“The better you feel, the harder you fall”: Health perception biases and mental health among Chinese adults during the COVID-19 pandemic

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Abstract

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. To assess predictors of poor mental health in the context of the COVID-19 pandemic, this study first implements survey-based measures of health perception biases 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. Our results offer clear guidelines for the implementation of effective interventions to temper health overconfidence, particularly in uncontrollable situations like the COVID-19 pandemic.

Keywords: health perception bias, overconfidence, underconfidence, mental health, China

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1. Introduction

As of November 10, 2021, the novel coronavirus disease 2019 (COVID-19) was responsible for over 250 million confirmed cases and more than 5 million deaths across 196 countries and territories. On that day, China officially counted 110,331 cases and 4,849 deaths.[1] Because of the virus's contagiousness and lethality, as well as the many policy measures taken by governments worldwide, the COVID-19 pandemic is profoundly influencing all aspects of society (Giuntella et al., 2020; Holmes et al., 2020; Proto & Zhang, 2021; Torales et al., 2020; Wan, 2020; Yamamura & Tsustsui, 2021), 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 a flow of negative information on TV and social media. A growing 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, one crucial aspect has received no scientific attention during the COVID-19 pandemic: the role of biased health perceptions and health overconfidence. Economists, and in particular behavioral economists, have taken overconfidence under closer scrutiny mainly "*because it helps to answer the question of why we all tend to hold so tightly to our own views, even when the rational part of our brains has been quite well-informed.*" (Malmendier & Taylor, 2015, p.6). In one seminal study of the relation between mental health and "positive illusions" – defined specifically as unrealistically positive self-evaluations, exaggerated perceptions of control and mastery, and unrealistic optimism − Taylor and Brown (1988) demonstrate

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

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 et al. (2017) relate "intelligence overconfidence" to better mental health, and "sports overconfidence" to higher self-esteem, life satisfaction and less loneliness. Nevertheless, several authors question the generality of this beneficial association between overconfidence and mental health (Colvin & Block, 1994; Colvin et al., 1995; McGraw et al., 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 pandemic. The dataset we use is the *Social Attitudes and Psychological Health in the COVID-19 Pandemic Survey* which was administered in early March 2020. It is particularly well suited for our research because, although the National Health Commission (NHC) issued guidelines in January 2020 for emergency psychological crisis interventions for those affected by COVID-19, the population's mental health needs were poorly met (Duan & Zhu, 2020; Xiang et al., 2020). Moreover, by early March, China had been experiencing this pandemic for around 3 months and had various response tactics implemented for weeks, including quarantine, social distancing, city lockdowns, and community containment, thereby potentially accentuating the mental health problems (Wu & McGoogan, 2020). Although China has subsequently managed to control COVID-19—opening up businesses, factory operations, and schools in an effort to revive the economy—we still witness strong COVID-19 activity and deaths across Europe, the USA, India, South America, and many other countries. 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, we draw on the growing psychological and economic literature to construct an individual measure of health perception biases, and we develop a conceptual framework that illustrates how these biases can affect mental health and life satisfaction. In contrast to the voluminous psychological research on the evidence of overconfidence, the evidence on the association between mental health and overconfidence is thin. To the best of our knowledge, this paper provides a first attempt at uncovering the linkage between relative health perception biases and mental health amidst the COVID-19 outbreak. Second, we conduct both parametric and nonparametric assessments of the empirical association between biased health perceptions and mental health. Given the scant and inconsistent evidence of this link in the otherwise rich psychological and economic research on overconfidence, to our knowledge, it is the first attempt to model and empirically test this relation. Lastly, by addressing positive (happiness and life satisfaction, Frey & Stutzer, 2002; Kahneman & Deaton, 2010), as well as negative (depression, Radloff, 1977) aspects of mental health, we are able to produce a nuanced picture of the connection between health perception biases and mental health.[2]

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] In our study we adopt the World Health Organization (WHO)'s definition of mental health. Specifically, the WHO defines mental health as "a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community" (WHO, 2001, p.1). Mental health is thereby "not just the absence of mental disorder". Mental disorders include anxiety, depression, schizophrenia, and alcohol and drug dependency (Herrman et al., 2005). In other words, people living with mental disorder can also achieve good levels of well-being – living a satisfying, meaningful, contributing life within the constraints of painful, distressing, or debilitating symptoms. Accordingly, we introduce life satisfaction and happiness as positive and depression as negative measures of mental health. These measures have been used in other studies related to the COVID-19 pandemic and also routinely in the well-being literature (see, e.g., Dolan et al. 2019; Lu et al., 2021; Tubadji, 2021; Yamamura & Tsustsui, 2021).

2. Theoretical framework

A rich body of psychological, economic, and sociological research documents the link between frequent positive experiences, emotions, happiness and life satisfaction (Dolan & Kaheman, 2008; Dolan et al., 2008; Haller & Hadler, 2006; Shaw & Taplin, 2007). 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 (Frey & Stutzer, 2002; Maslow, 1943) − good physical and mental health play a major role, with perceptions of better health typically associated with higher life satisfaction and personal utility (Dolan & Kaheman, 2008; Grossman, 1972). 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. (2021) show that not only objective health but also *perceived* health can be a significant determinant of individual behavior. This observation is confirmed by Nie et al. (2021) who show that health overconfidence is associated with more alcohol consumption, overweight and obesity among Chinese adults aged 45 and older. Lei et al. (2021) also find that Chinese adults aged 45+ who became aware that they are hypertensive are more likely to take medication and quit smoking. 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 (in “normal” times). While Arni et al. (2021) 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 and, ultimately, life satisfaction. 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 happiness and well-being.

This latter conjecture is consistent with the psychological evidence that isolation and quarantine often have negative impacts on mental health and life satisfaction, for example, by preventing engagement in many social activities. Subjects quarantined because of exposure to Severe Acute Respiratory Syndrome (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 possible 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 possible decrease in well-being.

Figure 1 illustrates this possibility considering a Cobb-Douglas function $U(x, H, R) = (x^a H^{1-a})R$, where $U(\cdot)$ describes life satisfaction, x is the consumption of material and non-material goods, including social relations and time spent in enjoyable activities, H is objective health, and R is the health perception bias (whose construction is described in detail in Section 3.3). For given health and consumption, life satisfaction is higher when perceived health R is higher. Accordingly, the black curve (which corresponds to a positive health perception bias: $R>1$) is higher than the red curve (negative health perception bias: $R<1$). If the consumption level of x decreases due to, for example, the loss of social relations, two effects arise.

Figure 1

First, life satisfaction drops for all levels of perceived and objective health, as described by the dotted curves. Second, the drop is larger when perceived health bias is larger, and smaller when the perceived health bias is small or negative. Formally, the former effect is consistent with life satisfaction increasing in the health perception bias, while the latter is consistent with a positive interaction between the health perception bias R and the consumption level x (i.e. $\partial^2 U(x, H, R)/(\partial x \partial R) = a\ (H/x)^{1-a} > 0$).[3] In the empirical exercise described in Section 4, we measure the latter effect: we consider individuals hit by a negative shock on x and we estimate how their health perception bias affects life satisfaction

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 between 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 employing a snowball sampling technique. Specifically, we first circulated the survey weblink and QR code to academic staff and students residing in various geographical locations. Then they were instructed to use their social networks to extend the link to individuals residing or working in the 31 target areas. The questionnaire was developed in Chinese (Mandarin) and independent experts reviewed and validated the questionnaire. 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

[3] In principle, the opposite case can hold: if the cross derivative is negative, the opposite prediction would arise, whereby the change in utility is larger, after a reduction in consumption, for those individuals with small (possibly negative) health perception bias. Empirically, this does not seem to be the case, as shown in Section 4.

(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 use 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 et al., 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 et al., 2017).

3.3 Measuring relative health bias

Following Arni et al. (2021), we define the objective relative position (the ranking) in the population health distribution as:

$$r_i \equiv 100 * F(H_i) \tag{1}$$

where H_i represents individual i's health. $F(H_i) \equiv \int_0^{H_i} dF(H)$ is the cumulative distribution function (CDF) of population health, which is multiplied by 100 in order to generate a ranking with a scale ranging from 0 to 100 (Arni et al., 2021). Empirically, we calculate r_i, by using SAH to infer both individual health H_i and the population health CDF. After each respondent self-categorizes into one of the five SAH groups (1 = very unhealthy, 2 = unhealthy, 3 = satisfactory, 4 = healthy, and 5 = very healthy), we assign every respondent to an upper 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.

