HEALTHCARE USE BY ADULTS WITH OBESITY AND OVERWEIGHT: EVIDENCE FROM THE CATALAN HEALTH SURVEY, 2013-2022

Oscar Navarro-Campàs

Nil Criach-García

Natàlia Pascual-Argenté

Jaume Puig-Junoy

Curso 2024 - 2025

Working Paper Series No. 17

Estudio empírico

Healthcare use by adults with obesity and overweight: evidence from the Catalan Health Survey, 2013-2022.

Informe final

upf. BARCELONA SCHOOL OF MANAGEMENT

Actividad de investigación realizada en el marco la Cátedra NovoNordisk - UPF Barcelona School of Management, sobre Farmacoeconomía y Salud. Financiación no condicionada.

En este documento encontrará una versión del borrador final del estudio. Por favor, no comparta este documento con terceros, ya que se trata de una versión preliminar a la publicación en una revista científica.

Final Report 17/12/2024

Healthcare use by adults with obesity and overweight: evidence from the Catalan Health Survey, 2013-2022.

Oscar Navarro Campàs ID , Nil Criach-García ID, Natàlia Pascual-Argenté ID, Jaume Puig-Junoy ID,

INTRODUCTION

Obesity and overweight (OAO) have emerged as a major public health challenge globally, with their prevalence rising dramatically over the past few decades. According to the Global Burden of Disease study 2021, the obesity epidemic is already shaping future health trends around the world (Murray, 2024). Diabetes led the largest increase (25,9%) in global age-standardised years of healthy life lost due to disability (YLD) rates between 2010 and 2021 globally, being type 2 diabetes and obesity its main drivers (Ferrari et al, 2024). High BMI and obesity also stand out among the risk factors that require immediate actions to reduce their health burden around the world (GBD 2021 Risk Factors Collaborators, 2024).

It is well established in epidemiological literature that a body-mass index (BMI, the weight in kilograms divided by the square of the height in meters) is a risk factor for a multitude of chronic conditions, mainly, diabetes, cardiovascular disease, chronic kidney disease and many cancers, among others (Singh et al, 2013; Wormser et al, 2011; CDC, 2024). Because of the impact of high BMI on other chronic conditions, obesity and overweight relate to higher healthcare utilisation and economic impact driven by more hospitalisations, medical visits, diagnostic tests and medications than in non-obese population.

Generally, BMI is analysed as a categorical variable (with classes following WHO criteria) rather than as a continuous variable. In few cases, other measures such as waist-to-height ratio or body adiposity percentage are used, as a better measure for overweight but unfortunately it is not commonly registered (König et al. 2015). Age, gender and comorbidities are commonly included in the existing models in the literature. Comorbidities associated to obesity such as diabetes, cardiovascular diseases and chronic kidney diseases, among others, are incorporated in different ways, either using indices or dichotomous variables for more general or specific diseases. Socio-demographic variables such as education, ethnicity, employment situation and place of residence are commonly used as control variables (Cawley, 2021; Suehs, 2017; Kamble, 2018).

In recent years literature has increasingly focused on the association between OAO and healthcare use. Studies for the US, Europe and Australia show that a higher BMI correlates with higher health care utilisation on physician visits, prescriptions, hospitalisations and emergency room visits (König et al, 2015; Espallardo et al, 2017; Nortfolt et al, 2018; Le Roux et al, 2018; Ishida et al, 2023; Alén de Hoyos et al 2023). The odds of being a high utilizer were found to be 1.1 for overweight and between 1.2 to 1.4 for obese patients times that of patients without OAO (Feral-Piersens et al, 2021; Ishida et al, 2023; Pressman et al, 2023; Alén de Hoyos et al 2023). Studies indicate that obesity-related healthcare costs draw a J-shape with BMI and account for a significant portion of national health expenditures, restraining public health budgets and highlighting the need for effective obesity prevention and management strategies (Ward et al, 2021).

This article aims to explore the multifaceted impact of obesity and overweight on healthcare utilisation and the trends in the adult population in Catalonia during the period 2013-2022. By examining the relationship between OAO and healthcare service use, we seek to describe patterns in health care utilisation of primary care visits, specialist, medication consumption, emergency room visits and hospitalisations, among patients with and without OAO.

METHODS

Survey data from health questionnaires to the general population from Catalonia (cohorts 2013-2022) was used. The Catalan Health Survey (Department of Health, 2023) is carried out through personal interviews to individuals legally residing in Catalonia. They are randomly selected to participate in this survey all year long, focusing on health status, health related behaviours and health services use. The interview is conducted in person at the interviewee residence, so the unit of analysis is the individual at a point in time. Interviewees are different at each wave (two waves per year), selected through a stratified three-stage sampling strategy. The first stage consists of a deterministic definition of strata and the municipalities included in each stratum. The second stage randomly selects which of the municipalities are selected, with proportional probabilities based on the weight of the municipality in each stratum.

The third and last stage consists of selecting the individuals in each of the included municipalities stratified into age and gender groups.

Of the 46,598 individuals initially included in the database, the following exclusions are applied: i) individuals aged 17 or younger, due to the limitations of BMI measures in children and adolescents (Vanderwall et al, 2017); ii) individuals aged 75 or older, following the criterion of the BMI measure by the Catalan Health Survey; iii) missing data for weight, for which BMI could not be calculated; iv) missing data for height, for which BMI could not be calculated; v) pregnant women, for whom gaining weight and thus higher BMI is expected; vi) missing data for the socioeconomic covariates included in the models, to reach a constant sample for all of them.; vii) extreme BMI values (over 70). Therefore, the final sample consisted of 26,404 individuals, corresponding to 56.66% of the original sample, shown in Figure 1.

BMI was calculated using self-reported weight (kg) and height (cm) data to use it as a continuous variable. A categorical BMI was also used following the cut-off points for adults proposed by the WHO (underweight: BMI < 18.5 kg/m2; normal weight: between 18.5 kg/m2 and 24.99 kg/m2; overweight: between 25.0 kg/m2 and 29.99 kg/m2; obesity: ≥30.0 kg/m2).

Analysed outcomes of use of health resources included binary variables (yes/no) for primary care visits (last year), specialist visits (last year) and medication use (last 15 days) and continuous variables for emergency room visits and hospitalisations (last year). Information on private/public use was not retrieved in the survey.

Specification for binary dependent variables: logit model

Logistic regression analyses were used for binary variables (primary care visits, specialist visits and medication) to estimate the odds ratios of healthcare utilisation for BMI (continuous and categorial variables). We model health services use for individual i as follows:

$$\log\big(P/(1-P)\big) = c_0 + c_1 B_1 + \gamma X_i + \varepsilon_i \quad (1)$$

where P is the probability of either primary care visits, specialist visits, or medication use; B is a measure of BMI (continuous or categorical variable); and X is a vector of individual characteristics. ε is an error term, and c and γ are coefficients to be estimated. Our primary models are logit models for each of the outcomes. After estimating the model, the exponentiated coefficients (variation in the odds ratio) are reported in the table corresponding to each binary dependent variable. Lastly, the expected probability along the range of body mass index of the sample is represented on the plots. This plot was constructed based on conditional margins in intervals of 10 units of BMI, as the marginal effects may vary. As the BMI has been centred, the intervals are the difference compared to the average BMI in the sample.

Specification for continuous dependent variables: two-part model

Due to the high prevalence of zeroes on the two continuous variables, two-part models were used. This method allows to model separately the consumption decision (e.g., at least one emergency visit/hospitalisation) and the amount decision, once the individual has reported at least one event. In the first part of the model (selection model), the probability of visiting emergency visits or being hospitalised at least one time was estimated using a logit model, as in Equation (1). In the second part of the model (outcome model), the estimated utilisation (number of times) was estimated by implementing a Generalized Linear Model (GLM) with the same covariates than in the first part. A negative binomial with a logit link function was used. Obtained coefficients were reported in the corresponding table. As in the binary variables, the different specifications were plotted in order to capture the differences along the BMI range, following the same intervals of the centred variable. Average number of emergency visits at each interval were used, combining both the effect on the probability of having visited emergencies and the effect on the total number of visits.

For all specifications models were constructed sequentially, starting with BMI and adjusting for demographic and clinical variables, adding BMI squared, followed by obesity-related comorbidities and building to a final model that included interactions (BMI-private insurance and BMI-year). We included the following covariates in each regression: age, age squared, gender, private insurance (binary), education (three categories), employment (three categories), smoking status (three categories), alcohol consumption (three categories, living alone (binary), health region (nine categories), survey year (ten categories) and survey wave (20 categories). BMI was the main variable of interest, and we used BMI and BMI squared. Centred mean and used to allow for non-linear relationships with healthcare use (Cohen et al, 2002; Ward et al 2021). Statistical analysis was carried out on Stata 18.5.

RESULTS

Sample characteristics are detailed in Table 1. The table is organized in three sections: first, healthcare use variables, as dependent variables; second, basic information and socioeconomic control variables; third, comorbidities related to obesity and overweight (hypertension, diabetes and heart attack).

While 91.5% of the sample declared at least one medical visit in the last 12 months, the percentage decreases 63.3% for specialist visits. Medication use in the last 15 days is more than 50% (54.8%). Emergency room visits and hospital admissions show an average lower than 1 in the last 12 months (0.541 and 0.105 respectively). Average BMI was 26.9, with 2.2% underweight, 47.4% normal weight, 35.0% overweight and 15.4% obesity. The sample was gender balanced, with mean age 45.9 years. Survey years were evenly distributed, except for 2020 when we have less interviews due to the COVID pandemic. Half of the sample (50.6%) has secondary education, 61.4% are employed, 28.6% have private insurance and 8.9% live alone. Regarding risky behaviours, 70.4% drinks alcohol (low risk represent 64.5 and 4,9% are high-risk alcohol consumers) and 53% are smokers or former smokers. Obesity-related comorbidities included show significant increasing prevalence as BMI increases.

Overall, the sample is divided into two groups: 49.6% of the sample has normal weight or underweight and 50.4% has overweight or obesity. Distribution of BMI in the study sample is shown in Figure 2. Figure 3 shows the distribution of BMI categories by year. Proportions of categories, with slight changes over time in OAO, are constant over time, with 35% of overweight and 15% of obesity prevalence.

Tables 2, 3 and 4 present the results for the logistic regression models used to analyse the relationship between OAO and binary variables of healthcare use (primary care visits, specialist visits and medication). The results are presented in different specifications where control variables, comorbidities and squared BMI are added in stages. For each model both the R-squared and the percentage of individuals that report a visit/medication use during last year are reported.

Table 2 reports the results for the primary care visits. BMI has a positive effect on visiting the GP during last year. In model (2), the odds of visiting the GP increases by 1.6% for each unit of BMI above the average of the sample. However, when incorporating BMI-related comorbidities this effect ceases to be significant, as these variables capture most of the effect. Older individuals also have higher odds of utilisation. Males have lower odds than women of visiting GP. As expected, both private insurance and suffering from BMI-related comorbidities are positively related to visiting GP.

Table 3 presents the results for SP visits. Linear BMI seems to be significant only in model (1). However, results from models (2), (3) and (4) suggest that the relationship between BMI and visiting the SP follows an exponential shape. As expected, older individuals have higher odds of utilisation. Male individuals report lower levels of utilisation on every model. Being male implies a reduction in 61.11% of the odds of visiting the specialist during the last year compared to women. As before, both private insurance and BMI-related comorbidities are also related to higher levels of utilisation.

Table 4 presents the results for consumption of pharmaceuticals. The results are quite similar than in GP and specialist. However, they present some notable differences. First, the relationship between BMI and pharmaceutical consumption is linear in all the specifications. Second, both age and age-squared coefficients are positive, indicating that the effect of age on pharmaceutical consumption is always positive, although marginally increasing by age. Private insurance is only significant in models (3) and (4). As before, BMI-related comorbidities also have a positive effect.

The relationship between BMI and the probability of the outcome can be observed in Figures 4, 5 and 6. These figures plot the predicted probability of reporting utilisation by BMI difference with respect to the average. Figure 4 presents a slight upward trend of the BMI effect in primary care visits in models (1) and (2) but is not significant in models (3) and (4). Figure 5 also presents an upward trend in specialized care, that follows an exponential pattern in models (2), (3) and (4). For instance, in model (2), a 10-point BMI increase with respect to the mean is associated with 2.55 percentual points (p.p.) higher probability of reporting a visit to specialised care (average 25.69 with respect to 35.69 BMI). Given the non-linear specification, the subsequent 10-point BMI increase induces a 5.97p.p. increase in the probability of receiving specialized care (35.69 with respect to 45.69 BMI).

Figure 6 follows the same interpretation, despite the introduction of comorbidities and interactions partially mitigates the effect of BMI in models (3) and (4), respectively. However, even when including comorbidities and interactions, the magnitude remains quite high. In model (2), a 10-point BMI increase with respect to the mean is associated with an increase in the probability of pharmaceutical consumption of 10.64p.p. (average 25.69 with respect to 35.69 BMI). This increase is reduced to the half in models (3) and (4), where comorbidities and interactions are included.

Tables 5, 6 and 7 replicate the analysis of primary care, specialized care and pharmaceuticals, but using BMI as a categorical variable. Normal weight is used as a reference category. In table 5, the only significant category is obesity in model (1). Being obese represents an increase of 17.5% in the odds of visiting primary care compared to normal weight. The rest of the variables present similar results to those of the continuous variable. In the case of specialist care, in Table 6, the results are quite similar, despite overweight individuals seem to have lower probabilities of visiting specialist than normal weight ones. Regarding the consumption of pharmaceuticals, both overweight and obesity categories present higher odds of drug consumption than normal weight. For instance, overweight individuals have 27.7% more odds than normal weight individuals in model (3). The increase is more pronounced for obese individuals, that face 79.5% more odds of consuming pharmaceuticals.

Table 8 presents the results for emergency visits, the first continuous variable. The first section of the table corresponds to the selection model, whereas the following section corresponds to the outcome model. Regarding the former, BMI is significant in all specifications and we can observe a non-linear association, taking a U-shaped association. Introducing obesity-related comorbidities reduces the size of the effect, despite remains significant. Gender effect also follows previous estimations. Contrarily to previous models, age presents a significative negative relationship with emergency visits. In the outcome model, most of the results remain. However, BMI ceases to be significant after incorporating the comorbidities.

The emergency visits along the BMI range is represented in Figure 7. This figure shows the upward trend of the relationship between BMI and emergency visits. Due to the prevalence of individuals reporting 0 emergency visits, some of the expected emergency visits are below 0. As BMI gets higher, the confidence intervals grow wider, especially in the specifications with quadratic BMI, due to the low number of individuals.

Table 9 presents the results for hospitalisations, the other continuous variable. As before, the first section of the table models the probability of having been hospitalised or not. The second section models the number of hospitalisations of those individuals that have reported at least one event. Regarding the selection model, BMI is significant in the first three specifications, despite the squared coefficient is not. Contrarily to the selection model, the effect of BMI in the outcome model follows an exponential relationship. As before, private insurance has a positive effect on utilisation, whereas males present a negative one.

Hospitalisation trend by BMI is represented in Figure 8. There is an upward trend, but the confidence intervals are notably wide, mostly due to the skewness of the distribution of observations to the right.

DISCUSSION

Our main findings are that OAO in adults increase the probability of health care use for primary care visits, specialist, medication use, emergency room visits and hospitalisation. However, the results differ by type of utilisation and specification. For instance, the positive effect of BMI on primary care visits ceases to be significant when obesity-related comorbidities are incorporated. This is not the case of specialist visits, consumption of pharmaceuticals, emergency visits, and hospitalisations, even though introducing obesity-related comorbidities mitigates significantly the magnitude of the effect. If those comorbidities are a direct consequence of obesity and mediate the health care use, controlling for them will not consistently estimate the relationship between BMI and utilisation. More topics on identification are later addressed in the discussion.

An increasing marginal effect of BMI on health care use is also found. Most specifications with quadratic relationships report exponential patterns. These findings are in line with previous works focusing on the association of OAO and health services use, a mix of significant and insignificant positive associations (Ward et al, 2021). This relationship is clearer on the continuous outcome variables (emergency visits and hospitalisations), as they might provide a more nuanced distinction of utilisation rates than binary variables.

Regarding data of analysis, we used BMI computed from height and weight values reported by the interviewees. Self-reported values increase the likelihood of measurement error, but as interviews were conducted face-to-face, we expect some correction of this bias by the interviewer (Béland et al, 2007). Even though our study could not distinguish between private or public healthcare utilisation, we could explore the impact of having private insurance.

OAO as measured by BMI, are likely to be related to unobservable variables that have an impact on health and health care resource utilisation: physical activity, time discount preferences (Dodd, 2014). A first methodological challenge is to deal with unobserved characteristics. Even after considering a high number of covariates in the models, omitted variables may be relevant though unknown. Some authors have used the BMI of relatives (children) as an instrument in case of analysing the effect on the parents and vice versa (Meyer, 2016; Biener et al, 2020; Cawley et al, 2021). The underlying assumption is that the BMI of siblings is not related to the unobservable variables of their parents and vice versa. In our models, endogeneity issues have not been completely solved. A second challenge is to deal with reverse causality. To avoid this bias would require using instrumental variables as a gold standard (Kinge & Morris 2018), which was not possible in our study.

This study adds to the existing literature by estimating sequential models using both continuous and class BMI and obesity-related comorbitidities and private insurance. We found that obesity-related comorbitidities and private insurance variables capture most of the effect of OAO on health care use. First, private insurance captures higher health care use that could be consequence of a combination of two factors: i) easier accessibility to health services for patients in need, that otherwise would face waiting times on the public sector; and/or ii) induced demand, as patients face no/little costs once private insurance is already paid. Second, including obesity-related comorbidities seems to absorb part of the effect of OAO on health care use. If these comorbidities are a consequence of OAO, then our models may underestimate its impact on health care use with respect to individuals with normal weight. Therefore, further research is needed to disentangle the relationship between OAO, obesity-related comorbidities and private insurance on health care use.

REFERENCES

Alén de Hoyos MJ, Romero-Collazos JF, Martín-Almena FJ, López-Ejeda N. Impact of obesity on the use of healthcare resources by young adults aged 18-45 years: Results of the 2017 National Health Survey. Endocrinol Diabetes Nutr (Engl Ed). 2023 Jun;70 Suppl 2:45-54. doi: 10.1016/j.endien.2023.05.011. PMID: 37268357.

Béland Y, St-Pierre M. Mode effects in the Canadian community health survey: A comparison of CATI and CAPI. In: Advances in Telephone Survey Methodology. New York: John Wiley & Sons, Inc; 2007:297-314.

Biener AI, Cawley J, Meyerhoefer C. The medical care costs of obesity and severe obesity in youth: An instrumental variables approach. Health Econ. 2020 May;29(5):624-639. doi: 10.1002/hec.4007. Epub 2020 Feb 23. PMID: 32090412.

Cawley J, Biener A, Meyerhoefer C, et al. Direct medical costs of obesity in the United States and the most populous states. J Manag Care Spec Pharm. 2021;27(3):354-366. doi:10.18553/jmcp.2021.20410

CDC, Obesity and Cancer Available at https://www.cdc.gov/cancer/es/risk-factors/obesity.html, Dec 2023.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2002). Applied multiple regression/ correlation analysis for the behavioral sciences (3rd ed.). Hillsdale, NJ: Lawrence Erlbaum

Department of Health, Health Survey of Catalonia (ESCA). Last updated June 2023. Accessed 10/10/2024. Available at: https://salutweb.gencat.cat/ca/departament/estadistiques-sanitaries/enquestes/esca/

Dodd MC. Intertemporal discounting as a risk factor for high BMI: evidence from Australia, 2008. Econ Hum Biol. 2014 Jan;12:83-97. doi: 10.1016/j.ehb.2013.05.005. Epub 2013 May 29. PMID: 23787352.

Espallardo, O. et al. The impact of severe obesity on healthcare resource utilisation in Spain. Obes. Surg. 27(8), 2058–2066 (2017).

Feral-Pierssens AL, Matta J, Rives-Lange C, Goldberg M, Zins M, Carette C, Czernichow S. Health care use by adults with obesity: A French cohort study. Obesity (Silver Spring). 2022 Mar;30(3):733-742. doi: 10.1002/oby.23366. Epub 2022 Feb 10. PMID: 35142072.

Ferrari, Alize J et al. Global incidence, prevalence, years lived with disability (YLDs), disability-adjusted life-years (DALYs), and healthy life expectancy (HALE) for 371 diseases and injuries in 204 countries and territories and 811 subnational locations, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021. GBD 2021 Diseases and Injuries Collaborators. The Lancet, Volume 403, Issue 10440, 2133 – 2161 (2024).

GBD 2021 Risk Factors Collaborators. Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990-2021: a systematic analysis for the Global Burden of Disease Study 2021. Lancet. 2024 May 18;403(10440):2162-2203. doi: 10.1016/S0140-6736(24)00933-4. Erratum in: Lancet. 2024 Jul 20;404(10449):244. doi: 10.1016/S0140-6736(24)01458-2. PMID: 38762324; PMCID: PMC11120204.

Ishida M, D'Souza M, Zhao Y, Pan T, Carman W, Haregu T, Lee JT. The association between obesity, health service use, and work productivity in Australia: a cross-sectional quantile regression analysis. Sci Rep. 2023 Apr 24;13(1):6696. doi: 10.1038/s41598-023-33389-4. Erratum in: Sci Rep. 2023 May 31;13(1):8839. doi: 10.1038/s41598-023-35911-0. PMID: 37095191; PMCID: PMC10126067.

Kamble PS, Hayden J, Collins J, et al. Association of obesity with healthcare resource utilization and costs in a commercial population. Curr Med Res Opin. 2018;34(7):1335-1343. doi:10.1080/03007995.2018.1464435

Kinge JM, Morris S. The Impact of Childhood Obesity on Health and Health Service Use. Health Serv Res. 2018 Jun;53(3):1621-1643. doi: 10.1111/1475-6773.12708. Epub 2017 May 17. PMID: 28516496; PMCID: PMC5980327.

König HH, Lehnert T, Brenner H, Schöttker B, Quinzler R, Haefeli WE, Matschinger H, Heider D. Health service use and costs associated with excess weight in older adults in Germany. Age Ageing. 2015 Jul;44(4):616-23. doi: 10.1093/ageing/afu120. Epub 2015 Mar 31. PMID: 25829392.

Le Roux CW, Chubb B, Nortoft E, Borglykke A. Obesity and healthcare resource utilisation: results from clinical practice research database (CPRD). Obes Sci Pract. 2018;4(5):409-416.

Meyer SC. Maternal employment and childhood overweight in Germany. Econ Hum Biol. 2016 Dec;23:84-102. doi: 10.1016/j.ehb.2016.05.003. Epub 2016 Jun 11. PMID: 27592271.

Murray, Christopher J L; Findings from the Global Burden of Disease Study 202;The Lancet, Volume 403, Issue 10440, 2259 – 2262, May 18, (2024)

Nortoft E, Chubb B, Borglykke A. Obesity and healthcare resource utilisation: comparative results from the UK and the USA. Obes Sci Pract. 2018;4(1):41-45.

Pressman A, Jones JB, Xu X, Scott A, Alvarez S, Watkins S, Durden E. Characterizing obesity in a large health care delivery system. Am J Manag Care. 2023 Nov;29(11):558-564. doi: 10.37765/ajmc.2023.89451. PMID: 37948642.

Singh GM, Danaei G, Farzadfar F, et al. The age-specific quantitative effects of metabolic risk factors on cardiovascular diseases and diabetes: a pooled analysis. PLoS One 2013; 8(7): e65174.

16. Suehs BT, Kamble P, Huang J, et al. Association of obesity with healthcare utilization and costs in a Medicare population. Curr Med Res Opin. 2017;33(12):2173-2180. doi:10.1080/03007995.2017.1361915

Vanderwall C, Randall Clark R, Eickhoff J, Carrel AL. BMI is a poor predictor of adiposity in young overweight and obese children. BMC Pediatr. 2017 Jun 2;17(1):135. doi: 10.1186/s12887-017-0891-z. PMID: 28577356; PMCID: PMC5457636.

Wormser D, Kaptoge S, et al. Emerging Risk Factors Collaboration. Separate and combined associations of body-mass index and abdominal adiposity with cardiovascular disease: collaborative analysis of 58 prospective studies. Lancet 2011; 377: 1085-95.

FIGURES AND TABLES

Figure 1. Sample population from ESCA and exclusion criteria.

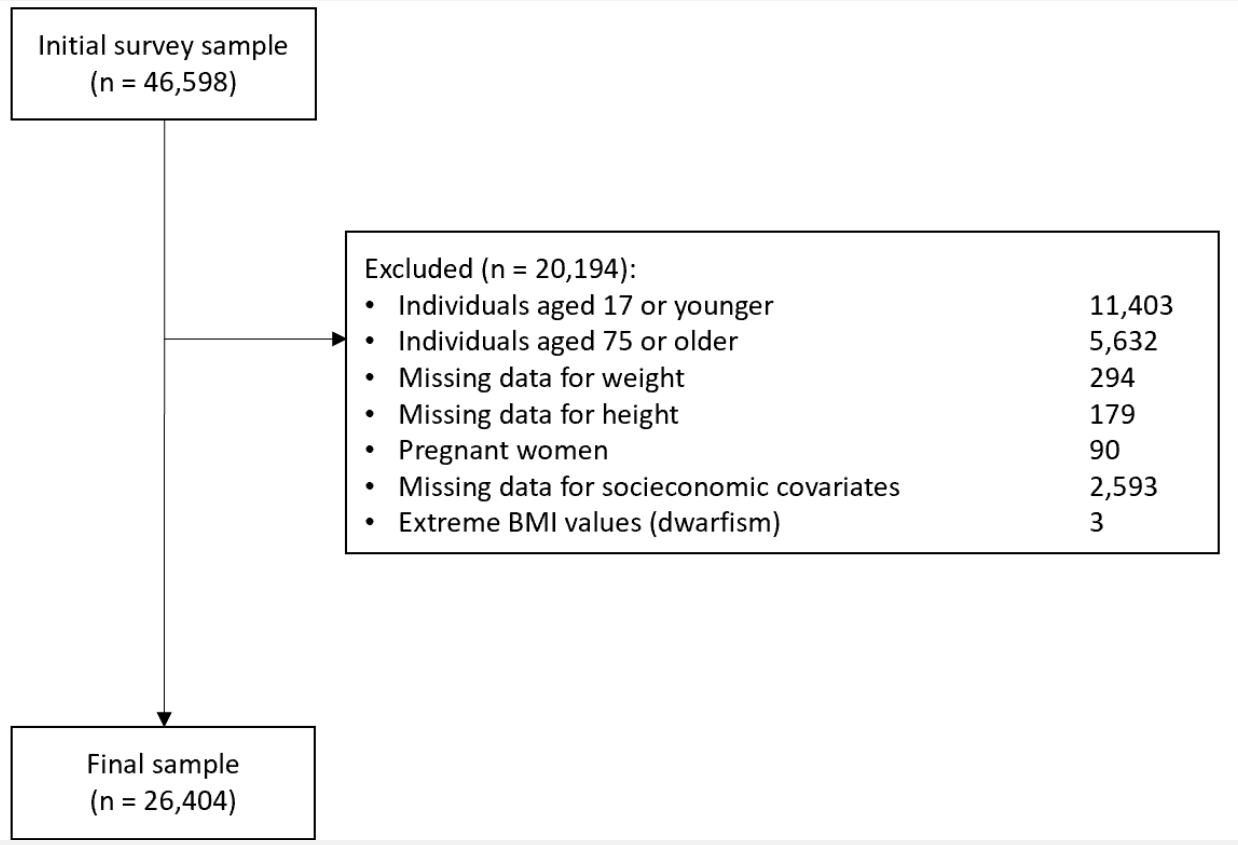
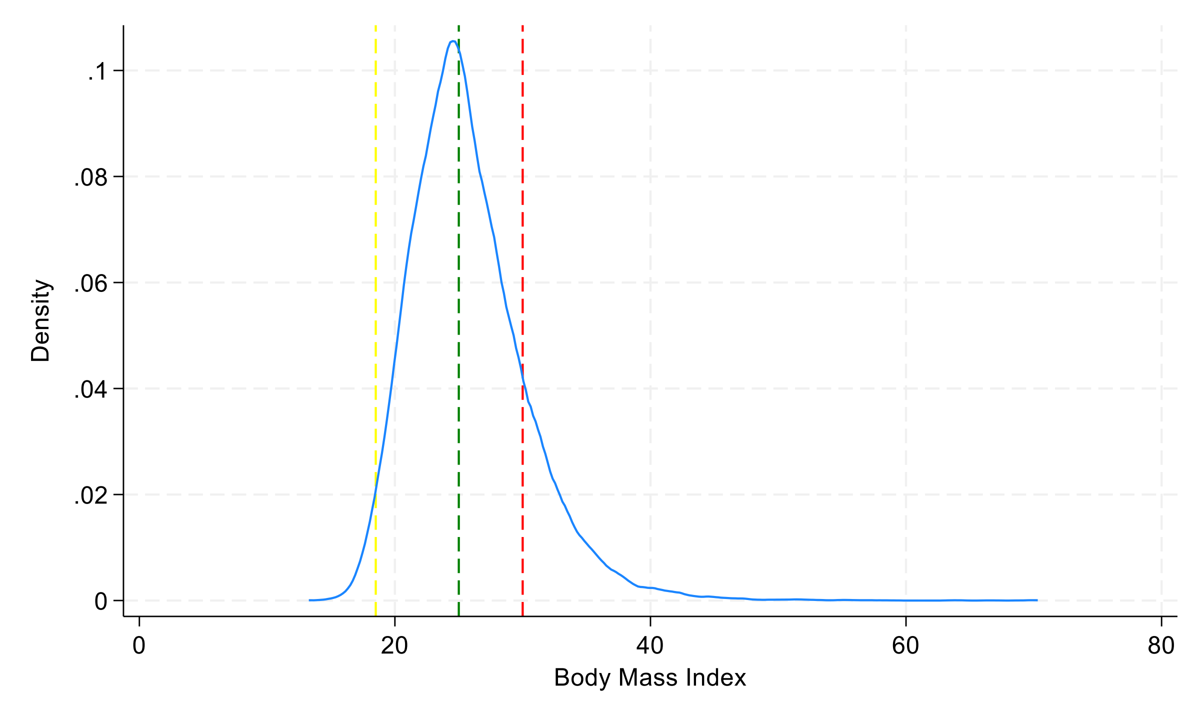


Figure 2. Sample distribution of BMI (2013-2022).



Notes: The vertical lines in the graph indicate the cut-off points for adults proposed by the WHO (underweight: BMI < 18.5 kg/m2; normal weight: between 18.5 kg/m2 and 24.99 kg/m2; overweight: between 25.0 kg/m2 and 29.99 kg/m2; obesity: ≥30.0 kg/m2).

Figure 3. BMI distribution over time (2013-2022).

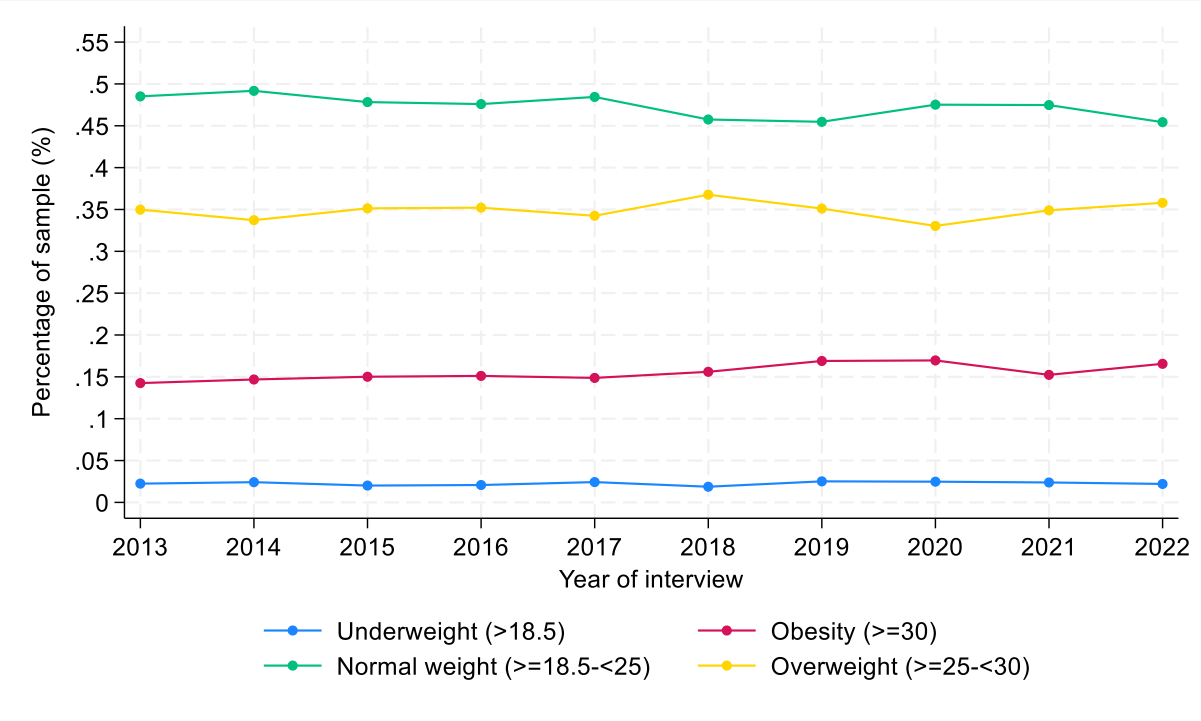


Table 1. Sample characteristics and descriptive statistics.

	Body mass index					
	Underweight (>18.5)	Normal weight (>=18.5-<25)	Overweight (>=25-<30)	Obesity (>=30)	Total	Test
N	591 (2.2%)	12,507 (47.4%)	9,236 (35.0%)	4,070 (15.4%)	26,404 (100.0%)	
Medical visits (last 12 months)						
Yes	551 (93.2%)	11,345 (90.7%)	8,472 (91.7%)	3,802 (93.4%)	24,170 (91.5%)	<0.001
Specialist visits (last 12 months)						
Yes	390 (66.0%)	7,903 (63.2%)	5,706 (61.8%)	2,709 (66.6%)	16,708 (63.3%)	<0.001
Medication use (last 15 days)						
Yes	273 (46.2%)	5,862 (46.9%)	5,412 (58.6%)	2,926 (71.9%)	14,473 (54.8%)	<0.001
Emergency room visits (number, last 12 months)	0.697 (1.641)	0.517 (1.293)	0.517 (1.297)	0.650 (1.801)	0.541 (1.394)	<0.001
Hospital admissions (number, last 12 months)	0.108 (0.551)	0.087 (0.773)	0.108 (0.645)	0.154 (0.622)	0.105 (0.704)	<0.001
Year of interview						
2013	68 (11.5%)	1,476 (11.8%)	1,054 (11.4%)	432 (10.6%)	3,030 (11.5%)	0.171
2014	75 (12.7%)	1,527 (12.2%)	1,047 (11.3%)	456 (11.2%)	3,105 (11.8%)	
2015	73 (12.4%)	1,733 (13.9%)	1,273 (13.8%)	544 (13.4%)	3,623 (13.7%)	
2016	57 (9.6%)	1,307 (10.5%)	967 (10.5%)	415 (10.2%)	2,746 (10.4%)	
2017	47 (8.0%)	938 (7.5%)	663 (7.2%)	288 (7.1%)	1,936 (7.3%)	
2018	53 (9.0%)	1,293 (10.3%)	1,039 (11.2%)	441 (10.8%)	2,826 (10.7%)	
2019	67 (11.3%)	1,211 (9.7%)	935 (10.1%)	450 (11.1%)	2,663 (10.1%)	
2020	33 (5.6%)	633 (5.1%)	440 (4.8%)	226 (5.6%)	1,332 (5.0%)	
2021	61 (10.3%)	1,215 (9.7%)	893 (9.7%)	390 (9.6%)	2,559 (9.7%)	
2022	57 (9.6%)	1,174 (9.4%)	925 (10.0%)	428 (10.5%)	2,584 (9.8%)	
Age (years)	34.783 (14.197)	41.833 (14.764)	49.641 (14.075)	52.100 (13.482)	45.989 (15.049)	<0.001
Gender						
Female	481 (81.4%)	7,015 (56.1%)	3,605 (39.0%)	1,937 (47.6%)	13,038 (49.4%)	<0.001
Male	110 (18.6%)	5,492 (43.9%)	5,631 (61.0%)	2,133 (52.4%)	13,366 (50.6%)	
Weight (kg)	49.014 (4.969)	63.595 (8.956)	77.634 (9.427)	93.091 (14.246)	72.726 (15.011)	<0.001
Body mass index	17.613 (0.806)	22.456 (1.711)	27.138 (1.387)	33.537 (3.854)	25.694 (4.583)	<0.001
Education						
Primary	46 (7.9%)	1,285 (10.6%)	1,244 (14.1%)	681 (17.8%)	3,256 (12.8%)	<0.001
Secondary	261 (45.1%)	5,763 (47.6%)	4,707 (53.2%)	2,159 (56.6%)	12,890 (50.8%)	
University	272 (47.0%)	5,069 (41.8%)	2,902 (32.8%)	976 (25.6%)	9,219 (36.3%)	
Working status						
Employed	332 (56.2%)	8,197 (65.5%)	5,676 (61.5%)	2,004 (49.2%)	16,209 (61.4%)	<0.001
Unemployed	212 (35.9%)	2,981 (23.8%)	1,691 (18.3%)	955 (23.5%)	5,839 (22.1%)	
Retired/Unable	47 (8.0%)	1,329 (10.6%)	1,869 (20.2%)	1,111 (27.3%)	4,356 (16.5%)	
Private health insurance						
Yes	188 (31.8%)	3,870 (30.9%)	2,547 (27.6%)	936 (23.0%)	7,541 (28.6%)	<0.001
Living alone						
Yes	43 (7.3%)	1,099 (8.8%)	841 (9.1%)	365 (9.0%)	2,348 (8.9%)	0.453
Alcohol consumption						
Never	229 (38.7%)	3,663 (29.3%)	2,682 (29.0%)	1,492 (36.7%)	8,066 (30.5%)	<0.001
Low-risk drinker	332 (56.2%)	8,163 (65.3%)	6,127 (66.3%)	2,421 (59.5%)	17,043 (64.5%)	
High-risk drinker	30 (5.1%)	681 (5.4%)	427 (4.6%)	157 (3.9%)	1,295 (4.9%)	
Smoking						
Smoker	183 (31.0%)	3,878 (31.0%)	2,421 (26.2%)	904 (22.2%)	7,386 (28.0%)	<0.001
Former smoker	90 (15.2%)	2,568 (20.5%)	2,632 (28.5%)	1,303 (32.0%)	6,593 (25.0%)	
Never	318 (53.8%)	6,061 (48.5%)	4,183 (45.3%)	1,863 (45.8%)	12,425 (47.1%)	
Hypertension diagnostic						
Yes	32 (5.4%)	1,358 (10.9%)	2,464 (26.7%)	1,666 (40.9%)	5,520 (20.9%)	<0.001
Diabetis diagnostic						
Yes	12 (2.0%)	378 (3.0%)	748 (8.1%)	633 (15.6%)	1,771 (6.7%)	<0.001
Heart attack diagnostic						
Yes	13 (2.2%)	303 (2.4%)	393 (4.3%)	281 (6.9%)	990 (3.7%)	<0.001

Notes: Mean (Standard deviation): p-value from a pooled t-test. Frequency (Percent %): p-value from Pearson test.

Table 2: Continuous BMI effect on primary care visits, 2013-2022.

	(1)	(2)	(3)	(4)
BMI	1.015**	1.016**	1.002	1.012
	(0.00605)	(0.00660)	(0.00655)	(0.0205)
BMI^2		1.000	1.000	1.000
		(0.000631)	(0.000535)	(0.000547)
Private insurance	1.682***	1.681***	1.710***	1.717***
	(0.0999)	(0.0999)	(0.102)	(0.104)
Age	1.020***	1.020***	1.009***	1.009***
	(0.00229)	(0.00230)	(0.00236)	(0.00236)
Age^2	1.000***	1.000***	1.000	1.000
	(0.000134)	(0.000135)	(0.000137)	(0.000137)
Male	0.366***	0.365***	0.364***	0.363***
	(0.0189)	(0.0191)	(0.0190)	(0.0190)
Hypertension			3.057***	3.061***
			(0.298)	(0.299)
Diabetes			2.544***	2.579***
			(0.460)	(0.470)
Stroke			3.000***	2.998***
			(0.802)	(0.801)
Controls	Yes	Yes	Yes	Yes
BMI-squared	No	Yes	Yes	Yes
Comorbidities	No	No	Yes	Yes
Interactions	No	No	No	Yes
R-squared	0.0913	0.0913	0.108	0.108
Dep. var. mean	0.915	0.915	0.915	0.915

Notes: Logistic regression models to estimate the odds ratio of the dependent variable based on BMI. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Table 3: Continuous BMI effect on specialist visits, 2013-2022.

	(1)	(2)	(3)	(4)
BMI	1.009***	1.003	0.994	1.003
	(0.00328)	(0.00389)	(0.00390)	(0.00939)
BMI^2		1.001***	1.001***	1.001**
		(0.000356)	(0.000335)	(0.000331)
Age	1.011***	1.011***	1.006***	1.006***
	(0.00121)	(0.00123)	(0.00128)	(0.00128)
Age^2	1.000*	1.000*	1.000***	1.000***
	(0.0000744)	(0.0000745)	(0.0000758)	(0.0000758)
Male	0.389***	0.394***	0.390***	0.389***
	(0.0114)	(0.0117)	(0.0116)	(0.0116)
Private insurance	2.141***	2.142***	2.177***	2.173***
	(0.0711)	(0.0711)	(0.0725)	(0.0727)
Hypertension			1.478***	1.478***
			(0.0594)	(0.0594)
Diabetes			1.562***	1.560***
			(0.102)	(0.101)
Stroke			2.480***	2.478***
			(0.245)	(0.245)
Controls	Yes	Yes	Yes	Yes
BMI-squared	No	Yes	Yes	Yes
Comorbidities	No	No	Yes	Yes
Interactions	No	No	No	Yes
Observations	26404	26404	26404	26404
R-squared	0.0976	0.0979	0.106	0.107
Dep. var. mean	0.633	0.633	0.633	0.633

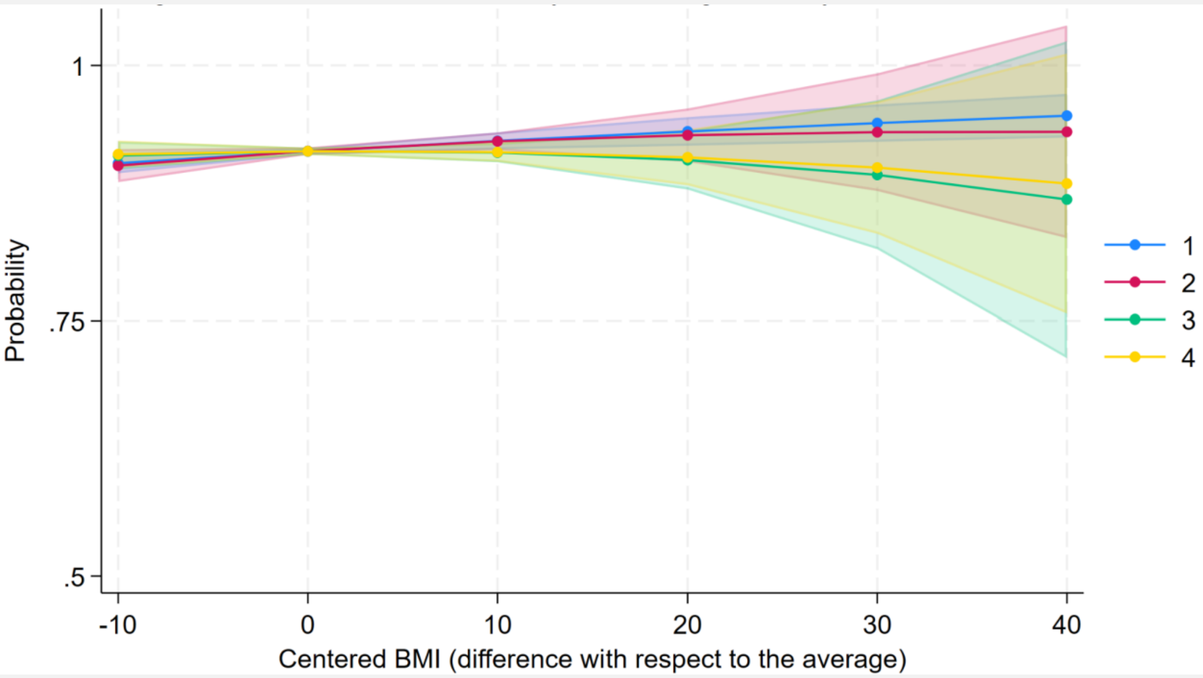
Notes: Logistic regression models to estimate the odds ratio of the dependent variable based on BMI. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Table 4: Continuous BMI effect on consumption of pharmaceuticals, 2013-2022.

	(1)	(2)	(3)	(4)
BMI	1.055***	1.056***	1.031***	1.043***
	(0.00363)	(0.00410)	(0.00413)	(0.0112)
BMI^2		1.000	1.000	1.000
		(0.000451)	(0.000427)	(0.000427)
Private insurance	1.024	1.024	1.056*	1.067**
	(0.0325)	(0.0325)	(0.0345)	(0.0353)
Age	1.042***	1.042***	1.027***	1.027***
	(0.00128)	(0.00130)	(0.00137)	(0.00137)
Age^2	1.001***	1.001***	1.000***	1.000***
	(0.0000788)	(0.0000789)	(0.0000820)	(0.0000821)
Male	0.514***	0.513***	0.480***	0.479***
	(0.0150)	(0.0152)	(0.0148)	(0.0148)
Hypertension			4.843***	4.828***
			(0.237)	(0.236)
Diabetes			5.110***	5.123***
			(0.544)	(0.545)
Stroke			2.431***	2.436***
			(0.253)	(0.253)
Controls	Yes	Yes	Yes	Yes
BMI-squared	No	Yes	Yes	Yes
Comorbidities	No	No	Yes	Yes
Interactions	No	No	No	Yes
R-squared	0.146	0.146	0.197	0.197
Dep. var. mean	0.548	0.548	0.548	0.548

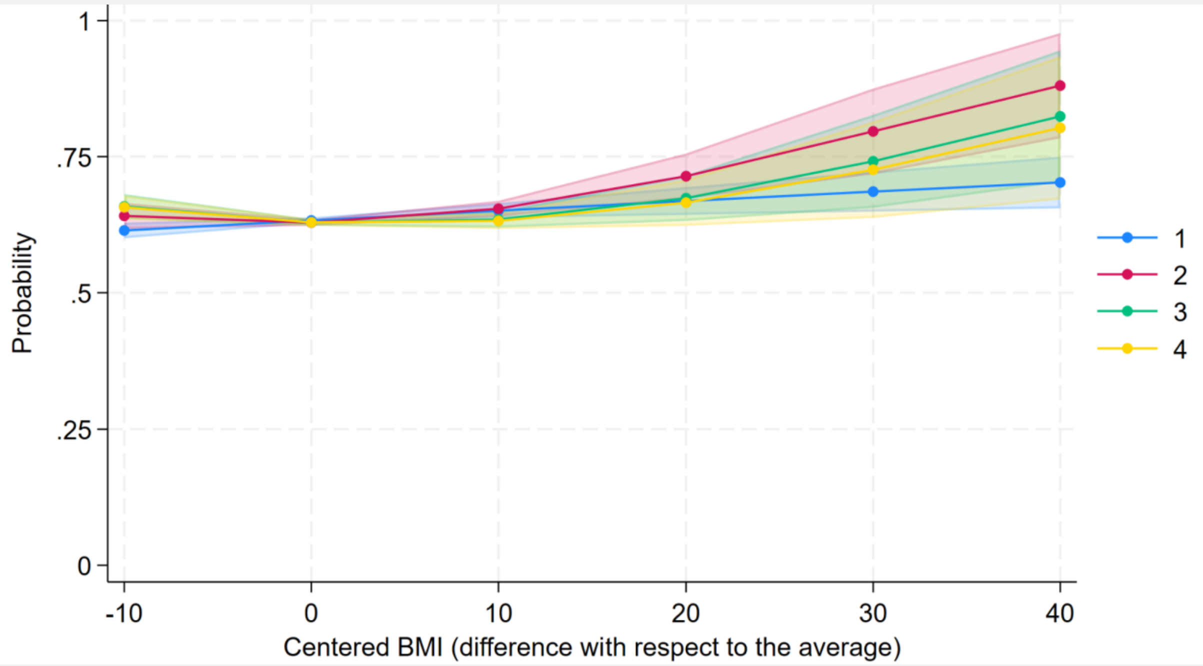
Notes: Logistic regression models to estimate the odds ratio of the dependent variable based on BMI. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Figure 4: Expected probability of visiting primary care, 2013-2022.



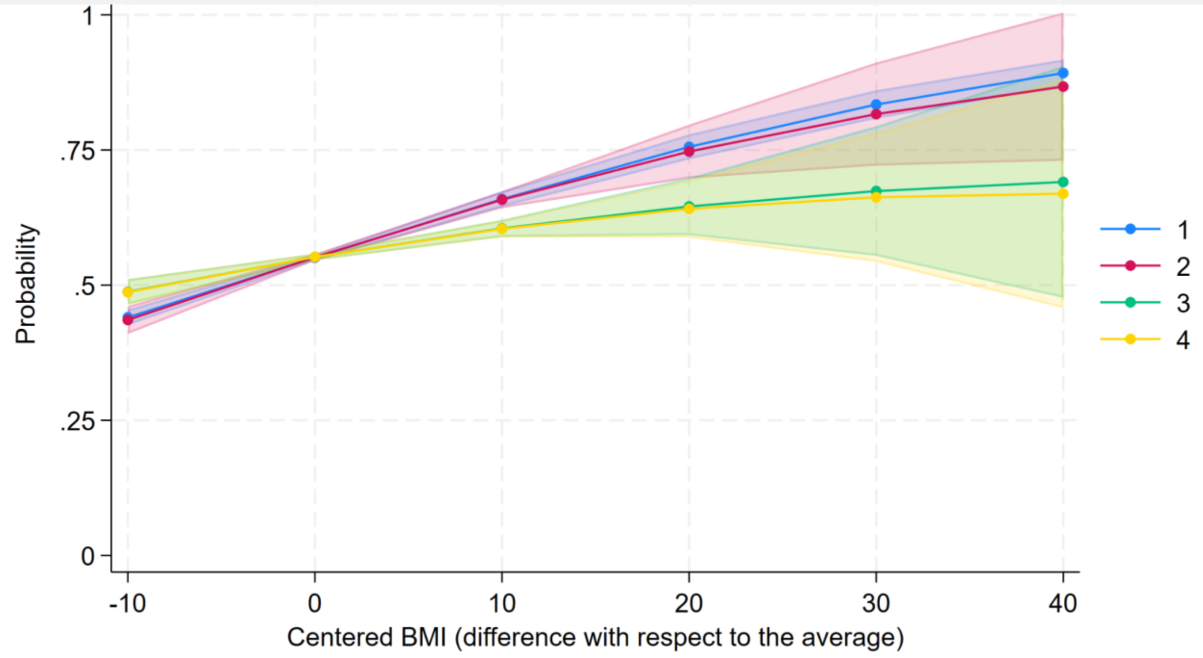
Notes: Expected probability from the logistic regression model with 95% confidence intervals. The horizontal axis represents the centred BMI where 0 represents the average BMI of the sample. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios.

Figure 5: Expected probability of visiting specialized care, 2013-2022.



Notes: Expected probability from the logistic regression model with 95% confidence intervals. The horizontal axis represents the centred BMI where 0 represents the average BMI of the sample. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios.

Figure 6: Expected probability of pharmaceutical consumption, 2013-2022.



Notes: Expected probability from the logistic regression model with 95% confidence intervals. The horizontal axis represents the centred BMI where 0 represents the average BMI of the sample. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios.

Table 5: Categorical BMI effect on primary care visits, 2013-2022.

	(1)	(2)	(3)
Underweight	1.178	1.159	1.342
	(0.202)	(0.199)	(0.859)
Overweight	1.090	1.025	1.125
	(0.0574)	(0.0538)	(0.206)
Obesity	1.175**	0.978	1.206
	(0.0888)	(0.0745)	(0.310)
Private insurance	1.679***	1.710***	1.700***
	(0.0998)	(0.102)	(0.136)
Age	1.020***	1.009***	1.009***
	(0.00227)	(0.00234)	(0.00235)
Age^2	1.000***	1.000	1.000
	(0.000135)	(0.000137)	(0.000137)
Male	0.371***	0.366***	0.365***
	(0.0191)	(0.0190)	(0.0189)
Hypertension		3.061***	3.065***
		(0.298)	(0.298)
Diabetes		2.544***	2.553***
		(0.460)	(0.463)
Stroke		2.999***	2.982***
		(0.802)	(0.796)
Controls	Yes	Yes	Yes
Comorbidities	No	Yes	Yes
Interactions	No	No	Yes
R-squared	0.0912	0.108	0.109
Dep. var. mean	0.915	0.915	0.915

Notes: Logistic regression model to estimate the odds ratio of the dependent variable based on categorical BMI (reference category is normal weight). Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds comorbidities (hypertension, diabetes and heart stroke); Model 3 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Table 6: Categorical BMI effect on specialist visits, 2013-2022.

	(1)	(2)	(3)
Underweight	0.999	0.996	0.650
	(0.0947)	(0.0945)	(0.171)
Overweight	0.977	0.937**	0.984
	(0.0310)	(0.0300)	(0.0932)
Obesity	1.120***	0.997	1.039
	(0.0480)	(0.0436)	(0.128)
Private insurance	2.138***	2.176***	2.178***
	(0.0709)	(0.0725)	(0.0726)
Age	1.011***	1.006***	1.006***
	(0.00121)	(0.00127)	(0.00127)
Age^2	1.000*	1.000***	1.000***
	(0.0000744)	(0.0000756)	(0.0000757)
Male	0.394***	0.388***	0.387***
	(0.0116)	(0.0115)	(0.0115)
Hypertension		1.479***	1.483***
		(0.0594)	(0.0596)
Diabetes		1.563***	1.561***
		(0.102)	(0.102)
Stroke		2.484***	2.479***
		(0.246)	(0.245)
Controls	Yes	Yes	Yes
Comorbidities	No	Yes	Yes
Interactions	No	No	Yes
R-squared	0.0977	0.106	0.107
Dep. varbl mean	0.633	0.633	0.633

Notes: Logistic regression model to estimate the odds ratio of the dependent variable based on categorical BMI (reference category is normal weight). Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds comorbidities (hypertension, diabetes and heart stroke); Model 3 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Table 7: Categorical BMI effect on consumption of pharmaceuticals, 2013-2022.

	(1)	(2)	(3)
Underweight	1.057	1.033	0.928
	(0.0963)	(0.0942)	(0.248)
Overweight	1.316***	1.169***	1.277**
	(0.0418)	(0.0387)	(0.131)
Obesity	2.052***	1.542***	1.795***
	(0.0886)	(0.0710)	(0.246)
Private insurance	1.020	1.054	1.055
	(0.0323)	(0.0344)	(0.0345)
Age	1.043***	1.028***	1.028***
	(0.00128)	(0.00136)	(0.00136)
Age^2	1.001***	1.000***	1.000***
	(0.0000788)	(0.0000819)	(0.0000821)
Male	0.526***	0.487***	0.487***
	(0.0154)	(0.0148)	(0.0149)
Hypertension		4.821***	4.806***
		(0.235)	(0.234)
Diabetes		5.106***	5.102***
		(0.544)	(0.544)
Stroke		2.435***	2.431***
		(0.254)	(0.254)
Controls	Yes	Yes	Yes
Comorbidities	No	Yes	Yes
Interactions	No	No	Yes
R-squared	0.147	0.197	0.198
Dep. var. mean	0.548	0.548	0.548

Notes: Logistic regression model to estimate the odds ratio of the dependent variable based on categorical BMI (reference category is normal weight). Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds comorbidities (hypertension, diabetes and heart stroke); Model 3 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Table 8: Continuous BMI effect on emergency visits, 2013-2022.

Part 1 - Selection	(1)	(2)	(3)	(4)
BMI	1.019***	1.015***	1.008**	1.010
	(0.00318)	(0.00376)	(0.00379)	(0.00873)
BMI^2		1.001**	1.001**	1.001**
		(0.000304)	(0.000302)	(0.000307)
Age	0.981***	0.981***	0.978***	0.978***
	(0.00118)	(0.00119)	(0.00125)	(0.00126)
Age^2	1.000	1.000	1.000	1.000
	(0.0000731)	(0.0000732)	(0.0000741)	(0.0000741)
Male	0.753***	0.761***	0.760***	0.761***
	(0.0215)	(0.0220)	(0.0221)	(0.0221)
Private insurance	0.974	0.974	0.981	0.903
	(0.0307)	(0.0307)	(0.0310)	(0.0807)
Hypertension			1.350***	1.348***
			(0.0514)	(0.0514)
Diabetes			1.168***	1.167***
			(0.0660)	(0.0660)
Stroke			1.638***	1.645***
			(0.113)	(0.113)
Part 2 - Outcome	**(1)**	**(2)**	**(3)**	**(4)**
BMI	1.011***	1.008**	1.006	1.007
	(0.00299)	(0.00373)	(0.00377)	(0.00792)
BMI^2		1.000	1.000	1.000
		(0.000257)	(0.000256)	(0.000255)
Age	0.991***	0.991***	0.990***	0.990***
	(0.00117)	(0.00119)	(0.00125)	(0.00126)
Age^2	1.000***	1.000***	1.000***	1.000***
	(0.0000707)	(0.0000708)	(0.0000715)	(0.0000716)
Male	0.833***	0.838***	0.838***	0.838***
	(0.0245)	(0.0248)	(0.0248)	(0.0249)
Private insurance	0.984	0.984	0.985	1.059
	(0.0323)	(0.0323)	(0.0324)	(0.0924)
Hypertension			1.147***	1.152***
			(0.0437)	(0.0441)
Diabetes			0.999	0.997
			(0.0563)	(0.0563)
Stroke			1.170**	1.163**
			(0.0738)	(0.0735)
Controls	Yes	Yes	Yes	Yes
Comorbidities	No	No	Yes	Yes
BMI-squared	No	Yes	Yes	Yes
Interactions	No	No	No	Yes
AIC	61466.3	61462.6	61318.0	61360.4
BIC	61989.9	62002.6	61907.1	62243.9
Observations	26404	26404	26404	26404
Dep. var. mean	0.541	0.541	0.541	0.541

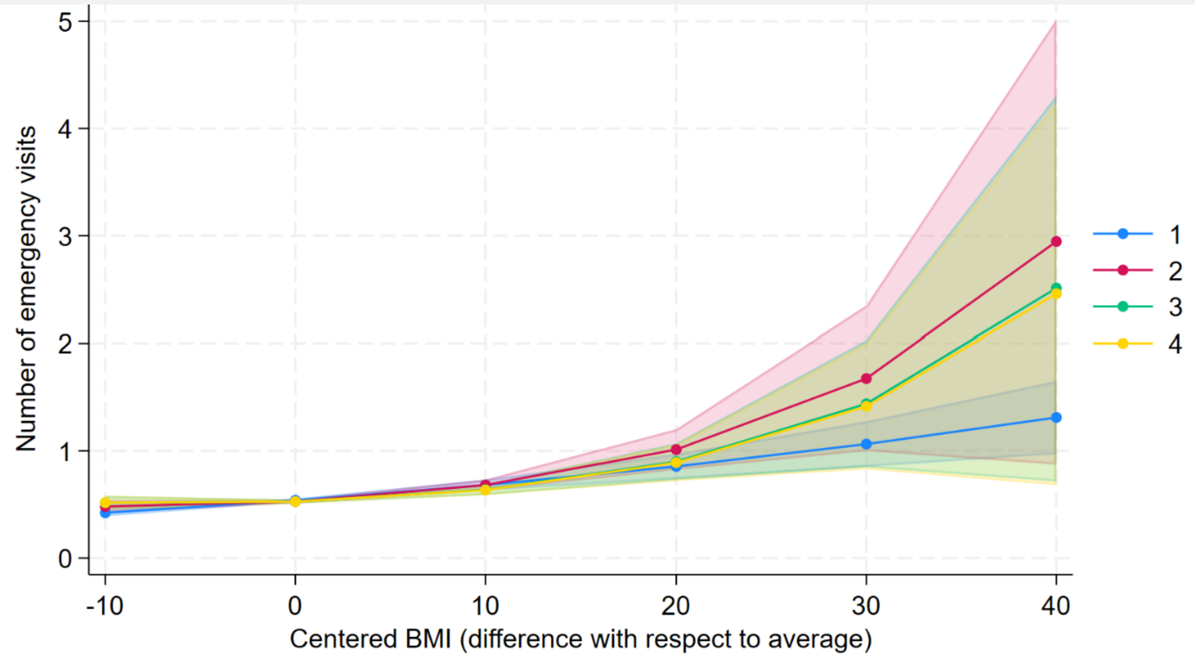
Notes: Two-part models to estimate the odds ratio of the dependent variable based on BMI. The first part of the table reports the selection model (logistic regression); the second part of the table reports the outcome model (GLM model with a negative binomial link function). