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RESEARCH PAPER

# The Scale Goes Up, the Joy Goes Down? Investigating the Causal Effect of Body Weight on Happiness

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## Abstract

Overweight and obesity represent significant public health challenges in many contemporary Western societies. In countries such as Germany, the majority of the population is classified as overweight. While being overweight is well-documented as a risk factor for adverse health outcomes, the relationship between overweight status and happiness remains less clear. This study investigates the impact of overweight and obesity on happiness, utilizing large-scale German panel data (N = 8,815) collected across ten survey waves. Employing fixed-effects regression models that account for relevant time-varying confounders—such as age, health, and employment status—I estimate the causal effect of body mass index (BMI) as a measure of overweight on happiness. The results indicate that being overweight, whether BMI is treated as a continuous or categorical variable, does not have a negative impact on happiness. These findings hold across both genders and all age groups. In some models or subgroups, even small positive associations between weight gain and happiness are observed, despite the exclusion of underweight individuals from the analyses. Further validation is provided by a random intercept cross-lagged panel model (RI-CLPM), which corroborates the initial findings and offers additional insights into the temporal dynamics of this relationship.

**Keywords** Happiness · Life satisfaction · BMI · Overweight · Obesity · Causal analysis · RI-CLPM · Germany

## 1 Introduction

Overweight is a highly prevalent problem in most Western societies (Peralta et al., 2018). As official statistics indicate, a little more than 50 percent of the population in Germany is overweight and this share has been steadily growing for the last decades (Schienkiewitz et al., 2022). More than 60% of all men are overweight or obese; for

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women, this share is above 40% (numbers from 2021).[1] These statistics are based on body height and body weight, which are used to compute the Body-Mass-Index (BMI). According to the WHO, a BMI between 18.5 and 25 is considered normal, values between 25 and 30 are considered overweight, and values above 30 are considered obese (Consultation, 2000). As it has been well known for decades, being overweight can lead to serious health problems and decrease life expectancy and overall quality of life through a large number of mechanisms (Reilly et al., 2003). Given these hard facts, it is surprising that the association between weight and happiness (or related terms, such as well-being or life satisfaction) is under-researched. As obesity is not only correlated but also causally linked to decreased health and vitality, one would suspect that there is a negative effect of being overweight on happiness. However, separating associations from causal links appears relevant since confounding factors, such as injuries, general health status, substance abuse, or gene influences, might be present. However, current research findings are rather sparse and often inconclusive. Some research designs are either not convincing to recover causal effects or only report correlations. One possible explanation is data limitations, as it is much harder to investigate causal processes than associations. Since it is almost impossible to randomize weight (gain) and conduct experimental studies, observational data must be sufficient to answer these research questions. Using high-quality and large-scale German panel data, I attempt to answer two questions: How are being overweight and overall happiness associated? Moreover, does gaining weight causally influence happiness? Using fixed-effect regression models and random-intercept cross-lagged panel models (RI-CLPM) with annual data from 2011 to 2021, I am confident that I can provide robust empirical evidence for Germany. For further insight, following the design of previous studies, I analyze men and women separately to account for gender differences.

## 2 Theoretical Expectations and State of Research

To understand how BMI and happiness are linked, it is relevant to know about the potential mechanisms. One such prominent mechanism is health. There is a clear and broad consensus in the medical literature that being overweight or even obese leads to worse health outcomes (Hruby et al., 2016; Lemieux & Després, 2020; Reilly et al., 2003), even if this link is not always strictly linear and can vary with gender (Hübler, 2017). While explaining the exact mechanisms is beyond the scope of this paper, one can assume that negative health outcomes are associated with lower life satisfaction and happiness. Various studies have shown that health is a strong and robust predictor of happiness and well-being (Bittmann, 2024; Ngamaba et al., 2017; Sabatini, 2014). Hence, negative health outcomes are one potential reason why being overweight is associated with lower happiness. If one understands this as the primary influence of BMI on happiness via health, there is also a secondary

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[1] https://www.destatis.de/DE/Themen/Querschnitt/Gleichstellungsindikatoren/adipositas-f23.html (2024–01-17).

one. Most people are aware that being overweight will probably have negative consequences for their health, so they can expect these negative influences to happen, even if they are still healthy. The awareness of the potential danger is another factor explaining why being overweight might reduce happiness. A third mechanism is completely different from health and is related to social desirability. In most modern Western societies, being fit and lean is a prevalent beauty standard. Being overweight, in contrast, is viewed by many individuals as not attractive (Hebl et al., 2008; Tovée et al., 1998; Wang et al., 2015, 2018). Overweight and especially obese people might suffer from these negative influences, as they might think that they are less attractive due to their high weight. This is a normative aspect, but it is present in most Western societies, which might explain why overweight individuals are less happy. Taken together, there are good reasons to believe that being overweight is not only related to unhappiness (Hypothesis 1), but is also a causal contributing factor (Hypothesis 2).

While the potential mechanisms between weight and happiness are understood, there is currently little and often no conclusive empirical evidence. This is surprising given that overweight is not only a local but a global problem, resulting in massive healthcare costs, reduced life expectancy, and lower overall happiness. Given the massive impact that overweight creates, the main reasons for the absence of sound studies is potentially the lack of specialized surveys or datasets. If one is not only interested in correlations but also wants to check causal interdependencies, either longitudinal data or special research designs are required, which are often not easily available. To start with cross-sectional or correlational results, two large-scale analyses report negative associations between being overweight and happiness (Kuroki, 2016; Wadsworth & Pendergast, 2014). Another large cross-sectional analysis including multiple countries reports positive associations of overweight on life satisfaction for men but negative ones for women (Gugushvili & Jarosz, 2021). A study with Swiss cross-sectional data investigates the relation between BMI and happiness by also taking the aspect of self-control into account (Stutzer & Meier, 2016). The authors report small negative effects of overweight or obesity on well-being, which are larger for individuals with low self-control. Supporting the notion that health is a relevant mediator or confounder, there is also evidence that the negative association between overweight and happiness can be explained away by focusing on health factors (cross-sectional analysis with Finnish data) (Böckerman et al., 2014). However, these cross-sectional results are usually not able to make causal claims. One approach to expand the insight is the usage of instrumental variable approaches with cross-sectional data. One study reports that a healthy BMI increases life satisfaction, exploiting time spent watching TV as an instrument, which is not fully convincing since the instrument is correlated with the outcome variable (Habibov et al., 2019). Another study utilizes a sample of Spanish adolescents and regards the frequency of consuming alcohol as an instrument (Prieto-Latorre et al., 2023). The authors report a negative influence of higher BMI values on life satisfaction. However, keep in mind that some instruments are not reliable, hence the need to longitudinal data, which can be seen as the gold standard in the absence of (ethical) experiments. A study with German panel data finds negative associations between BMI and happiness (Hübler, 2019). However, the causal findings are much less clear. Using a set of equations (modeling health, satisfaction, and income simultaneously and adding a matching procedure), there are no clear-cut conclusions for the effect of BMI on satisfaction, even though the sample size is large. A comparison of the effect of BMI on happiness between the USA and China finds a positive effect on happiness in China (especially for men), where being overweight is seen as a form of status (Sato, 2021). In contrast, no effect of overweight or obesity is present in the USA. The paper uses fixed-effect regression models with lagged BMI, which is a convincing statistical approach. A study with Canadian data utilizes a similar approach and reports no effects of obesity for men and small negative effects for women (Latif, 2014).

Summarized, while many studies report negative associations or correlations between BMI and happiness, there is only a very limited selection of studies available that come close to estimating causal effects. Interestingly, these studies sometimes come to different conclusions and find no negative effects, sometimes even positive ones (in the case of China). The following analyses will contribute to this literature by providing estimates based on large-scale German panel data.

## 3 Data, Variables, and Methods

### 3.1 Data Source and Sample Selection

To answer the posed research questions, I utilize German National Educational Panel Study (NEPS) data (Blossfeld & Roßbach, 2019). The NEPS is the most ambitious German research project to study the role of education in the life course.[2] Since 2010/11, participants are surveyed approximately annually. For the analyses, the adult cohort (SC6) is used. "The target population of respondents in Starting Cohort 6 comprises all persons born between 1944 and 1986 who live in private households in Germany, irrespective of the language they speak, their nationality, or their employment status. Persons living in shared facilities (old people's homes, prisons, etc.) are excluded" according to the data manual. For this aim, 281 sampling points from 250 German municipalities were randomly selected.[3] In this process, the size of the municipalities was respected to account for different probabilities of being sampled, depending on the size of the municipality. Per sampling point, 152 individuals were randomly drawn from the official register. Based on these data, a total of 22,565 addresses with phone numbers could be recovered, which were used to conduct 10,404 interviews successfully. Study participating was incentivized with 10€. The SC6 dataset contains a rich set of relevant variables, such as health, happiness, sociodemographic background variables, or educational and employment status. Currently,

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[2] This paper uses data from the National Educational Panel Study. The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network. National Educational Panel Study, Scientific Use File of Starting Cohort Adults. Leibniz Institute for Educational Trajectories (LIfBi), Bamberg. 10.5157/NEPS:SC6:14.0.0.

[3] https://www.neps-data.de/Portals/0/NEPS/Datenzentrum/Forschungsdaten/SC6/1-0-0/Methodenbericht_SC6_W2_B72.pdf (2024–10-10).

there are 14 survey waves available for research purposes. However, a huge refreshment sample was drawn in wave 4, which gives a total sampling frame of 17,140 individuals with a participation rate of 97.6% in this wave (2011/12). As the key constructs weight and height have been measured for the first time in this wave, one can regard this as the beginning of the observation window of interest, which gives a total of ten waves until survey wave 13 (2020/21). To ensure a high data-quality in the longitudinal setting, only individuals are retained who participated in at least four out of the ten mentioned waves (N = 10,159). Furthermore, I only retain individuals who are at beginning of the observation window at most 60 years old (that is, in 2011/12). This restriction is imposed for two reasons: first, while body height is virtually constant for adults, it can decrease in old age due to biological processes. As height is self-reported and individuals might remember their height from earlier times when they were taller, BMI values can be compromised. Second, survivorship bias needs to be regarded, meaning that the least healthy individuals (potentially related to BMI) might die earlier and are removed from the survey. This leaves 8,819 individuals. Finally, I remove individuals who report a BMI below 18.5 (0.6% of the sample) or above 45 (0.5% of the sample) or have missing information on key constructs such as gender (40 cases). By doing so, one avoids biased results due to underweight participants (which are extremely rare) and people who are extremely overweight. This gives a final sample size of 8,815 individuals. Missing information will be imputed, which is described in more detail below.

## 3.2 Analytical Strategy and Statistical Models

### 3.2.1 FE-Regression Models

In the following analyses, fixed-effects (FE) regression models are employed to support causal inferences. These models are widely regarded as one of the most robust methods for approximating causal effects (Brüderl & Ludwig, 2015; Gangl, 2010). However, their application is often constrained by data limitations, as they require survey data from the same individuals at least twice, with more frequent measurements enhancing the precision of estimates. The data from the National Educational Panel Study (NEPS), which include BMI measurements in five waves spanning from 2011/12 to 2020/21, allow for the estimation of FE regression models. FE regression models rely exclusively on within-person variation to estimate coefficients, effectively removing the influence of time-constant factors that could introduce bias, such as gender, migration background, and potentially even innate characteristics like personality traits, intelligence, or willpower. This methodological advantage distinguishes FE regressions from ordinary least squares (OLS) regressions or panel models with random effects (RE regressions), as it mitigates the risk of confounding by these stable, unobserved variables. The FE models essentially mean-center the values for each individual, ensuring that only variations within individuals across time are used to estimate the relationships of interest.

To arrive at unbiased estimates, two aspects must hold. First, all relevant variables (cause and effect) must have enough within-person variation (that is, be subject to change over time and not always stay constant). Second, bias can still occur through the influence of time-varying confounders. These variables change with time and influence both the cause and the effect. If such variables are not accounted for, estimates do not necessarily indicate causal effects. Such variables must hence be selected on a theoretical base. I decided to consider the following: first, place of residence. In Germany, the cultures and standards of living can still differ between East and West Germany; any movement of an individual between the two regions will be regarded (Kasinger et al., 2023). Second, I measure whether a person reports any episode of not being in the labour force in a given survey wave (Clark & Oswald, 1994). The reasons can be manifold (retirement, unemployment, or parental leave). In any case, I would argue that not working can be a relevant change that can both affect weight and happiness (unemployed individuals might move less and gain weight but also be unhappy since work provides meaning to many people).[4] Third, individuals report whether they live together with a partner or spouse in the same household or not. This has drastic implications for weight and happiness (divorcing or the death of the partner), potentially through health behaviour (Blekesaune, 2016). Fourth and final, health and age. These are the most biasing factors as failing health can drastically impact both key variables, closely related to age. For example, suppose an individual gets into a serious accident and becomes bedridden. In that case, weight can change as the normal diet and daily activities (e.g., work or sport) will be affected. In addition, happiness can drastically decrease (e.g. new life situation, temporary or constant disability, physical and mental pain). While one could also argue that health is a consequence of weight (being overweight has adversarial health effects), I see the other direction of causality as more relevant. If one follows this logic, health is a mediator that explains how and why BMI influences happiness, which could result in an overcontrol bias (Elwert & Winship, 2014), meaning that estimates are potentially downward biased. This is the smaller error to make, so I decided to include health as a control variable, which aligns with the design of previous high-quality studies (also see the robustness checks for an empirical test). Age is also relevant as a large number of studies has shown that the age-happiness relationship is sometimes complex and of greatest importance (Bartram, 2022; Bittmann, 2021). A flexible modeling using higher-order terms appears to be the logical consequence. This makes it also possible to investigate non-linear effects, which seems plausible from a theoretical point of view. One could suspect that the additional effect of more weight diminishes from a certain point on and is not strictly linear (law of diminishing returns). This can be easily captured in flexible modeling by adding higher-order terms of BMI (such as BMI squared). After presenting a first linear model, more flexible models will be included as well to investigate that aspect in more detail. Figures are a popular approach to visualize the results properly and offer an intuitive interpretation.

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[4] The related measure of income is also discussed in the robustness section further below.