Similarly, we define the subjective health ranking as:

$$\widetilde{r_i} \equiv 100 * P_i F(\widetilde{H}_i) \tag{2}$$

where P_i denotes individual i's perception bias of the CDF of population health and $F(\widetilde{H}_i)$ is the CDF computed at the perceived health $(\widetilde{H}_i)$. This formulation allows to take into account that an individual may have a biased perception of own health H and, for a given perceived health, a biased perception P_i of the population distribution of health (more precisely: of how many people are perceived to be in worse health condition). In our study, we measure $\widetilde{r_i}$ using the following question: *"Imagine a randomly chosen group of 100 people in the same age as you; how many would be in better health than you?"*[4]

We then define relative health perception biases (R_i) as the difference between the subjectively perceived ($\widetilde{r_i}$) and the objectively measured rank (r_i) in the population health distribution:

$$R_i = \widetilde{r_i} - r_i \tag{3}$$

A positive relative health perception bias exists when $R_i > 0$, whereas a negative relative health perception bias displays when $R_i < 0$. It should be noted that in our

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

sample, there are only 25 observations with correct health perceptions.

The concept of "overconfidence," examined extensively in the psychology literature (e.g., Fischhoff et al., 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, 2019), the second corresponds to relative overconfidence (Benoît & Dubra, 2011; Benoît et al., 2015; Burks et al., 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., 2021), 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 between age and well-being (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 et al., 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.[5] In addition, because mental health risks are more likely in a household suffering from a shortage of food or water (Jones, 2017; Wutich & Ragsdale, 2008), 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:

$$MH_i = \beta_0 + \beta_1 R_i^+ + \beta_2 R_i^- + X_i\beta_3 + \beta_4 F_i + \beta_5 G_i + \varepsilon_i \tag{4}$$

where MH_i represents individual i's mental health score (i.e., life satisfaction, happiness and depression in our case) and R_i denotes 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 $R_i^- = \{R_i \mid R_i \in (-100;0)\}$, truncated from above, denoting the degree of positive and negative health perception biases, respectively. Following Arni et al. (2021), such a split specification allows to explicitly test for possible differences between the outcome and positive as well as negative health perception biases, respectively. X_i is a vector of individual and

5 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.

household sociodemographic factors. F_i is a rural dummy (1=rural, 0=urban) and G_i is a regional dummy (1 = east, 2 = central, 3 = north, and 4 = northeast, with east as the reference). 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:

$$MH_i = \alpha_0 + \alpha_1 R_i^+ + \alpha_2 HI_i + \alpha_3 R_i^+ * HI_i + \alpha_4 R_i^- + \alpha_5 R_i^- * HI_i + X_i \alpha_6 + \alpha_7 F_i + \alpha_8 G_i + \vartheta_i \quad (5)$$

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 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 Lewbel's (2012) heteroscedasticity-based two-stage least squares (2SLS) estimation

There are possible endogeneity concerns in the above specification. For example, it is possible that respondents who have mental health problems tend to have health perceptions being affected. It is also possible that certain common factors – for example, individual traits or genetics – influence both health perceptions and mental health. Identifying causality can therefore be hindered by reverse causality or omitted factors. Without addressing the possible endogeneity problem of health perceptions, the OLS results might be biased. However, finding an instrument that fulfils the exclusion restriction is very challenging as both the dependent and main independent variable are subjective in nature.

In the absence of an obvious exogenous IV, a promising approach is Lewbel's (2012) heteroscedasticity-based 2SLS, which requires the presence of heteroscedasticity as a precondition for identification (confirmed here by a Breusch and Pagan (1979) test). This approach has been used in previous studies on mental health and subjective well-being (Awaworyi Churchill & Smyth, 2021; Prakash & Smyth, 2019) as well as in other fields of economics (Belfield & Kelly, 2012; Mishra & Smyth, 2015). Both Lewbel (2012) and Mishra and Smyth (2015) confirm that results produced using Lewbel's 2SLS approach are comparable to those produced using a conventional external IV in cases where a suitable external IV is available. We thus use this approach. Specifically, we first consider a structural model of the following form:

$$Y_1 = X'\alpha_1 + Y_2\gamma_1 + \varepsilon_1 \tag{6}$$

$$Y_2 = X'\alpha_2 + \varepsilon_2, \text{ where } \varepsilon_2 = \rho_2 U + \omega_2 \tag{7}$$

In our case, Y_1 is the mental health outcome and Y_2 is health perception bias, U represents unobserved factors such as individual traits or genetics, and ε_1 and ε_2 are idiosyncratic error terms. As Lewbel (2012) suggests, we can take a vector Z of observed exogenous variables and employ *[Z-E(Z)]* ε_2 as an instrument if

$$E(X\varepsilon_1) = 0,\ E(X\varepsilon_2) = 0,\ cov(Z, \varepsilon_1, \varepsilon_2) = 0 \tag{8}$$

The rationale for using *[Z-E(Z)]* ε_2 as an instrument is that identification can be achieved by obtaining regressors that are uncorrelated with the product of the heteroscedastic errors (Lewbel, 2012). In practice, Z could either be a subset of X or equal to X. We use the latter case for our IV estimation. Drawing on this instrument, we use 2SLS to run the IV estimation.

3.5.3 Relative health bias and mental health: nonparametric model

When assumptions such as normality do not hold, parametric estimates may be inefficient, making nonparametric approaches a more appropriate choice. In particular, the 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:

$$MH_i = m(R_i^+) + \varepsilon_i,\ \varepsilon_i \sim iid(0, \sigma_\varepsilon^2) \tag{9}$$

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

4. Results

4.1 Descriptive statistics

As Table 1 shows, the mean values of life satisfaction and happiness are 7.63 (SD=1.77) and 7.27 (SD=1.94), with an average depression score of 16.4 (SD=7.63). Table 1 also shows all four outcomes and splits the sample into respondents who underestimate and overestimate their population health rank, respectively. The mean depression score is significantly higher among respondents with a positive health bias compared with a negative bias (18.09 vs. 15.45). Respondents with a positive bias have lower mean values of happiness and life satisfaction compared to those with negative bias (happiness: 7.18 vs. 7.86; life satisfaction: 6.84 vs. 7.49). Note that all these measures were elicited during times of COVID-19 (i.e., in terms of our model, all individual are already hit by a negative shock on x); hence the negative link between health overconfidence and mental health is consistent with a positive interaction between the marginal utility of consumption and health perception bias. Although it is not the purpose of this study to analyze the determinants of health misperceptions, we do note (see also, Hansson et al., 2008) that older individuals appear more likely to be overconfident[6] – an observation which is of particular relevance in the context of the COVID-19 pandemic.

It should be noted that with 37% of the sample being male, women are oversampled. Furthermore, the average age in our sample (30.5 years old) is younger than that of nationally representative data in China, such as the 2018 China Family Panel Studies (CFPS) (45.7 years old). The average education level is also higher for such a relatively young sample. Additionally, a large proportion of individuals report being single (56%

[6] Results are available upon request.

vs. 18% for the CFPS), and a slightly smaller fraction of respondents resides in rural areas compared to the CFPS (38% vs. 39%). Yet, the regional distribution of our sample is comparable to that of CFPS except for Northeast (our sample: 7% vs. CFPS: 12%).[7] As these results indicate, our sample is not representative of the Chinese population, particularly with regards to age, education and gender. Nevertheless, online surveys such as ours provide a unique (and often the only) opportunity for empirical research during the COVID-19 pandemic, especially as conventional face-to-face surveys are often difficult to conduct (Hlatshwako et al., 2021). Online surveys also provide a fast turnaround and an opportunity to assess the immediate impact of the pandemic. Whereas only slightly over 9% of respondents reported household shortages of food or water, 92% 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

4.2 Relative health bias and SAH

Figure 2 shows the untransformed distribution of b_i which indicates the number of people 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. (2021) find using 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, that is, they rank

[7] Detailed summary statistics of the 2018 China Family Panel Studies are in Appendix Table A1.

themselves in the 70th to 90th percentile of the population health distribution ($\widetilde{r_i} \in$ (70, 90)). This result indicates the existence of health perception biases in our sample.[8]

Figure 2

Figure 3 plots the entire distribution of the health perception bias $R_i = \widetilde{r_i} - r_i$, described as the rank difference between perceived health and true health in the population health distribution.

Figure 3

4.3 Relative health bias and mental health: parametric estimates

Next, we run multivariate regressions following Eq. (1). Table 2 reports the OLS estimates of the association between relative health perception biases and mental health. In the odd 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 either depression, happiness or life satisfaction.

In our sample of Chinese residents, as above, those who believe that they are healthier than they actually are (positive health perception bias), 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).

[8] According to the notation used in Section 3, the responses plotted in Figure 2 correspond to 100-r_i, as r_i indicates the percentage of people in worse health.

