The Value of Normal Body Weight: Evidence from Iceland

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Abstract

Calculations of societal costs of underweight, overweight and obesity have generally failed to include the value of the utility reductions, associated with deviations from normal weight. To remedy this, the monetary compensation needed to offset the welfare loss associated with being underweight, overweight or obese is estimated. For this purpose, the compensating income variation (CIV) method is applied to individual-level data from an Icelandic health and lifestyle survey carried out in 2007, 2009, 2012, and 2017. The results show that both males and females would on average be willing to pay a positive amount to move from obesity to normal weight, albeit a varying amount by income group. The CIV for moving from obesity to normal weight among males for the low-, medium-, and high-income groups are $18,022, $25,768, and $632,002 per year. In comparison the same results for females are $9,191, $16,239, and $95,494. However, only females show a positive willingness to pay for not being overweight. The CIV for overweight females for the three income groups is $3,608, $6,375, and $37,488 per year.

Keywords: Compensating income variation, Body weight, Value, Willingness to pay, Happiness, Iceland

JEL classification: I1, I3

Introduction

The problem with calculations of societal costs of underweight, overweight and obesity is a failure to incorporate utility losses from deviations from normal weight (Cawley & Meyerhoefer, 2012; Colagiuri, Lee, Colagiuri, Magliano, Shaw, Zimmet et al., 2010; Hammond & Levine, 2010; Kim & Basu, 2016; Nagai, Kuriyama, Kakizaki, Kaori, Sone, Hazawa et al., 2012; Tsai, Williamson, & Glick, 2011). We estimate the monetary value of deviations from normal weight.

The standard way of obtaining the value of a non-market good, is by estimating willingness to pay (WTP), although within health economics, calculating the quality-adjusted life-year (QALY) is a common alternative. Both measures take into account an individual's health-related utility but only WTP is measured in monetary terms. The advantage of obtaining the monetary value of a non-market good such as BMI categories is that it allows for comparisons to desiderata that are not health related and for use in cost-benefit analyses (CBA). QALYs, however, limit subsequent efficiency calculations to cost-utility analyses (CUA) that make comparisons only within health systems.

The most commonly used methods to estimate WTP are subject to methodological drawbacks. The contingent valuation method involves asking people directly about their WTP. Subjects' answers to such hypothetical questions have been found to overestimate real WTP (Murphy, Allen, Stevens, & Weatherhead, 2005). The hedonic wage method is based on the idea that workers are willing to receive a monetary compensation to accept increased risk of fatalities in a workplace (Thaler & Rosen, 1976). Although this method might present opportunities to calculate the value for certain work-related health problems or injuries it is not suitable for the case of body weight.

A less frequently used method to estimate WTP is compensating income variation (CIV). The idea behind the CIV method is to estimate the amount of money a person would need to receive/give up in order to be just as well off with as without a utility-generating desideratum, which here is normal body weight. The CIV estimate is based on self-reported well-being measures, taken as proxies for utility. Regression techniques are then used to estimate the trade-off between weight loss and market goods. By using this method, respondents do not have to state their preferences directly as in the contingent-valuation method and as responses to questions are indirectly used to evaluate the monetary compensation, strategic responses are unlikely. This approach can be seen as theoretically sound and empirically tried and tested. It has been used to calculate the WTP for e.g.

religious practices (Brown, 2013), social capital (Groot, van den Brink, & Van Praag, 2007), fear of crime (Moore & Shepherd, 2006), and residential mobility (Weinberg, Friedman, & Mayo, 1981). In health economics this method has been used to estimate the value of cardiovascular disease in Britain and Canada (Groot & van den Brink, 2006; Latif, 2012), migraine and headache in the Netherlands (Groot & van der Brink, 2004), chronic pain in Australia and the US (McNamee & Mendolia, 2014; Ólafsdóttir, Ásgeirsdóttir, & Norton, 2020), cancer, cardiovascular disease, thyroid disease, arthritis and infectious disease in Costa Rica (Rojas, 2009), EQ5D conditions, pain and anxiety in Latin America (Graham, Higuera, & Lora, 2011), 13 and 15 health conditions in Britain (Powdthavee & van den Berg, 2011; Howley, 2017), general health status (Brown, 2015; McNamee & Mendolia, 2019), 18 and 34 health conditions in Iceland (Ásgeirsdóttir, Birgisdottir, Henrysdottir, & Olafsdottir, 2019; Ásgeirsdóttir, Birgisdottir, Ólafsdóttir, & Ólafsson, 2017). To the authors knowledge, the CIV method has been used only once to calculate the WTP for obese and overweight males and females (Kuroki, 2016). Kuroki (2016) focused on the relationship between body weight and life satisfaction, applying the CIV method to calculate the WTP for obese and overweight males and females in the US.

