Biased health perceptions and risky health behaviors—Theory and evidence



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# Biased Health Perceptions and Risky Health Behaviors—Theory and Evidence

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**Abstract**

This paper investigates the role of biased health perceptions as a potential driving force of risky health behaviors. We define absolute and relative health perception biases, illustrate their measurement in surveys and provide evidence on their relevance. Next, we decompose the theoretical effect into its extensive and intensive margin: When the extensive margin dominates, people (wrongly) believe they are healthy enough to "afford" unhealthy behavior. Finally, using three population surveys, we provide robust empirical evidence that respondents who overestimate their health are less likely to exercise and sleep enough, but more likely to eat unhealthily and drink alcohol daily.

**Keywords:** health bias, health perceptions, subjective beliefs, overconfidence, overoptimism, risky behavior, smoking, obesity, exercising, SF12, SAH, BASE-II, SOEP-IP

**JEL classification:** D11, D83, D91, I12, I18, P46

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# 1 Introduction

> "I am so healthy I can do dangerous things and still be unlined, as yet unscathed, and beautiful."
>
> (Nancy Etcoff, psychologist at Harvard Medical School, in: *Survival of the Prettiest: The Science of Beauty*, 2011)

Can risky health behavior be "optimal"? While most non-economists would immediately refute this thought, economists would probably answer "it depends" and observe that, although drinking alcohol or eating junk food can be detrimental to health, people pursue those activities because they are also pleasurable. For economists, the optimality of a risky health behavior ultimately depends on the associated cost and benefits as perceived by the individual (Grossman, 1972; Becker and Murphy, 1988; Dragone, 2009; Cawley and Ruhm, 2011).

According to the benchmark theoretical framework, economic agents have perfect information and infinite computational capacity, which allows them to correctly assess costs and benefits of each alternative and, accordingly, choose optimal risky behavior. Behavioral economists have challenged this view by empirically and theoretically studying behavior that deviates from the predictions obtained under perfect rationality and information (cf. Rabin, 2013). In health economics, influential studies have shown that consumers pick dominated health plans and leave money on the table (Abaluck and Gruber, 2011, 2016; Ketcham et al., 2012, 2016; Bhargava et al., 2017; Kettlewell, 2020). Research has also cited behavioral phenomena as explanations for why people engage in "too much" risky health behavior. For example, theoretical papers model the role of hyperbolic discounting and time inconsistencies for smoking and overeating (Gruber and Kőszegi, 2001; Strulik and Trimborn, 2018). In a field experiment among college students, Avery et al. (2019) show that present-biased individuals are more likely to take up commitment devices to sleep enough, which reduces their insufficient sleep significantly. To explain the fact that many gym members overpay (Della Vigna and Malmendier, 2006), other field experiments find that nudges to exercise more regularly are mostly effective in the short-run (Royer et al., 2015; Carrera et al., 2018, 2020).

This paper is one of the first to investigate whether biased health perceptions could be a potential driving force of risky health behaviors. The causes and consequences of biased beliefs about own health are inherently difficult to study in causal effects frameworks, which is one reason why the health economics literature on this topic is very scant. One of the notable exceptions is Harris (2017) who finds that people who overestimate their activity levels consume more calories.[1] As a first main contribution, we formally introduce the concept of *health perception biases* into the (health) economics literature and document the existence of biased health perceptions in the population using three high quality datasets. Specifically, we propose two individual measures of *absolute* and *relative* health perception biases. Absolute perception biases are biased perceptions solely of own health, whereas relative perception biases are biased perceptions of own health *relative* to the health of the population and peers (c.f. Blanchflower et al., 2009; Mathieu-Bolh and Wendner, 2020). We show that, under plausible assumptions, there exists a one-to-one positive mapping between these two health perception measures.

Although we deliberately choose the much broader definition and interpretation of "health perception biases", our measures could also be interpreted in the context of the concept of "overconfidence" (Camerer and Lovallo, 1999; Barber and Odean, 2001; Burks et al., 2013; Spinnewijn, 2015; Bago d'Uva et al., 2020; Cowan, 2018) or, outside economics, of overoptimism biases (Weinstein, 1980, 1989; Sharot, 2011) and self-esteem (Himmler and Koenig, 2012). Overconfidence implies that a person believes that her ability, performance or information is better than it actually is (Benoît and Dubra, 2011; Ortoleva and Snowberg, 2015; Heidhues et al., 2019). It is an intuitive notion that has, however, no unambiguous definition or measurement in the economics literature. Studies have operationalized it as (i) overestimation of own performance, (ii) overplacement of own performance relative to others, or (iii) overprecision of own information or beliefs (Moore and Healy, 2008).

Our definitions of absolute and relative health perception biases are akin to the first two operationalizations of overconfidence, (i) overestimation and (ii) overplacement. However, it is important to emphasize that we do not aim at explaining *why* people have biased health perceptions, nor does this paper argue about the rationality of such beliefs. Our main goal is to theoretically and empirically investigate biased health perceptions as a potential underlying mechanism for health-related behavior and outcomes. To avoid confusion among the many notions of overconfidence, in this paper we simply refer to "health perception biases." Moreover, we would like to clarify that this paper investigates the role of biased perceptions about own health, not the role of biased perceptions about the *consequences* of risky behavior (cf. Viscusi, 1990; Lundborg, 2007; Ziebarth, 2018; Belot et al., 2019).

[1] In another study about health perception biases, Cawley and Philipson (1999) use life insurance data and the differential between perceived and predicted mortality risk to show that observed empirical patterns are inconsistent with standard insurance theory under perfect information. A possible explanation is that insurance mandates make low risk individuals worse off if many market participants are overconfident (Sandroni and Squintani, 2007).

As the quote in the epigraph demonstrates, but as also evident from the medical literature and guidelines, humans make decisions about their health behavior not just based on the health consequences of such behavior but also based on their personal (perceived) health status (National Institutes of Health, 2000; Maguire et al., 2000; Zwald et al., 2019). This is the core of this paper: If an individual's perception about her health status is biased, how could this health perception bias possibly affect her health behavior, and under what conditions does it deviate from behavior under correct beliefs?

Note that, to identify perception biases, the researcher must not only know the individual's perception of her health but also her true health status. To measure *absolute health perception biases*, we use objectively diagnosed health conditions (high cholesterol and high blood pressure) and elicit how respondents' perceptions about having such a condition deviate from the truth. In a representative German survey, we find that 30% of the population have biased perceptions about their high cholesterol levels.

To measure *relative health perception biases*, we asked respondents to rank their health status relative to a reference group. Specifically, for the purpose of this paper, we included the question in two high-quality surveys from Germany (one representative survey and one interdisciplinary survey). Comparing the elicited subjective ranking to the objective ranking within the population health distribution produces our measure of relative health perception biases. Consistent with the absolute measure, we find that about 30% of the respondents overestimate their rank in the population health distribution by at least 30 ranks. That is, for instance, they believe that they rank at the $70^{th}$ percentile when they actually only rank at the $40^{th}$ percentile of the population health distribution. In particular, we find an excess mass of people who believe that they rank between the $70^{th}$ and the $90^{th}$ percentile of the population health distribution.

To bound the impact of reporting errors in subjective health (cf. Lindeboom and van Doorslaer, 2004; Ziebarth, 2010), we benchmark our relative health perception measure against the standard Self Assessed Health (SAH) measure as well as the 12-Item Short Form (SF12) health survey measure. By construction, generic health measures like the SF12 include fewer systematic response biases as they are designed to produce unbiased continuous measures of physical and mental health. As the researcher requires an unbiased benchmark health measure to empirically identify perception biases, we test the robustness of our findings and the relevance of reporting errors by using both the SAH and SF12 as benchmark measures while controlling for a rich set of socio-demographics. While our true benchmark health measures for the *absolute* *health perception bias* are objective but also narrowly focused on physical health, the SAH and SF12 measures measure overall health and follow a broader concept. The empirical pattern and population distributions of two absolute and two relative bias measures across three different datasets yield important insights into the robustness and prevalence of such biases.

Next, we provide a theoretical framework that shows how biased health perceptions can affect risky health behavior. The framework is simple and flexible enough to explain nonlinear patterns between biased beliefs and risky behavior. Moreover, it highlights that biased health perceptions affect behavior through an extensive and an intensive margin, and that these margins operate in opposite directions. When the extensive margin dominates, risky health behavior and biased health perceptions are complements. This means that, the higher the perception of own health, the more an individual engages in unhealthy behavior, such as consuming fast food or not exercising. This is akin to saying: "Because I believe I am very healthy and can afford it, I eat more fast food and exercise less." On the contrary, when the intensive margin of perceived health dominates, risky health behavior and health biases are substitutes, hence a higher perceived health reduces risky behavior. This is akin to saying: "Because I perceive large health costs of risky behavior, I will eat less fast food and exercise more." Whether the extensive or intensive margin dominates is an empirical question.

Hence, as a final contribution, we document robust statistical links between health perception biases and risky health behaviors across all three datasets. Specifically, individuals who overestimate their health are significantly more likely to not exercise, to eat unhealthy, to be overweight and to sleep fewer hours. The statistical relationships are robust to controlling for socio-demographics, personality traits, cognitive skills, and risk aversion. They are also robust across our two notions of health perception biases. In the context of our model, these results are consistent with a dominant role of the extensive margin of health perception biases. Conversely, we do not find significant relationships for unbiased respondents and for those who are pessimistic about their health, a finding that is consistent with the extensive and intensive margin of health perception bias offsetting each other.[2] Notably, we find that smoking is not correlated with biased health perceptions. This result is consistent with Darden (2017), who finds that cardiovascular biomarker information at repeated health exams does not significantly alter smoking behavior. A possible explanation is that signals and information about own health, be it objective as in Darden (2017) or perceived as in this paper, are not powerful

[2]As it is common in this literature, our results cannot exclude that biased health perceptions and risky health behaviors are linked via unobservables, for instance genes (Linnér et al., 2019), or that the causality runs from risky behaviors to perception biases in the form of self-serving biases (Bénabou and Tirole, 2002).

drivers of smoking behavior, possibly because its addictive nature prevents the proper evaluation of the health consequences of smoking.

## 2 Defining Health Biases

In this section, we define absolute and relative health biases. Given the cross-sectional data used for the empirical exercise, we consider a static model in which, depending on health perceptions, an agent chooses risky health behavior that negatively affects her health. In the empirical section, we will investigate how such biases relate to risky health behaviors.

Before we begin, we would like to reiterate that this paper remains agnostic about the sources of biased beliefs. The origins of biased beliefs are still poorly understood. They have been linked to image motivation (Bénabou and Tirole, 2002) and humans' desire of being perceived positively by others (Burks et al., 2013; Goette et al., 2015; Charness et al., 2018), as opposed to managing a favorable self-image (Santos-Pinto and Sobel, 2005; Kőszegi, 2006; Weinberg, 2006) or self-serving biases (Babcock and Loewenstein, 1997; Di Tella et al., 2015). For example, Benoît and Dubra (2011) show that overconfidence—defined as overplacement—can result from a rational Bayesian updating process. In addition, conformism to social norms or "state-dependent reporting bias" may lead to systematic response error in self-reported health (c.f. Kerkhofs and Lindeboom, 1995; Lindeboom and van Doorslaer, 2004). In this paper, we neither study the origins of biased beliefs, nor do we make claims about the rationality of such beliefs.

Rather, consider a risky health behavior $x_i$ which impairs individual health $H_i$ according to the health production function $H_i = g(x_i)$, with $g' < 0$ and $g'' > 0$. For each individual $i$, we define the individual's *perceived* health status $\widetilde{H}_i$ as

$$\widetilde{H}_i \equiv A_i H_i = A_i g(x_i). \tag{1}$$

The term $A_i$ measures the individual's *absolute health perception bias*. If $A_i = 1$, the individual has a correct perception of her own health ($\widetilde{H}_i = H_i$), and a correct perception of the impact of her risky health behavior on health ($\widetilde{H}_i = g(x_i)$). If $A_i > 1$, individual $i$ displays a *positive absolute health bias*. This could be the case because she believes that her health is better than it really is, or because she believes that her risky health behavior is less health-damaging than it actually is. In either case, for a given health behavior, perceived health is better than true health. If instead $A < 1$, individual $i$ displays a *negative absolute health bias*. Our notion of an absolute health perception bias focuses on the uncertainty about one's own health condition whose sources could be, for example, optimism or pessimism biases, self-deception, a lack of health knowledge or reference group-dependent reporting biases. However, it is different from uncertainty about future health consequences (which in our static notation would be captured by uncertainty in $g(x_i)$).[3]

Next, given $H_i$, define the objective relative position (the "ranking") in the population health distribution as:

$$r_i \equiv 100 \cdot F\left(H_i\right), \tag{2}$$

where $F\left(H_i\right) \equiv \int_0^{H_i} dF(H)$ is the cumulative distribution function of population health (it is multiplied by 100 to provide a ranking on a 0–100 scale, as in the survey question that elicits this measure). Analogously, let the subjective health ranking be

$$\widetilde{r}_i \equiv 100 \cdot P_i F(\widetilde{H}_i), \tag{3}$$

where $P_i$ is the bias in the perception of the cumulative distribution function of population health.[4] If $P_i > 1$, individual $i$ believes that there are more people in bad health than there actually are; this can also be interpreted as pessimism bias about population health.

The comparison between $r_i = r_i\left(H_i\right)$ and $\widetilde{r}_i = \widetilde{r}_i\left(P_i, A_i H_i\right)$ allows us to identify the drivers of health biases. Both rankings depend on risky health behavior and objective health. However, the subjective ranking $\widetilde{r}_i$, also depends on the absolute health perception bias $A_i$, and the perception of the population health distribution $P_i$.

**Remark 1** *For a given reference population:*

[3]Self-serving biases can be considered assuming that perceived health is $\widetilde{H}_i \equiv A_i H_i = A_i g\left(x_i, B_i\right)$, where $B_i$ is a measure of the self-serving bias and $g_B > 0$. This is the case, for example, when individuals underestimate the health consequences of risky behavior because they believe that risky behaviors are less detrimental to health than they actually are. Since both $A$ and $B$ increase perceived health for a given risky behavior, henceforth, we assume that self-serving bias B is absent, and we focus on the effect of absolute and relative health biases.

[4]Note that the precise wording of our survey question to elicit $\widetilde{r}_i$ is designed to minimize what has been identified and called "state-depending reporting bias" in SAH (Lindeboom and van Doorslaer, 2004; Etilé and Milcent, 2006; Jürges, 2007; Bago d'Uva et al., 2008; Ziebarth and Karlsson, 2010). That is, the literature finds that survey respondents have an implicit age-dependent reference group in mind when responding to the standard SAH question; for example, older people tend to rate their health relatively better than younger people on the SAH scale. In our survey question to elicit $\widetilde{r}_i$, we therefore specify "Imagine one would randomly select 100 people in your age, [...]."