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). 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 associated to negative health perception biases.

Table 2

Next, we estimate the model in Eq. (2) to test for differences in more and less affected COVID-19 regions. To this end, we re-estimate the model but add a "High Impact of COVID-19" variable both in levels and in interaction with health perception biases. Table 3 presents 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.[9]

In the case of depression in Panels A of Tables 3 and 4, the interaction terms are positive and slightly smaller than those of the main effect of biased health perceptions, though insignificant in Table 4. 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 effect 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 twice as likely to report lower happiness levels when they have biased health

[9] The definition of highly affected areas is based on whether confirmed cases (deaths) at the province level 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 case counts are more likely to affect mental health than relative ones, also because of the media exposure. When using population-weighted measures, 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).

perceptions. This illustrates that the pandemic itself is a driving force for unhappiness among people who have unrealistic self-perceptions. Note that we view this finding as an "intensive margin" finding as all empirical results have been elicited during COVID-19 and we will see below that higher health confidence is generally linked to lower mental health during these times.

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 positive health perception biases and highly affected regions to be large in size and statistically significant at the 1% level in all four models. (However, the negative health perception bias and its interaction term with highly affected regions are consistently and statistically insignificant for depression and happiness, see Panels A and B of Tables 3 and 4.)

Table 3

Table 4

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 Fig. 4). The nonlinear association between $R_i>0$ (health overconfidence) and depression is clearly illustrated in Fig. 4a 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 larger depression scores, although the average depression level for positive health bias does increase monotonically. Hence, the more individuals overestimate their health, the more depressed they are. Note that all these empirical findings are elicited during COVID-19 and, thus, in line with Section 2, we expect that baseline link between positive health perception biases and mental health to be negative (unlike in normal times, where theory would suggest a main positive link as perceived health R is linked to better mental health, see Figure 1).

Figure 4

Figures 4b and 4c 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 (Fig. 4b) and life satisfaction (Fig. 4c). Taken together, our results consistently show no association between mental health and a negative health bias, but a robustly significant link between positive health bias and worse mental health.

4.5 Lewbel's (2012) heteroscedasticity-based 2SLS

To investigate possible endogeneity concerns of health perception biases in the absence of any obviously exogenous instruments, we employ Lewbel's (2012) heteroscedasticity-based 2SLS, which requires the presence of heteroscedasticity as a precondition for identification. As Table 5 shows, the Breusch-Pagan tests show that heteroskedasticity exists, making our sample suitable for Lewbel's 2SLS method. Our results from Lewbel's (2012) heteroscedasticity-based 2SLS estimates show that respondents who overestimate their health are more likely to have a higher level of depression and lower levels of happiness and life satisfaction (although the estimated coefficients for life satisfaction are insignificant), which is consistent with those from the OLS results in Table 2.

Table 5

4.6 Robustness checks

4.6.1 Non-representativeness of study sample

As stated before, our sample is primarily non-representative in three characteristics: age, education, and gender. To better gauge possible biases related to oversampling young, well-educated and female respondents, we first conduct our analysis for subsamples: 35 and older vs. less than 35 years of age, men vs. women, and university vs. no university degree holders (see Appendix Tables 4-6). Our main results do not change substantively.

An additional concern when using a non-representative sample is about the construction of the health bias measure. Specifically, the health bias measure is based on a comparison between the health quantile of subjective (i.e., the individual SAH) and objective (i.e., the population distribution of SAH) measurements. If, for example, many respondents in our non-representative sample are overconfident, then those respondents without health perception biases may be wrongly classified as having a negative bias. In other words, using a non-representative distribution of SAH as a basis for the comparison between subjective and objective health rank can be problematic. In order to take this into account, we use the CDF of SAH from the CFPS when calculating our health bias measure and rerun the estimates. The main results are quite robust, except for positive health perception biases for life satisfaction (see Appendix Table A7).

4.6.2 Measurement error of SAH

As a self-reported subjective measure of health, SAH may suffer from measurement error. Sometimes it is argued that the mapping of "true health" onto SAH categories may differ with respondents' characteristics (Hernández-Quevedo et al., 2005; Ziebarth, 2010). This source of measurement error has been termed "state-dependent reporting bias" (Kerkhofs & Lindeboom, 1995) and "response category cut-point shift" (King et al., 2004). This occurs when subgroups of the population use systematically different cut-offs when reporting their SAH, although they have the same level of 'true health' (Hernández-Quevedo et al., 2005). Studies have attempted to address this issue of measurement error by using objective health indicators (Au & Johnston, 2014; Chen et al., 2021; Lindeboom & van Doorslaer, 2004) and vignettes to adjust the scale (Bago d'Uva et al., 2008; King et al., 2004; Xu & Xie, 2017). As our data were collected during the COVID-19 pandemic, it was impossible for us to use objective measures of health or vignettes. However, the Lewbel's (2012) heteroscedasticity-based 2SLS would account for measurement error.

As a further robustness test on this issue, we re-estimate models with SAH collapsed to four[10] and three[11] categories, see Appendix Table A8. The reasoning for such an approach is that, as highlighted by Hernández-Quevedo et al. (2005), the categories of SAH are an artefact of the design of the survey question and they reflect choices available to the individual. We try to take this issue into account by assessing whether the use of different SAH cut-offs affect our results.

Results show that after merging "1=very unhealthy" and "2=unhealthy" into the new category of "1=unhealthy", people who overestimate their health are more likely to have a higher level of depression and lower levels of life satisfaction and happiness (see Appendix Table A9). We observe similar results when merging "4=healthy" and "5=very healthy" into the new category of "4=healthy" (using SAH 4 categories) and SAH 3 categories (see Appendix Tables 10 and 11).

4.6.3 Trimming the distribution and addressing multicollinearity

By definition, the better the actual relative health status, the lower the probability that

[10] Merging "1=very unhealthy" and "2=unhealthy" into the new category of "1=unhealthy" or merging "4=healthy" and "5=very healthy" into the new category of "4=healthy."

[11] Merging "1=very unhealthy" and "2=unhealthy" into the new category of "1=unhealthy", and "4=healthy" and "5=very healthy" into the new category of "3=healthy."

someone displays a positive health perception bias. Following Arni et al. (2021), we thus perform a robustness check that trims the relative health perception bias distribution and eliminates the top and bottom quintiles of *Ri*. We also provide a robustness check to avoid possible guesses of $\tilde{r}_i$, since it is possible that the peak at $\tilde{r}_i$ =50 denotes respondents who did not know the response and just guessed. Considering this, we also remove those samples with potentially guessing respondents. As Appendix Table A12 shows, those 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.

In addition, our main model introduces positive and negative health perception bias simultaneously, thereby resulting in possible multicollinearity. This might partially explain the insignificance of the coefficient of "negative health perception bias". To rule out this possibility, we perform two robustness checks: First, we solely use one single continuous measure of "health perception biases" without distinguishing between positive or negative health misperceptions. The results in Appendix Table A13 show that health perception biases are positively and significantly related to depression, whereas they are negatively and significantly associated with happiness and life satisfaction. This is consistent with our key findings. Second, we solely include one "positive health perception bias" regressor into the regression (using both the negative and zero values as reference). Relative to negative and no biases, positive biases are positively linked with depression, and negatively linked with happiness and life satisfaction (see Appendix Table A14).

4.6.4 Controlling for city-level and day FE

Finally, we control for regional and provincial fixed effects in the main estimation. To check the robustness of our main results, we also rerun the estimates by introducing city-level fixed effects and day fixed effects. The results are in Appendix Table A15. Our key findings are quite robust to this extension.

5. Discussion and Conclusions

This paper assesses the role of biased health self-perceptions as a potential risk factor for Coronavirus induced mental health problems. We draw on data from the internet based *Social Attitudes and Psychological Health in COVID-19 Pandemic Survey*. We first elicit survey-based indicators of Chinese respondents to construct a continuous measure of health perception bias. Our findings confirm previous research and shows that the proposed survey measure yields valid responses with little non-response. 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 the regional severity of the pandemic, based on province-level numbers of confirmed cases and deaths. Our study thereby makes a threefold contribution to the literature.

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 our sample of adult Chinese: 34% of all respondents exhibited health overconfidence by overestimating their own health ranking. This observation is in line with the 30% overconfidence reported by Arni et al. (2021) for Germany. Second, our results provide 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.

Although our results may at first seem counterintuitive, a large body of literature in psychology documents how overconfidence may affect mental well-being. Much of this literature is based on decision affect theory. It posits that emotional reactions are amplified, the wider the gap between what one believes will occur and what actually occurs. Overconfident people expect successes, and expected successes are less pleasurable than surprising successes (McGraw et al., 2004). Overconfident people may be more surprised by sudden shocking events outside their own control and “failure”, and as such experiencing detrimental health outcomes. As surprising failures are more painful than expected failures, this may explain our findings (McGraw et al., 2004).

