ and r_i stands for the health ranking based on SAH (see Section 3.3. for details on the calculation). In other words, the density plot in Figure 2 shows the rank difference between perceived health and try health in the population health distribution.

Figure 2 Distribution of relative health bias R_i (based on SAH)

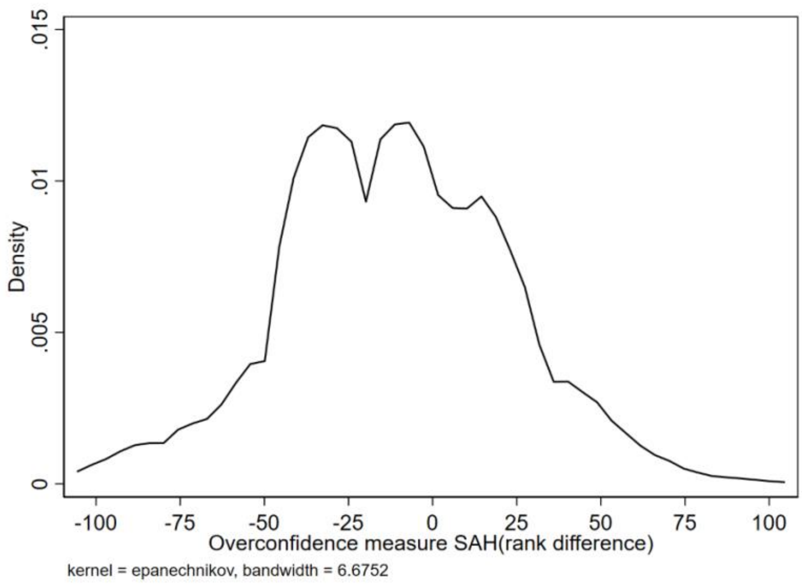


Table A2 shows all four outcomes and splits the sample into respondents who underestimate (column [1]) and overestimate (column [2]) their population health rank, respectively. As seen, overconfident respondents have a significantly higher level of depression, but have lower levels of happiness and life satisfaction compared to underconfident ones.

4.3 Relative health bias and mental health: Parametric estimates

Next, we run multivariate regressions following equation (1). Table 2 reports the OLS estimates of the association between relative health perception biases and mental health. In the uneven columns, we do not control for socio-demographics and region fixed effects, whereas we do in the even columns. Each panel reports the findings for one of the outcomes depression, happiness and life satisfaction.

As seen, Chinese residents who believe that they are healthier than they actually are, are significantly more likely to report higher depression scores and lower levels of happiness and life satisfaction. The statistical links are very robust to controlling for sociodemographic characteristics and regional dummies; the effect sizes of the point estimates only shrink slightly in column (2) and are not statistically different from the estimates in column (1).

Table 2 Relative health bias and mental health

Panel A: Depression	(1)	(2)
Overconfidence	0.094***	0.078***
	(0.015)	(0.015)
Underconfidence	0.005	0.007
	(0.009)	(0.009)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.038	0.111
Panel B: Happiness	(1)	(2)
Overconfidence	-0.021***	-0.015***
	(0.003)	(0.003)
Underconfidence	0.003	0.001
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.044	0.168
Panel C: Life satisfaction	(1)	(2)
Overconfidence	-0.022***	-0.014***
	(0.004)	(0.003)
Underconfidence	0.002	0.000
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.035	0.186

Note: The dependent variables are life satisfaction, happiness and depression. The controls include individual characteristics (age, age squared, education level, marital status, trust), household economic status (poorest, poorer, middle, richer, with poorest as the reference), shortage of food or water (1 = yes, 0 = no), isolation measures in place (1 = yes, 0 = no), rural dummy (1 = rural, 0 = urban), and regional dummies (1 = east, 2 = central, 3 = west and 4 = northeast, with east as the reference). Standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specifically, an increase in the health perception bias (R_i) by 10 ranks is associated with a 0.78-point increase in the depression score (column 2, Panel A). Overestimating own health is also negatively linked to happiness. An increase in the health perception bias (R_i) by 10 ranks is associated with a 0.15-point decline in happiness (column 2, Panel B). And an increase in R_i by 10 ranks is associated with a 0.14-point decrease in life satisfaction. One interesting observation is that none of these mental health measures is significantly signed to underconfidence.