- *The objective health ranking $r_i$ decreases with risky health behavior and increases with better objective health:* $\frac{\partial r_i}{\partial x_i} < 0, \frac{\partial r_i}{\partial H_i} > 0$

- *The subjective health ranking $\widetilde{r}_i$ decreases with risky health behavior and increases with better objective health, the absolute health perception bias, and the population health pessimism bias:* $\frac{\partial \widetilde{r}_i}{\partial x_i} < 0, \frac{\partial \widetilde{r}_i}{\partial H_i}, \frac{\partial \widetilde{r}_i}{\partial A_i}, \frac{\partial \widetilde{r}_i}{\partial P_i} > 0.$

For each individual $i$, we define the *relative health perception bias* $R_i$ as the difference between the subjective and the objective ranking in the population health distribution:

$$R_i = \widetilde{r}_i - r_i \tag{4}$$

We say that individual $i$ displays a *positive relative health bias* when $R_i > 0$, and that she displays a *negative relative health bias* when $R_i < 0$. Manipulating equation (4) allows us to decompose the relative health bias into two components:

$$\begin{aligned} R_i &= 100\left[P_i F(A_i H_i) - F(H_i)\right] \\ &= 100\left[F(A_i H_i) - F(H_i)\right] + 100\left(P_i - 1\right) F\left(A_i H_i\right) \end{aligned} \tag{5}$$

The first component of equation (6) depends on the absolute health bias $A_i$: it is equal to zero if $A_i = 1$, and it increases as $A_i$ increases.[5] The second component is equal to zero if the perception of the population health distribution is correct $(P_i = 1)$, and it increases as $P_i$ increases.

Based on equation (5), we can state the following

**Remark 2** *For a given reference population and for a given belief $P_i$ about population health, there exists a one-to-one positive correlation between the absolute and the relative health perception bias.*

The above remark emphasizes a convenient property that allows us to use the *relative health perception bias* $R_i$ as a proxy for the *absolute health perception bias* $A_i$. In the following, we assume that this property holds.

[5]In principle, the beliefs about population health could depend on the individual's perceived health, i.e., $P_i = P_i(A_i H_i)$. In such a case, based on equation (5), higher perceived health $A_i H_i$ increases the relative perception bias if $P'(A_i H_i) F(A_i H_i) + P(A_i H_i) F'(A_i H_i) > 0$. As $F(AH)$, $F'(AH)$ and $P(AH)$ are positive, the condition always holds when P is constant (Remark 2), and also when $P'(A_i H_i) > 0$.

# 3 Model

To investigate the role of perceived health for health behavior, consider an individual that derives utility from risky health behavior $x$, perceived health $\widetilde{H} = AH = Ag(x)$, and consumption of a numeraire good $q$. To fix ideas, consider the following utility function

$$V(x, \widetilde{H}, q) = B(x) + \mathcal{H}(\widetilde{H}) + q \tag{6}$$

The first term $B(x)$ is the utility of a risky health behavior such as smoking, overeating, not exercising or not sleeping enough. The second term $\mathcal{H}(\widetilde{H})$ describes the benefits of perceived health. It can include mental and physical health, as well as any motive that links perceived health to, e.g., social image concerns, peer pressure, conformism to social norms or self-esteem. We assume that both, the utility of risky health behavior and the utility of health, are increasing and concave.

Given income $M$ and prices $p$, the individual chooses risky behavior $x$ by maximizing equation (6) subject to $M = px + q$ and $\widetilde{H} = Ag(x)$, with $x \in [0, M/p]$. Replacing the constraints in the objective function, this is equivalent to maximize $U(x)$, where

$$U(x) = B(x) + \mathcal{H}(Ag(x)) + M - px \tag{7}$$

For an internal solution, the optimal amount of risky behavior $x^*$ satisfies the following first order condition:

$$x^*: \qquad U'(x) = B'(x) - p + A\mathcal{H}'(Ag(x))g'(x) = 0 \tag{8}$$

Equation (8) implies that optimal risky behavior trades-off the marginal benefits $B' > 0$ of risky behavior, its price $p$, and its marginal impact on perceived health $A\mathcal{H}'g' < 0$. The latter term has a negative sign because more risky behavior reduces health ($g' < 0$), with a magnitude that depends on the absolute health perception bias $A$. In fact, the absolute health bias $A$ plays a double role for optimal risky behavior. First, it affects perceived health ($\widetilde{H} = Ag(x)$) in the marginal perceived health function $\mathcal{H}'(\cdot)$. Because changes in $A$ affect perceived health at the margin, that is, the "last unit" of perceived health, we will call it the *extensive margin of perceived health.* Second, $A$ affects the magnitude of the marginal cost of risky behavior ($\mathcal{H}'g'$). Because this channel determines the impact of $A$ for all "inframarginal units" of risky behavior, we will call it the *intensive margin of perceived health*.[6]

Ultimately, we want to assess how an increase in the health perception bias $A$ (or its proxy $R$, as per Remark 2) affects risky health behavior. This amounts to studying, omitting the arguments,

$$\frac{dx^*}{dA} = -\frac{g'}{U''}\widetilde{H}\mathcal{H}'' - \frac{g'}{U''}\mathcal{H}' \tag{9}$$

The first and the second term on the right hand side describe the extensive and the intensive margin of perceived health, respectively. The extensive margin implies a positive effect of the health perception bias on optimal risky behavior ($-g'\widetilde{H}\mathcal{H}''/U'' > 0$). To give an example, the effect on the extensive margin is akin to saying "Because (I think) I am healthy enough to not exercise, I decide to not exercise." In contrast, the intensive margin implies a negative effect of the health perception bias on optimal risky behavior ($-g'\mathcal{H}'/U'' < 0$). It is akin to saying "Because I don't want to jeopardize my (perceived) high health status, I will exercise more."

Based on equation (9), the following holds:

**Remark 3** *When the absolute health perception bias increases, optimal risky behavior increases if the impact of the absolute health perception bias on perceived health is larger than the impact on the marginal costs of risky behavior, and it decreases otherwise.*

The above remark shows that the balance between the extensive margin and the intensive margin of perceived health determines whether optimal risky health behavior ultimately increases or decreases with health perception biases. Recall that the extensive margin refers to the effect of perceived health on risky behavior: as the agent thinks she is very healthy, she believes she can afford engaging in risky behavior. Accordingly, the better the perceived health, the more she engages in risky behavior, which implies they they are complements. The intensive margin, instead, implies that the absolute health bias increases the marginal costs of risky behavior. Accordingly, the agent reduces her risky health behavior the larger her bias, which implies that they are substitutes. Overall, when the health perception bias dominates the costs of risky behavior (that is, when the extensive margin dominates), a larger health bias results in more risky behavior.

[6] Our notions of extensive and intensive margin of perceived health are inspired by, but different from the notions of extensive and intensive margin used to distinguish work participation and work effort.

Alternatively, we can describe equation (9) and the remark in terms of relative risk aversion. Define $\sigma \equiv -\widetilde{H}\mathcal{H}''/\mathcal{H}' > 0$ as the coefficient of relative risk aversion of perceived health, denote $\alpha \equiv \mathcal{H}'g'/U'' > 0$, and replace in equation (9) to obtain $dx^*/dA = \alpha\,(\sigma - 1)$. Hence the sign of $dx^*/dA$ depends on whether the relative risk aversion of perceived health is larger or smaller than 1. In the special case of a CRRA perceived health function, $\mathcal{H}(\widetilde{H}) = \frac{1}{1-\sigma}\widetilde{H}^{1-\sigma}$, the coefficient of relative risk aversion $\sigma$ is constant and independent of perceived health. Accordingly, risky behavior monotonically increases with the health perception biases if $\sigma > 1$, and it monotonically decreases if $\sigma < 1$. If instead $\sigma = 1$, the effect of $A$ on $x^*$ is nil. In general, however, the effect can be non-monotonic. For example, if the health function is quadratic or exponential, the relation between health perception biases and health behavior is U-shaped.[7]

# 4 Datasets

To empirically identify the relationship between health perception biases and risky health behaviors, we exploit three representative German surveys. The first survey is the German National Health Survey East-West 1991 (GNHSEW91s), which is representative of the German population. The GNHSEW includes objective health measures, taken by health care professionals. By comparing specific clinical diagnoses of high cholesterol and high blood pressure to respondents' perceptions about such conditions, we generate measures of absolute health perception biases.

The second survey is the Berlin Aging Study II (BASE-II), which is representative of elderly residents in Berlin. This dataset includes objective health measures, taken by health care professionals, cognitive tests and rich socio-demographic background information. The BASE-II also contains subjective health measures and the continuous and generic health measure SF12. Most importantly, for this paper, we added a question to BASE-II that elicits respondents' perceived rank $\widetilde{r}_i$ in the population health distribution.

The third survey is the Innovation Panel of the representative German Socio-Economic Panel Study (SOEP-IP). The SOEP-IP includes the standard socio-demographics of the SOEP, self-reported health measures as well as the SF12. In addition to adding it to BASE-II, we also included the same measure on respondents' perceived rank in the population health distribu-

[7]For simplicity, in this example, $A$ does not affect the utility of risky health behavior. In the more general case $U(x, \widetilde{H}) + q$ where risky behavior and perceived health are non-separable, the sign of $dx^*/dA$ depends on whether the marginal utility of perceived health $U_{\widetilde{H}}$ is large enough, as in the separable case. Specifically: $dx^*/dA > 0$ if and only if $U_{\widetilde{H}} > -\widetilde{H}U_{\widetilde{H}\widetilde{H}} - gU_{\widetilde{H}x}/g'$

tion to SOEP-IP. Hence we can measure perceived ranking $\widetilde{r}_i$ and, together with the objective ranking $r_i$ from the SF12, generate measures of relative health perception biases, $R_i$.

### 4.1 German National Health Survey East-West 1991 (*GNHSEW91*)

The GNHSEW91 is a representative cross-sectional survey of the German population. It was in the field in East and West Germany between 1990 and 1992 (Robert Koch Institut, 2012). Many questions are nutrition and health-related; our *GNHSEW91* working sample consists of 6,429 respondents. Importantly, health care professionals measured both, the clinical blood pressure as well as the cholesterol levels of all respondents (Panel B of Table A1, Appendix). In addition, before the clinical examination by nurses and physicians, GNHSEW91 surveys respondents' perceptions about whether they have high blood pressure or high cholesterol levels in a self-completed questionnaire (Panel C of Table A1, Appendix).[8] Comparing perceived ($\widetilde{H}_i$) and true health ($H_i$) allows us to measure absolute health perception biases (Panel A of Table A1 and Section 5.1).

**Health Behavior**. Panel D of Table A1 (Appendix) lists measures of risky health behaviors. Thirty-three percent are current *smokers* and 49% do not exercise at all (*No sports*). Thirteen percent consume alcohol daily and the average BMI is 26.6.

### 4.2 Berlin Aging Study II (BASE-II)

The BASE-II consists of several parts: The first part is the *Socio-Economic Module* that comprises standard questions of the Socio-Economic Panel Study (SOEP) (Wagner et al., 2007). This part includes self-reported socio-demographics, health and health behavior measures (Böckenhoff et al., 2013).

The second part is the *Clinical Module*. It includes clinical health measures, taken in the Charité University Hospital of Berlin. Additional parts include cognitive and other tests which were administered by psychologists but which are not the focus of this paper.[9] The BASE-II is representative of the elderly Berlin population up to age 89. As a supplement, BASE-II also surveys a sample of younger Berlin residents aged 18 and above; the ratio between respondents above and below 60 is 3:1 (see Appendix, Table A2). Bertram et al. (2014) provide

[8] Robert Koch Institut (1995) describes the exact protocol and the order of the examination. For example, after the blood samples were taken by a registered physician, the serum was analyzed in a lab. The findings were summarized and commented and sent by mail to the survey participants.

[9] Our findings are robust to controlling for cognitive measures. Detailed results are available upon request.

more information on the BASE-II. Our working sample consists of 1,804 respondents without missings on relevant variables.

For this paper, we included a measure to elicit $\widetilde{r}_i$ in the *Socio-Economic Module* of BASE-II, which was in the field between September and December 2012. Section 5.2 discusses the health bias measures in detail, also see Panel A of Table A2.

**Health Behavior**. Panel B of Table A2 lists measures of risky health behaviors: *smoker*, *no sports*, *unhealthy diet*, *obese* and *BMI*. As seen, 12% smoke, 36% do not exercise, 39% have an unhealthy diet, and 13% are obese.

**Socio-Demographics.** Panel C of Table A2 lists socio-demographic control variables. There are five main categories: *(i)* Demographics, *(ii)* Education, *(iii)* Employment, *(iv)* Risk Aversion, and *(v)* Big-Five personality traits (openness, conscientiousness, extraversion, neuroticism, agreeableness). The average age of BASE-II respondents is 60; slightly more than half of them are female and married; a quarter are single. Fifty-six percent of the sample finished high school (*13 school years*) and almost half are still full-time employed. In our regression models, we also control for risk aversion and trust, which are important covariates when eliciting subjective beliefs (e.g. Harrison et al., 2015, 2017). Accordingly, 15% of BASE-II respondents are risk loving (highest three categories of the standard 0 to 10 Likert risk aversion scale, see Dohmen et al., 2011). Finally, we also control for the Big-Five. The five dimensions are simple averages over three or four subscales which range from one to seven (Richter et al., 2013). *Conscientiousness* has the highest average of 5.6 and *Agreeableness* the lowest with 3.8 (Panel C, Table A2).

### 4.3 Socio-Economic Panel Study – Innovation Panel (SOEP-IP)

Since 2012, the SOEP has been inviting researchers to submit proposals for innovative survey questions (Richter and Schupp, 2015). Proposals are then reviewed by an expert committee. If accepted, the questions become part of SOEP-IP, which is in the field annually from September to December. SOEP-IP respondents also answer the regular SOEP core questions (Richter and Schupp, 2017). In 2014, a total of 1,377 respondents answered the same health perception measure, $\widetilde{r}$, that we also included in BASE-II. Comparing relative health perceptions to true health allows us to construct relative health perception bias measures $R_i$ (see Panel A of Table A3 and Section 5.2).

**Health Behavior**. In 2014, the SOEP-IP did not ask about smoking, exercising, and respondents' diet. However, the SOEP-IP elicited the average hours of sleep (Richter and Schupp, 2015). On average, Germans sleep 6.8 hours during the week and 7.6 hours on weekends (Panel B of Table A3). We use these information to generate *sleep gap* measures that indicate the difference to eight hours of sleep.

**Socio-Demographics.** As above, Panel C of Table A3 lists socio-demographics. Because BASE-II and SOEP-IP both include SOEP's socio-demographic core questions, we generate almost identical socio-demographic control variables. By design, representative SOEP-IP respondents are younger (51 vs. 60 years) but the shares of female and married respondents are very similar, slightly above fifty percent. In SOEP-IP, two thirds are full-time employed and the average monthly net income is €1,768.

# 5 Measuring Health Perception Biases

This section shows how we operationalize our measurement of health perception biases using survey data.