Theoretical considerations across the social sciences also serve as explanations for our 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.

Our study is subject to some limitations: First, as stated before, our sample is not nationally representative because of the convenience sampling design. Yet although generalizations may be difficult, our use of a national representative sample (the CFPS) to construct the health bias measure did not alter our main results in a meaningful way. Second, although we tried to correct for SAH measurement error using an IV approach, objective health indicators and vignettes could provide more accurate measures of health biases. Finally, future studies should explore other underlying mechanisms through which health perception biases operate on mental health in the context of the pandemic.

One important policy implication of our findings is that, although the COVID-19 pandemic affects the entire population, making worries and uncertainties pervasive, policy measures aimed at curbing the outbreak (e.g., lockdown, quarantine, working from home, social distancing) have a disproportionate impact on certain population subgroups. Our analysis provides initial evidence that individuals with biased (in this case, overoptimistic) 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 phenomenon and its interaction with regional shocks as risk factors, our study provides guidance for a targeted policy response to ameliorate adverse mental health effects. That is, public health interventions should target individuals with biased health perception. Our results also indicate that health overconfidence is more pronounced among the older population in our sample, which, considering their higher susceptibility to serious COVID-19 infections, makes them an important policy target group.

One possible starting point for such interventions is suggested by China's new *Basic Healthcare and Health Promotion Law* (enacted on June 1, 2020), which addresses mental health issues through information campaigns, the promotion of healthy lifestyles, and integration of health education into the national curriculum. It also expands and improves existing mental health service systems by developing new programs, especially for vulnerable groups such as the disabled and elderly. Based on our findings, it would be advisable for such programs to include measures that correct biased – particularly overly optimistic − self-perceptions of health. They should also provide effective regular mental health counseling, especially in the aftermath of such devastating shock events as the COVID-19 pandemic.

Conflicts of interest

None.

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References

Arni, P., Dragone, D., Goette, L., & Ziebarth, N. R. (2021). Biased health perceptions and risky health behaviors—theory and evidence. *Journal of Health Economics*, *76*, 102425.

Au, N., & Johnston, D. W. (2014). Self-assessed health: What does it mean and what does it hide? *Social Science & Medicine*, *121*, 21-28.

Awaworyi Churchill, S., & Smyth, R. (2021). Energy poverty and health: Panel data evidence from Australia. *Energy Economics*, *97*, 105219.

Bago d'Uva, T., O'Donnell, O., & van Doorslaer, E. (2008). Differential health reporting by education level and its impact on the measurement of health inequalities among older Europeans. *International Journal of Epidemiology*, *37*(6), 1375-1383.

Bartolini, S., Mikucka, M., & Sarracino, F. (2017). Money, trust and happiness in transition countries: Evidence from time series. *Social Indicators Research*, *130*(1), 87-106.

Belfield, C. R., & Kelly, I. R. (2012). The benefits of breast feeding across the early years of childhood. *Journal of Human Capital*, *6*(3), 251-277.

Benoît, J.-P., & Dubra, J. (2011). Apparent overconfidence. *Econometrica*, *79*(5), 1591-1625. https://doi.org/10.3982/ECTA8583

Benoît, J.-P., Dubra, J., & Moore, D. A. (2015). Does the better-than-average effect show that people are overconfident?: Two experiments. *Journal of the European Economic Association*, *13*(2), 293-329.

Bharadwaj, P., Pai, M. M., & Suziedelyte, A. (2017). Mental health stigma. *Economics Letters*, *159*, 57-60.

Blanchflower, D. G., & Oswald, A. J. (2008). Is well-being U-shaped over the life cycle? *Social Science and Medicine*, *66*, 1733–1749.

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, *47*(5), 1287-1294.

Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., & Rubin, G. J. (2020). The psychological impact of quarantine and how to reduce it: Rapid review of the evidence. *The Lancet*, *395*(10227), 912-920.

Burks, S. V., Carpenter, J. P., Goette, L., & Rustichini, A. (2013). Overconfidence is a social signaling bias. *Review of Economic Studies*, *80*(3), 949-983.

Chen, L., Clarke, P. M., Petrie, D. J., & Staub, K. E. (2021). The effects of self-assessed health: Dealing with and understanding misclassification bias. *Journal of Health Economics*, 102463.

Chen, Q., Liang, M., Li, Y., Guo, J., Fei, D., Wang, L., He, L., Sheng, C., Cai, Y., Li, X., Wang, J., & Zhang, Z. (2020). Mental health care for medical staff in China during the COVID-19 outbreak. *The Lancet Psychiatry*, *7*(4), e15-e16.

Chen, S., & Schildberg-Hörisch, H. (2019). Looking at the bright side: The motivational value of confidence. *European Economic Review*, *120*, 103302.

Colvin, C. R., & Block, J. (1994). Does positive illusions foster mental health? An examination of the Taylor and Brown formulation. *Psychological Bulletin*, *116*, 3-20.

Colvin, C. R., Block, J., & Funder, D. C. (1995). Overly positive self evaluations and personality: Negative implications for mental health. *Journal of Personality and Social Psychology*, *68*, 1152–1162.

Cox, N. J. (2015). *LOCALP: Stata module for kernel-weighted local polynomial smoothing. Statistical Software Components S458001*. Boston College Department of Economics.

DiNardo, J., & Tobias, J. L. (2001). Nonparametric density and regression estimation. *Journal of Economic Perspectives*, *15*(4), 11-28.

Dolan, P., & Kaheman, D. (2008). Interpretations of utility and their implications for the valuation of health. *The Economic Journal*, *118*(525), 215-234.

Dolan, P., Kavetsos, G., Krekel, C., Mavridis, D., Metcalfe, R., Senik, C., Szymanski, S., & Ziebarth, N. R. (2019). Quantifying the intangible impact of the Olympics using subjective well-being data. *Journal of Public Economics*, *177*, 104043.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, *29*(1), 94-122.

Duan, L., & Zhu, G. (2020). Psychological interventions for people affected by the COVID-19 epidemic. *The Lancet Psychiatry*, *7*(4), 300-302.

Fischhoff, B., Lichtenstein, S., & Slovic, P. (1977). Knowing with certainty: The appropriateness of extreme confidence. *Journal of Experimental Psychology*, *3*(4), 552–564.

Frey, B. S., & Stutzer, A. (2002). What can economists learn from happiness research? *Journal of Economic Literature*, *40*(2), 402-435.

Friehe, T., & Pannenberg, M. (2019). Overconfidence over the lifespan: Evidence from Germany. *Journal of Economic Psychology*, *74*, 102207.

Giuntella, O., Hyde, K., Saccardo, S., & Sadoff, S. (2020). *Lifestyle and mental health disruptions during COVID-19. IZA DP No. 13569*. IZA.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, *80*(2), 223-255.

Haller, M., & Hadler, M. (2006). How social relations and structures can produce happiness and unhappiness: An international comparative analysis. *Social Indicators Research*, *75*(2), 169-216.

Hansson, P., Rönnlund, M., Juslin, P., & Nilsson, L. G. (2008). Adult age differences in the realism of confidence judgments: Overconfidence, format dependence, and cognitive predictors. *Psychology and Aging*, *23*(3), 531–544.

Hernández-Quevedo, C., Jones, A. M., & Rice, N. (2005). *Reporting bias and heterogeneity in selfassessed health. Evidence from the British Household Panel Survey. HEDG Working Paper 05/04*. University of York.

Herrman, H., Saxena, S., & Moodie, R. (2005). *Promoting mental health: concepts, emerging evidence, practice report of the World Health Organization, Department of Mental Health and Substance Abuse in collaboration with the Victorian Health Promotion Foundation and the University of Melbourne*.

Hlatshwako, T. G., Shah, S. J., Kosana, P., Adebayo, E., Hendriks, J., Larsson, E. C., Hensel,

D. J., Erausquin, J. T., Marks, M., Michielsen, K., Saltis, H., Francis, J. M., Wouters, E., & Tucker, J. D. (2021). Online health survey research during COVID-19. *The Lancet Digital Health*, *3*(2), e76-e77.

Holmes, E. A., O'Connor, R. C., Perry, V. H., Tracey, I., Wessely, S., Arseneault, L., Ballard, C., Christensen, H., Cohen Silver, R., Everall, I., Ford, T., John, A., Kabir, T., King, K., Madan, I., Michie, S., Przybylski, A. K., Shafran, R., Sweeney, A., Worthman, C. M., Yardley, L., Cowan, K., Cope, C., Hotopf, M., & Bullmore, E. (2020). Multidisciplinary research priorities for the COVID-19 pandemic: A call for action for mental health science. *The Lancet Psychiatry*, *S2215-0366*(20), 30168-30161.