### 3.2.2 RI-CLPM

As a second analytical model, I compute a random-intercept cross-lagged panel model (RI-CLPM). In contrast to the FE-regression models, the RI-CLPM allows it to model the potential co-development of happiness and BMI with longitudinal data explicitly. The RI-CLPM takes out person-constant trait-like properties of the key variables and only models deviations from a person-constant mean value (of either BMI or happiness). This model tests specifically: Do individuals with higher deviations from their long-time average BMI at time point $t_0$ have higher deviations from their long-term average happiness at time point $t_1$? In other words, do individuals change their happiness by changing their BMI in the previous survey wave? Note how this RI-CLPM facilitates a causal interpretation of *within-person* changes, further strengthened by including relevant control variables as outlined above (Mulder & Hamaker, 2021). While by design, the RI-CLPM accounts for-time-constant confounders, it assumes that the effect a potential confounder has on the outcome variables is stable over time and does not change with the survey waves (Mund et al., 2021). However, if this assumption is violated, bias can be introduced. This is the main reason for including the control variables as described above, even if they are time-constant by nature. In general, I also would like to acknowledge that the RI-CLPM is not a panacea, and there is valid criticism of the model as well (Lüdtke & Robitzsch, 2021). The authors even outline that the RI-CLPM is not always able to account for time-constant confounding variables, which is one of the reasons why I opted for the inclusion of relevant control variables. In the RI-CLPM, I use waves 4 to 13 regarding happiness and waves 4, 7, 10, 12, and 13 for BMI since this variable has been measured in these waves only. The structure of the model is that previous waves can only influence following ones directly (respecting the direction of causality; autoregressive pathways) and that crossed pathways are included (so that happiness can influence BMI and vice-versa). The RI-CLPM is estimated using a maximum likelihood estimator. The goodness of fit of the models is checked using five indicators: chi-square test, comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Conventionally, a good model fit is demonstrated by a small, preferably statistically nonsignificant chi-square,[5] large CFI and TLI values, and a low RMSEA / SRMR. In this study, I do not rely on cut-off values as they often lead to binary conclusions, which does more harm than good as has been shown in the literature (Marsh et al., 2004; McNeish & Wolf, 2023).

To sum up, the main benefit of including two statistical models is increased robustness and additional insight. If two rather distinct models arrive at the same conclusions, this strengthens the results and also demonstrates that they are not driven by the statistical software, coding decisions, imputation of missing values (as both approaches use different methods for imputation), or some specific assumptions

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[5] It should be emphasized that the chi-square value can be rather meaningless when the sample size is large. In large-scale samples, a statistically significant result is almost always produced. Hence, the other statistics might be more relevant to judge the model fit.

on the data (as they are different between the models). They enable deeper insight as well, as the RI-CLPM models all crossed pathways explicitly while the FE-model only computes one overall effect. However, the FE-model is more flexible with regard to operationalization and allows the inclusions of non-normally distributed variables, which are used in the robustness supplements.

### 3.2.3 Imputation of Missing Information

To address missing data, I employ multiple imputation with chained equations (MICE) in both the descriptive analyses and the fixed-effects (FE) regression model. This method represents the standard approach in contemporary statistical analysis and offers substantial reductions in bias compared to listwise deletion or less sophisticated imputation techniques. Imputation is performed in wide format to maximize the use of time-varying variables. Additionally, several time-constant factors not included in the analytical model—such as first-language German and educational attainment—are incorporated as auxiliary variables to improve imputation accuracy.

For all variables, predictive mean matching is employed, which is well-suited for both continuous and binary variables (Austin & Van Buuren, 2023). This technique identifies donor individuals, without missing data, who are highly similar to the target individual on all relevant variables. Six potential donors are selected, and one is randomly chosen. A notable advantage of this method is that it precludes the generation of out-of-range values. The quality of the imputed data was assessed through diagnostic plots, confirming that the imputed values do not systematically deviate from the observed data.

A total of 50 imputed datasets are generated separately for each gender, with all analyses conducted using Stata 16.1 (Bittmann, 2019). The random intercept cross-lagged panel model (RI-CLPM) is estimated using the *lavaan* package (version 0.6.17) in R (Rosseel, 2012). Missing data in the structural equation models are handled using full information maximum likelihood (FIML), which is asymptotically equivalent to multiple imputation. For visualization purposes, the *coefplot* package (Jann, 2014) and the *mimrgns* package (Klein, 2014) are also utilized within Stata.

## 3.3 Variables and Operationalization

The dependent variable, BMI, is computed using the body weight in kilograms and the height in meters. The formula is $\mathrm{BMI} = \mathrm{weight[kg]} / \mathrm{height[m]}^2$. Both weight and height are self-reported by the respondents. The WHO defines a BMI between 18.5 and 25 as normal. Values above 25 are classified as „overweight “, values above 30 as „obese “. Values below 18.5 are defined as „underweight “. However, due to the very few observations in the data in this range, such cases are removed. The following analyses utilize BMI as a continuous and categorical variable. Oriented on the WHO definition and for further insight, the following categories are coded: 18.5 to 22 (low-normal), 22 to 25 (high-normal), 25 to 30 (overweight), 30 to 35 (obese I), and 35 to 45 (obese II).[6] Individuals with values above 45 are removed to avoid bias through extreme outliers since these cases are rare. The key constructs, weight and height, were surveyed in waves 4 (2011/12), 7 (2014/15), 10 (2017/18), 12 (2019/20) and 13 (2020/21). Waves in between (5, 6, 8, 9, 11) are imputed by linear interpolation between the two adjacent waves available. While this process can potentially introduce bias, I argue that it should be small and outweigh its benefits. The interpolation approach should be fine since BMI has been measured multiple times with at most two waves in between without a measurement. In contrast to other constructs, such as happiness or income, which can change potentially rapidly, BMI is a rather stable construct with natural inertia. Body weight usually does not change drastically within a year in adults but tends to follow a more stable trajectory over time, even if increasing or decreasing (Guo et al., 2024). See also the robustness checks further below for an investigation of this modeling approach. Since all other variables are available from every wave in the survey, it would be unfortunate to lose all this extra information by restricting the analyses to the waves with BMI available.

Age is measured as the time between date of birth and time of interview (in years). While year and month of birth are known for all participants, the interview date is not, so some values also need to be imputed. However, this error is tiny as the range of the interview dates within a survey only comprises a few weeks to months and only concerns the subsample with missing age information (less than ten percent of the data).

Happiness is measured using a single item, which is as follows: “First of all, I would like to ask you some questions about your current satisfaction with various aspects of your life. Please answer on a scale from 0 to 10. ’0’ means that you are ‚completely unsatisfied’, ’10’ means that you are ‚completely satisfied’. You can gradate your answer with the numbers in between. All in all, how satisfied are you with your life at the moment?” This variable has eleven distinct values and will be regarded as a continuous variable. This variable is an established measurement of happiness and has shown good statistical properties (Abdel-Khalek, 2006).

As explained in more detail below, some control variables are utilized in the regression models to strengthen claims of a causal interpretation. The first is whether a respondent lives in the same household with a partner or spouse: “And with whom do you currently live in a household—With spouse/partner.” This is a binary item. The second is whether a person is currently not working. The NEPS research data center has coded this variable based on all available episode data about employment. Furthermore, this variable has been amended by information on whether a respondent is retired. If the person reports at least a single episode of non-employment (for any reason) per survey wave, it is counted as non-working (code 1), otherwise as working (code 0). The third is whether an individual lives in East (code 1) or West Germany (code 0) in the current survey wave; this is a binary item. Finally,

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[6] Note that when recoding continuous values into categories, “22 to 25” means that all values above 22 up to including 25 are in this category. This handling concerns all recoded continuous variables in this study.