## 5.1 Measuring Absolute Health Perception Biases

To measure *absolute health perception biases*, we use the German National Health Survey East-West 1991 (GNHSEW91). This dataset contains information on individual blood pressure and cholesterol levels, collected by the *Institute for Prevention and Public Health* in Berlin, Germany. We use these measures as proxies for the individual objective health status $H_i$. We dichotomize these continuous objective measures depending on whether they are above or below the medically defined threshold to indicate specific clinical conditions. Specifically, for blood pressure, we define that a respondent has high blood pressure, and $BP_i$ equals one, if the systolic value is larger than 160 mmHg and/or the diastolic value exceeds 95 mmHg; $BP_i$ equals zero otherwise. Analogously, for high cholesterol levels, we define a dummy $Chol_i$ equal to one for values larger than 6.2 mmol/l, and zero otherwise. Because GNHSEW91 also elicits perceptions about these conditions, we then compare these objective clinical outcomes $BP_i$ and $Chol_i$ with respondents' *perceived* high blood pressure, $\widetilde{BP_i}$, and high cholesterol levels, $\widetilde{Chol_i}$, to obtain an assessment of *absolute health bias*. Each surveyed individual provides self-assessed binary measures of $\widetilde{BP_i}$ and $\widetilde{Chol_i}$.[10]

Panel B of Table A1 (Appendix) shows a mean cholesterol level of 6.1 millimole per liter (mmol/l) and that 44% of all Germans have high cholesterol levels ($BP_i = 1$). Panel B of Table A1 also shows mean systolic blood pressure levels of 135 millimetres of mercury (mmHg) and mean diastolic blood pressure levels of 83 mmHg.[11] Following the official WHO definition at the time, 21% of Germans had hypertension ($Chol_i = 1$).[12] Panel C shows that 21% of respondents knew that they suffered of hypertension ($\widetilde{BP_i} = 1$) and that 25% knew that they had high cholesterol ($\widetilde{Chol_i} = 1$).

**[Insert Figure 1 about here]**

As good health corresponds to $BP_i = 0$ or $Chol_i = 0$, positive health biases results if $\widetilde{BP_i} < BP_i$ or $\widetilde{Chol_i} < Chol_i$. Figure 1a illustrates the four possible combinations of the binary measures of objective and perceived health for cholesterol. Individuals in the bottom-right corner display positive absolute health bias. This corresponds to 30% of respondent who actually have high cholesterol levels, but are not aware of it. The bottom-left corner shows that 50% of all respondents do not have high cholesterol levels and consistently report that they do not have high cholesterol. As shown in the top-right corner, 14% correctly state that they have high blood cholesterol levels. Henceforth, we ignore the 6.5% in the top-left corner of Figure 1a who had no high cholesterol at the time of the survey, but who claim that they have been diagnosed. The reason is that we cannot accurately assign these respondents to either being accurate or being pessimistic about their health. This is because the language of the German question asks whether respondents have ever been diagnosed with high cholesterol levels. It could well be that respondents had high cholesterol levels in the past (which is why the respondents answered with "yes") but have changed their lifestyle and do not have high cholesterol levels at the time of the survey (which is why the clinical measurement yielded no such indication).

Figure 1b has the same setup and shows the analogous distribution for high blood pressure. Accordingly, 66% of all respondents correctly state that they do not have high blood

[10]Note that there is a small literature on misreporting of clinical diagnoses (Baker et al., 2004; Davillas and Pudney, 2017; Choi and Cawley, 2018). It is certainly up to scientific debate on how to define this phenomenon. People are either unaware and have biased health perceptions (our interpretation) or they are aware of their health condition but deliberately misreport it, for example, due to a desirability bias.

[11]Each measure was taken three times from each respondent; we use data from the second measure.

[12]In the meantime, the official definitions have been downgraded. In November 2017, the American Heart Association and the American College of Cardiology redefined the thresholds to 130/80 (American Heart Association, 2017).

pressure (bottom-left corner), and 12% correctly state that they do have high blood pressure (top-right corner). Nine percent indicate that they never had high blood pressure although the clinical measures show the opposite (bottom-right corner).[13] The smaller perception bias for high blood pressure as compared to high cholesterol is consistent with the notion that it is easier to check for high blood pressure than high cholesterol levels outside of clinical settings. Following the arguments above, we also ignore the 13.5% of respondents in the top-left corner of Figure 1b.

Finally, we would like to comment on the fact that the GNHSEW91 is already three decades old. One may hypothesize that health knowledge was not as advanced at the time as it is today. There is certainly reason to believe that the average person's—and also science's—understanding on the negative health effects of high blood cholesterol and high blood pressure was not as advanced as it is today, but they were clearly known (cf. Glanz, 1988; Weiss, 1972). Moreover, it was known already at the time that smoking, obesity and heavy alcohol consumption are detrimental to health while exercising has a positive impact (cf. Feinleib, 1985; Institute of Medicine, 1990; Trichopoulos et al., 1981).

What's more, the GNHSEW91 was in the field shortly after the German Reunification of 1990 and it was precisely a purpose of this survey to produce a representative picture of the health and diet of East and West Germans. Consequently, Figure A1 (Appendix) plots the shares of respondents with health perception biases regarding high blood cholesterol and high blood pressure levels separately for East and West Germans. As seen, the shares of East Germans who were not aware of their high blood cholesterol (39%) and high blood pressure (14%) is significantly higher than the shares of East Germans who were not aware of their high blood cholesterol (25%) and high blood pressure (7%). As an unbalanced diet is one main risk factor for high blood cholesterol and high blood pressure, this in line with research showing that, after the fall of the Wall, East Germans consumed a significant amount of novel Western food when it became readily accessible (Dragone and Ziebarth, 2017).

### 5.2 Measuring Relative Health Perception Biases $R_i$

To measure *relative health perception biases* $R_i = \widetilde{r}_i - r_i$, we make use of the BASE-II and the SOEP-IP.

[13] Note that the prevalence of the medical condition also determines the prevalence of the absolute health bias. However, correcting responses by the prevalence rate is outside the scope of this paper.

To measure $H_i$ (which is needed to construct $r_i$), both the BASE-II and the SOEP-IP contain the standard SAH measure as well as the SF12 measure. Both measures have been routinely used by health economists and public health scientists. SAH asks about the overall health status; respondents self-categorize as being in excellent, very good, good, fair, or poor health. However, although widely available and easy to collect, the literature has documented systematic SAH response biases with respect to age and gender (Lindeboom and van Doorslaer, 2004; Jürges, 2008; Bago d'Uva et al., 2008; Ziebarth, 2010; Spitzer and Weber, 2019), which we control for in our regressions.

However, to minimize concerns about reporting biases, in our main specifications, we employ the generic and continuous SF12 as $H_i$ measure (Andersen et al., 2007). The SF12 belongs to the "health-related quality of life measures." Using a specific algorithm, the SF12 weights and aggregates the answers to twelve health questions into a physical health (pcs) and a mental health (mcs) summary scale. Compared to SAH, the SF12 is a "more" objective health measure and was developed to minimize reporting biases. It "can be used to compare the health of different groups, for example, the young and the old or the sick and the well" (RAND, 1995). Both subscales of the SF12, pcs and mcs, have continuous values between 0 and 100, mean 50, and a standard deviation of 10. We use equal weights of 0.5 to generate the overall continuous SF12 measure. In a robustness check, we also use the physical and mental health components separately as the benchmark $H_i$ measure. Figures A2 and Figure A3 in the Appendix show the distributions of SAH and SF12 in our BASE-II (Figure A2) and SOEP-IP sample (Figure A3). The left panels refer to SAH and the right panels refer to SF12. The health distributions appear very similar, both across measures and across databases.

SAH and SF12 allow us to infer $H_i$ as well as the population health distribution $F(H_i)$. Then we calculate the individual rank $r_i$ in the health distribution. For SAH, each respondent self-categorizes into one of the five SAH categories. We assign every respondent the upper cdf threshold of the category chosen in the SAH distribution. For example, 9% of all respondents are in the highest category "excellent" health. Hence, we assign $r_{i,SAH} = 91$ to all respondents in the *second* highest category "very good" and, using the same principle, we do the same for the other categories. Because SF12 is continuous, ranges from 0 to 100 and has mean 50, it directly yields $r_i$ without further manipulation.

To measure $\widetilde{r}_i$, we added the following question to BASE-II and SOEP-IP: *"Imagine one would randomly select 100 German residents in your age, what do you think: How many of* *those 100 people would be in better health than you?"*.[14] From the raw untransformed response to this question, $\widetilde{b}_i$, we compute $\widetilde{r}_i = 100 - \widetilde{b}_i$.

In both surveys, we obtain high response rates of above 90% for our $\widetilde{b}_i$ measure. Even among the elderly in BASE-II, only 10 respondents (<1%) are coded "don't know" and 129 respondents (6%) are coded "does not apply." The high response rates may be a function of the natural reference group—100 German residents in the same age group. This framing allows meaningful comparisons without being too restrictive or too complex. Note that, despite avoiding many of the methodological criticisms of earlier studies (Benoît and Dubra, 2011), our question does not elicit entire belief distributions (Di Girolamo et al., 2015). Moreover, we did not specifically incentivize respondents (Harrison and Rutström, 2006). Eliciting entire belief distributions in an incentive-compatible environment is typically feasible in lab experiments (Harrison, 2015), which is costly and can only be implemented in large samples under specific conditions. In addition to the advantages above, maybe the main advantage of our measure of $\widetilde{b}_i$ is its simplicity and cost-effectiveness. Using one simple question, our proposed question has the power to elicit subjective relative beliefs in representative population surveys.

**[Insert Figure 2 about here]**

Figure 2 shows the raw untransformed distributions of $\widetilde{b}_i$ for BASE-II and SOEP-IP. Under the assumption of 100 random German residents being orderly ranked from 1 to 100 and under full rationality and common priors, $\widetilde{b}_i$ would be uniformly distributed between 0 and 100 with a mean of 50 (Goette et al., 2015). However, as seen in Figure 2, few respondents say that more than 50 respondents in their age would be in better health and the distribution is clearly skewed to the left. It is worthwhile to emphasize the similarity of the $\widetilde{b}_i$ distributions in BASE-II and SOEP-IP; the mass of the distributions lies between 10 and 30. In other words, a significant share of respondents believe that (only) 10-30 out of 100 people are in better health ($\widetilde{b}_i \in (10; 30)$) implying that they rank themselves in the $70^{th}$ to $90^{th}$ percentile of the population health distribution, $\widetilde{r}_i \in (70; 90)$. This yields first evidence for the existence of health overconfidence at the population level.

**[Insert Figure 3 about here]**

[14] This survey question has been successfully tested in other contexts. For example, using the same format, respondents in the Swiss "Amphiro" study were asked about their income position, their water use, and their knowledge of energy conservation (Tiefenbeck et al., 2018; Friehe and Pannenberg, 2019).

More evidence for the existence of relative health perception biases is illustrated in Figure 3, which plots the bins of $\widetilde{r}_i$ on the x-axis and the average values for $r_i$ on the y-axis. The scatters, whose size indicate the share of respondents falling into each bin, would be lined up along the 45-degree line if $\widetilde{r}_i = r_i$. However, as seen, while the scattered line has a slightly positive slope, it is clearly flatter than the 45-degree line. Again, the similarity between BASE-II and SOEP-IP is worthwhile to emphasize. Moreover, the size of the scatters reflect the mass of the perceived health rank distributions which fall into the $70^{th}$ to $90^{th}$ percentile bins, whereas the true health status of respondents who believe that only 10 to 30 randomly selected people would be in better health is only about average.

Using $r_i$ and $\widetilde{r}_i$, we can now calculate $R_i$ for each respondent in BASE-II and SOEP-IP. Because BASE-II is representative of the elderly Berlin population, whereas SOEP-IP is representative of the entire German population, comparing the results of both surveys will inform us about the generalizability of the empirical findings. Calculating $R_{i,SF12} = \widetilde{r}_i - r_{i,SF12}$ is straightforward because both the SF12 and $\widetilde{r}_i$ are continuous. When calculating $R_{i,SAH} = \widetilde{r}_i - r_{i,SAH}$, recall that $\widetilde{r}_i$ is continuous, but SAH has five categories. However, because $\widetilde{r}_i$ is continuous *and* varies within SAH categories, $R_{i,SAH}$ is continuous as well, as shown by Figures 4a (SOEP-IP) and A4a (BASE-II). Both figures also demonstrate that $R_{i,SAH}$ looks very similar in BASE-II and SOEP-IP and that the gender differences are negligible.

**[Insert Figure 4 about here]**

Figures 4b (SOEP-IP) and A4b (BASE-II) show the distributions of $R_{i,SF12}$. As seen in Panels A of Tables A2 and A3, the mean $R_{i,SF12}$ values are 14 (SOEP-IP) and 20 (BASE-II), that is, clearly positive and implying that respondents overestimate their ranks on average by 14 and 20 positions. Conditional on having a positive absolute health bias, respondents overestimate their health rank by 23 (BASE-II) and 19 (SOEP-IP) positions. Again, the $R_{i,SF12}$ distributions are very similar for BASE-II and SOEP-IP.

Table A4 (Appendix) shows determinants of $R_{i,SF12}$ using the representative SOEP-IP. As seen, women are more likely to be positively biased, as are childless respondents. Interestingly, educational and job characteristics as well as risk tolerance levels are not significant predictors of positive health perception biases. The fact that education is no significant predictor of the biases suggests that it is not health knowledge related to formal education that is a main underlying mechanism in this setting.[15] Interestingly, female and being childless also predict negative biases significantly and carry the same sign, implying that women and childless respondents are *less* likely to have negative biases, as are white collar workers. Finally, when investigating the Big-Five measures as predictors of health perception biases using the BASE-II, we find that that conscientiousness, extraversion and agreeableness are negatively related to positive and negative health biases, whereas neuroticism and openness are stronger and highly significant predictors of health overconfidence (see Table A5 in the Appendix).

## 6 Health Perception Biases and Risky Health Behaviors

In this section, we first study the empirical link between *absolute health perception biases* and risky health behaviors using the GNHSEW91. Then, we study the link between *relative health perception biases* and risky health behaviors using the BASE-II and SOEP-IP. We will provide non-parametric evidence and evidence from multivariate regression models.

### 6.1 Absolute Health Perception Biases and Risky Health Behaviors

Figure 5 tests whether respondents who have biased perceptions about their blood cholesterol levels are more likely to (a) not exercise, (b) have higher BMIs, (c) drink alcohol daily, (d) smoke. Figure 6 tests the same relationships for respondents who have biased perceptions about their blood pressure levels, see Section 5 for details about how we generate the perception bias measures. Each of the figures shows four bar diagrams along with 95% confidence intervals.

**[Insert Figures 5 and 6 about here]**

Figure 5a shows that respondents who state that they do not have high cholesterol but who, in fact, do have high cholesterol are a highly significant 11 percentage points (ppt) more likely (43% vs. 54%) to not exercise at all. The BMI differential is also significant (Figure 5b). Similarly, respondents with absolute health perception biases are significantly more likely to drink alcohol daily—the share of daily drinkers is almost 50% higher among this group (21%

[15] In line with that finding, the $R^2$ only increases very slightly by 0.003 when adding education controls separately to our main regressions and the size and significance of the main regressors remain unchanged. On the other hand, there is some evidence that formal education is a significant predictor for biases in BASE-II (see Table A5); however, this database is only representative for elderly people in Berlin.

vs. 14%, Figure 5c).[16] Figure 6d, however, does not provide much evidence that smoking is significantly linked to biased perceptions about high cholesterol levels.

Comparing Figure 6 to Figure 5, the similarity and robustness of the link between both absolute health perception bias measures and four risky health behavior measures is worthwhile to point out. Not only do all statistical links have identical signs and significance levels, but the risky behavior differentials and their sizes are also very similar. This is even more surprising, given the low correlation between the two perception bias measures of only 0.11.[17]

In conclusion, there is robust evidence that absolute health perception biases are significantly linked to three out of four risky health behaviors. According to Proposition 3, this implies that the extensive margin effect dominates the intensive margin effect meaning that positive health biases induce people to engage in more risky behavior because they (wrongly) believe that they can "afford" it. One exception appears to be smoking, where the intensive margin effect appears to be stronger. This intensive margin effect lowers the inclination to engage in risky behavior because the bias increases the marginal costs of risky behavior, see Section 3 for more details.