Hsieh, C.-R., & Qin, X. (2018). Depression hurts, depression costs: The medical spending attributable to depression and depressive symptoms in China. *Health Economics*, *27*(3), 525-544.

Jones, A. D. (2017). Food insecurity and mental health status: A global analysis of 149 countries. *American Journal of Preventive Medicine*, *53*(2), 264-273.

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, *107*(38), 16489-16493.

Kahneman, D., & Lovallo, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science*, *39*(1), 17-31.

Kahneman, D., & Tversky, A. (1982). Heuristics and biases. In D. Kahneman & A. P. Slovic (Eds.), *Judgement Under Uncertainty: Heuristics and Biases*. Cambridge University Press.

Kerkhofs, M., & Lindeboom, M. (1995). Subjetive health measures and state dependent reporting errors. *Health Economics*, *4*, 221-235.

King, G., Murray, C. J. L., Salomon, J. A., & Tandon, A. (2004). Enhancing the validity and cross-cultural comparability of measurement in survey research. *American Political Science Review*, *97*(4), 567-583.

Lei, X. Y., Song, G. X., & Su, X. J. (2021). Information, belief, and health behavior: Evidence from China. Department of Economics, University of Alberta Working Paper No. 2021-09.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, *30*(1), 67-80.

Lindeboom, M., & van Doorslaer, E. (2004). Cut-point shift and index shift in self-reported health. *Journal of Health Economics*, *23*(6), 1083-1099.

Lu, H., Nie, P., & Qian, L. (2021). Do quarantine experiences and attitudes towards COVID-19 affect the distribution of mental health in China? A quantile regression analysis. *Applied Research in Quality of Life*, 16: 1925-1942.

Malmendier, U., & Taylor, T. (2015). On the verges of overconfidence. *Journal of Economic Perspectives*, *29*(4), 3-8.

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, *50*(4), 370–396.

McGraw, A. P., Mellers, B. A., & Ritov, I. (2004). The affective costs of overconfidence. *Journal of Behavioral Decision Making*, *17*(4), 281-295.

Mellers, B. A., & McGraw, A. P. (2001). Anticipated emotions as guides to choice. *Current Directions in Psychological Science*, *10*(6), 210-214.

Mishra, V., & Smyth, R. (2015). Estimating returns to schooling in urban China using conventional and heteroskedasticity-based instruments. *Economic Modelling*, *47*, 166-173.

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, *115*(2), 502-517.

Moore, D. A., & Schatz, D. (2017). The three faces of overconfidence. *Social and Personality Psychology Compass*, *11*(8), e12331.

Murphy, S. C., Barlow, F. K., & von Hippel, W. (2017). A longitudinal test of three theories of overconfidence. *Social Psychological and Personality Science*, *9*(3), 353-363.

NHC. (2020). *Recent development on COVID-19 in China*. National Health Commission of the People's Republic of China. Retrieved April 17 from

Nie, P., Wang, L., & Sousa-Poza, A. (2021). Health perception biases and risky health behaviors in China. *Applied Economics Letters* (forthcoming).

Paulhus, D. L. (1998). Interpersonal and intrapsychic adaptiveness of trait self-enhancement: a mixed blessing? *Journal of Personality and Social Psychology*, *74*, 1197–1208.

Pénard, T., Poussing, N., & Suire, R. (2013). Does the Internet make people happier? *The Journal of Socio-Economics*, *46*(0), 105-116.

Pirinsky, C. (2013). Confidence and economic attitudes. *Journal of Economic Behavior & Organization*, *91*, 139-158.

Prakash, K., & Smyth, R. (2019). ‘The quintessential Chinese dream’? Homeownership and the subjective wellbeing of China's next generation. *China Economic Review*, *58*, 101350.

Proto, E., & Zhang, A. (2021). *COVID-19 and mental health of individuals with different personalities. IZA DP No. 14388*. IZA.

Qiu, Y., Chen, X., & Shi, W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, *33*, 1127–1172.

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, *1*(3), 385-401.

Shaw, I., & Taplin, S. (2007). Happiness and mental health policy: A sociological critique. *Journal of Mental Health*, *16*(3), 359-373.

Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: A social psychological perspective on mental health. *Psychological Bulletin*, *103*(2), 193-210.

Tiefenbeck, V., Goette, L., Degen, K., Tasic, V., Fleisch, E., Lalive, R., & Staake, T. (2016). Overcoming salience bias: How real-time feedback fosters resource conservation. *Management Science*, *64*(3), 1458-1476. https://doi.org/10.1287/mnsc.2016.2646

Torales, J., O’Higgins, M., Castaldelli-Maia, J. M., & Ventriglio, A. (2020). The outbreak of COVID-19 coronavirus and its impact on global mental health. *International Journal of Social Psychiatry*, *66*(4), 317-320.

Tubadji, A. (2021). Culture and mental health resilience in times of COVID-19. *Journal of Population Economics*, 34: 1219-1259.

Wan, W. (2020, May 4, 2020). The coronavirus pandemic is pushing America into a mental health crisis. *Washington Post*.

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C. S., & Ho, R. C. (2020). Immediate psychological responses and associated factors during the initial stage of the 2019 Coronavirus Disease (COVID-19) epidemic among the general population in China. *International Journal of Environmental Research and Public Health*, *17*, 1729.

World Health Organization. (2001). *The World Health Report 2001. Mental health: New Understanding. New Hope*.

Wu, Z., & McGoogan, J. M. (2020). Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: Summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention. *JAMA*.

Wutich, A., & Ragsdale, K. (2008). Water insecurity and emotional distress: Coping with supply, access, and seasonal variability of water in a Bolivian squatter settlement. *Social Science & Medicine*, *67*(12), 2116-2125.

Xiang, Y.-T., Yang, Y., Li, W., Zhang, L., Zhang, Q., Cheung, T., & Ng, C. H. (2020). Timely mental health care for the 2019 novel coronavirus outbreak is urgently needed. *The Lancet Psychiatry*, *7*(3), 228-229.

Xu, H., & Xie, Y. (2017). Socioeconomic inequalities in health in China: A reassessment with data from the 2010–2012 China Family Panel Studies. *Social Indicators Research*, *132*(1), 219-239.

Yamamura, E., & Tsustsui, Y. (2021). School closures and mental health during the COVID-19 pandemic in Japan. *Journal of Population Economics*, 34: 1261-1298.

Ziebarth, N. (2010). Measurement of health, health inequality, and reporting heterogeneity. *Social Science & Medicine*, *71*(1), 116-124.

Tables and Figures

Table 1 Descriptive statistics.

	Full sample		R_i<0	R_i>0	
Variable	Mean	SD	Mean	Mean	MD
Relative health bias	-11.206	33.32	-	-	-
R_i>0, SAH	8.563	15.848	-	-	-
R_i<0, SAH	19.769	22.811	-	-	-
Mental health					
Depression	16.358	7.434	15.448	18.086	-2.638***
Happiness	7.625	1.771	7.859	7.180	0.679***
Life satisfaction	7.266	1.935	7.489	6.842	0.647***
Male	0.372	0.484	0.345	0.424	-0.079***
Age	30.530	9.245	29.775	31.959	-2.183***
Education					
Primary school or	0.009	0.093	0.011	0.005	0.006
Secondary school	0.052	0.222	0.050	0.055	-0.005
Vocational school	0.092	0.289	0.081	0.112	-0.031**
University or higher	0.848	0.360	0.858	0.828	0.031*
Religion (1 = yes; 0 =	0.082	0.274	0.070	0.104	-0.034**
Marital status					
Married	0.430	0.495	0.405	0.476	-0.071***
Single	0.555	0.497	0.583	0.503	0.079***
Other	0.015	0.123	0.013	0.021	-0.008
Household shortage of food or water	0.090	0.286	0.088	0.095	-0.007
Community-level	0.923	0.266	0.927	0.916	0.011
Trust					
1 = fully disagree	0.022	0.146	0.018	0.028	-0.010
2	0.080	0.272	0.059	0.120	-0.061***
3	0.402	0.490	0.360	0.483	-0.123***
4	0.451	0.498	0.510	0.339	0.171***
5 = fully agree	0.045	0.207	0.053	0.030	0.023**
Household economic status					
Poorest	0.023	0.150	0.023	0.024	-0.001
Poorer	0.143	0.350	0.132	0.165	-0.033*
Middle	0.788	0.409	0.799	0.767	0.031
Richer/richest	0.046	0.209	0.047	0.044	0.002
Rural	0.375	0.484	0.407	0.315	0.092***
Region					
East	0.353	0.478	0.335	0.388	-0.053**
Center	0.208	0.406	0.213	0.199	0.013