**Table 1** Descriptive statistics

| | Mean / Share | Median | SD | Min | Max | Share imputed (%) |
|---|---|---|---|---|---|---|
| Happiness* | 7.56 | 8 | 1.54 | 0 | 10 | 8.7 |
| BMI* | 26.4 | 25.7 | 4.58 | 18.5 | 45.0 | 15.5 |
| Age in years* | 48.5 | 50.0 | 9.47 | 27.8 | 64.0 | 8.7 |
| Living in East Germany* | 0.21 | | | 0 | 1 | 9.5 |
| Self-reported health status* | 3.77 | 4 | 0.81 | 1 | 5 | 8.8 |
| Not working in wave* | 0.22 | | | 0 | 1 | 14.6 |
| Living together with partner* | 0.89 | | | 0 | 1 | 28.1 |
| Female respondent | 0.51 | | | 0 | 1 | 0 |
| Mother tongue not German | 0.065 | | | 0 | 1 | < 1 |
| Education level | | | | | | 0 |
| Low (*Hauptschulabschluss*) | 0.18 | | | 0 | 1 | |
| Intermediate (*Mittlere Reife*) | 0.33 | | | 0 | 1 | |
| HEE (*Abitur*) | 0.19 | | | 0 | 1 | |
| UAS | 0.10 | | | 0 | 1 | |
| University | 0.19 | | | 0 | 1 | |
| Observations | 8,815 | | | | | |

*Source: NEPS SC6, waves 4–13, imputed data (M = 50). Time-varying variables are marked with an asterisk and reported from wave 7. HEE = Higher education eligibility, UAS = University of applied sciences*

self-rated health is surveyed using this item: "I now have a brief question about your health. How would you generally describe your state of health?". The response scale is Likert-type with values ranging from 1, "Very poor," to 5, "Very good". This item is included as a continuous variable in the models.

## 4 Results

### 4.1 Descriptive Findings

Before inspecting the central variables of the study, it is helpful to get an overview of the background characteristics to understand the sample, which are presented in Table 1. Regarding gender, the sample is highly balanced as 51% of the respondents are female. The average age is 48.5 years with a standard deviation of 9.5 years. This shows that the sample has a rather relatively old age but this corresponds rather well to the overall German population age of 44.6 in 2022.[7] This means that the sample does not show relevant deviations from the overall population, which underscores

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[7] https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/bevoelkerungsstand-gebietsstand-werte.html (2024–10-11).

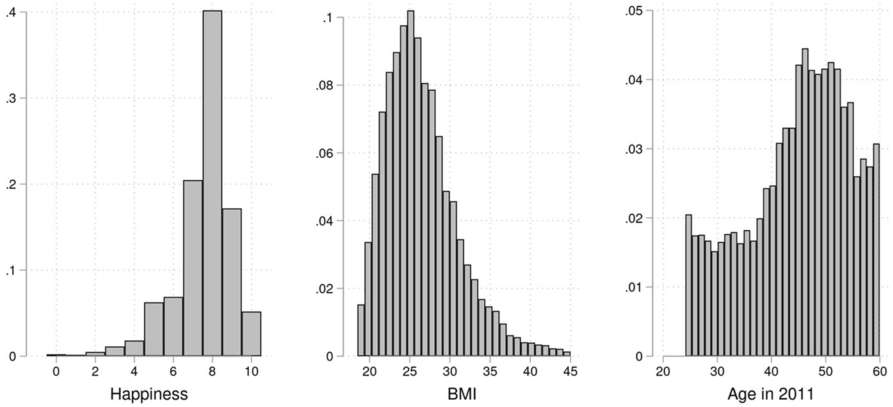

**Fig. 1** Univariate distributions of happiness, BMI, and age. Source: NEPS SC6, waves 4–13, imputed data (M = 50)

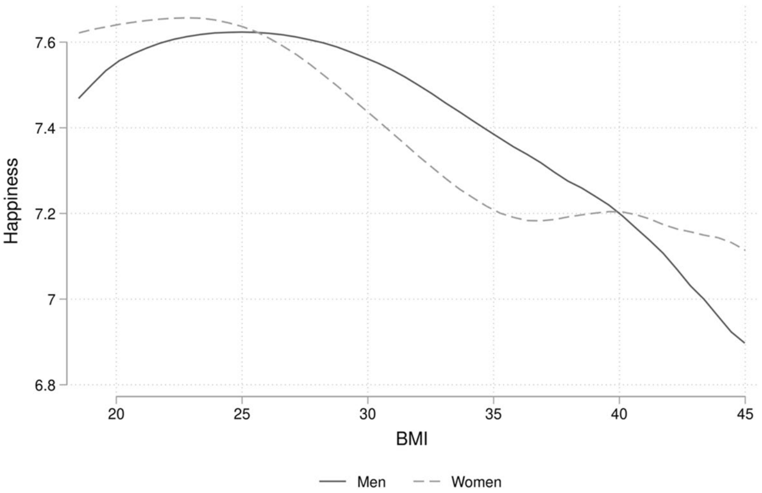

**Fig. 2** Association between happiness and BMI by gender. Source: NEPS SC6, waves 4–13, imputed data (M = 50)

the rather good generalizability. To get an impression of the distribution of some key constructs, Fig. 1 is helpful, which shows histograms of happiness, BMI, and age in 2011. The average happiness in the sample is rather high, as most individuals report a value above 7. BMI is a skewed variable, with most values between 22 and 27 with a rather long tail ranging up to 45. Age includes the entire range, with an over-representation of ages 45 to 55.

Next, the association between BMI and happiness is visualized in Fig. 2. For this type of visual analysis I utilize local polynomial smoothing and include all survey waves. The graph shows that men report the highest happiness values with BMI values between 23 and 27. Afterwards, it falls rather linearly. For women, it is for BMIs between 18.5 and 24.

Afterward, happiness also falls, but only up to about 35; from there on, it is rather constant. A numerical correlation analysis supports the graphical interpretation ($r(589) = -0.072$, $p < 0.001$). The overall conclusion is that the association is negative, even if not strictly linear, which aligns with hypothesis 1. The following analyses should consider this initial finding by accounting for non-linearities. Also, note that this is only an association. It would be incorrect to state that higher BMI values *cause* unhappiness, as confounders are not accounted for until now.

Next, a few descriptive figures are presented to understand better how some more key variables are associated with each other. First, it is tested how happiness and BMI vary with age (see Fig. 5 in the appendix). On the left side of the panel, it is clear that happiness is highest in younger individuals and decreases over time for both men and women. Note that here, individual and cohort effects are taken together, and not only individual trajectories are shown. This means one can only interpret a correlation here, showing that age and happiness are linearly and negatively associated ($r(2562) = -0.058$, $p < 0.001$). The opposite conclusion holds for BMI and age, which are positively associated in men and women. This means that older people report higher BMIs, on average. This trend is also rather linear ($r(994) = 0.132$, $p < 0.001$). Men have higher BMIs than women, on average. These first findings highlight that age is a highly relevant factor for both key constructs, which must be regarded in the analytical models.

Before computing the statistical models, it is necessary to test a few assumptions first. In FE-regressions, only within-person changes of the dependent and independent variables contribute to the model. This is desirable as time-constant factors are automatically controlled for. However, this also requires that the main constructs have sufficient variation within each individual. This means that both BMI and happiness must vary to some extent over time. To test this, the within-person standard deviation of these two variables has been computed and visualized using histograms (see Fig. 6 in the appendix). Both variables have enough within-person variance to support the usage of FE-models. For further insight, a few (demographic) key variables, such as gender, age, or educational qualification, are summarized in Table 1 to characterize the sample.

## 4.2 Fixed-Effect Regression Results

The main model computes fixed-effect regressions with BMI as a categorical variable, separately for men and women. The results are presented in Table 2. 95% confidence intervals are provided based on robust standard errors. Note that the category "18.5 to 22" is the reference category. The main result for men is that all regression coefficients are positive, and some are statistically significant. For example, if the BMI of a man would change from "18.5 to 22" to "30 to 35", the happiness would increase by about 0.19 points, which is statistically significant on the 5% level. For women, results are rather similar. I would argue that these coefficients approximate causal effects under the given data constellation, model, and control variables. Remember that these effects are, even if sometimes statistically significant, rather small. For example, if health increases by 1 point on the 5-point Likert scale, average happiness would increase by

**Table 2** FE-regression results for happiness by gender

| | Men | Women |
|---|---|---|
| BMI category | | |
| 18.5–22 (Normal) | Ref | Ref |
| 22–25 (Normal) | 0.061 | $0.127^{***}$ |
| | [-0.039,0.161] | [0.054,0.200] |
| 25–30 (Overweight) | 0.117 | $0.137^{**}$ |
| | [-0.001,0.236] | [0.037,0.236] |
| 30–35 (Obese I) | $0.192^{*}$ | 0.127 |
| | [0.044,0.340] | [-0.002,0.257] |
| 35–45 (Obese II) | $0.207^{*}$ | 0.177 |
| | [0.019,0.395] | [-0.017,0.370] |
| Age in years | $-0.047^{***}$ | $-0.047^{***}$ |
| | [-0.072,-0.022] | [-0.074,-0.021] |
| Age in years$^2$ | $0.001^{***}$ | $0.001^{***}$ |
| | [0.000,0.001] | [0.000,0.001] |
| Not working | -0.017 | -0.003 |
| | [-0.057,0.023] | [-0.043,0.038] |
| Living with partner | $0.300^{***}$ | $0.227^{***}$ |
| | [0.180,0.419] | [0.119,0.334] |
| Self-reported health | $0.384^{***}$ | $0.418^{***}$ |
| | [0.353,0.415] | [0.389,0.446] |
| East Germany | -0.043 | 0.009 |
| | [-0.231,0.145] | [-0.209,0.226] |
| Constant | $6.758^{***}$ | $6.759^{***}$ |
| | [6.115,7.401] | [6.081,7.437] |
| $R^2$ (overall) | 0.188 | 0.183 |
| $R^2$ (within) | 0.038 | 0.042 |
| Observations | 42,930 | 45,220 |
| Individuals | 4,293 | 4,522 |

*Source: NEPS SC6, waves 4–13, imputed data (M = 50). 95% confidence intervals in brackets based on robust standard errors.* $^{*}$ *$p < 0.05$,* $^{**}$ *$p < 0.01$,* $^{***}$ *$p < 0.001$*

about 0.39 points (for men). This means that health changes are much more substantial than BMI changes for happiness.

For a more visual interpretation, I have computed another FE-regression model where BMI is entered as a continuous variable. As the effects are potentially nonlinear, BMI$^2$ and BMI$^3$ are also included in this model, and predicted values are generated. The results of this flexible modeling approach are shown in Fig. 3.

The effect of BMI on happiness for men is rather linear. If BMI increases, happiness also always increases. For women, the effect is linear in the region of BMI between 19 and 27 but then reaches a plateau and does not increase any further. Overall, both models (using BMI as a categorical or continuous variable) support the same conclusion: Happiness increases (slightly) as BMI increases. Consequently,

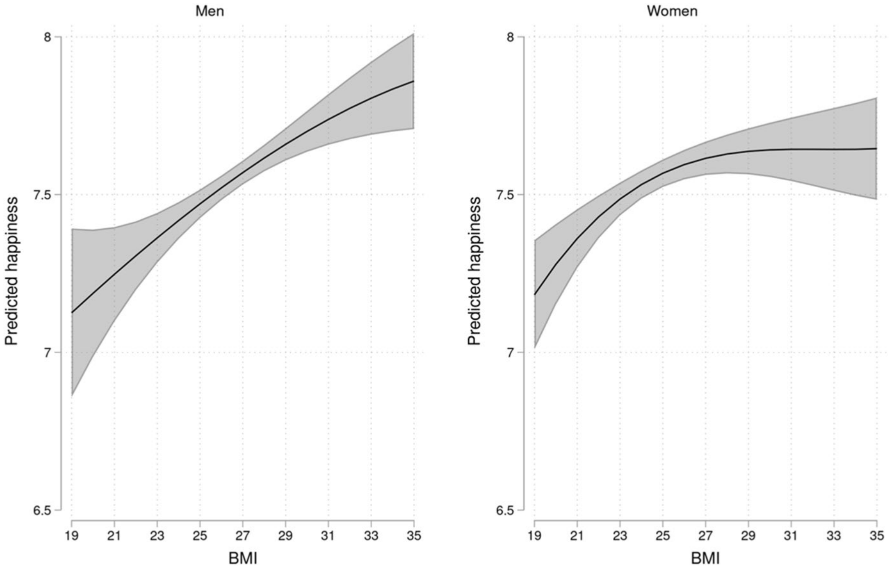

**Fig. 3** Predicted happiness by BMI (continuous) Source: NEPS SC6, waves 4–13, imputed data (M = 50). 95% confidence bands included, based on robust standard errors. Control variables: age, age$^2$, not working, living with partner, health status, living in East Germany

I reject hypothesis 2, which expected the contrary. To ensure the statistical soundness of the results and test their overall robustness, I have conducted a large number of additional tests or applied different coding schemes, which are reported in the appendix. Summarized, the results are highly robust and not a single FE-model reaches different conclusions.

### 4.3 RI-CLPM

Before inspecting the path coefficients of the RI-CLPM, the fit statistics are inspected. These are highly relevant to assess whether the statistical model fits the theoretical specifications at all. The results are as follows: $\chi^2(451) = 2{,}897$, $p < 0.0001$; CFI = 0.990; TLI = 0.986; RMSEA = 0.025, 90% confidence interval [0.025, 0.026]; SRMR = 0.044. The CFI and TLI are very high and indicate a good model fit. The RMSEA and SRMR are low, which is also a good result. While a statistically non-significant chi-squared value is preferred, it is well known that given a large sample size, such as in my case (N = 8,815), a small p-value is very likely and should not be used to judge the overall model fit (Schermelleh-Engel et al., 2003; Vandenberg, 2006). Summarized, these results indicate that the model fit is fine. For a convenient interpretation, I summarize the path coefficients of the model graphically in Fig. 4.

Of interest are the path coefficients between the red ovals, which indicate within-person changes over time. As one would expect, earlier waves predict later waves.

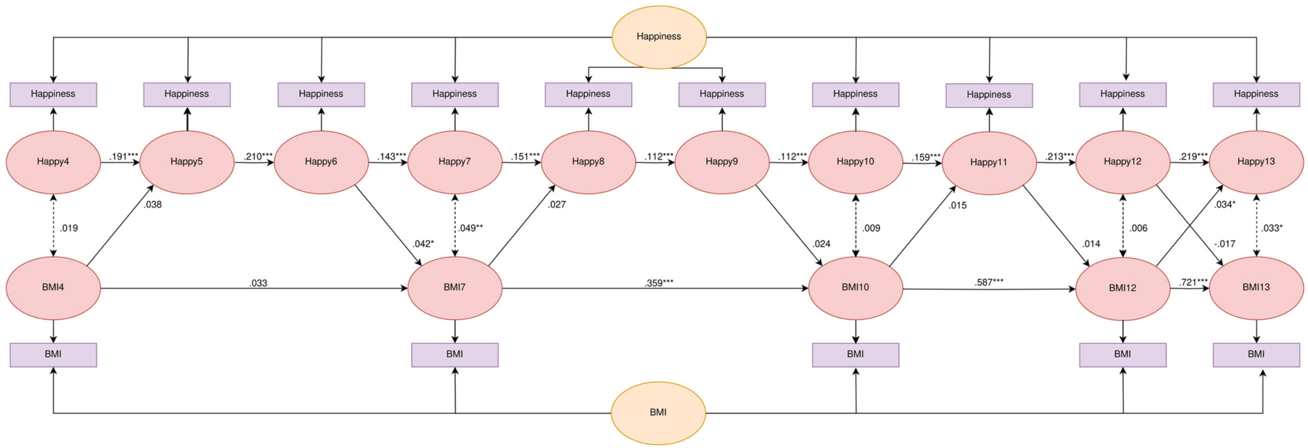

**Fig. 4** RI-CLPM for BMI and happiness (survey waves 4 to 13) Source: NEPS SC6 (N = 8,815). Control variables: gender, age, place of residence, mother tongue not German, self-reported health, living together with partner, being out of the work force, social origin indicators. Dashed lines represent covariances. Reported are standardized coefficients (β). The between-subject part (the top and bottom ovals) captures individuals' average level. The within-subject part (red ovals in the middle) shows the within-person associations. *$p < 0.05$, **$p < 0.01$,. ***$p < 0.001$

For example, if the happiness increases by one standard deviation in survey wave 11, the happiness also increases by about 0.213 standard deviations in wave 12. This is the autocorrelation inherent to the data. Of greatest interest are the crossed pathways. Regarding the influence of happiness on BMI, note that the coefficients are almost always positive but very small. This means that, on average, happiness has a small positive effect on BMI. For the other crossed pathway, from BMI to happiness, a similar pattern emerges. The coefficients are always positive and very small. For example, if the BMI increases by one standard deviation in wave 12, the happiness increases by about 0.034 standard deviations in wave 13. The numbers reported by the RI-CLPM are in accordance with the FE-regressions. No negative effect of BMI on happiness can be detected. Potentially, if BMI increases (individuals gain weight), the happiness even increases (although these effects are tiny and for most waves not statistically significant). Summarized, what these numbers clearly indicate is that if BMI increases, the happiness does certainly not decrease. Given that the model is sophisticated, includes a large number of controls and has a high statistical power, one can be confident that these results are rather robust. Note that the Random Intercepts of BMI and happiness (depicted by the orange ovals in Fig. 4) are not correlated (0.015, $p > 0.10$), which means that most of the trait associations are at the within-person level.

## 5 Discussion

As the first descriptive findings indicate, BMI and happiness are negatively correlated, as expected. This means that heavier individuals report lower happiness values, on average. This fact holds for both genders. I have assumed this to be the case due to the various negative associations between being overweight and health, influencing happiness. In this regard, the findings are in line with various publications that come to the same negative correlative results (Kuroki, 2016; Wadsworth & Pendergast, 2014). As these first analyses also reveal, this association is not strictly linear, but there is a range, usually up to a BMI of 25, where happiness is stable. This makes sense, as the WHO defines a BMI between 18.5 and 25 as “normal”; hence, one would not expect many negative effects on happiness. Only for overweight and obese individuals does happiness decrease. This association is stronger for men than women, changing from about 7.6 points to about 6.9 points. Of greatest interest is how the conclusions change after the regression models are inspected. Various confounding factors, such as age, overall health, or even working situation, are accounted for, and only within-variation contributes to the results. What one can see here is that changing and increasing weight has no negative influence on happiness at all. Not a single model or subgroup has a negative point estimate for the effect of increasing BMI. This holds for both categorical and continuous operationalizations. Sometimes, even positive and statistically significant results arise (even if the effect size is tiny). The RI-CLPM comes to exactly the same conclusions, even if the modeling strategy and assumptions are rather different from the FE-regression. Given these results, one can conclude that increasing the BMI by gaining weight (as height changes are rather unlikely) does not negatively affect happiness. In this regard, the study is well aligned with two other large-scale longitudinal assessments, as neither results from Germany (Hübler, 2019) nor from the USA (Sato, 2021) report any negative causal effects on happiness. Given that the participants, time of sampling, research designs, variable operationalizations and even analytical methods are different between these various studies, one can assert confidently that there seems to be a rather robust research consensus that there is no negative causal effect of gaining weight on happiness.

This finding is somewhat surprising as it is a fact that being overweight or obese is causally linked to worse health outcomes. As it is also known that health is a predictor of happiness, one could suspect that the negative effect of BMI on happiness is completely mediated through health, which is included in the regression models as a covariate. However, why does BMI then sometimes even show positive effects? Even if health effects are accounted for, there are social desirability issues. Being overweight or being even obese is rarely seen as attractive in Western societies, so this is hardly a convincing explanation. As the models also consider age through various aspects, such as sample selection and as a control variable, survivorship bias should not be an issue. If one keeps in mind that being overweight is mostly caused by eating too many calories, could the benefits outweigh the costs? Is eating more calories making people so much happier that a higher weight is acceptable? This is rather speculative. Future studies should focus on these details and investigate mechanisms that explain how central aspects such as happiness, health and weight are related. This issue is of greatest interest to the general health of the population, which tends to get heavier and heavier on average. As most Germans are already overweight, this is not a positive development. This study helps to understand why the situation worsens, as losing weight is not incentivized. If gaining weight does not influence happiness at all or, in the end, is even a positive factor, why should people bother to work hard or eat less food? Even if people are aware that being overweight or obese is a problem for their health, if it feels good, there might be less motivation to change the situation. I also presume that age might be relevant to explain the apparent divergence between descriptive and causal findings. As demonstrated, age is positively correlated with BMI but negatively with happiness, potentially by the mechanism of health. As soon as age is accounted for, the negative association between BMI and happiness vanishes.

Another potential explanation is a change in perceptions of weight. The body-positivity movement calls for the acceptance of all forms of body weights and shapes (Cohen et al., 2021). The content, that is especially distributed on social media sites, might convince individuals that happiness and self-worth are not tied to weight or BMI and breaks the supposed causal relationship. While this might be a potential explanation, it is rather unlikely to have a strong effect due to being relatively new. In any case, the link between happiness and weight is apparently more complex as supposed and especially the perceptions of weight and body might be interesting targets for further studies. Here, qualitative studies might fill a gap that even large-scale quantitative assessments can currently not close. It would be highly relevant to understand in detail, why people gain weight in the first place and whether this is a consequence of some other changes in life. While disentangling causal effects is difficult, it can also be highly relevant and rewarding to better understand why the obesity epidemic is increasing even further, despite the fact that the medical and social knowledge on happiness and obesity grows.

Finally, the limitations of the study should be discussed. First, this study relies on BMI to operationalize overweight and obesity. While easy to measure, there are downsides to this construct (Rothman, 2008). The BMI does not regard the weight composition (for example, the share of fat to muscle tissue). Consequently, some healthy and fit athletes, such as bodybuilders, would be classified as overweight, even if the share of fat tissue in their body is very low. For them, one would not expect negative health outcomes. This is a general limitation of all studies using the BMI. However, since alternatives are more complex to measure and often unavailable, BMI is still one of the most widespread statistics utilized in empirical research. Second, this study does not examine the effects of being or becoming underweight. The main reason for this is that being underweight is much less common in the German population (less than 2% of the German population[8]), and there are only a few cases in the data that can be utilized, which leads to very low statistical power. Consequently, this study focuses on overweight rather than the contrary. While relevant from a medical perspective, as being underweight is detrimental to physical and mental health, other data must be used to investigate these research questions. Third, as always with observational data, the effects reported are not necessarily purely causal. If one believes that strong confounding factors are disregarded in the current analyses, the findings can be spurious. Some relevant control variables are not included in the data, such as detail information on pregnancies, which can influence both weight and happiness and hence act as confounders. However, given the comparison with related studies, there are usually similar time-varying covariates included. Fourth, weight and height are self-reported by the respondents. One must assume that these reports are somewhat biased as weight might be underestimated and body height over-estimated due to social desirability or shame. This can affect the findings. However, as the comparison with official statistics has shown, the deviations are not large, which means that reported BMI values are in line with what one would expect from the overall German population. For causality, underestimating BMI is not critical as long as this bias is constant over time. Since FE-regressions only rely on within-person variation, a consequent underestimation of BMI does not invalidate these estimators. The robustness checks show that even a selective under-estimation (stronger underestimation in the higher BMI categories) does not lead to different conclusions. Finally, keep in mind that the age range has been restricted and the results do not cover the population of the very old. As no weights are available for the longitudinal analyses conducted, I cannot guarantee that my sample is perfectly representative of the overall German population.