### 6.2 Relative Health Perception Biases and Risky Health Behavior

Figure 7 non-parametrically links $R$ to $x$ across the entire $R$ distribution using kernel-weighted local polynomial smoothing plots. Table 1 provides analogous parametric multivariate regressions using a rich set of controls.

**[Insert Figure 7 about here]**

Figure 7a shows a monotonically increasing relationship between positive relative health biases, $R > 0$, and not exercising. On average, 30% of those who accurately assess, or who underestimate their health, do not exercise at all. This share monotonically increases to 50% for respondents who overestimate their rank in the population distribution by 50 ranks; that is, who exhibit a strong positive health bias.

[16] While moderate drinking has been linked to health and labor market benefits (Renaud et al., 1999; Ziebarth and Grabka, 2009; Holst et al., 2017), heavy drinking has detrimental health effects and national guidelines recommend to abstain from drinking two days per week (Rehm et al., 2001; National Health Service, 2012).

[17] An attentive referee suggested to check for information about medication intake to lower the blood pressure or high cholesterol levels. Indeed, the GNHSEW91 does collect this information in self-reports before the clinical examination. However, as expected, only 6 out of 1,908 respondents who say that they don't have high cholesterol and 9 out of 600 respondents who say that they don't have high blood pressure indicate that they take medications against that disease at the same time. The results are robust to dropping these respondents.

Next, we run the following parametric regression model controlling for a rich set of socio-demographics:

$$x_i = \beta_0 + \beta_1 R_i^+ + \beta_2 R_i^- + \boldsymbol{Z_i}\beta_3 + \rho_t + \epsilon_i \tag{10}$$

where $x_i$ represents risky health behavior and $R_i$ stands for our measure of relative health perception bias. Specifically, we will replace the continuous $R_i$ measure with two measures $R_i^+\{R_i \mid R_i \in (0;100)$ and $R_i^-\{R_i \mid R_i \in (-100;0)$. $R_i^+$ is truncated from below and measures the degree of positive health bias. $R_i^-$ is truncated from above and measures the degree of negative health bias. Below we provide robustness checks on the appropriateness of this spline which allows us to separately study health overconfidence and health underconfidence.

$\boldsymbol{Z_i}$ contains socio-demographic controls as listed in the descriptive statistics in the Appendix. Moreover, we include interview month fixed effects, $\rho_t$; $\epsilon_i$ is the error term.

**[Insert Table 1 about here]**

Tables 1 and 2 show our main results using $R_i$ based on the SF12 benchmark and 10 regression models as in equation (10).[18] The equivalent table using $R_i$ based on the SAH benchmark is in Table A6 (Appendix). The first two columns of Table 1 show the results for not exercising as an outcome, the next pairs of columns document the results for being obese, following an unhealthy diet, and being a smoker, respectively. Table 2 shows results for sleeping less than 8 hours during the week. While the odd-numbered columns solely control for socio-demographics, education and interview month fixed effects, the even-numbered columns additionally control for employment characteristics and income.

**No Sports.** Beginning with the outcome *no sports* in the first two columns of Tables 1 and A6, the results confirm the non-parametric findings in Figure 7: there is no evidence that a negative health perception bias is significantly linked to not exercising. By contrast, we find a highly significant link between $R_i > 0$ and not exercising: an increase in $R_i$ by 10 ranks is associated with a 2.2ppt higher likelihood to not exercise (column (2), Table 1). The size of the association is larger when using $R_{SAH}$ (columns (1) and (2), Table A6) but overall robust. Also note the very consistent evidence for the same outcome when using absolute health bias measures in Figures 5a and 6a.

[18] In Table A7 in the Appendix, we replicate Tables 1 using probit estimation instead of OLS. The results (marginal effects) are almost identical.

**BMI, Obesity and Unhealthy Diet.** Figure 7b and columns (3) and (4) of Tables 1 and A6 show the equivalent findings for *BMI* and *obesity*, while Figure 7c and columns (5) and (6) of Tables 1 and A6 show the findings for following an *unhealthy diet*. Both figures and all eight regressions reinforce our previous findings.

Figure 7b shows a non-linear relationship between $R_i > 0$ and BMI which is very similar to Figure 7a: Respondents who accurately assess their health or who underestimate their health do not have higher BMIs. However, the average BMI increases monotonically in the size of the health bias for $R_i > 0$. In other words, the more people overestimate their health, the heavier they are. To test this link parametrically, we generate a binary obesity indicator as dependent variable[19] and run regressions similar to equation (10). The results in Tables 1 and A6 confirm the non-parametric visual evidence: An increase in the health bias $R_i$ by 10 ranks is associated with a 1.2ppt (about 9%) higher probability to be obese in columns (3) and (4) of Table 1; as above, the effect size is larger for $R_{SAH}$ but generally robust (Table A6, Appendix). The inclusion of rich sets of individual control variables do not affect the size of the empirical relationship.

Figure 7c and columns (5) and (6) of Tables 1 and A6 corroborate the findings above. Whereas no link exists for respondents with $R_i \leq 0$, that is, unbiased or pessimistic respondents, we find a clear and positive statistical link between having a positive health bias and eating unhealthy. An increase in the bias by 10 ranks increases the likelihood of an unhealthy diet by 1.2ppt (or about 3.1%).

**Smoking.** Figure 7d and columns (7) and (8) of Tables 1 and A6 show the results for being a smoker. The graphical evidence provides no evidence for a statistical link between health perception biases and smoking status. This is confirmed by the parametric regressions—none of the health bias measures is significantly linked to smoking status and the effect sizes are very small.[20] This finding is in line with the findings from above in Figures 5 and 6, where we found no association between the absolute health bias and smoking. According to our model, this implies that the health perception biases operate through a strong intensive margin effect, which emphasizes the costs of smoking (Section 3). This finding is consistent with Darden (2017), who reports that updated (and objective) cardiovascular biomarker information has

[19] Using the continuous BMI measure yields robust results.

[20] We also assessed the intensive margin of smoking, i.e., the number of cigarettes smoked by each smoker per day. There as well we do not find any significant link and the effect sizes are very small (detailed results available upon request).

not altered smoking behavior in the population of the Framingham Heart Study—Offspring Cohort.

**[Insert Figure 8 and Table 2 about here]**

**Sleep.** Finally, using the representative SOEP, we study relative health perception biases and sleep. Our outcome indicates the "sleep gap" between the actual hours of sleep and eight hours.[21] Figure 8a shows that the sleep gap is monotonically increasing in the size of the health bias for most parts of the bias distribution from about -15 to +40. Interestingly, it looks like this link weakens for both very high positive as well as negative biases such that we obtain what looks like an inverse U-shaped pattern. Note that our model is flexible and powerful enough to rationalize such non-linear pattern. Specifically, through the lens of the model, the pattern would imply that the extensive margin in equation (9) dominates over the [-15;40] range of support, whereas the intensive margin dominates outside this range among extreme positively or negatively biased people. In Figure 8b, for sleep on weekends, we see again no clear association for respondents with no or negative biases but a positive relationship among very positively biased respondents.

Table 2 shows the equivalent regression results using the sleep gap during the week as dependent variable (results for the weekend are similar and available upon request). We find a robust and clear link between a positive health perception bias and the likelihood to sleep fewer hours. The findings in the first two columns even suggest that the association could carry over for people with negative health biases, but with reversed signs; that is, those who are overly pessimistic about their health may sleep significantly more than those who correctly assess their health, implying that the intensive margin and thus the marginal costs of not sleeping enough dominates here and negatively biased people do not want to jeopardize their health through a lack of sleep (Section 3).

**Robustness.** In the following, we conduct a series of robustness checks. First, Table 3 replicates Table 1 but additionally adds several risk aversion measures as well as all measures of the Big-Five as listed in Table A2 (Appendix). As seen, the results are robust.

**[Insert Tables 3 and 4 about here]**

[21] There is heterogeneity in the hours of sleep that an individual needs but the large majority of people need between 7 and 9 hours of sleep. However, a significant share of people in industrialized countries are permanently sleep deprived, which has strong negative health consequences (Giuntella and Mazzonna, 2019; Jin and Ziebarth, 2020).

Second, we examine the robustness of our findings with regard to the specification of spline estimates that cut the spline at $R = 0$ in equation (10). As we argue above, the distinction between overconfidence and underconfidence is theoretically meaningful. This makes the choice of $R = 0$ the natural starting point. We assess its robustness by asking whether there is a break point for the spline that better fits the data than $R = 0$. We do this by performing a grid search over the interval $R \in [-15, 30]$ (in steps of 0.1 points) to define the break point $R$, and conditionally on $R$, estimate the remaining parameter by OLS. This allows us to estimate the best-fitting spline to the data. Specifically, we test whether $R = 0$ is rejected by the data, as $R = 0$ is nested within the class of models we estimate. Table A8 in the Appendix shows the results. Most importantly, we cannot reject the null hypothesis of $R = 0$, with the lowest $p$-value being 0.19 (in column 1 of Table A8). The point estimates for the upper part of the spline are unchanged, though their standard errors are larger. Further, we never find an estimate of $R$ that is significantly different from zero. Thus, we conclude that $R = 0$ is an appropriate specification for the spline.

Third, in addition to various possible interpretations of empirical measures of health biases as well as the challenge to induce clean exogenous variation, there exists another structural challenge in the literature: "ceiling effects." Specifically, from a statistical standpoint, the better the actual relative health status $r_i$, the lower the probability that someone has a positive health perception bias, by definition. Table 4 shows a robustness check that trims the relative health perception bias distribution and eliminates the top and bottom quintiles of $R_i$.[22] Otherwise the model is the same as in equation (10). The column headers of Table 4 show the dependent variables; the models in the uneven columns do not control for employment characteristics and income, whereas the models in the even columns do.

Table 4 also provides a robustness check for eliminating potential guesses of $\widetilde{r}_i$. Because it could be that the peak at $\widetilde{r}_i = 50$ in Figure 2 represents respondents who did not know the response and simply guessed.[23] In addition to trimming the distribution, the sample used for Table 4 also omits these potentially guessing respondents. The result of the eight models in Table 4 corroborate our findings above: While there is no evidence that the likelihood to smoke increases or decreases in the bias, the likelihood to engage in risky health behavior increases in the bias for the other health behavior measures.

[22] The findings are robust to alternative ways to trim the distribution, e.g., trimming the top and bottom 30 percentiles. Those results are available upon request.

[23] Because of space restrictions in the surveys, we could not elicit the certainty with which respondents answered. Future research should address this limitation.

Finally, Table A9 (Appendix) makes an attempt to differentiate the effects by physical and mental health. This exercise comes with the limitation that our question to elicit $\widetilde{r}_i$ asks about health in general, not specifically about physical and mental health. However, the SF12 allows us to compute continuous measures of mental and physical health which we use as the benchmark in Table A9 (Appendix). As seen, in line with the prior that most people likely think about physical health when answering our question to rank themselves in the population health distribution, the results suggest that our main findings are driven by physical health. Moreover, most of the risky behaviors studied here are linked to negative physical health effects.

To summarize our empirical findings: First, except for the case of smoking, we find stable and statistically significant links between health perception biases and risky health behaviors. Second, no such links exist for respondents without bias or who exhibit a negative health perception bias. Third, the findings are robust with respect to two self-reported general health measures as well as two very specific objective physical health measures. Fourth, the findings are also robust for four health behaviors: exercising, eating, drinking and sleeping. Fifth, the empirical findings are consistent for both absolute and relative health perception biases. Lastly, interpreted in the context of our model, except for smoking, the results imply that the extensive margin effect of the bias dominates the intensive margin effect. In other words, people who overestimate their health engage in a suboptimally high level of risky health behavior because they wrongly believe that their bodies could tolerate such behavior.

## 7 Conclusion

This paper formally introduces the notion of health perception biases to the health economics literature. It proposes an empirical quantification and discusses its prevalence using three different datasets from Germany. Then, it investigates theoretically and empirically whether and how health perception biases could affect risky health behavior.

We consider two related notions, absolute and relative health perception biases. The relative measure, which is based on the difference between the objective and the perceived rank in the population health distribution, was explicitly elicited for the purpose of this study. One advantage of this measures is the possibility to elicit it in large-scale surveys at relatively low costs. Moreover, both measures provide comparable information as we show that, under plausible conditions, there exists a one-to-one positive mapping between these two health perception measures.

Using a simple model, we show that health perception biases affect individual health behavior at both the extensive and the intensive margin. These margins operate in opposite directions. The extensive margin refers to the perceived health status, inducing an individual to engage in more risky behavior because she believes she is healthy enough to "afford" it. The intensive margin of health biases operates in the opposite direction: it inflates the perception of the marginal costs of risky behavior, inducing an individual to refrain from it. In the former case, health biases and risky behavior are substitutes, while in the latter case, they are complements.

Which effect dominates is an empirical question. We study it using three German datasets. Our empirical findings are robust and consistent across the different health bias measures and the three datasets. First, we show that health perception biases are pervasive in the health domain. For example, about 30% of all respondents of a representative German health survey which includes blood sampling were unaware of their high cholesterol levels. Similarly, using two other representative surveys, we find that about 30% of all respondents overestimate their position in the population health distribution by at least 30 ranks. We take these findings as evidence that absolute and relative health perception biases exist systematically and are widespread.

Second, we find that health perception biases are significantly linked to risky health behaviors, with the notable exception of smoking. We find that people who overestimate their health are more likely to not exercise, to eat unhealthy, drink alcohol on a daily basis, and sleep fewer hours. They also have significantly higher BMIs and are more likely to be obese. Interpreted through the lenses of our model, these statistical findings are consistent with the notion that the extensive margin of health perception biases dominates the intensive one. In other words, people who overestimate their health engage in excessive (suboptimal) risky behavior because they believe they are healthier than they really are.

However, third, among those who more accurately assess or underestimate their health, we do not find much evidence that health perception biases are related to risky health behaviors—a result that is consistent with the intensive margin of perceived health offsetting the extensive margin. Interestingly, smoking is not significantly correlated with health biases either. If future research corroborates this finding, it could suggest that public health anti-smoking campaigns aimed at altering smokers' perceptions by emphasizing the health cost of smoking are less effective than alternative policy tools such as, e.g., taxation and smoking bans (Viscusi, 1990; Becker et al., 1994; Chaloupka, 1991; Gruber and Kőszegi, 2001).

In terms of policy implications, our general results show that people with biased health perceptions can be a fruitful target group for effective public health campaigns aimed at reducing risky health behaviors. Adding regular health check-ups and screenings to the essential health benefit packages, in addition to nudging people to seek regular feedback about their health, can be a desirable policy. However, we also find that debiasing individuals' health perceptions would not only operate on the extensive margin of perceived health biases, but also affect the intensive margin. Accordingly, people could possibly engage in *more* risky behavior because a better than expected health assessment could reduce the fear of the negative consequences (that is, the perceived marginal costs) of risky behavior. This result is particularly relevant when the risky behavior produces negative externalities, because the underestimation of the marginal cost to society adds to the underestimation of the individual costs.