West	0.368	0.482	0.381	0.343	0.037
Northeast	0.071	0.257	0.072	0.070	0.002
Obs.	1830		1198	632	

Note: MD stands for mean difference. The observations for depression are 1828. The significance of the mean difference is based on independent t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table 2 Relative health bias and mental health

Panel A: Depression	(1)	(2)
Positive health perception bias	0.094***	0.078***
	(0.015)	(0.015)
Negative health perception bias	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)
Positive health perception bias	-0.021***	-0.015***
	(0.003)	(0.003)
Negative health perception bias	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)
Positive health perception bias	-0.022***	-0.014***
	(0.004)	(0.003)
Negative health perception bias	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 depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 3 Relative health bias and mental health by COVID-19 outbreak severity

Panel A: Depression	(1)	(2)
Positive health perception bias	0.071***	0.059***
	(0.019)	(0.019)
High impact of COVID-19	-0.630	-1.066*
	(0.603)	(0.601)
Positive health perception bias x high impact of COVID-19	0.058**	0.048*
	(0.029)	(0.029)
Negative health perception bias	-0.008	-0.003
	(0.012)	(0.011)
Negative health perception bias x high impact of COVID-19	0.032*	0.024
	(0.019)	(0.018)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.042	0.114
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.016***	-0.010**
	(0.004)	(0.004)
High impact of COVID-19	0.001	0.108
	(0.138)	(0.144)
Positive health perception bias x high impact of COVID-19	-0.012*	-0.012**
	(0.007)	(0.006)
Negative health perception bias	0.004	0.002
	(0.003)	(0.003)
Negative health perception bias x high impact of COVID-19	-0.002	-0.002
	(0.004)	(0.004)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.048	0.170
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.014***	-0.006
	(0.005)	(0.004)
High impact of COVID-19	0.103	0.208
	(0.154)	(0.154)
Positive health perception bias x high impact of COVID-19	-0.020***	-0.019***
	(0.007)	(0.007)
Negative health perception bias	0.006*	0.004
	(0.003)	(0.003)
Negative health perception bias x high impact of COVID-19	-0.009*	-0.009*
	(0.005)	(0.005)
Sociodemographics	No	Yes
Regional dummies	No	Yes

	(1)	(2)
N	1830	1830
R^2	0.044	0.192

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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. The dummy for high impact of COVID-19 is 1 if the provincially confirmed cases are above the average of confirmed cases nationwide, and 0 otherwise.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Panel A: Depression	(1)	(2)
Positive health perception bias	0.079***	0.066***
	(0.017)	(0.017)
High impact of COVID-19	0.276	0.004
	(0.666)	(0.682)
Positive health perception bias x high impact of COVID-19	0.051	0.043
	(0.033)	(0.032)
Negative health perception bias	-0.002	0.001
	(0.011)	(0.010)
Negative health perception bias x high impact of COVID-19	0.020	0.018
	(0.021)	(0.020)
N	1828	1828
R^2	0.045	0.114
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.017***	-0.010***
	(0.004)	(0.004)
High impact of COVID-19	0.062	0.176
	(0.148)	(0.151)
Positive health perception bias x high impact of COVID-19	-0.015**	-0.015**
	(0.007)	(0.007)
Negative health perception bias	0.004	0.003
	(0.003)	(0.003)
Negative health perception bias x high impact of COVID-19	-0.004	-0.006
	(0.005)	(0.004)
N	1830	1830
R^2	0.049	0.171
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.015***	-0.007**
	(0.004)	(0.004)
High impact of COVID-19	0.221	0.355**
	(0.163)	(0.162)
Positive health perception bias x high impact of COVID-19	-0.024***	-0.023***
	(0.008)	(0.007)

Negative health perception bias	0.006**	0.005*
	(0.003)	(0.003)
Negative health perception bias x high impact of COVID-19	-0.012**	-0.014***
	(0.005)	(0.005)
N	1830	1830
R^2	0.045	0.194

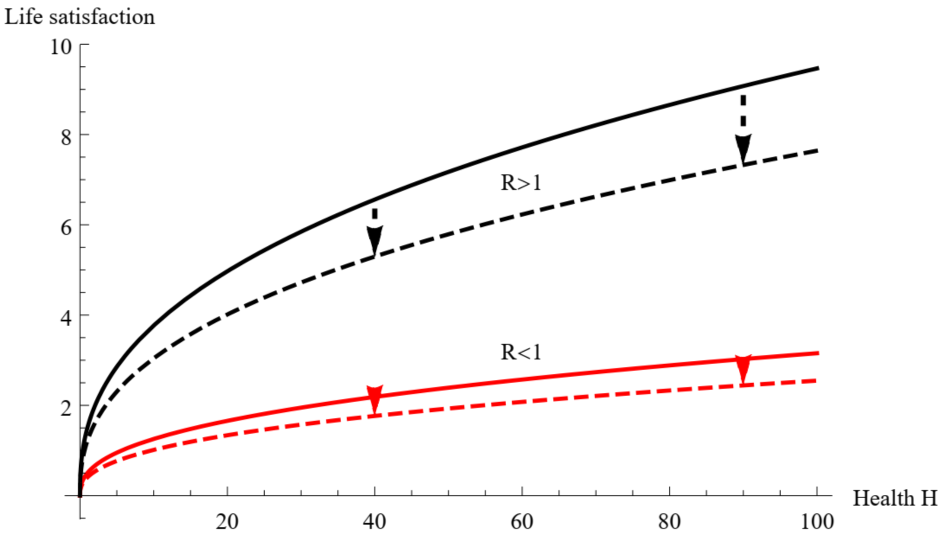
Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). The controls include individual characteristics (age, age squared, education level, marital status, and trust), household economic status (poorest, poorer, middle, and richer, with poorest as 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. The dummy for high impact of COVID-19 is 1 if the provincially confirmed deaths are above the average of confirmed deaths nationwide, and 0 otherwise.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 Lewbel's heteroscedasticity-based 2SLS estimates for relative health bias and mental health

Panel A: Depression	(1)	(2)
Positive health perception bias	0.070**	0.088***
	(0.032)	(0.029)
Negative health perception bias	0.014	0.069**
	(0.030)	(0.031)
Breusch-Pagan test	Chi2(31) = 129.837	Chi2(31) = 122.355
	p-value = 0.000	*p*-value = 0.000
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.016**	-0.012*
	(0.007)	(0.007)
Negative health perception bias	-0.009	-0.005
	(0.007)	(0.007)
Breusch-Pagan test	Chi2(31) = 190.216	Chi2(31) = 183.884
	p-value = 0.000	*p*-value = 0.000
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.013	-0.004
	(0.008)	(0.007)
Negative health perception bias	-0.005	-0.000
	(0.007)	(0.008)
Breusch-Pagan test	Chi2(31) = 142.590	Chi2(31) = 133.810
	p-value = 0.000	*p*-value = 0.000

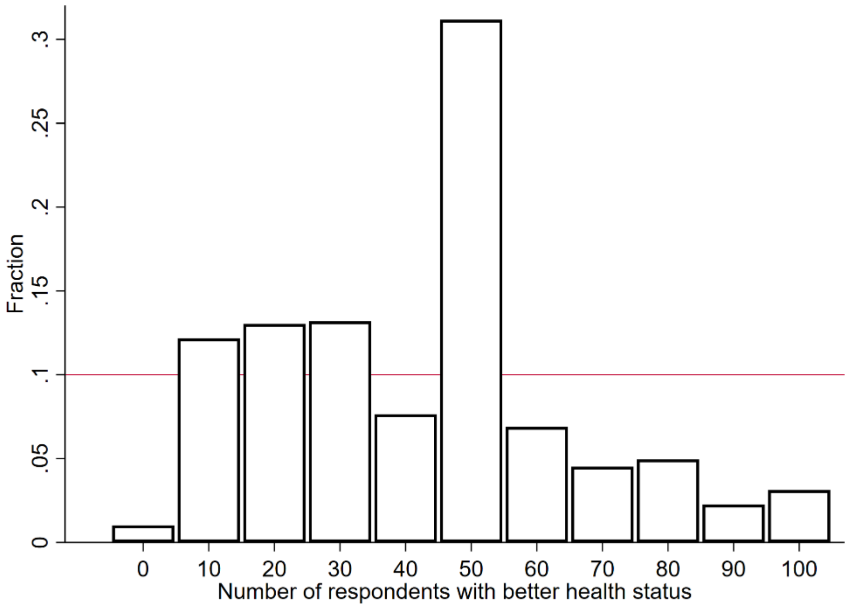
Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). The controls include individual characteristics (age, age squared, education level, marital status, trust), household economic status (poorest, poorer, middle, richer, with poorest as the reference), 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). For column 1, instruments generated by Z including education, marital status and trust. For column 2, instruments generated by Z including gender, age, household shortage of food or water and trust. Standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Fig. 1 Health perception bias and life satisfaction



Note: Individuals with a positive perception bias (black curve) have a higher utility of individuals with a negative health perception (red curve). After a reduction in the consumption of material or non-material goods, a proxy for higher COVID19 cases and the related lockdown measures, both curves move downward (dashed curves). Individuals with a large health perception bias experience a larger drop in life satisfaction.