## 6 Conclusion

Are individuals with a higher BMI less happy with their lives on average? Descriptive analyses indicate that this is indeed the case. However, does gaining weight decrease happiness? Quite the contrary. When examining causal effects

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[8] Destatis Health Indicators 2017; Publication 5,239,003,179,004.

rather than mere associations, I find no negative impacts; in some instances, there are even tiny positive effects. This conclusion holds true for both men and women, regardless of age group or initial BMI level. Given that a wide range of model specifications and robustness checks were conducted, these results are stable and not easily attributed to specific methodological choices. They align with comparable studies from the United States, which also fail to identify any negative causal effects. These findings may help explain the prevalence of overweight and obesity in many countries, suggesting that the psychological incentive to lose weight is potentially limited. If individuals do not suffer significantly due to their weight, they may be less inclined to invest time and effort into addressing the issue. Conversely, if they perceive improvements in well-being with increased weight, what motivation exists for change? While it is well known that high BMI values contribute to adverse health outcomes and overall lower life expectancy, subjective perceptions likely play a more substantial role in motivating changes to diet and lifestyle. I propose that follow-up studies investigate the mechanisms through which BMI influences weight and well-being, which may yield valuable insights for practical advice and interventions.

## Appendix

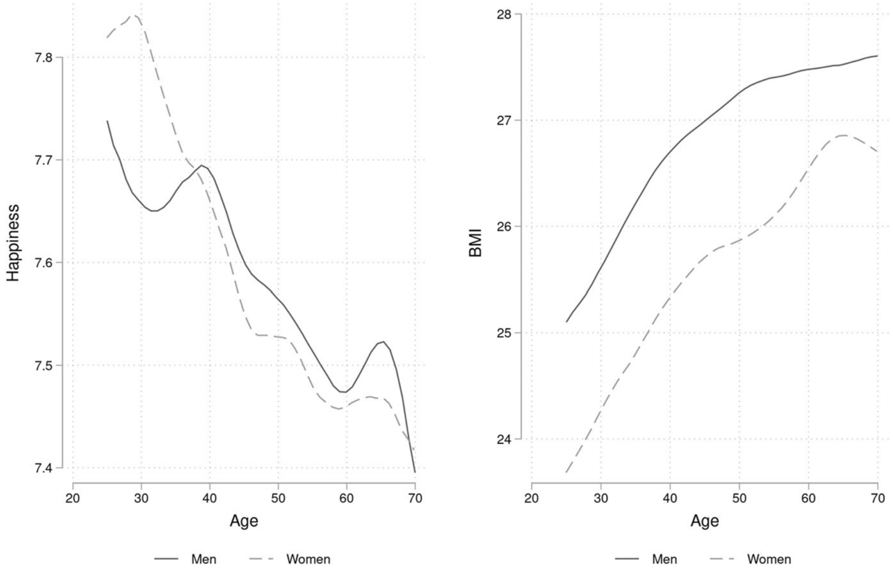

**Fig. 5** Association between happiness and age (left side) and BMI and age (right side) by gender. Source: NEPS SC6, waves 4–13, imputed data (M = 50)

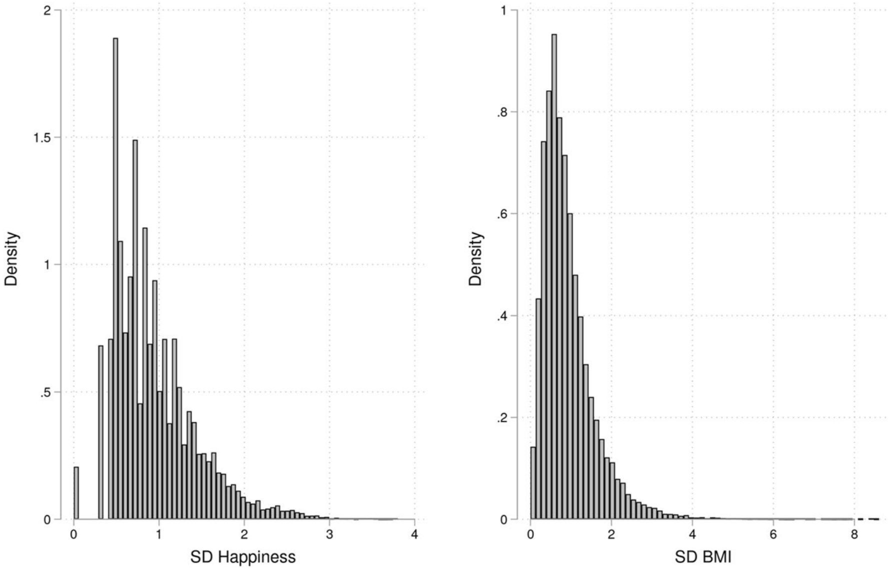

**Fig. 6** Within-person variation of happiness and BMI over all survey waves. Source: NEPS SC6, waves 4–13, imputed data (M = 50)

## Robustness Checks on FE Models

To ensure the statistical validity of the findings, I conducted a large range of robustness and sensitivity analyses. First, as age is potentially one of the most central confounders, I tested how the findings change when age is not used as a continuous control variable but by sorting respondents into age categories, measured at the age of the survey in 2011/12. These categories are 20 to 40, 40 to 50, and 50 to 60. The results are shown graphically in Fig. 7. The main finding is that the conclusions do not change; the coefficients remain positive. Especially for older women, the effects are larger and sometimes statistically significant on the 5% level.

(Fig. 7)

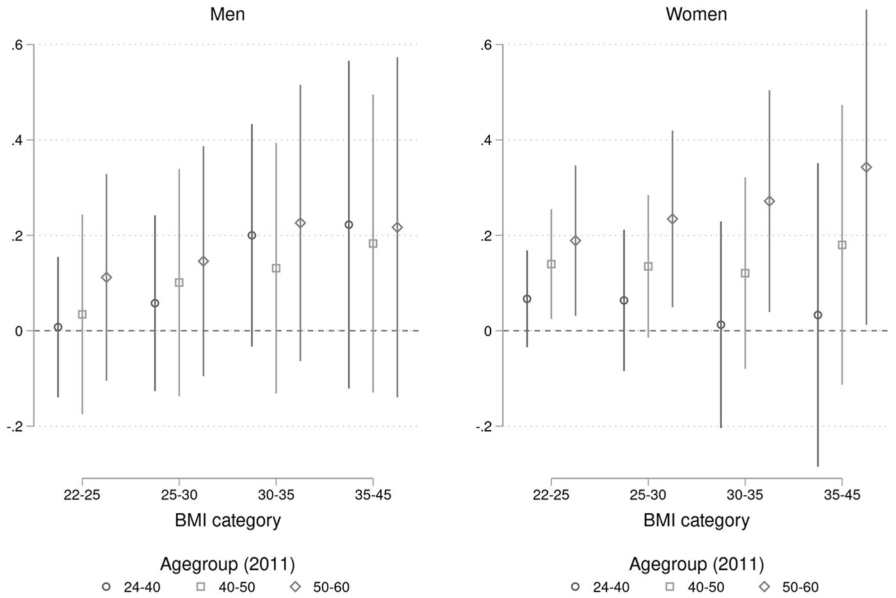

**Fig. 7** Regression coefficients of BMI group by initial age in 2011. Source: NEPS SC6, waves 4–13, imputed data (M = 50). 95% confidence intervals included, based on robust standard errors. Control variables: not working, living with partner, health status, living in East Germany. Reference category: BMI 18.5–22