For decades, a rich strand of research in health economics has theoretically and empirically identified what researchers have labeled "reporting heterogeneity," "state-dependent reporting bias" or "scale of reference bias" (cf. Lindeboom and van Doorslaer, 2004; Etilé and Milcent, 2006; Jürges, 2007, 2008; Bago d'Uva et al., 2008; Spitzer and Weber, 2019). This paper shows that "health perception biases" exist. However, it is beyond the scope of this paper to investigate the sources of such biases. The literature discusses optimism biases, self-deception biases, a lack of health knowledge or conformism to social norms as possible sources. An open question for future research is whether and how such implicit biases could also affect self-reported health measures and, in fact, be part of what has been previously identified as "reporting heterogeneity."

Finally, our study is a first attempt to marry research on biased beliefs and risky health behavior, both from a theoretical and an empirical perspective. Although our empirical analysis is solely based on statistical associations, we believe it is a fruitful avenue of research to study the relevance of individual perceptions and beliefs for health behavior. In particular, future research should investigate the generalizability of our results for different countries and different institutional setups.

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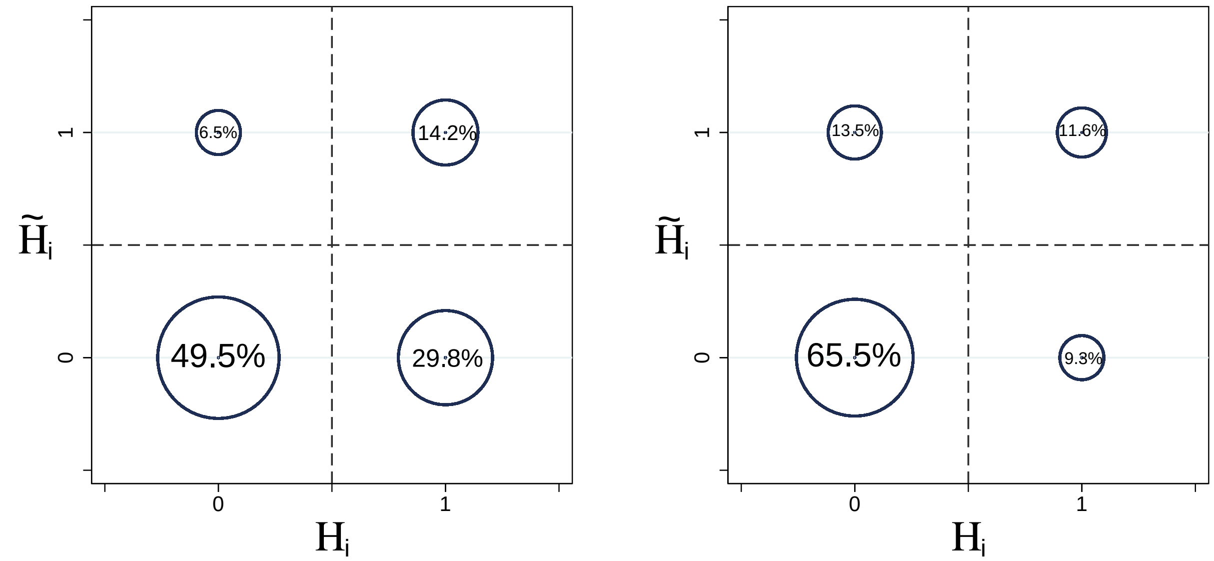
# Figures

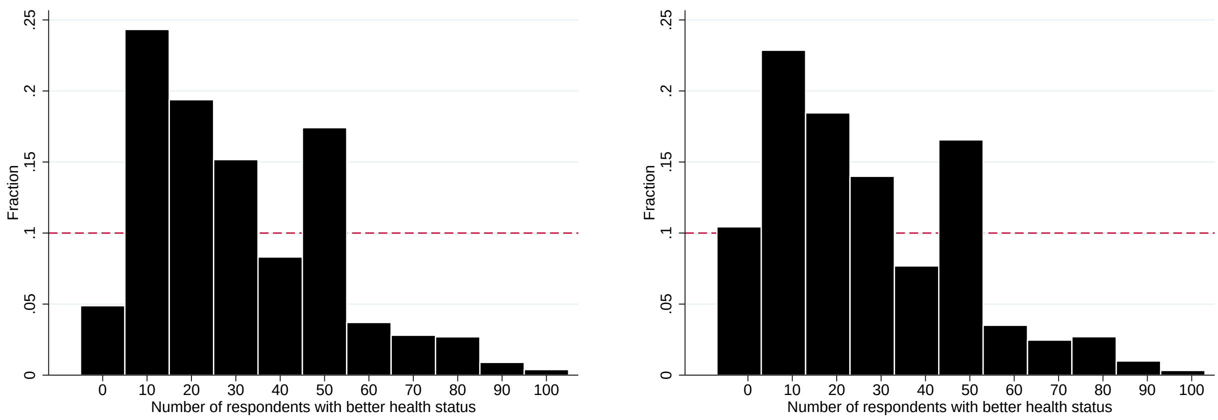
**Figure 1: Absolute Health Perception Bias about High Cholesterol Levels**

(a) High Cholesterol Levels (b) High Blood Pressure



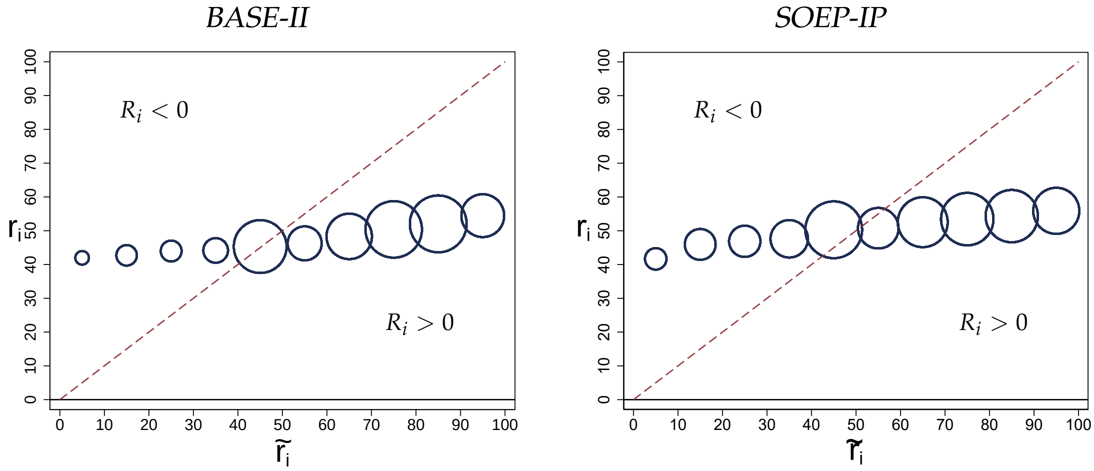

*Source:* GNHSEW91. See Section 4.3 and 5 for more details. The total number of observations is 6,429. The number of observations in Figure 1a, counting clockwise and starting in the upper left corner are 420, 912, 3184, and 1913. In Figure 1b, the number of observations are 873, 746, 4209, and 601.

**Figure 2: Perceived Population Share in Better Health ($\widetilde{b_i}$)**



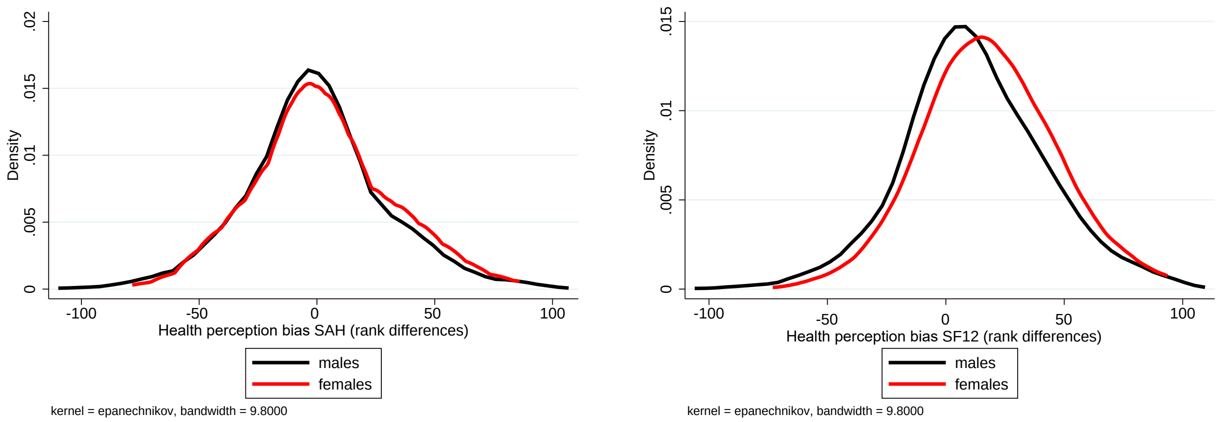

*Sources:* BASE-II (left panel), SOEP-IP (right panel). Responses to the question are plotted: "Imagine one would randomly select 100 people in your age. How many of those 100 people would be in better health than you?" People answering 0 believe nobody is in better health; people answering 99 believe everybody is healthier than them."

**Figure 3: Actual ($r_i$) and Perceived ($\tilde{r}_i$) Ranking in Population Health Distribution**



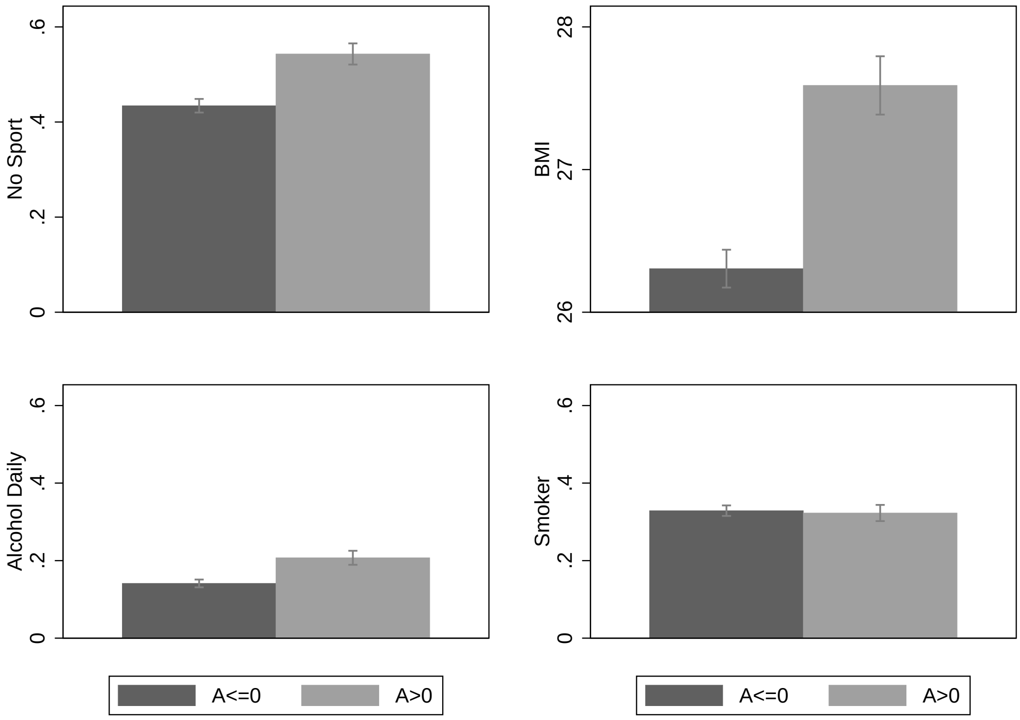

*Source:* BASE-II, SOEP-IP. Relative health perception biases are defined as $R_i = \tilde{r}_i - r_i$, with $\tilde{r}_i = 1 - b_i$, see Figure 2 and main text. The true rank in the population health distribution, $r_i$, is based on the SF12. The x-axes indicate $\tilde{r}_i$ and the y-axes indicate $r_i$ where the true population health ranks $r_i$ are averaged by $\tilde{r}_i$-bins of ten ranks. The size of the scatters indicate the number of respondents in each bin. For example, in Figure 3a, we observe a mass of respondents who believe that they rank between the $70^{th}$ and $90^{th}$ percentile of the population health distribution but whose actual health status is just average.

**Figure 4: Distribution of $R_i$ Based on (a) SAH, (b) SF12 in SOEP-IP**



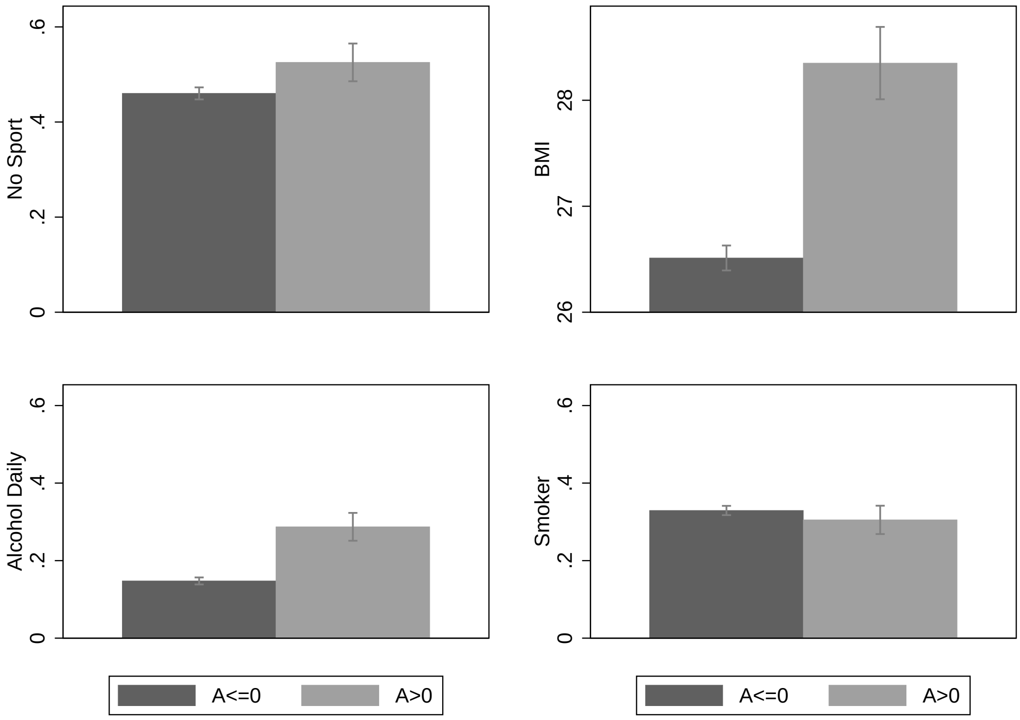

*Source:* SOEP-IP. Figure displays distributions of $R_i = \tilde{r}_i - r_i$ in the representative SOEP-IP, with $\tilde{r}_i = 1 - \tilde{b}_i$, see Figure 2 and main text. Subfigure (a) uses SAH and subfigure (b) uses the SF12 as $r_i$.