Fig. 2 Perceived Population Share in Better Health (b_i)



Note: Responses are based on the question: "Imagine one would randomly select 100 people in your age. How many of those 100 people would be in better health than you?" Respondents who answer 0 believe nobody is in better health, and those who answer 99 believe everybody is healthier than them.

Fig. 3 Distribution of relative health bias R_i (based on SAH)

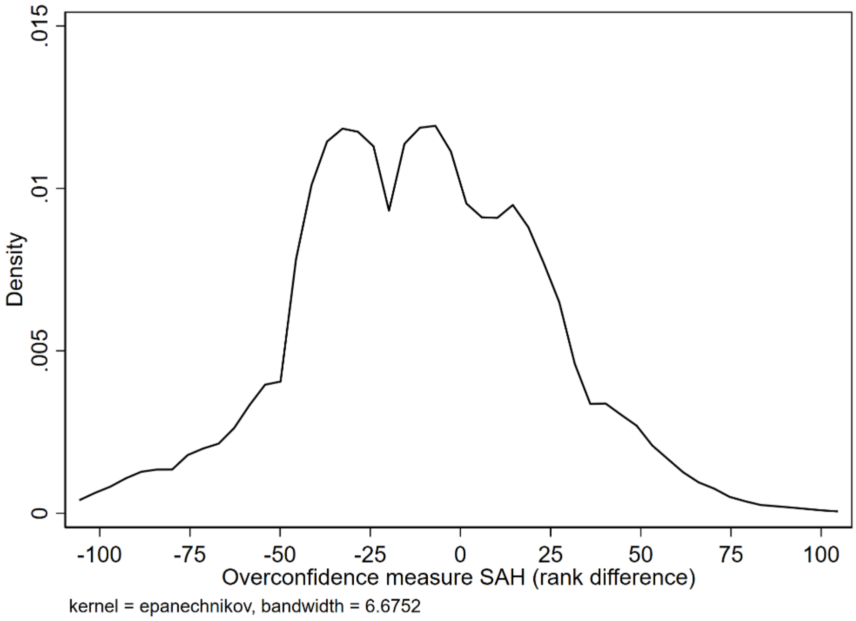
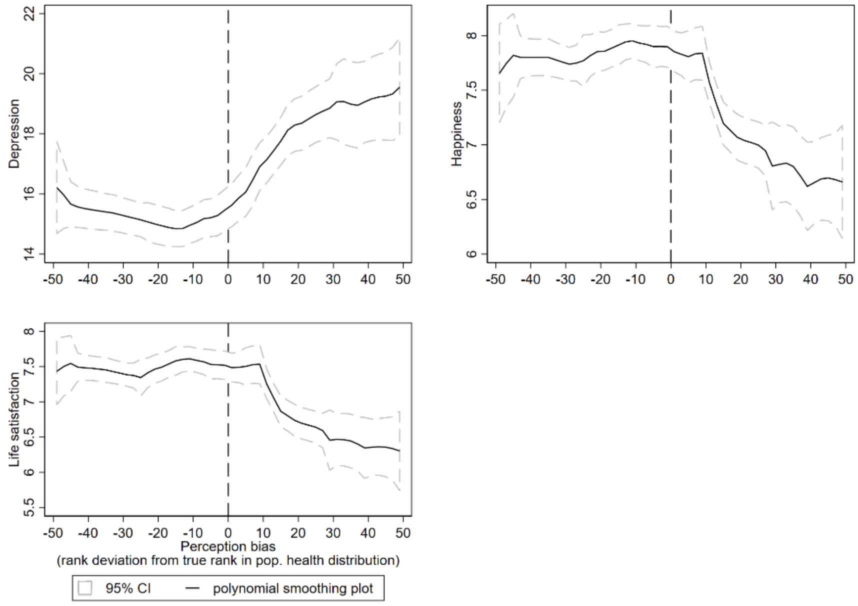


Fig. 4 Nonparametric plot of biased health perceptions and mental health



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

Appendix

Table A1 Descriptive statistics: CFPS 2018 (adjusted by sampling weights).

Variable	Mean	SD
Gender (1 = male; 0 = female)	0.514	0.004
Age	45.741	0.288
Education		
Primary school or below	0.379	0.012
Secondary school	0.297	0.006
Vocational school	0.253	0.009
University or higher	0.071	0.005
Marital status		
Married	0.742	0.007
Single	0.178	0.006
Other	0.080	0.003
Household economic status		
Poorest	0.205	0.012
Poorer	0.238	0.008
Middle	0.267	0.007
Richer/richest	0.290	0.016
Rural	0.394	0.023
Region		
East	0.371	0.041
Center	0.239	0.035
West	0.270	0.043
Northeast	0.120	0.029
Self-report health		
Poor	0.151	0.005
Fair	0.129	0.006
Good	0.427	0.009
Very good	0.160	0.006
Excellent	0.133	0.005
N	27352	

Note: Table shows the summary statistics of the 2018 China Family Panel Studies as a benchmark comparison. The variables are weighted by CFPS sample weights to ensure representativeness.

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

Panel A: Depression	(1)	(2)
Positive health perception bias	0.064***	0.055***
	(0.020)	(0.019)
High impact of COVID-19	-0.044	-0.177
	(0.376)	(0.476)
Positive health perception bias 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)
Positive health perception bias	-0.016***	-0.012***
	(0.004)	(0.004)
High impact of COVID-19	-0.052	-0.103
	(0.091)	(0.109)
Positive health perception bias 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)
Positive health perception bias	-0.016***	-0.012***
	(0.005)	(0.004)
High impact of COVID-19	-0.020	-0.070
	(0.100)	(0.117)
Positive health perception bias 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 depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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)
Positive health perception bias	0.109***	0.094***
	(0.020)	(0.019)
High impact of COVID-19	1.402***	1.211***
	(0.374)	(0.384)
Positive health perception bias 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)
Positive health perception bias	-0.019***	-0.013***
	(0.004)	(0.004)
High impact of COVID-19	-0.052	-0.024
	(0.091)	(0.090)
Positive health perception bias 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)
Positive health perception bias	-0.019***	-0.012***
	(0.005)	(0.004)
High impact of COVID-19	-0.145	-0.066
	(0.100)	(0.097)
Positive health perception bias 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 depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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.

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

Table A4 Relative health bias and mental health by age

	Age<35		Age⩾35	
Panel A: Depression	(1)	(2)	(3)	(4)
Positive health perception bias	0.116***	0.099***	0.047*	0.029
	(0.018)	(0.017)	(0.026)	(0.027)
Negative health perception bias	0.014	0.019*	-0.023	-0.020
	(0.010)	(0.010)	(0.020)	(0.019)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	1301	1301	527	527
R^2	0.051	0.130	0.023	0.110
Panel B: Happiness	(1)	(2)	(3)	(4)
Positive health perception bias	-0.020***	-0.014***	-0.025***	-0.018***
	(0.004)	(0.004)	(0.006)	(0.006)
Negative health perception bias	0.002	-0.000	0.006	0.002
	(0.002)	(0.002)	(0.005)	(0.005)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	1302	1302	528	528
R^2	0.038	0.174	0.061	0.198
Panel C: Life satisfaction	(1)	(2)	(3)	(4)
Positive health perception bias	-0.019***	-0.012***	-0.028***	-0.019***
	(0.005)	(0.004)	(0.006)	(0.006)
Negative health perception bias	0.001	-0.001	0.006	0.002
	(0.003)	(0.003)	(0.005)	(0.004)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	1302	1302	528	528
R^2	0.026	0.174	0.070	0.276

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). The controls include individual characteristics (age, 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 A5 Relative health biases and mental health by gender