Next, we estimate the model in equation (2) to test for differences by more and less affected COVID-19 regions. To this end, we re-estimate the model but add a High COVID-19 variable both in levels and in interaction with overconfidence. Table 3 reports results when we use officially reported COVID-19 case numbers as a stratifying factor and Table 4 reports results when we use COVID-19 deaths instead.[3]

As seen, for depression in Panels A of Tables 3 and 4, the interaction terms are positive and about half the size of the main effect of biased health perceptions, but the standard errors are large. In contrast, for happiness in Panels B of Tables 3 and 4, we find statistically significant interaction terms in all four models. Moreover, the effect sizes of these interaction terms are almost identical to the effects size of the main effect in our preferred specifications in column (2). In other words, respondents who reside in a highly affected COVID-19 region in China are as twice as likely to report lower happiness levels when they have biased health perceptions. This illustrates that the pandemic itself is a driving force for unhappiness and people who have unrealistic self-perceptions.

[3] The definition of highly affected areas is based on whether the provincially confirmed cases (deaths) are above the average of confirmed cases (deaths) nationwide. In defining the provinces that were strongly affected by the COVID-19 outbreak, we use absolute values for the cases and deaths in each province. Arguably, absolute measures are more likely to affect mental health than relative ones. When conducting the analysis by using population-weighted measures (i.e., defining strongly affected provinces as those that have cases or deaths per 100,000 inhabitants above the country median) we observe that living in a highly affected region accentuates the negative association on depression, but has no significant association with happiness and life satisfaction (see Tables A2 and A3).

Table 3 Relative health bias and mental health by COVID-19 outbreak severity

Panel A: Depression	(1)	(2)
Overconfidence	0.080***	0.066***
	(0.019)	(0.018)
High COVID-19	0.188	-0.465
	(0.376)	(0.425)
Overconfidence x high COVID-19	0.036	0.031
	(0.026)	(0.025)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.040	0.113
Panel B: Happiness	(1)	(2)
Overconfidence	-0.017***	-0.010***
	(0.004)	(0.004)
High COVID-19	-0.058	0.047
	(0.090)	(0.102)
Overconfidence x high COVID-19	-0.011*	-0.011*
	(0.006)	(0.005)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.048	0.170
Panel C: Life satisfaction	(1)	(2)
Overconfidence	-0.016***	-0.009**
	(0.004)	(0.004)
High COVID-19	-0.129	-0.014
	(0.099)	(0.112)
Overconfidence x high COVID-19	-0.013**	-0.013**
	(0.006)	(0.006)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.042	0.190

Note: The dependent variables are life satisfaction, happiness, and depression. The controls include individual characteristics (age, age squared, education level, marital status, trust), household economic status (poorest, poorer, middle, richer, with poorest as the reference), shortage of food or water (1 = yes, 0 = no), isolation measures in place (1 = yes, 0 = no), rural dummy (1 = rural, 0 = urban), and regional dummies (1 = east, 2 = central, 3 = west, and 4 = northeast, with east as the reference). Standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 Relative health bias and mental health by level of COVID-19 morbidity

Panel A: Depression	(1)	(2)
Overconfidence	0.082***	0.068***
	(0.017)	(0.017)
High impact COVID-19	0.837**	0.357
	(0.396)	(0.471)
Overconfidence x high impact COVID-19	0.036	0.032
	(0.027)	(0.027)
N	1828	1828
Panel B: Happiness	(1)	(2)
Overconfidence	-0.017***	-0.011***
	(0.004)	(0.003)
High impact of COVID-19	-0.061	-0.010
	(0.093)	(0.109)
Overconfidence x high impact of COVID-19	-0.012**	-0.011*
	(0.006)	(0.006)
N	1830	1830
Panel C: Life satisfaction	(1)	(2)
Overconfidence	-0.017***	-0.010***
	(0.004)	(0.004)
High impact of COVID-19	-0.122	-0.031
	(0.103)	(0.118)
Overconfidence x high impact of COVID-19	-0.014**	-0.013**
	(0.007)	(0.006)
N	1830	1830

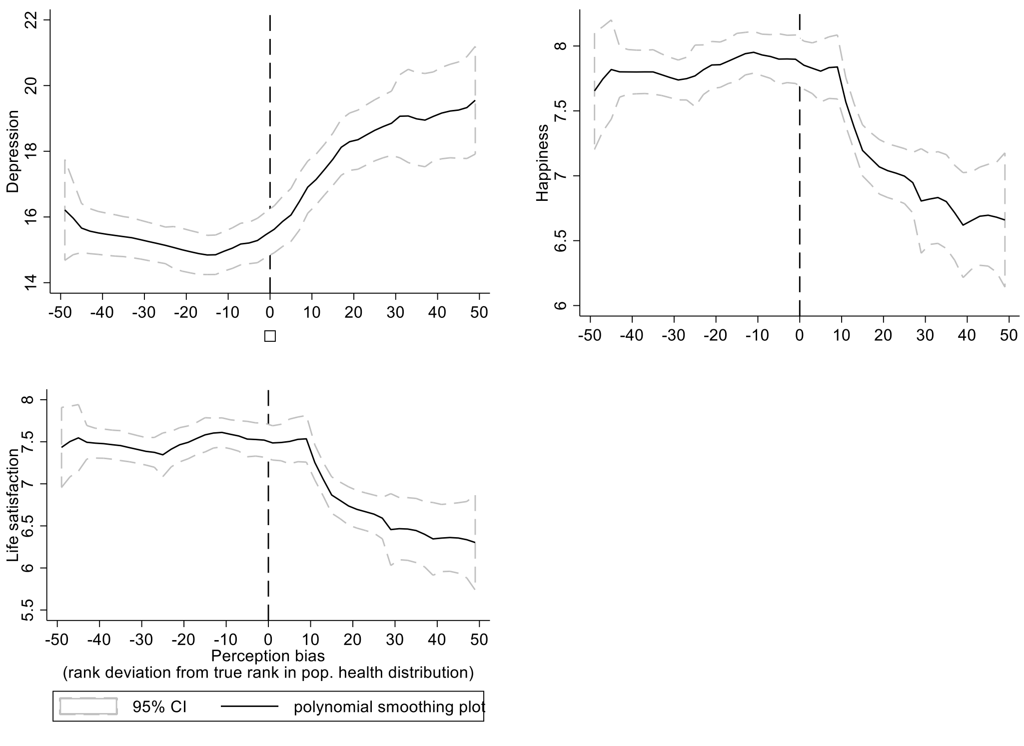
Note: The dependent variables are life satisfaction, happiness, and depression. The controls include individual characteristics (age, age squared, education level, marital status, and trust), household economic status (poorest, poorer, middle, and richer, with poorest as the reference group), shortage of food or water (1 = yes, 0 = no), isolation measures in place (1 = yes, 0 = no), a rural dummy (1 = rural, 0 = urban), and regional dummies (1 = east, 2 = central, 3 = west, and 4 = northeast, with east as the reference). Standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This finding that areas strongly affected by the COVID-19 pandemic accentuate the negative impact of health overconfidence on positive domains of mental health is reinforced in Panels C of Tables 3 and 4. The outcome here is life satisfaction. Again, we find the interaction term between overconfidence and highly affected regions to be large in size and statistically significant at the 5% level in all four models.

4.4 Relative health biases and mental health: nonparametric estimates

To supplement the point estimates from the multivariate models (Tables 2−4), we provide nonparametric evidence on the relation between health perception bias and mental health by linking R_i to our three mental health measures over the entire R_i distribution via kernel-weighted local polynomial smoothing (see Figure 3). The nonlinear nexus between R_i >0 (health overconfidence) and depression is clearly illustrated in Figure 3a by the monotonically increasing association between depression and having a positive health perception bias (R_i >0). That is, respondents who accurately assess or underestimate their own health have no elevated depression scores, although the average depression level for positive health bias does increase monotonically. Put simply, the more individuals overestimate their health, the more depressed they seem.

Figure 3 Nonparametric plot of biased health perceptions and mental health



Note: The y-axis denotes (a) depression, (b) happiness, and (c) life satisfaction

Figures 3b and 3c offer very consistent corroborating evidence for happiness and life satisfaction, with flat scores over the negative and neutral R_i range indicating no link between these variables and those who correctly assess or even underestimate their health. Those who overestimate their population health rank by more than 10 points, however, show strongly decreasing levels of both happiness (Figure 3b) and life satisfaction (Figure 3c). Taken together, therefore, our results consistently show no association between mental health and a negative (underconfidence) or zero health bias but a robustly significant link between positive health bias (overconfidence) and worse mental health.

5. Discussion and Conclusions

To assess health self-perceptions as a potential risk factor for novel coronavirus-induced mental health problems, we first use survey-based indicators of Chinese respondents' over- or underconfidence in their own mid-pandemic health status to construct a continuous measure of health perception bias. We then link this measure to three different positive and negative mental health outcomes − the CES-D depression score and standard measures of happiness and life satisfaction – while also stratifying our findings by regional severity of the COVID-19 pandemic based on province level numbers of confirmed cases and deaths. Our study thereby makes a threefold contribution to the knowledge base:

First, by defining relative health perception biases as the difference between the objective and perceived rank difference in the population health distribution, we confirm the existence of biased health perceptions in the Chinese adult population: 34% of all respondents exhibited health overconfidence by overestimating their own health ranking in a representative random group. This observation is well in line with the 30% overconfidence reported by Arni et al. (2020) for Germany. Second, our results provide highly consistent and robust evidence that those who overestimate their health, in direct contrast to those who accurately assess or underestimate it, are more likely to suffer from depression and have lower levels of happiness and life satisfaction. Third, we demonstrate that living in an area strongly affected by the COVID-19 outbreak accentuates the negative impacts of health overconfidence on both happiness and life satisfaction.

Theoretical considerations across the social sciences serve as explanations for these findings. Research in psychology clearly shows that isolation and quarantine can negatively affect mental health. Moreover, economic models suggest that the imposed shutdown of social life through social distancing and forced abstention from leisure events can negatively affect perceived health and reduce happiness and wellbeing through this channel. As perceived health and utility from life activities affect each other, it is plausible that, the higher the initial level of wellbeing, the larger the decrease in wellbeing due social isolation. In addition, if good mental health and being overly optimistic about own health is linked, predictions suggest a larger decrease in mental health, the more positively biased people are regarding their own health.

One extremely important policy implication of our findings is that although the entire population is affected by the COVID-19 pandemic, making worries and uncertainties pervasive; policy measures to curb the outbreak (e.g., lockdown, quarantine, working from home, social distancing) have a disproportionate impact on certain population subgroups. In particular, our analysis provides initial evidence that individuals with biased (in this case, overestimated) self-perceptions of health are particularly vulnerable to large drops in psychological well-being when confronted with major health crises like the COVID-19 outbreak. By identifying this overconfidence and its interaction with regional shock severity as crucial risk factors, our study provides valuable guidance for a targeted policy response to ameliorate adverse mental health effects. That is, to be effective, public health interventions should target individuals with biased health perceptions − especially health overconfidence − who reside in regions strongly affected by the COVID-19 pandemic with the aim of ensuring that their health self-perceptions are well-calibrated.

One possible starting point for such interventions is suggested by China's new *Basic Healthcare and Health Promotion Law* (to be enacted on June 1, 2020), which will address mental health issues through information campaigns, the promotion of healthy lifestyles, and integration of health education into the national curriculum. It will also expand and improve existing mental health service systems by developing new programs, especially for vulnerable groups such as the disabled and elderly. Based on our analytical findings, it would be advisable for all such programs to include measures that correct biased – and particularly, overly optimistic − self-perceptions of health and provide effective regular mental health counseling, especially in the aftermath of such devastating shock events as the COVID-19 pandemic. In addition, although the documented difficulty of "debiasing" an overconfident individual (Roberto & Kawachi, 2016) implies a need for much additional research on how policy makers can best temper overconfidence, one proposed approach to handling this problem is to learn from situations in which individuals show no overconfidence. One such situation is an event perceived to be uncontrollable (Roberto and Kawachi, 2016), a condition typified by the COVID-19 pandemic.

Conflicts of interest

None.

Acknowledgments

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Appendix

Figure A1 Distribution of SAH

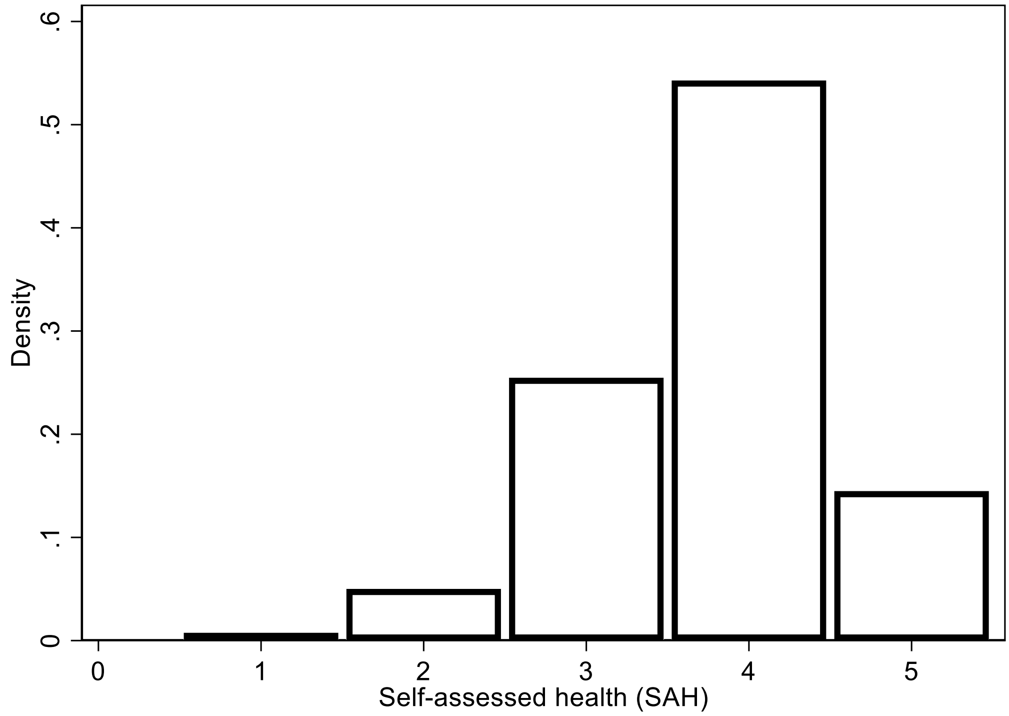

Table A1 Relative health perception biases and mental health outcomes

	$R_i < 0$ (underconfidence)	$R_i > 0$ (overconfidence)	t-tests
Depression	15.448	18.086	-7.3155***
Happiness	7.859	7.180	7.9250***
Life satisfaction	7.489	6.842	6.8897***
Observations	1198	632	

Notes: Depression scale: 9 (low) to 45 (high likelihood of depression), happiness and life satisfaction: 1 (very unsatisfied/very unhappy) to 10 (very satisfied/very happy).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, with significance based on independent *t*-tests.

Table A2 Relative health bias and mental health by COVID-19 outbreak severity (population-weighted measures)

Panel A: Depression	(1)	(2)
Overconfidence	0.064***	0.055***
	(0.020)	(0.019)
High impact of COVID-19	-0.044	-0.177
	(0.376)	(0.476)
Overconfidence x high impact of COVID-19	0.058**	0.046*
	(0.026)	(0.025)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.042	0.113
Panel B: Happiness	(1)	(2)
Overconfidence	-0.016***	-0.012***
	(0.004)	(0.004)
High impact of COVID-19	-0.052	-0.103
	(0.091)	(0.109)
Overconfidence x high impact of COVID-19	-0.009	-0.005
	(0.006)	(0.005)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.047	0.169
Panel C: Life satisfaction	(1)	(2)
Overconfidence	-0.016***	-0.012***
	(0.005)	(0.004)
High impact of COVID-19	-0.020	-0.070
	(0.100)	(0.117)
Overconfidence x high impact of COVID-19	-0.010	-0.005
	(0.006)	(0.006)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.038	0.187

Note: The dependent variables are life satisfaction, happiness, and depression. The controls include individual characteristics (age, age squared, education level, marital status, trust), household economic status (poorest, poorer, middle, richer, with poorest as the reference), shortage of food or water (1 = yes, 0 = no), isolation measures in place (1 = yes, 0 = no), rural dummy (1 = rural, 0 = urban), and regional dummies (1 = east, 2 = central, 3 = west, and 4 = northeast, with east as the reference). High-impact provinces as those that have cases per 100,000 inhabitants above the country median. Standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 Health perception biases and mental health by level of COVID-19 morbidity (population-weighted measures)

Panel A: Depression	(1)	(2)
Overconfidence	0.109^{***}	0.094^{***}
	(0.020)	(0.019)
High impact of COVID-19	1.402^{***}	1.211^{***}
	(0.374)	(0.384)
Overconfidence x high impact of COVID-19	-0.027	-0.029
	(0.026)	(0.025)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.045	0.116
Panel B: Happiness	(1)	(2)
Overconfidence	-0.019^{***}	-0.013^{***}
	(0.004)	(0.004)
High impact of COVID-19	-0.052	-0.024
	(0.091)	(0.090)
Overconfidence x high impact of COVID-19	-0.004	-0.003
	(0.006)	(0.005)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.045	0.168
Panel C: Life satisfaction	(1)	(2)
Overconfidence	-0.019^{***}	-0.012^{***}
	(0.005)	(0.004)
High impact of COVID-19	-0.145	-0.066
	(0.100)	(0.097)
Overconfidence x high impact of COVID-19	-0.005	-0.004
	(0.006)	(0.006)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.038	0.187

Note: The dependent variables are life satisfaction, happiness, and depression. The controls include individual characteristics (age, age squared, education level, marital status, and trust), household economic status (poorest, poorer, middle, and richer, with poorest as the reference group), shortage of food or water (1 = yes, 0 = no), isolation measures in place (1 = yes, 0 = no), a rural dummy (1 = rural, 0 = urban), and regional dummies (1 = east, 2 = central, 3 = west, and 4 = northeast, with east as the reference). High-impact provinces as those that have deaths per 100,000 inhabitants above the country median. Standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.