Second, I have repeated the analyses not by age group but by initial BMI, measured in wave 4 in 2011/12. This checks whether not only the change in BMI matters but also the initial level. The results are shown graphically in Fig. 8. This model uses BMI as a linear term for simplicity ($BMI^2$ and $BMI^3$ not included). The main conclusion is that starting BMI only makes a small difference. For men, the most increase in happiness is seen in individuals with an average BMI (25 to 30), while it is smaller for lower or higher BMIs. However, the point estimates are always positive. For women, effects are strongest for low BMIs and decrease with higher values.

Third, what happens if BMI is selectively under-reported? While there is no reference to compare the reported values, one can test what happens if one decreases BMI as in a simulation. Starting from 2.5% for the lowest BMI group to 12.5% for the highest BMI group (in steps of 2.5% for each group), I repeated the main regression analysis when decreasing BMI by these percentages for each individual (results not shown in detail). However, the conclusions do not change at all, as the linear effects of BMI on weight are still positive.

(Fig. 8)

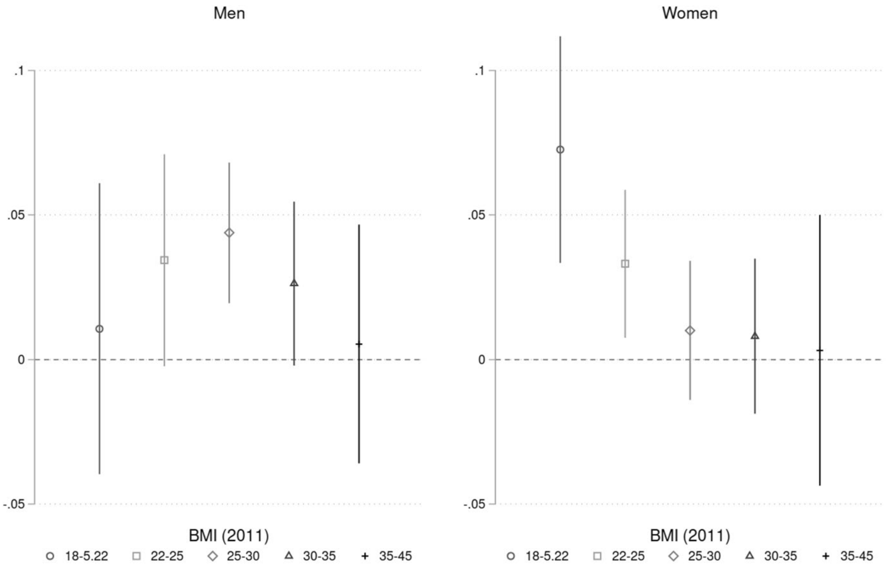

**Fig. 8** Regression coefficients of BMI (continuous / linear models) by initial BMI group in 2011. Source: NEPS SC6, waves 4–13, imputed data (M = 50). 95% confidence intervals included, based on robust standard errors. Control variables: age, age$^2$, not working, living with partner, health status, living in East Germany

As an extra model check, BMI is lagged; that is, the value of $t_{-1}$ is used as a regressor. Again, the conclusion remains stable. In addition to these regression models, even more adaptions were tested (results not shown in detail). Instead of interpolating BMI, using available waves makes no difference. Using listwise deletion instead of multiple imputation also does not change conclusions. Excluding the two last survey waves (2020 to 2022) also gives the same conclusions, even if these waves are somewhat special since they were surveyed after the onset of the global COVID-19 pandemic, which did influence overall happiness rather drastically in Germany (Bittmann, 2022). Adding logarithmized household income as a further time-variant control also does not affect the conclusions. This variable has been omitted from the main results as the share of missingness is comparatively high, increasing the variance of all results. Finally, as one can regard health as a potential mediator, resulting in overcontrol bias, I remove this variable from the regressions. However, the results are almost unchanged by doing so. Overall, the results are robust as no single model or operationalization reaches different conclusions. I summarize the robustness checks in Table 3, reporting the regression coefficient of BMI. The original result is shown for comparison (O1). The conclusions never change as all coefficients are positive and, in almost all cases, statistically significant on the 5% level.

**Table 3** Overview of various robustness tests applied (FE-regressions)

| # | Robustness test | Men | Women |
|---|---|---|---|
| O1 | Original result (no changes made) | 0.031<br>[0.015; 0.047] | 0.020<br>[0.006; 0.035] |
| R1 | Selective under-reporting of BMI simulated | 0.040<br>[0.020; 0.060] | 0.026<br>[0.008; 0.045] |
| R2 | Lagged BMI ($t_{-1}$) as regressor | 0.025<br>[0.007; 0.042] | 0.012<br>[-0.005; 0.029] |
| R3 | No linear interpolation of BMI | 0.038<br>[0.021; 0.055] | 0.023<br>[0.007; 0.038] |
| R4 | Using listwise deletion (no imputation) | 0.056<br>[0.034; 0.078] | 0.029<br>[0.011; 0.047] |
| R5 | Exclusion of waves 12 and 13 (COVID-19 affected) | 0.021<br>[0.001; 0.041] | 0.017<br>[-0.001; 0.035] |
| R6 | Adding household income as a control | 0.034<br>[0.018; 0.050] | 0.019<br>[0.005; 0.034] |
| R7 | Removing health as a control variables | 0.026<br>[0.008; 0.0431] | 0.013<br>[-0.0015; 0.028] |

*Source: NEPS SC6. 95% confidence intervals in brackets, based on robust standard errors. Reported are coefficients of BMI as a linear independent variable. Control variables: age, age$^2$, not working, living with partner, health status, living in East Germany*

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**Data Availability** Data are available after registration as a researcher from http://dx.doi.org/https://doi.org/10.5157/NEPS:SC6:14.0.0. Stata and R do-files are available from https://github.com/fbittmann/replication_iapp.

## Declarations

**Ethical Approval** The NEPS study is conducted under the supervision of the German Federal Commissioner for Data Protection and Freedom of Information (BfDI) and in coordination with the German Standing Conference of the Ministers of Education and Cultural Affairs (KMK) and – in the case of surveys at schools – the Educational Ministries of the respective Federal States. All data collection procedures, instruments and documents were checked by the data protection unit of the Leibniz Institute for Educational Trajectories (LIfBi). The necessary steps are taken to protect participants' confidentiality according to national and international regulations of data security. Participation in the NEPS study is voluntary and based on the informed consent of participants. This consent to participate in the NEPS study can be revoked at any time.

**Informed Consent** All study participants, or their legal guardian, provided informed written consent prior to study enrollment.

**Conflict of Interest** The author declares that he has no conflict of interest.

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