	Male		Female	
Panel A: Depression	(1)	(2)	(3)	(4)
Positive health perception bias	0.101***	0.083***	0.092***	0.074***
	(0.021)	(0.021)	(0.020)	(0.021)
Negative health perception bias	0.024	0.030*	-0.005	-0.006
	(0.017)	(0.016)	(0.011)	(0.011)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	680	680	1148	1148
R^2	0.046	0.146	0.036	0.104
Panel B: Happiness	(1)	(2)	(3)	(4)
Positive health perception bias	-0.016***	-0.011**	-0.025***	-0.020***
	(0.005)	(0.005)	(0.005)	(0.004)
Negative health perception bias	0.003	0.000	0.002	0.000
	(0.004)	(0.004)	(0.003)	(0.003)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	681	681	1149	1149
R^2	0.033	0.179	0.048	0.163
Panel C: Life satisfaction	(1)	(2)	(3)	(4)
Positive health perception bias	-0.015***	-0.008*	-0.026***	-0.022***
	(0.005)	(0.005)	(0.005)	(0.005)
Negative health perception bias	0.004	0.001	-0.000	-0.001
	(0.004)	(0.004)	(0.003)	(0.003)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	681	681	1149	1149
R^2	0.030	0.226	0.038	0.180

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A6 Relative health biases and mental health by education

	No university		University or higher	
Panel A: Depression	(1)	(2)	(3)	(4)
Positive health perception bias	0.086**	0.066	0.096***	0.080***
	(0.038)	(0.041)	(0.016)	(0.015)
Negative health perception bias	-0.006	-0.007	0.008	0.012
	(0.024)	(0.023)	(0.010)	(0.010)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	279	279	1549	1549
R^2	0.033	0.182	0.039	0.119
Panel B: Happiness	(1)	(2)	(3)	(4)
Positive health perception bias	-0.026***	-0.019**	-0.020***	-0.014***
	(0.008)	(0.008)	(0.004)	(0.003)
Negative health perception bias	0.000	-0.003	0.004*	0.002
	(0.006)	(0.006)	(0.002)	(0.002)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	279	279	1551	1551
R^2	0.043	0.168	0.045	0.179
Panel C: Life satisfaction	(1)	(2)	(3)	(4)
Positive health perception bias	-0.027***	-0.015*	-0.020***	-0.013***
	(0.008)	(0.009)	(0.004)	(0.004)
Negative health perception bias	0.002	-0.002	0.002	0.001
	(0.007)	(0.006)	(0.003)	(0.002)
Sociodemographics	No	Yes	No	Yes
Regional dummies	No	Yes	No	Yes
N	279	279	1551	1551
R^2	0.043	0.168	0.033	0.177

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A7 Relative health bias and mental health (using the CDF of SAH from the CFPS 2018)

Panel A: Depression	(1)	(2)
Positive health perception bias	0.131***	0.100***
	(0.034)	(0.033)
Negative health perception bias	0.010	0.013
	(0.009)	(0.009)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1846	1846
R^2	0.015	0.106
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.024***	-0.014**
	(0.008)	(0.007)
Negative health perception bias	0.001	-0.002
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1848	1848
R^2	0.010	0.161
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.023***	-0.012
	(0.008)	(0.007)
Negative health perception bias	0.000	-0.002
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1848	1848
R^2	0.008	0.182

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A8 Recategorization of SAH

Category	SAH 5 categories	SAH 4 categories	SAH 4 categories	SAH 3 categories
1	very unhealthy	very unhealthy/unhealthy	very unhealthy	very unhealthy/unhealthy
2	unhealthy	OK	unhealthy	OK
3	OK	healthy	OK	healthy/very healthy
4	healthy	very healthy	healthy/very healthy	
5	very healthy			

Table A9 Relative health bias and mental health (merging 1=very unhealthy and 2=unhealthy merged into the new category of "unhealthy")

Panel A: Depression	(1)	(2)
Positive health perception bias	0.092***	0.076***
	(0.015)	(0.015)
Negative health perception bias	0.003	0.006
	(0.009)	(0.009)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1833	1833
R^2	0.035	0.119
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.021***	-0.014***
	(0.003)	(0.003)
Negative health perception bias	0.003	0.001
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1835	1835
R^2	0.043	0.173
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.021***	-0.014***
	(0.004)	(0.003)
Negative health perception bias	0.002	0.001
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1835	1835
R^2	0.034	0.191

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A10 Relative health bias and mental health (merging "4=healthy" and "5=very healthy" into the new category of "4=healthy")

Panel A: Depression	(1)	(2)
Positive health perception bias	0.096***	0.081***
	(0.015)	(0.015)
Negative health perception bias	0.002	0.004
	(0.008)	(0.008)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1835	1835
R^2	0.041	0.113
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.022***	-0.016***
	(0.003)	(0.003)
Negative health perception bias	0.003	0.001
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1837	1837
R^2	0.049	0.172
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.023***	-0.016***
	(0.004)	(0.004)
Negative health perception bias	0.001	0.000
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1837	1837
R^2	0.040	0.191

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A11 Relative health bias and mental health (merging "1=very unhealthy" and "2=unhealthy" into the new category of "1=unhealthy", and "4=healthy" and "5=very healthy" into the new category of "3=healthy")

Panel A: Depression	(1)	(2)
Positive health perception bias	0.093***	0.078***
	(0.015)	(0.015)
Negative health perception bias	-0.001	0.002
	(0.008)	(0.008)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1840	1840
R^2	0.039	0.121
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.021***	-0.015***
	(0.003)	(0.003)
Negative health perception bias	0.003	0.001
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1842	1842
R^2	0.047	0.178
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.022***	-0.015***
	(0.004)	(0.004)
Negative health perception bias	0.002	0.001
	(0.002)	(0.002)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1842	1842
R^2	0.039	0.196

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A12 Relative health bias and mental health (trimmed R_i distribution and omitting possible guesses)

Panel A: Depression	(1)	(2)
Positive health perception bias	0.124***	0.107***
	(0.024)	(0.025)
Negative health perception bias	0.018	0.021
	(0.016)	(0.015)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1062	1062
R^2	0.031	0.132
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.033***	-0.025***
	(0.005)	(0.005)
Negative health perception bias	-0.005	-0.006
	(0.004)	(0.004)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1063	1063
R^2	0.037	0.174
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.033***	-0.025***
	(0.006)	(0.006)
Negative health perception bias	-0.010**	-0.010**
	(0.005)	(0.004)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1063	1063
R^2	0.0299	0.2081

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A13 Health perception biases (as a continuous measure) and mental health

Panel A: Depression	(1)	(2)
Health perception bias	0.032***	0.025***
	(0.006)	(0.006)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.021	0.099
Panel B: Happiness	(1)	(2)
Health perception bias	-0.010***	-0.006***
	(0.001)	(0.001)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.034	0.162
Panel C: Life satisfaction	(1)	(2)
Health perception bias	-0.009***	-0.006***
	(0.001)	(0.001)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.026	0.181

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A14 Positive health perception bias and mental health

Panel A: Depression	(1)	(2)
Positive health perception bias	2.638***	2.160***
	(0.380)	(0.381)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1828	1828
R^2	0.029	0.105
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.679***	-0.435***
	(0.088)	(0.086)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.033	0.163
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.647***	-0.399***
	(0.097)	(0.095)
Sociodemographics	No	Yes
Regional dummies	No	Yes
N	1830	1830
R^2	0.0253	0.1820

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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 A15 Relative health bias and mental health

Panel A: Depression	(1)	(2)
Positive health perception bias	0.105***	0.087***
	(0.016)	(0.016)
Negative health perception bias	0.009	0.013
	(0.010)	(0.010)
Sociodemographics	No	Yes
Regional dummies	No	Yes
City FE	Yes	Yes
Day FE	Yes	Yes
N	1828	1828
R^2	0.237	0.286
Panel B: Happiness	(1)	(2)
Positive health perception bias	-0.018***	-0.011***
	(0.003)	(0.003)
Negative health perception bias	0.005*	0.002
	(0.003)	(0.003)
Sociodemographics	No	Yes
Regional dummies	No	Yes
City FE	Yes	Yes
Day FE	Yes	Yes
N	1830	1830
R^2	0.242	0.329
Panel C: Life satisfaction	(1)	(2)
Positive health perception bias	-0.021***	-0.013***
	(0.004)	(0.004)
Negative health perception bias	0.003	0.001
	(0.003)	(0.003)
Sociodemographics	No	Yes
Regional dummies	No	Yes
City FE	Yes	Yes
Day FE	Yes	Yes
N	1830	1830
R^2	0.240	0.350

Note: The dependent variables are depression (Panel A), happiness (Panel B) and life satisfaction (Panel C). 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Fig. A1 Distribution of SAH