Iceland provides a good opportunity to study the utility losses related to deviations from normal weight because of A) richer data than has previously been used to value weight categories with the CIV method and B) it is representative of the western world with respect to bodyweight and income. For example, among the OECD countries 19.5% of adults were obese in 2015, with 19% of Icelandic adults recorded obese in that year (OECD, 2017). Iceland is furthermore a wealthy western country ranking among other western countries such as the Anglo-Saxon, Scandinavian and Western European ones. The similarities between these countries' wealth can be seen by comparing the average GDP per capita from 2008-2018 for Iceland ($43,036), the US ($50,598), Britain ($37,587), Germany ($41,818), and Denmark ($44,326) (OECD, 2019).

Studies from Germany, UK, US, and Australia have found overweight and obesity to negatively associate with subjective well-being (SWB) (Forste & Moore, 2012; Graham & Felton, 2005; Katsaiti, 2012; Kuroki, 2016; Powdthavee & Oswald, 2007; UL-haq, Mackay, Martin, Smith, Gill, Nicholl et al., 2014; Wadsworth & Pendergast, 2014). Furthermore, Forste & Moore (2012) and UL-haq, Mackay, Martin, Smith, Gill, Nicholl et al. (2014) found a negative relationship between underweight and SWB. Further evidence to support this are the results presented in Zeng & Yu (2019) which show a discontinuous reduction in SWB at the overweight and obese cutoff points, in China. Thus, the classification itself results in a SWB reduction. The reason for these negative relationships appears to be negative self-perception and social stigma (Forste & Moore, 2012; Graham & Felton, 2005; Katsaiti, 2012; Wadsworth & Pendergast, 2014).

This study adds to the literature in five ways. First, the CIV method is applied to estimate the WTP for being normal weight, compared to being underweight, overweight, or obese. Those who are underweight are included, instead of being dropped as in Kuroki (2016). Second, Kuroki (2016) only had a 4-point well-being measure, and 95% of his sample were in the highest two well-being categories. This level of crudeness in a key variable is likely to decrease estimation precision. Our results are based on a 10-point happiness scale with considerably greater variation. Third, we extend Kuroki (2016) by allowing a piecewise linear (PWL) relationship for income, in addition to using the traditionally employed log of income. This enables calculations of CIV measures for different income groups, low-income, medium-income, and high-income. By doing this the effects of outliers on the WTP estimates are reduced. Fourth, we calculate the WTP using estimation models with and without possible health mediators, to gauge the possible reasons for peoples´ WTP for obtaining normal weight. Although Kuroki (2016) reports regression results with and without health covariates, WTP is only reported from models including health covariates. However, the use of WTP estimates in cost-benefit analyses should arguably be based on the full WTP from being overweight or obese, including utility reductions from the related health consequences. In this study both the WTP estimates that do and don´t include those utility reductions are reported, which provides insight into the underlying explanations of the estimated WTP. Fifth, some light is shed on biases due to endogeneity of the income variable in the previously reported results by Kuroki (2016). A well-known endogeneity issue arises when estimating the relationship between subjective well-being and income. Even though this is not tackled directly in the current analysis, for example by instrumenting for income, what is known about the size of this bias from previous research is exploited to adjust the results.

Data and methods

Data

Data from the survey "Health and well-being of Icelanders", conducted by The Directorate of Health in Iceland in October 2007, 2009, 2012 and 2017 is used. In 2007 a stratified random sample of 9,807 Icelanders age 18 to 79 received the questionnaire and 5,963 responded. In 2009 the questionnaire was sent to the 2007 participants who had agreed to be contacted for a follow-up survey, which resulted in 4,129 responses. The 2012 wave contained 3,246 responses from the original sample and 3,537 from new participants, and the 2017 wave had 4,715 responses from previous respondents and 2,601 from new participants. After dropping observations with missing values, the final sample includes 9,936 observations on 6,245 females, and 8,990 observations on 5,394 males. The sample therefore does not have a strong panel structure.

As a utility proxy – the dependent variable in the empirical model – happiness is used, based on the following question: Taking all things together, how happy would you say you are? The response options ranged from one (extremely unhappy) and ten (extremely happy). Happiness had a mean value of 7.9, with about 10% reporting a value of five or less.

The independent variables of interest are weight categories based on BMI, and household income. Weight categories were calculated from self-reported height and weight according to the World Health Organization standards as follows: Underweight (BMI $<$ 18.5), normal weight ($18.5 \leq \text{BMI} \leq 24.9$), overweight ($25 \leq \text{BMI} \leq 29.9$) and obese (BMI $>$ 30). The average BMI for the whole sample is 27.46; 27.62 for males and 27.32 for females. Thus, the average person is overweight.

Household income was obtained from the question: In what range do you estimate your household's pre-tax income to have been within the last 12 months? Including salaries, overtime, interests and dividends, pensions, differentials, and grants/benefits. Fourteen answer options ranged from less than 900 thousand ISK (USD 7,563) to more than 18 million ISK (USD 151,261). The midpoint of a given range was used to code the responses. Income above 18 million ISK was coded as 19.75 million ISK (USD 165,966) based on the range of the preceding response options. The top-coding used should not have a significant effect on the analyses since the income distribution of the data used has previously been fitted to lognormal and gamma distributions and chi-square tests showed that there was not a statistical difference between the two fitted distributions and the data (Ólafsdóttir, Hrafnkelsson, & Ásgeirsdóttir, 2014).

The household income was CPI-adjusted to March 2019 price levels to prevent inflation from affecting the results. The exchange rate used to convert income in ISK into US dollars was USD = 119 ISK (Central Bank of Iceland, 2019). Household income was furthermore adjusted using the OECD modified equivalence scale to make the variable comparable across different household compositions, accounting for economies of scale within the household. This scale generally categorizes individuals over the age of fourteen as adults. However, in the data used here, household members are categorized as older or younger than 18. The respondent was assigned a weight of 1.0, additional adults over the age of 18 were assigned a weight of 0.5, and each child was assigned a weight of 0.3. The total household income was then divided by the sum of weights for all household members.

Other controls are age, age squared, education, marital status, degree of urbanization, year dummies, and the number of children in the household. Age squared is included as previous studies have found a non-linear relationship between age and well-being (Fritjers & Beatton, 2012). Indicators for obesity-related health conditions are included in some estimations to obtain the relationship between obesity and happiness, net of health effects.

Labor-market experiences and income vary greatly by gender (Hamermesh & Abrevaya, 2011; Knight, Song, & Gunatilaka, 2009; Kuroki, 2016). Similarly, gender differences in weight perception have been found. Females seem to worry more about being overweight or obese than males, and they are more concerned about dieting regardless of their actual weight (Ansari, Clausen, Mabhala, & Stock, 2010; Bergström, Stenlund, & Svedjehäll, 2000; Drewnowski, Riskey, & Desor, 1982; Musaiger & Al-Mannai, 2013; Unterhalter, Farrell, & Mohr, 2007). Being overweight or obese also affects women's self-esteem more than men's (Demarest & Allen, 2000; Franzoi & Shields, 1984; Lowery, Kurpius, Befort, Blanks, Sollenberger, Nicpon et al., 2005; Williamson & O'Neill, 1998). Furthermore, studies have found negative psychological effects of obesity to be more frequent among females (Fu, Lin, & Huang, 2011; Linde, Jeffrey, Finch, Simon, Ludman, Operskalski et al., 2007; Wardle, Haase, & Steptoe, 2006). In contrast, Böckerman, Johansson, Saarni, & Saarni (2014) found that being obese had more negative effects on the SWB of males than females. Thus, analyses are stratified by gender with summary statistics displayed in Table 1.

(Table 1 here)

Methods

An indirect well-being function W is specified, assuming that well-being, measured as happiness, is determined by income Y, BMI status B, and other individual characteristics X as described in equation (1):

$$W = W(Y, B, X), \tag{1}$$

where *B* contains dummy variables indicating a person's BMI category. That is, whether a person is underweight, normal weight, overweight or obese. *Y* represents real equivalized (yearly) household income. In the literature, income is generally presented as a logarithmic variable to account for decreasing marginal utility of income (Ásgeirsdóttir, Birgisdottir, Ólafsdóttir, & Ólafsson, 2017; Groot & van den Brink, 2007; Groot & van den Brink, 2004; Layard, Nickell, & Mayraz, 2008). This tradition is followed here. The empirical specification of the well-being function is then given by:

$$W = \beta_1 + \beta_1 \ln Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{it}, \tag{2}$$