**Figure 5: Absolute Health Perception Bias (High Cholesterol) and Risky Health Behavior**



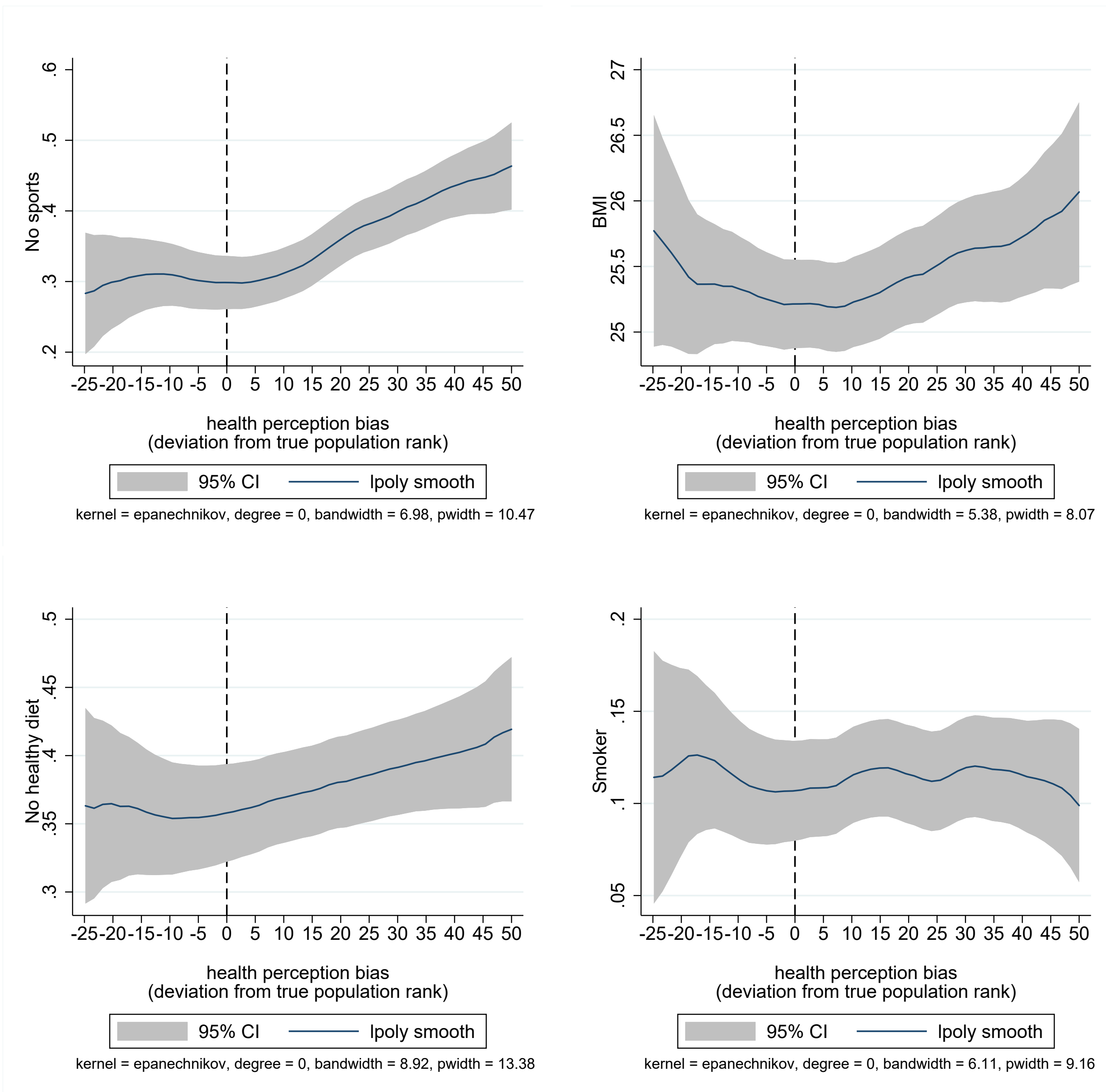

*Source:* GNHSEW91. Bar diagrams show, along with 95% confidence intervals, the (a) share of respondents who do not exercise, (b) mean BMI, as well as the share of respondents who (c) drink alcohol daily and (d) smoke. The light gray bars and '1' indicate respondents who exhibit absolute health perception biases (N=3184) and the dark gray bars and '0' indicate respondents who do not exhibit absolute health perception biases with respect to high blood cholesterol levels (N=4096).

**Figure 6: Absolute Health Perception Bias (High Blood Pressure) and Risky Health Behavior**



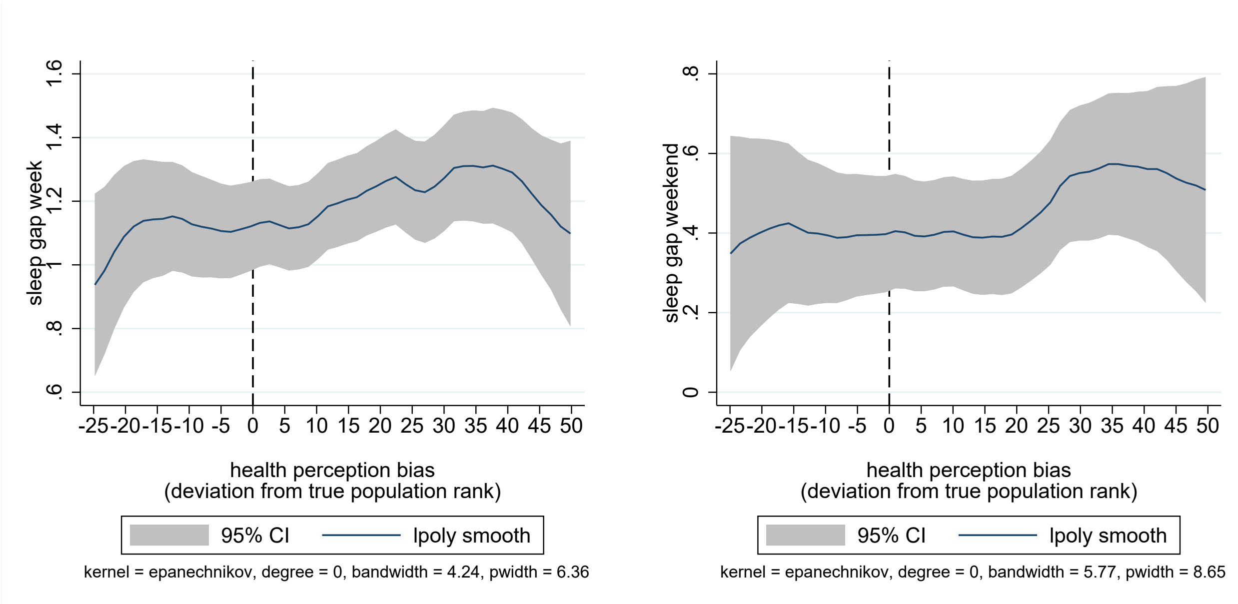

*Source:* GNHSEW91. Bar diagrams show, along with 95% confidence intervals, the (a) share of respondents who do not exercise, (b) mean BMI, as well as the share of respondents who (c) drink alcohol daily and (d) smoke. The light gray bar and ’1’ indicate respondents who exhibit absolute health perception biases (N=601) and the dark gray bar and ’0’ indicate respondents who do not exhibit absolute health perception biases with respect to high blood pressure levels (N=4955).

**Figure 7: Relative Health Perception Bias and Risky Health Behavior**




*Source:* BASE-II. Figure shows non-parametric kernel-weighted local polynomial smoothing plots. The y-axis shows (a) the likelihood that respondents do not exercise, (b) are obese (BMI>30), (c) follow an unhealthy diet, or (d) smoke. The x-axis indicates $R_i$, that is, the deviation of the perceived rank ($\tilde{r}_i$) in the population health distribution from the true rank ($r_i$).

**Figure 8: Relative Health Perception Biases and the Sleep Gap to 8 Hours (SOEP-IP)**




*Source:* SOEP-IP. Figure shows non-parametric kernel-weighted local polynomial smoothing plots. The y-axis shows the difference between 8 hours of sleep and actual hours of sleep (a) during the week, (b) on weekends. The x-axis indicates $R_i$, that is, the deviation of the perceived rank ($\tilde{r}_i$) in the population health distribution from the true rank ($r_i$).

**Table 1: Relative Perception Bias and Risky Health Behaviors: No Sports, Obesity, No Healthy Diet, Smoking**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ***No sports*** | | ***Obese*** | | ***No healthy diet*** | | ***Smoker*** | |
| **Positive health bias ($R_i > 0$)** | 0.0023*** | 0.0022*** | 0.0011*** | 0.0012*** | 0.0013** | 0.0012* | 0.0005 | 0.0004 |
| | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0006) | (0.0006) | (0.0004) | (0.0004) |
| **Negative health bias ($R_i < 0$)** | -0.0003 | -0.0008 | -0.0010 | -0.0011 | -0.0006 | -0.0007 | 0.0003 | 0.0002 |
| | (0.0014) | (0.0015) | (0.0010) | (0.0010) | (0.0014) | (0.0015) | (0.0009) | (0.0009) |
| $R^2$ | 0.0276 | 0.0380 | 0.0298 | 0.0340 | 0.0492 | 0.0579 | 0.0884 | 0.0925 |
| *socio-demographics & education* | yes | yes | yes | yes | yes | yes | yes | yes |
| *employment char. & income* | no | yes | no | yes | no | yes | no | yes |
| *month FE* | yes | yes | yes | yes | yes | yes | yes | yes |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). The model is estimated by OLS with n=1,804 observations. The binary dependent variables in columns (1) to (8) measure the likelihood that a respondent does not exercise at all, that a respondent is obese (BMI>30), that a respondent follows an unhealthy diet and that a respondent is a current smoker. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using SF12 to measure $H_i$. For more information, see Sections 4.2 and 5.

Table 2: **Relative Perception Bias and Sleep Gap to 8 Hours**

| ***Sleep Gap to 8 Hours*** | (1) (SF12) | (2) (SF12) | (3) (SAH) | (4) (SAH) |
|---|---|---|---|---|
| **Positive health bias ($R_i > 0$)** | 0.0037* | 0.0038* | 0.0068*** | 0.0066*** |
| | (0.0021) | (0.0021) | (0.0025) | (0.0025) |
| **Negative health bias ($R_i < 0$)** | 0.0089** | 0.0086** | 0.0028 | 0.0028 |
| | (0.0037) | (0.0038) | (0.0025) | (0.0025) |
| $R^2$ | 0.0455 | 0.0513 | 0.0417 | 0.0475 |
| *sociodem. & educ.* | yes | yes | yes | yes |
| *employment char. & income* | no | yes | no | yes |
| *month FE* | yes | yes | yes | yes |

*Source:* SOEP-IP; * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A3). The model is estimated by OLS with n=1,397 observations; the dependent variable measures the gap between the actual hours of sleep during the week and eight hours. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures. More information on the variables, see Sections 4.3 and 5.

**Table 3: Robustness Check: Additional Covariates: Risk Aversion and Personality Traits**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *No sports* | | *Obese* | | *No healthy diet* | | *Smoker* | |
| **Positive health bias ($R_i > 0$)** | 0.0021*** | 0.0018*** | 0.0012*** | 0.0012*** | 0.0011* | 0.0009 | 0.0004 | 0.0005 |
| | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0006) | (0.0006) | (0.0004) | (0.0004) |
| **Negative health bias ($R_i < 0$)** | -0.0008 | -0.0009 | -0.0011 | -0.0011 | -0.0007 | -0.0013 | 0.0002 | 0.0002 |
| | (0.0015) | (0.0015) | (0.0010) | (0.0010) | (0.0014) | (0.0014) | (0.0009) | (0.0009) |
| $R^2$ | 0.0441 | 0.0481 | 0.0351 | 0.0424 | 0.0669 | 0.1012 | 0.0947 | 0.0981 |
| *socio-demographics & education* | yes | yes | yes | yes | yes | yes | yes | yes |
| *employment char. & income* | yes | yes | yes | yes | yes | yes | yes | yes |
| *month FE* | yes | yes | yes | yes | yes | yes | yes | yes |
| *risk aversion indicators* | yes | yes | yes | yes | yes | yes | yes | yes |
| *personality traits* | no | yes | no | yes | no | yes | no | yes |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). This robustness check adds, for each health behavior outcome, risk aversion indicators (risk-averse is $\leq 3$ and risk-loving is $\geq 8$ on a risk-aversion scale ranging from 0 to 10) and the Big 5 personality traits as additional covariates. The model is estimated by OLS with n=1,804 observations; the columns indicate the dependent variables. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using SF12 to measure $H_i$. More information on the variables, see Sections 4.3 and 5.

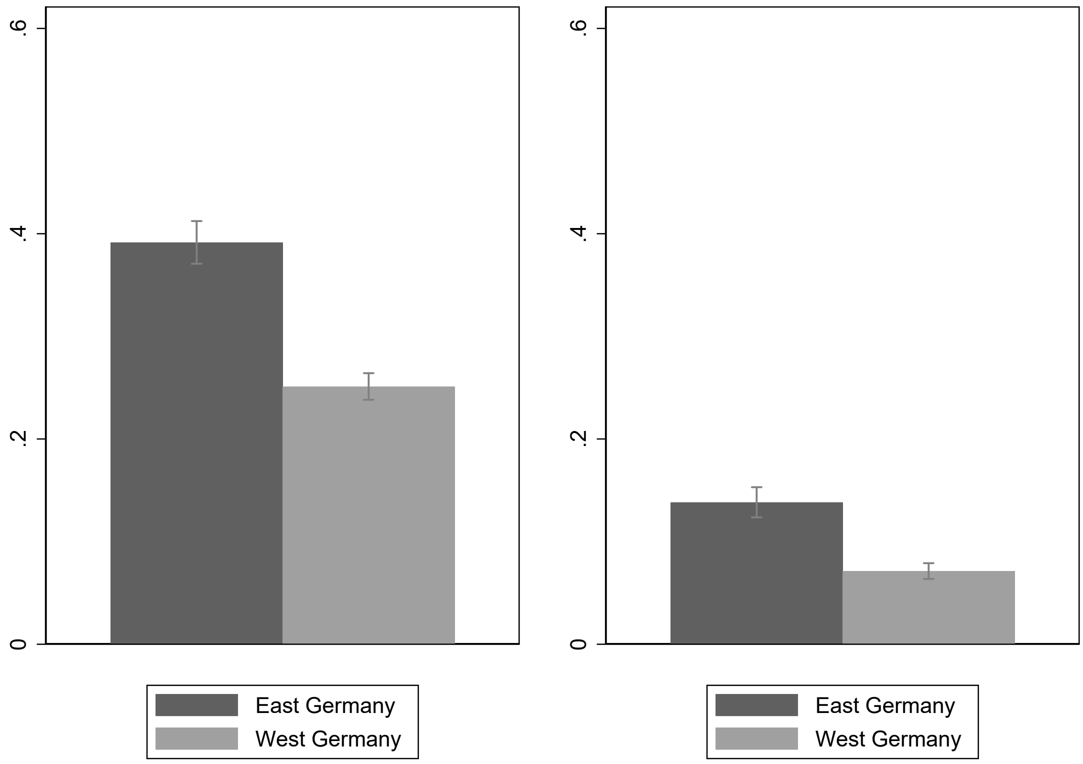
**Table 4: Robustness Check: Trimmed $R_i$ Distribution and Omitting Potential Guesses**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ***No sports*** | | ***Obese*** | | ***No healthy diet*** | | ***Smoker*** | |
| **Positive health bias ($R_i > 0$)** | 0.0020*** | 0.0020*** | 0.0008* | 0.0009** | 0.0013** | 0.0011* | 0.0005 | 0.0004 |
| | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0006) | (0.0006) | (0.0004) | (0.0004) |
| **Negative health bias ($R_i < 0$)** | -0.0011 | -0.0017 | -0.0013 | -0.0014 | -0.0013 | -0.0014 | -0.0002 | -0.0003 |
| | (0.0017) | (0.0017) | (0.0012) | (0.0012) | (0.0017) | (0.0017) | (0.0012) | (0.0012) |
| $R^2$ | 0.0213 | 0.0319 | 0.0253 | 0.0299 | 0.0469 | 0.0556 | 0.0726 | 0.0768 |
| *socio-demographics & education* | yes | yes | yes | yes | yes | yes | yes | yes |
| *employment char. & income* | no | yes | no | yes | no | yes | no | yes |
| *month FE* | yes | yes | yes | yes | yes | yes | yes | yes |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). This robustness check trims the $R_i$ distribution and eliminates the top and bottom quintiles; we also disregard respondents with $\widetilde{r}_i = 50$, who presumably guessed and may have low confidence in their estimate (the results are robust to not eliminating these respondents). The model is estimated by OLS with n=1,539 observations; the columns indicate the dependent variables. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using SF12 to measure $H_i$. More information on the variables, see Section 4.2 and 5.

# Appendix

**Figure A1: Absolute Health Perception Bias $A_i$ in East vs. West Germany**




*Source:* GNHSEW91. Bar diagrams show, along with 95% confidence intervals, absolute health perception biases for East and West Germans for (a) blood cholesterol levels, (b) high blood pressure. The light gray bars indicate East German respondents (N= 2,125) and the dark gray bars indicate West German respondents (N=4,304).

**Figure A2: Distribution of SAH and SF12 in BASE-II**

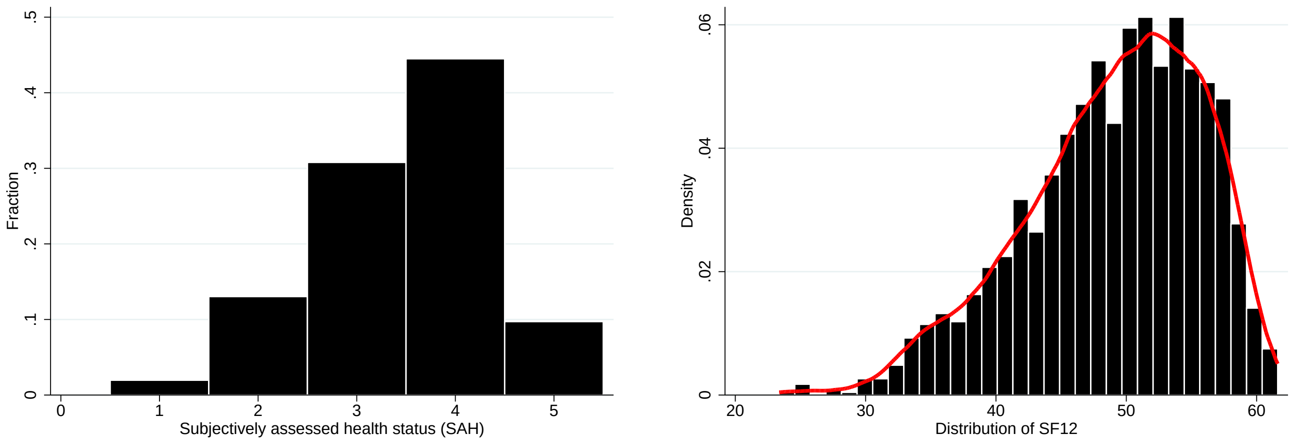



**Figure A3: Distribution of SAH and SF12 in SOEP-IP**

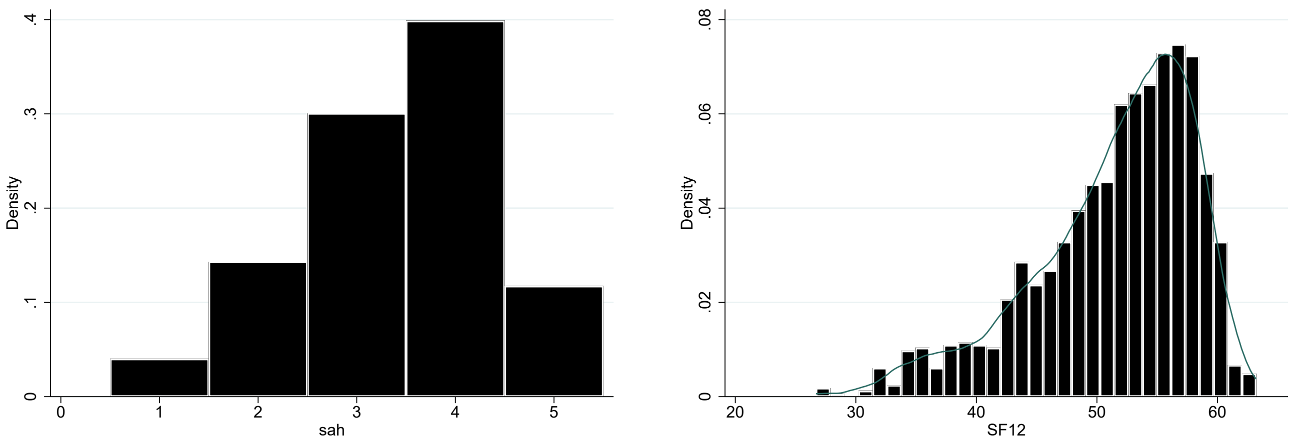
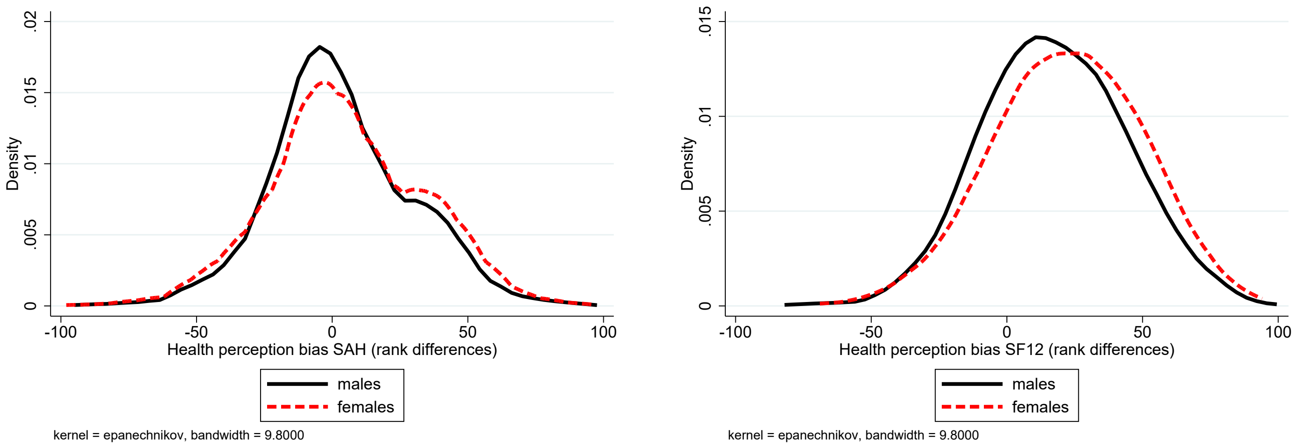


**Figure A4: Distribution of $R_i$ Based on (a) SAH, (b) SF12 in BASE-II**




*Source:* BASE-II. Figure displays distributions of $R_i = \widetilde{r}_i - r_i$, with $\tilde{r}_i = 1 - \widetilde{b}_i$, see Figure 2 and main text. Subfigure (a) uses SAH and subfigure (b) uses the SF12 as $r_i$.

**Table A1: Descriptive Statistics German National Health Survey East-West 1991**

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| ***A. Health Bias Measures*** | | | | | |
| Absolute Health Bias Cholesterol, $A_i > 1$ | 0.2976 | 0.4572 | 0 | 1 | 6429 |
| Absolute Health Bias Blood Pressure, $A_i > 1$ | 0.0935 | 0.2911 | 0 | 1 | 6429 |
| ***B. Objective Health Measures ($H_i$)*** | | | | | |
| Total blood cholesterol [mmol/l] | 6.13 | 1.23 | 2.33 | 12.9 | 6429 |
| High total blood cholesterol [>6.2 mmol/l] | 0.4394 | 0.4964 | 0 | 1 | 6429 |
| Systole, 2. measure [mmHg] | 134.66 | 20.263 | 88 | 256 | 6429 |
| Diastole, 2. measure [mmHg] | 83.40 | 12.129 | 34 | 158 | 6429 |
| Hypertension | 0.2095 | 0.407 | 0 | 1 | 6429 |
| ***C. Subjective Health Assessment ($\tilde{H}_i$)*** | | | | | |
| High Cholesterol | 0.2072 | 0.4053 | 0 | 1 | 6429 |
| High Blood Pressure | 0.2518 | 0.4341 | 0 | 1 | 6429 |
| ***D. Health Behavior*** | | | | | |
| Alcohol Daily | 0.1618 | 0.3683 | 0 | 1 | 6429 |
| Current Smoker | 0.3282 | 0.4696 | 0 | 1 | 6429 |
| Body-mass-index [kg per $m^2$] | 26.65 | 4.6113 | 15.02 | 75.47 | 6429 |
| Obese (BMI>30) | 0.2019 | 0.4014 | 0 | 1 | 6429 |
| No sports | 0.4652 | 0.4988 | 0 | 1 | 6429 |

*Sources:* GNHSEW91, own illustration.[mmol/l] stands for millimole per liter. [mmHg] stands for millimetres of mercury. [kg per $m^2$] stands for kilogram per square meter.

**Table A2: Descriptive Statistics BASE-II**

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| ***A. Health Bias Measures*** | | | | | |
| Relative Health Bias SF12, $R_i$ | 19.83 | 25.95 | -66.06 | 93.65 | 1804 |
| Positive ($R_i > 0$), SF12 | 23.03 | 21.36 | 0 | 93.65 | 1804 |
| Negative ($R_i < 0$), SF12 | -3.19 | 8.37 | -66.06 | 0 | 1804 |
| Relative Health Bias SAH, $R_i$ | 3.7605 | 26.24 | -98 | 95.77 | 1804 |
| Positive ($R_i > 0$), SAH | 11.47 | 17.23 | 0 | 95.12 | 1804 |
| Negative ($R_i < 0$), SAH | -2.1508 | 9.7383 | -98 | 0 | 1804 |
| ***B. Health Behavior*** | | | | | |
| No sports | 0.3564 | 0.4791 | 0 | 1 | 1804 |
| Obese | 0.1264 | 0.3324 | 0 | 1 | 1804 |
| BMI | 25.51 | 4.3106 | 13.71 | 64.09 | 1804 |
| No healthy diet | 0.3858 | 0.4869 | 0 | 1 | 1804 |
| Smoker | 0.1175 | 0.3221 | 0 | 1 | 1804 |
| ***C. Covariates*** | | | | | |
| **Demographics** | | | | | |
| Age | 60.35 | 16.81 | 18.18 | 89.98 | 1804 |
| Female | 0.5244 | 0.4995 | 0 | 1 | 1804 |
| Married | 0.5676 | 0.4955 | 0 | 1 | 1804 |
| Single | 0.2506 | 0.4335 | 0 | 1 | 1804 |
| Partner in Household | 0.6547 | 0.4756 | 0 | 1 | 1804 |
| # kids | 1.3126 | 1.1357 | 0 | 5 | 1804 |
| # daughters | 0.6613 | 0.8307 | 0 | 4 | 1804 |
| No kids | 0.3099 | 0.4626 | 0 | 1 | 1804 |
| German | 0.9878 | 0.1098 | 0 | 1 | 1804 |
| **Education** | | | | | |
| 8 school years | 0.1292 | 0.3355 | 0 | 1 | 1804 |
| 10 school years | 0.2517 | 0.4341 | 0 | 1 | 1804 |
| 13 school years | 0.5133 | 0.5 | 0 | 1 | 1804 |
| **Employment & Income** | | | | | |
| Blue collar worker | 0.0272 | 0.1626 | 0 | 1 | 1804 |
| White collar worker | 0.189 | 0.3916 | 0 | 1 | 1804 |
| Civil servant | 0.0183 | 0.134 | 0 | 1 | 1804 |
| Full-time employed | 0.4678 | 0.4991 | 0 | 1 | 1804 |
| Part-time employed | 0.1414 | 0.3485 | 0 | 1 | 1804 |
| Gross labor earnings | 549 | 1298 | 0 | 20,000 | 1804 |
| Net labor earnings (last month) | 378 | 831 | 0 | 10,000 | 1804 |
| Total income (last month) | 1563 | 1294 | 0 | 20950 | 1804 |
| **Risk Aversion** | | | | | |
| Risk aversion (scale) | 5.0837 | 2.2255 | 0 | 10 | 1804 |
| Risk-averse | 0.2611 | 0.4393 | 0 | 1 | 1804 |
| Risk-loving | 0.153 | 0.3601 | 0 | 1 | 1804 |
| **Big Five** | | | | | |
| Openness | 4.9916 | 1.15 | 1.3333 | 7 | 1804 |
| Conscientiousness | 5.6159 | 0.9726 | 1.6667 | 7 | 1804 |
| Extraversion | 4.7431 | 1.1737 | 1 | 7 | 1804 |
| Neuroticism | 3.7714 | 1.2776 | 1 | 7 | 1804 |
| Agreeableness | 5.2348 | 0.9828 | 1.3333 | 7 | 1804 |

*Sources:* Berlin Aging Study II (BASE-II).

**Table A3: Descriptive Statistics SOEP-IP**

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| ***A. Health Bias Measures*** | | | | | |
| Relative Health Bias SF12, $R_i$ | 13.89 | 27.41 | -97.14 | 98.69 | 1397 |
| $R_i > 0$, SF12 | 18.92 | 20.67 | 0 | 98.699 | 1397 |
| $R_i < 0$, SF12 | -5.02 | 11.59 | -97.14 | 0 | 1397 |
| Relative Health Bias SAH, $R_i$ | 1.0154 | 27.22 | -100 | 94.49 | 1397 |
| $R_i > 0$, SAH | 9.85 | 16.46 | 0 | 94.49 | 1397 |
| $R_i < 0$, SAH | -5.46 | 15.15 | -100 | 0 | 1397 |
| ***B. Health Behavior*** | | | | | |
| Sleep in hours, weekday | 6.8210 | 1.3153 | 2 | 13 | 1397 |
| Sleep deficit, week | 1.179 | 1.3153 | -5 | 6 | 1397 |
| Sleep in hours, weekend | 7.5719 | 1.5634 | 2 | 14 | 1397 |
| Sleep deficit, weekend | 0.4281 | 1.5634 | -6 | 6 | 1397 |
| ***C. Covariates*** | | | | | |
| **Demographics** | | | | | |
| Age | 51.03 | 18.44 | 16.35 | 93.23 | 1397 |
| Female | 0.5225 | 0.4997 | 0 | 1 | 1397 |
| Married | 0.5254 | 0.4995 | 0 | 1 | 1397 |
| Single | 0.2584 | 0.4379 | 0 | 1 | 1397 |
| # kids | 0.5841 | 0.9445 | 0 | 5 | 1397 |
| German | 0.9399 | 0.2378 | 0 | 1 | 1397 |
| **Education** | | | | | |
| No degree | 0.6535 | 0.476 | 0 | 1 | 1397 |
| Apprenticeship degree | 0.2004 | 0.4005 | 0 | 1 | 1397 |
| College degree | 0.1274 | 0.3336 | 0 | 1 | 1397 |
| **Employment & Income** | | | | | |
| Blue collar worker | 0.073 | 0.2603 | 0 | 1 | 1397 |
| White collar worker | 0.3472 | 0.4762 | 0 | 1 | 1397 |
| Civil servant | 0.0322 | 0.1766 | 0 | 1 | 1397 |
| Full-time employed | 0.3572 | 0.4793 | 0 | 1 | 1397 |
| Part-time employed | 0.1045 | 0.306 | 0 | 1 | 1397 |
| Gross labor earnings | 1292 | 1833. | 0 | 12,540 | 1397 |
| Net labor earnings (last month) | 878 | 1165 | 0 | 8000 | 1397 |
| Total income (last month) | 1768 | 1734 | 0 | 14,200 | 1397 |
| **Behavioral Attitudes** | | | | | |
| Risk averse (0-4/10) | 0.3092 | 0.4623 | 0 | 1 | 1397 |
| Risk loving (9-10/10) | 0.1482 | 0.3554 | 0 | 1 | 1397 |
| Risk Averse Health (0-4/10) | 0.554 | 0.4972 | 0 | 1 | 1397 |
| Risk Loving Health (9-10/10) | 0.0759 | 0.2649 | 0 | 1 | 1397 |
| Risk Averse Trust (0-4/10) | 0.4409 | 0.4967 | 0 | 1 | 1397 |
| Risk Loving Trust (9-10/10) | 0.0816 | 0.2739 | 0 | 1 | 1397 |

*Sources:* SOEP-IP.

Table A4: Determinants of Positive and Negative Health Perception Biases (SOEP-IP)

| | Positive Health Perception Bias | | | | Negative Health Perception Bias | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| **Demographics** | | | | | | | | |
| Age | 0.035 | (0.216) | -0.034 | (0.221) | 0.125 | (0.106) | 0.061 | (0.109) |
| Age2 | -0.001 | (0.002) | 0.000 | (0.002) | -0.001 | (0.001) | -0.000 | (0.001) |
| Female | 4.329*** | (1.098) | 4.765*** | (1.257) | 2.542*** | (0.657) | 2.699*** | (0.787) |
| Married | -2.297 | (1.506) | -2.170 | (1.529) | 0.915 | (0.900) | 0.830 | (0.920) |
| Single | -3.098 | (2.030) | -2.912 | (2.040) | 1.421 | (1.203) | 1.480 | (1.197) |
| # kids | 1.615** | (0.772) | 1.488* | (0.792) | 0.592 | (0.382) | 0.697* | (0.392) |
| German | 3.665 | (2.263) | 3.572 | (2.305) | 1.863 | (1.559) | 1.335 | (1.571) |
| **Education** | | | | | | | | |
| No degree | 1.958 | (2.042) | 1.907 | (2.058) | -0.205 | (1.056) | -0.002 | (1.038) |
| Apprenticeship degree | 2.236 | (2.029) | 1.795 | (2.070) | 1.636 | (1.013) | 1.143 | (1.002) |
| College degree | 2.511 | (2.480) | 2.726 | (2.511) | -0.832 | (1.615) | -0.319 | (1.574) |
| **Employment & Inc.** | | | | | | | | |
| Blue collar worker | | | 1.086 | (2.966) | | | -0.013 | (1.491) |
| White collar worker | | | 0.082 | (1.855) | | | 1.792** | (0.913) |
| Civil servant | | | -1.050 | (3.767) | | | 0.142 | (1.659) |
| Full-time employed | | | -1.389 | (2.594) | | | -1.298 | (1.214) |
| Part-time employed | | | 0.751 | (2.588) | | | -2.010* | (1.195) |
| Gross earnings | | | -0.000 | (0.001) | | | -0.000 | (0.001) |
| Net earnings (last mt)) | | | 0.001 | (0.002) | | | 0.001 | (0.001) |
| Total income (last mt) | | | 0.000 | (0.001) | | | 0.000 | (0.001) |
| **Risk aversion** | | | | | | | | |
| Risk averse | | | 0.108 | (1.309) | | | -0.578 | (0.679) |
| Risk loving | | | -1.156 | (1.674) | | | -2.873*** | (1.079) |
| Risk loving health | | | 1.060 | (2.329) | | | -2.015 | (1.603) |
| Risk averse health | | | -1.126 | (1.229) | | | -0.651 | (0.646) |
| Risk loving Trust | | | 1.482 | (2.292) | | | 0.474 | (1.052) |
| Risk averse Trust | | | 1.836 | (1.210) | | | -0.935 | (0.653) |
| $R^2$ | 0.023 | | 0.029 | | 0.021 | | 0.041 | |

Source: SOEP Innovation Panel (SOEP-IP); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in Table A3. The model is estimated by OLS and has 1,397 observations. All models include interview months fixed effects. The dependent variable in the first two columns use positive relative health perception biases ($R_i > 0$, SF12) and the second two columns use negative relative health perception biases ($R_i < 0$, SF12). For more information on variable generation, see Section 4.3

**Table A5: Determinants of Positive and Negative Health Perception Biases (BASE-II)**

| | Positive Health Perception Bias | | | | Negative Health Perception Bias | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| **Demographics** | | | | | | | | |
| Age | -0.840** | (0.335) | -1.004*** | (0.312) | -0.123 | (0.115) | -0.125 | (0.113) |
| Age2 | 0.008** | (0.003) | 0.011*** | (0.003) | 0.001 | (0.001) | 0.002* | (0.001) |
| Female | 4.271*** | (1.031) | 1.597 | (1.048) | 0.332 | (0.409) | 0.051 | (0.455) |
| Married | -1.897 | (1.744) | -1.256 | (1.657) | -1.203* | (0.646) | -1.025 | (0.643) |
| Single | 2.547 | (1.948) | 2.981 | (1.822) | -1.007 | (0.688) | -0.962 | (0.684) |
| Partner in Household | 2.838 | (2.135) | 1.711 | (2.025) | -0.007 | (0.766) | -0.049 | (0.765) |
| # kids | 1.608* | (0.825) | 1.394* | (0.780) | 0.279 | (0.318) | 0.182 | (0.306) |
| # daugthers | -1.170 | (0.809) | -0.741 | (0.752) | -0.444 | (0.309) | -0.295 | (0.297) |
| No kids | 1.418 | (1.876) | 0.653 | (1.774) | -0.753 | (0.751) | -1.020 | (0.745) |
| German | 1.676 | (4.658) | 3.679 | (4.689) | 1.772 | (1.976) | 2.563 | (2.064) |
| **Education** | | | | | | | | |
| 8 school years | -0.958 | (2.159) | -1.986 | (1.974) | -0.786 | (0.729) | -1.063 | (0.718) |
| 10 school years | -3.772** | (1.891) | -3.508** | (1.745) | -1.649** | (0.681) | -1.603** | (0.662) |
| 13 school years | -6.162*** | (1.743) | -5.425*** | (1.597) | -1.036* | (0.578) | -0.846 | (0.581) |
| **Employment & Inc.** | | | | | | | | |
| Blue collar worker | | | 6.778** | (2.852) | | | 0.293 | (1.323) |
| White collar worker | | | -0.809 | (1.800) | | | -0.568 | (0.659) |
| Civil servant | | | 5.445 | (5.068) | | | -1.467 | (1.960) |
| Full-time employed | | | -1.122 | (1.527) | | | -1.508*** | (0.506) |
| Part-time employed | | | -0.797 | (1.863) | | | -1.719** | (0.724) |
| Gross earnings | | | 0.002 | (0.002) | | | 0.002** | (0.001) |
| Net earnings (last mt) | | | 0.002 | (0.003) | | | -0.001 | (0.001) |
| Total income (last mt) | | | -0.002*** | (0.001) | | | -0.001*** | (0.000) |
| **Risk Aversion** | | | | | | | | |
| Risk-averse | | | -1.722 | (1.113) | | | -0.543 | (0.492) |
| Risk-loving | | | -1.256 | (1.422) | | | -0.472 | (0.621) |
| **Personality Traits** | | | | | | | | |
| Openness | | | 1.319*** | (0.467) | | | 0.239 | (0.184) |
| Conscientiousness | | | -0.909* | (0.497) | | | -0.639*** | (0.190) |
| Extraversion | | | -0.918** | (0.449) | | | -0.454** | (0.195) |
| Neuroticism | | | 5.456*** | (0.398) | | | 0.651*** | (0.171) |
| Agreeableness | | | -0.883* | (0.501) | | | -0.093 | (0.212) |
| $R^2$ | 0.032 | | 0.167 | | 0.014 | | 0.051 | |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). The model is estimated by OLS with n=1,804 observations. All models include interview months fixed effects. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using SF12 to measure $H_i$. More information on the variables, see Sections 4.2 and 5.

**Table A6: Relative Perception Bias and Risky Health Behaviors: Using SAH to Measure $H_i$**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ***No sports*** | | ***Obese*** | | ***No healthy diet*** | | ***Smoker*** | |
| **Positive health bias ($R_i > 0$)** | 0.0031*** | 0.0029*** | 0.0022*** | 0.0023*** | 0.0010 | 0.0009 | 0.0005 | 0.0004 |
| | (0.0007) | (0.0007) | (0.0005) | (0.0005) | (0.0007) | (0.0007) | (0.0004) | (0.0004) |
| **Negative health bias ($R_i < 0$)** | -0.0009 | -0.0011 | 0.0001 | 0.0000 | -0.0001 | -0.0003 | -0.0010 | -0.0010 |
| | (0.0012) | (0.0012) | (0.0008) | (0.0008) | (0.0012) | (0.0012) | (0.0008) | (0.0009) |
| $R^2$ | 0.0301 | 0.0401 | 0.0380 | 0.0422 | 0.0476 | 0.0568 | 0.0886 | 0.0930 |
| *socio-demographics & education* | yes | yes | yes | yes | yes | yes | yes | yes |
| *employment char. & income* | no | yes | no | yes | no | yes | no | yes |
| *month FE* | yes | yes | yes | yes | yes | yes | yes | yes |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). The model is estimated by OLS with n=1,804 observations. The binary dependent variables in columns (1) to (8) measure the likelihood that a respondent does not exercise at all, that a respondent is obese (BMI>30), that a respondent follows an unhealthy diet and that a respondent is a current smoker. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using SAH to measure $H_i$. For more information, see Sections 4.2 and 5.

**Table A7: Relative Perception Bias and Risky Health Behaviors: Main Results Estimated by Probit (Marginal Effects)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ***No sports*** | | ***Obese*** | | ***No healthy diet*** | | ***Smoker*** | |
| **Positive health bias ($R_i > 0$)** | 0.0022*** | 0.0021*** | 0.0011*** | 0.0012*** | 0.0013** | 0.0012** | 0.0004 | 0.0004 |
| | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0006) | (0.0006) | (0.0004) | (0.0004) |
| **Negative health bias ($R_i < 0$)** | -0.0002 | -0.0007 | -0.0011 | -0.0011 | -0.0006 | -0.0007 | 0.0004 | 0.0003 |
| | (0.0015) | (0.0015) | (0.0010) | (0.0010) | (0.0015) | (0.0015) | (0.0009) | (0.0009) |
| *socio-demographics & education* | yes | yes | yes | yes | yes | yes | yes | yes |
| *employment char. & income* | no | yes | no | yes | no | yes | no | yes |
| *month FE* | yes | yes | yes | yes | yes | yes | yes | yes |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). The model is estimated by Probit with n=1,804 observations. The binary dependent variables in columns (1) to (8) measure the likelihood that a respondent does not exercise at all, that a respondent is obese (BMI>30), that a respondent follows an unhealthy diet and that a respondent is a current smoker. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using SF12 to measure $H_i$. For more information, see Sections 4.2 and 5.

**Table A8: Estimating the Breakpoint $R$ for the Spline in the Baseline Specification**

| *Dependent variable:* | (1) No Sports | (2) Obesity | (3) Unhealthy Diet | (4) Smoker | (5) Sleep Gap |
|---|---|---|---|---|---|
| **Positive health bias ($R_i > 0$)** | 0.0021 | 0.0011* | 0.0013 | 0.0004 | 0.0042 |
| | (0.0016) | (0.0006) | (0.0010) | (0.0008) | (0.0049) |
| **Negative health bias ($R_i < 0$)** | -0.0043 | -0.0011 | -0.0011 | 0.0006 | 0.0130* |
| | (0.0039) | (0.0015) | (0.0024) | (0.0015) | (0.0072) |
| *socio-demographics & education* | yes | yes | yes | yes | yes |
| *employment char. & income* | no | no | no | no | no |
| *month FE* | yes | yes | yes | yes | yes |
| Optimal R | -20.0 | -1.6 | -7.1 | 9.6 | -18.7 |
| | (21.73) | (13.46) | (16.66) | (18.57) | (22.09) |
| p-value for likelihood ratio test | 0.192 | 0.800 | 0.712 | 0.877 | 0.337 |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). The models have 1,868 observations and estimate the breakpoint $R$ for the spline in the baseline specification in Table 1. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures. For more information, see Section 4.2 and 5.

**Table A9: Relative Perception Bias and Risky Health Behaviors: Physical vs. Mental Health as Benchmark**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Physicial Health (SF12) | | | | Mental Health (SF12) | | | |
| | *No sports* | *Obese* | *No healthy diet* | *Smoker* | *No sports* | *Obese* | *No healthy diet* | *Smoker* |
| **Positive health bias ($R_i > 0$)** | 0.0022*** | 0.0023*** | 0.0006 | -0.0002 | -0.0002 | -0.0006* | 0.0005 | 0.0001 |
| | (0.0006) | (0.0004) | (0.0006) | (0.0004) | (0.0005) | (0.0003) | (0.0005) | (0.0003) |
| **Negative health bias ($R_i < 0$)** | 0.0008 | -0.0000 | 0.0007 | -0.0000 | 0.0002 | 0.0019** | 0.0021** | -0.0009 |
| | (0.0013) | (0.0008) | (0.0013) | (0.0009) | (0.0010) | (0.0009) | (0.0010) | (0.0006) |
| $R^2$ | 0.0252 | 0.1333 | 0.0459 | 0.0461 | 0.0168 | 0.0318 | 0.0477 | 0.0855 |
| *socio-demographics & education* | yes | yes | yes | yes | yes | yes | yes | yes |
| *employment char. & income* | yes | yes | yes | yes | yes | yes | yes | yes |
| *month FE* | yes | yes | yes | yes | yes | yes | yes | yes |

*Source:* Berlin Aging Study II (BASE-II); * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses. The descriptive statistics are in the Appendix (Table A2). The model is estimated by OLS with n=1,804 observations. Positive health bias ($R_i > 0$) and negative health bias ($R_i < 0$) are continuous health bias measures, using the physical (columns (1) to (4)) and mental health (columns (5) to (8)) components of the SF12 to measure $H_i$. For more information, see Sections 4.2 and 5.