CIVs by income groups are also obtained by specifying income in a PWL form, which still allows for diminishing marginal utility of income (Ólafsdóttir, Ásgeirsdóttir, & Norton, 2020). The income data for each gender was split into three equally sized percentiles where the breakpoints of the income variable for the PWL relationship was chosen as the point where the percentiles meet. The breakpoints, denoted as BP1 and BP2, were \$32,473 and \$54,082 for males and \$29,118 and \$47,420 for females. The empirical specification of the well-being function is then given as:

$$W_{it} = \begin{cases} \beta_{10} + \beta_{11}Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{1it}, if\ Y_{it} \leq \mathrm{BP1} \\ \beta_{20} + \beta_{21}Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{2i}\ , if\ \mathrm{BP1} < Y_{it} \leq \mathrm{BP2} \\ \beta_{30} + \beta_{31}Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{3it}, if\ Y_{it} > \mathrm{BP2}\ . \end{cases} \tag{3}$$

where the following conditions must hold:

$$\begin{aligned} \beta_{10} + \beta_{11}\mathrm{BP1} &= \beta_{20} + \beta_{21}\mathrm{BP1}, \\ \beta_{20} + \beta_{21}\mathrm{BP2} &= \beta_{30} + \beta_{31}\mathrm{BP2}. \end{aligned} \tag{4}$$

Inserting these conditions into the system in (3) leads the following PWL model:

$$W_{it} = \begin{cases} \beta_{10} + \beta_{11}Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{1it}, if\ (i) \\ \beta_{10} + \mathrm{BP1}(\beta_{11} - \beta_{21}) + \beta_{21}Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{2it}, if\ (ii) \\ \beta_{20} + \mathrm{BP2}(\beta_{21} - \beta_{31}) + \beta_{31}Y_{it} + B_{it}'\beta_2 + X_{it}'\beta_3 + \varepsilon_{3it}, if\ (iii)\ . \end{cases} \tag{5}$$

The parameter estimates from system (5), based on ordinary least squares, are then used to calculate the CIV. As an example, the welfare of an individual who is obese ($B = 1$) and has characteristics X to attain happiness level W is denoted as $W(Y, X, B = 1)$, and that for an individual who is considered to be of normal weight, but has otherwise identical characteristics as $W(Y, X, B = 0)$. The same applies for a person who is overweight or underweight, with B taking the value 1 if a person is categorized in one of those groups. Thus, for these two states to generate the same welfare the following must hold:

$$W(Y, X, B = 0) = W(Y + CIV, X, B = 1), \tag{6}$$

then by solving for CIV the following expression is obtained:

$$CIV = -\ \beta_2/\beta_{s1}. \tag{7}$$

CIV in equation (7) is the additional equivalized household income per year necessary to compensate an individual that is not in the normal weight group to attain the same level of happiness as an individual in the normal weight group, ceteris paribus. However, the CIV equation corresponding to equation (2) will be:

$$CIV = \bar{Y}(\exp(-\ \beta_2/\beta_1) - 1), \tag{8}$$

where $\bar{Y}$ is the average income in the sample. In this case there will be only one income parameter β_1 but not one for each income bracket β_{s1} as in equation (7). For a derivation of equation (8) see for example Ásgeirsdóttir, Birgisdottir, Ólafsdóttir, & Ólafsson (2017). The standard errors for the CIV estimates are calculated using the delta method.

For each gender two models are defined. Model 1 includes basic controls but in Model 2 four indicators for the most common obesity-related health conditions are added; osteoarthritis, diabetes, cardiovascular disease and high blood pressure (Bray, 2004; Hu, 2013). Given previous research, it is not farfetched to assume that a BMI coefficient net of weight-related health conditions is reflecting poor body image and social-stigma effects (Demarest & Allen, 2000; Franzoi & Shields, 1984; Lowery Kurpius, Befort, Blanks, Ludman, Operskalski et al., 2005; Puhl & Brownell, 2006; Wang, Brownell, & Wadden, 2004; Williamson & O'Neill, 1998). Comparing the CIV estimates from Model 1 and Model 2 indicates if the WTP is driven by health compromising conditions or factors such as social stigma.

As the data is stratified with oversampling in certain groups, sample weights are used to make the data represent the population. Furthermore, the data has a panel structure, but using fixed effects was not possible due to little within variation in the variables of interest. This is a short panel of four waves with no more than two observations for most individuals and only one observation for about a third of the individuals. It was therefore possible to use either random effects or pooled OLS. However, incorporating random effects into a panel data model with probability weights is not straight forward. Methods that allow random effects in this type of data have been reported (see for example Skinner & Holms (2003), Veiga & Brown (2008), and Vieira & Skinner (2014)), but are computationally challenging and make strict assumptions regarding the structure of the covariance matrix. The gain from using these models instead of pooled OLS is the possibility of achieving an efficient estimator, which will only happen when the assumptions of the covariance structure hold. There is no possible gain in terms of unbiasedness from using random effects instead of pooled OLS since the same assumptions are needed for the two estimators to be unbiased. Thus, since the random effects models add another level of complexity without providing much additional gain, pooled OLS estimations are used with robust standard errors.

The main methodological shortcomings in the analysis relate to endogeneity issues and will to a substantial extent be left to future research as the data does not allow this to be fully addressed. Kuroki (2016) was also unable to account for endogeneity due to similar data limitations. The endogeneity of body weight in subjective well-being regressions is not well understood and the direction of possible biases due to this are not clear. An example can be found in an earlier version of Clark & Etilé (2011), specifically Clark & Etilé (2010), where the authors attempted to apply past BMI as an instrument for BMI, a strategy that they abandoned in their final version (Clark & Etilé, 2011). Katsaiti (2012) also tried to account for the endogeneity of BMI by using height as an instrument. That instrument is however unlikely to fulfill the exclusionary restriction since height has been shown to have a significant effect on well-being (Deaton & Arora, 2009). While IVs for BMI have been difficult to find, some have used poligenic risk scores, although not without critisism. Such studies have not been conducted using happiness as an outome variable, but have been used in regressions with a related dependent variable, namely depression (Huang et al., 2014; Jokela et al., 2012; Lawlor et al., 2011; Tyrell et al., 2019; Walter et al., 2015; Willage et al., 2018). In all six studies the non-instrumented results showed a positive relationship between BMI and depression, while the BMI coefficient either increased with instrumentation or decreased. This is mentioned to show that it is difficult to assess the direction of any endogeneity bias in the BMI coefficient, if such a bias exists.

The biases of income in SWB equations are better understood. In the CIV literature, the income parameter has been consistently found to be between 2 and 3.5 times larger when the endogeneity of income is accounted for by instrumenting for income (Howley, 2017; Huang, Fritjers, Dalziel, & Clarke, 2018; Powdthavee, 2010; Knight, Song, & Gunatilaka, 2009; Luttmer, 2005; Ólafsdóttir, Ásgeirsdóttir, & Norton, 2020). We report estimates that scale the income coefficient to adjust for this documented endogeneity bias. To make this as accurate as possible the results from an article that estimates models with and without instruments but that in other aspects closely resemble the ones in this paper are used. Unfortunately, there are no articles that estimate a similar relationship using a PWL model with instruments, but there is one paper that estimates the relationship between happiness and log-income. This article is Luttmer (2005), who finds that the income parameter increases by 2.93. Since Luttmer estimates the relationship between happiness and log-income and does not use a PWL formulation of income, we only report bias-adjusted CIV estimates when using the log-of-income specification. The income coefficient in equation (8) is thus multiplied with 2.93 to obtain the adjusted CIV estimates. Substituting household income with lottery winnings or other irregular sources of income, in SWB equations, has also been used to circumvent the endogeneity issue (Ambrey & Fleming 2014; Linqvist, Östling, & Cesarini 2018). Our data does not contain windfall income. However, our results will be compared to the results from Linqvist, Östling, & Cesarini.

Results

The main results are presented in Tables 2 and 3 by gender and model specification. Table 2 contains the regression coefficients for income and weight categories from equations (2) and (5) and Table 3 contains the CIV calculations based on those coefficients. Specifically, in Table 2, Panel A, the estimation results from models where income has a logarithmic form are reported, and in Panel B results where income takes the PWL form are reported. In Table 2, results show a negative relationship between obesity and happiness for both males and females, which is consistent with Kuroki (2016). Similarly, point estimates for underweight are negative, although none of the underweight coefficients are statistically significant. The most likely explanation for the non-significant relationship is that there are only 143 observations for underweight individuals. Interestingly, being overweight seems to affect males and females happiness differently. Point estimates for being overweight are positive for males but negative for females. It is however well known that BMI is overestimated among those with high muscle mass, which are dominantly males (Alasagheirin, 2011; Burkhauser & Cawley, 2008). This misclassification might be the reason for the positive relationship between happiness and overweightness among males. It should also be noted that the overweight coefficients for males are quite small and never statistically significant.

If the results from Models 1 and Models 2 in Table 2 are compared, it is clear that there is little difference between the parameter estimates of the two specifications, indicating that the relationship between BMI and happiness is not driven by health-related issues. This conclusion is consistent with the results from Kuroki (2016).

The decreasing marginal utility of income expected based on microeconomic theory is clear in Panel B of Table 2. This result is also consistent with the roughly linear-log relationship between subjective well-being and income found by Stevenson & Wolfers (2013), using multiple data sets.

Table 3 shows CIVs calculated using the coefficients in Table 2. Panel A presents the CIVs for males, and Panel B the CIVs for females. Columns one and two present the results from Model 1 and 2 where income has logarithmic form. Columns three and four, include CIV results based on the same estimations, but adjusted for income endogeneity. Columns five to seven show the PWL estimates using Model 1, and columns eight to ten show the PWL estimates using Model 2. Since the difference between point estimates in Models 1 and 2 is quite small, the following discussion will focus on results based on Model 1.

For males (Panel A), only the CIV estimates for obesity are statistically significant, as is consistent with the significance of the coefficients for income and obesity in Table 2. The CIV results for obesity presented by income group are \$18,022, \$25,768, and \$632,002. In comparison, the CIV estimate given in column one is \$86,592. This comparison highlights how the high-income group greatly inflates the WTP for the male sample. The majority of males have willingness to pay below \$26,000 but the estimated average CIV for the whole male sample is around \$86,600.

For women (Panel B), only the CIV estimates for overweightness and obesity are statistically significant. The CIV results for obesity by income group are \$9,191, \$16,239, and $95,494. In comparison, the CIV estimate presented in column one is $36,603. The diminishing returns to income in the utility function is less apparent in the female sample, although still obvious. The CIV estimates for overweightness by income group are $3,608, $6,375, and $37,488, whereas the CIV estimate for the female sample as a whole given in column one is $11,815. Thus, female WTP is much lower for overweightness than obesity, across all income levels.

The bias-adjusted CIVs shown in column three and four for all weight categories are significantly lower than the unadjusted CIVs. By looking at the results from Model 1 it can be seen that the CIV for obese males decreases from $86,592 to $20,192 and for obese females from $36,603 to $10,047. Furthermore, the CIV for overweight females decreases from $11,815 to $3,713. These results clearly demonstrate the importance of accounting for the endogeneity of income.

Discussion

We estimate the WTP for transitioning from underweight, overweight and obese weight categories to normal weight using data from Iceland, by gender and income. Results show a strong negative relationship between happiness and obesity. This is in accordance with previous research on the relationship between SWB and body weight (Graham & Felton, 2005; Katsaiti, 2012; Kuroki, 2016; Powdthavee & Oswald, 2007). There is however one exception to this as Böckerman, Johansson, Saarni, & Saarni (2014) found, that when controlling for health conditions and functional capacity, the negative association between obesity and satisfaction with life mostly disappeared. The main difference between Böckerman, Johansson, Saarni, & Saarni (2014) and the aformentioned articles is their inclusion of functional capacity in addition to obesity related deseases. The data used here only contain one variable on functional capacity, which is only available for the first three waves and is therefore not include it in the main results. However, including functional capacity in the estimations had little effect on the results and the strong negative relationship between happiness and obesity remained.

The point estimates from the PWL regressions show significant heterogeneity of WTP between income groups. If compared to the CIV estimates using log of income, it can be seen that the high-income groups´ WTP is driving up the CIV estimates and producing a result that is higher than the results for the low- and medium-income groups´. Thus, policy makers relying only on results aggregated across all income groups might incorrectly assume that the WTP for majority of society is much higher than it is, due to high-income individuals. Considering overweightness, only females show a positive WTP, possibly due to greater misclassification in male BMI (Alasagheirin, 2011; Burkhauser, & Cawley, 2008).

All estimates from Kuroki (2016) leave income endogeneity untreated. Our CIV results that are adjusted for income endogeneity, based on the results from Luttmer (2005), differ significantly from the unadjusted estimates. For example, the CIV for obese males decreases from $86,592 to $20,192 and for obese females the CIV decreases from $36,603 to $10,047. However, if we standardize the income coefficients from our OLS estimates to make them comparable to the results from Linqvist, Östling, & Cesarini (2018) the difference is considerably smaller when detected at all. Our coefficient for males is the same as theirs and our coefficient for females is only 1.64 times larger. Thus, if we believe that the model estimated by Lindqvist, Östling, & Cesarini (2018) is correct, then the severity of the income endogeneity bias, in our case, is negligible and we should be less wary about drawing conclusions from our PWL estimates.

In comparison to contingent valuation estimates of obesity treatments and weight-loss programs, our most conservative estimates are still quite high. Narbo & Sjöström (2000) find WTP for obesity treatment to be $3,280, and Fu, et al. (2011) estimate the WTP for a three-month weight-loss program, that can reduce weight by 5kg, to be $362. If we assume that the program could be repeated multiple times with the same results, the WTP, for example, for a 50kg weight loss would be $3,620, which is still much lower than the adjusted WTP estimates, presented in this study. Possible reasons for this difference are the uncertainty in weight-loss due to programs or treatments, as well as the multiple utility-reducing behavioral sacrifices such programs entail.

Similar to Kuroki (2016), results did not change when controlling for obesity related diseases. This could indicate that the results are predominantly due to subjective factors, such as stigma and body image. Graham & Felton (2005) found that in the US, BMI-related well-being reductions were greater for people whose social cohorts were less accepting of obesity. In contrast, they found the correlation between obesity and happiness to be positive in Russia, possibly due to the prosperity associated with high BMI in Russia. This highlights the role of norms in the relationship between obesity and happiness. Wardle, Haase, & Steptoe (2006) similarly found differences in perceived body image among females across countries, with Asian women having the highest perceptions of overweight and Mediterranean women the lowest.

The main policy implications of the results are the following. First, there is significant cost associated with obesity for both males and females. The same holds true for female overweightness. Since the CIV method is used and not QALY's, the results allow for CBA calculations, not just CUA. When evaluating optimal allocation of resources, policy makers can thus compare costs associated with body weight to that of goods and services in general and not just to health. Presenting those utility losses in monetary terms also reveals their size compared to other overweight and obesity-related costs. For example, it is possible to calculate the aggregate costs for the adult Icelandic population (ages 18-79) associated with individual utility reductions from being obese, given the obesity prevelence in the data in 2017 (male prevelence was 26.6% and female prevelence was 28.9%). The resulting aggregate costs, using this studies most conservative estimates, are around $322 million for females and $614 million for males, or a total of $936 million. This is just above 4% of Iceland's 2017 GDP (Statistics Iceland, n.d.-a; Statistics Iceland, n.d.-b). In comparison, Fry & Finley (2005) found obesity expenditures, net of welfare losses, to be 0.28% of GDP in France, 0.33% in the UK and, 0.42% in Austria. Dobbs et al. (2014) estimated the global economic impact of obesity to be 2.8% of global GDP. Comparison of direct costs of obesity and the utility reductions to the individuals themselves thus shows that the latter are relatively large and decisions on their exclusion or inclusion in economic evaluations is thus likely to affect results substantially. Second, significant heterogeneity in WTP accross income groups raises some difficult policy questions. For example, it would be difficult to argue that a benevolent dictator should prioritize services to the high income group since that would create the greatest net benefit. If one rejects that idea and opts for the use of the estimate that is generated using all income groups together, it is also evident from the results that this WTP is driven largely by WTP by the the highest income group and is higher than the WTP for both the low and medium income groups. Thus, interventions that are estimated as cost-benefical based on this WTP for all income groups together could be welfare decreasing for the majority of the population – that is for both the low and middle income groups who would prefer other consumption over this intervention. Those are only hypothetical examples, but the economic, ethical and political implications of these heterogeneous results across income groups need to be considered in future academic work and practical applications.

There are two main limitations to this study that are left for future research. Firstly, endogeneity is only tackled indirectly. The endogeneity of income influcences results greatly and thus future results would do well to try to tackle this more directly. Although the endogeneity of body weight may not be as consequential, future researchers should be mindful of possibilities to obtain estimates of the causal relationship between body weight and happiness. Secondly, despite having panel data, using fixed effects to account for individual heterogeneity was not feasible due to limited within variation in body weight. This may be important as subjective utility proxies may be used very differently accross individuals. Despite those limitations, it should be clear that the utility loss from overweightedness and obesity is not trivial and overlooking this cost can cause substantially biased estimations of the societal cost stemming from deviations from optimal body weight.

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Tables

Table 1: *Summary statistics for the pooled sample*

	Males		Females	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Happiness	7.95	1.75	7.96	1.71
Equivalized income (USD)	47,540	31,845	42,707	26,921
Underweight %	0.34	5.80	0.89	9.38
Normal weight %	26.49	44.13	37.04	48.29
Overweight %	49.86	50.00	35.98	48.00
Obese %	23.31	42.28	26.09	43.91
Osteoarthritis %	12.30	32.85	24.08	42.76
Diabetes %	6.02	23.79	3.81	19.15
Cardiovascular diseases %	3.07	17.26	1.77	13.20
High blood pressure %	22.42	41.71	23.05	42.12
Number of Children	2.55	1.57	2.52	1.49
Age	56.42	16.47	53.82	17.00
Junior high school or less %	29.61	45.66	43.28	49.55
Vocational education %	20.93	40.68	2.55	15.77
High school %	25.46	43.57	24.93	43.26
Bachelor or technical degree %	14.54	35.25	20.92	40.678
Master or doctoral degree %	9.45	29.26	8.31	27.61
>5000 inhabitants %	63.13	48.25	65.76	47.45
<5000 inhabitants %	19.68	39.76	18.40	38.75
<1000 inhabitants %	7.56	26.43	7.15	25.78
<200 inhabitants %	9.63	29.50	8.68	28.15
Year 2007 %	25.12	43.37	24.53	43.03
Year 2009 %	17.56	38.05	17.40	37.91
Year 2012 %	29.04	45.40	29.11	45.43
Year 2017 %	28.28	45.04	28.97	45.36

Notes: The equivalized household income variable is CPI-adjusted to March 2019 price levels.

Table 2: *Point estimates of interest from happiness equations*

Panel A: OLS	Males		Females	
Independent variables	Model 1	Model 2	Model 1	Model 2
Log income	0.2886***	0.2782***	0.4610***	0.4534***
	(0.0518)	(0.0515)	(0.0420)	(0.0418)
Underweight	-0.1563	-0.1265	-0.3888	-0.3696
	(0.5302)	(0.5296)	(0.2966)	(0.2920)
Overweight	0.0434	0.0455	-0.1126**	-0.1061**
	(0.0620)	(0.0620)	(0.0490)	(0.0491)
Obese	-0.2994***	-0.2741***	-0.2854***	-0.2649***
	(0.0844)	(0.0862)	(0.0633)	(0.0644)
Observations	8,990	8,990	9,936	9,936
R-squared	0.0583	0.0641	0.0534	0.0574
Panel B: PWL	Males		Females	
Independent variables	Model 1	Model 2	Model 1	Model 2
Low income	0.0166***	0.0163***	0.0311***	0.0311***
	(0.0058)	(0.0058)	(0.0054)	(0.0054)
Medium income	0.0116***	0.0113***	0.0176***	0.0168***
	(0.0037)	(0.0037)	(0.0036)	(0.0035)
High income	0.0005	0.0004	0.0030***	0.0029***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Underweight	-0.1553	-0.1247	-0.3898	-0.3709
	(0.5381)	(0.5374)	(0.2937)	(0.2894)
Overweight	0.0400	0.0424	-0.1121**	-0.1057**
	(0.0620)	(0.0619)	(0.0490)	(0.0491)
Obese	-0.2993***	-0.2733***	-0.2857***	-0.2658***
	(0.0843)	(0.0861)	(0.0633)	(0.0645)
Observations	8,990	8,990	9,936	9,936
R-squared	0.0601	0.0659	0.0569	0.0609

Notes: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors are in parenthesis. The benchmark for BMI groups is normal weight. Control variables are age, age squared, education, number of children, level of urbanization and year dummies. Model 2 furthermore includes an indicator for osteoarthritis, diabetes, cardiovascular disease and high blood pressure.

Table 3: *CIV estimates*

Panel A	OLS		Adjusted OLS		PWL					
Males	Model 1	Model 2	Model 1	Model 2	Model 1			Model 2		
					Low income	Medium income	High income	Low income	Medium income	High income
Underweight	34,168	27,369	9,652	7,981	9,354	13,375	328,039	7,652	11,072	355,176
	(150,853)	(143,145)	(36,035)	(36,208)	(32,735)	(46,592)	(1,384,950)	(33,216)	(47,900)	(1,913,498)
Overweight	6,633	7,178	-2,377	-2,583	2,411	3,448	84,558	2,604	3,768	120,861
	(8,820)	(9,028)	(3,323)	(3,432)	(3,807)	(5,506)	(231,434)	(3,883)	(5,701)	(412,649)
Obese	86,592*	79,789	20,192**	19,000**	18,022 **	25,768**	632,003	16,771**	24,267**	778,417
	(49,416)	(48,601)	(8,516)	(8,668)	(8,057)	(11,368)	(1,543,669)	(7,939)	(11,418)	(2,543,982)
Panel B	**OLS**		**Adjusted OLS**		**PWL**					
Females	Model 1	Model 2	Model 1	Model 2	Model 1			Model 2		
					Low income	Medium income	High income	Low income	Medium income	High income
Underweight	56,548	53,794	14,244	13,700	12,541	22,160	130,310	11,924	22,074	128,477
	(64,404)	(62,717)	(12,612)	(12,512)	(9,603)	(17,442)	(109,530)	(9,459)	(17,985)	(111,934)
Overweight	11,815**	11,264*	3,713**	3,552**	3,608**	6,375**	37,488*	3,399**	6,292*	36,623*
	(5,968)	(6,005)	(1,734)	(1,757)	(1,674)	(3,137)	(21,307)	(1,662)	(3,274)	(21,911)
Obese	36,603***	33,901***	10,047***	9,426***	9,191***	16,239***	95,494**	8,546***	15,820***	92,073**
	(11,932)	(11,770)	(2,709)	(2,734)	(2,560)	(5,043)	(39,613)	(2,514)	(5,221)	(40,261)

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors calculated with the delta method are in parenthesis. The benchmark for BMI groups is normal weight. Control variables are age, age squared, education, number of children, level of urbanization and year dummies. Model 2 furthermore includes an indicator for osteoarthritis, diabetes, cardiovascular disease and high blood pressure.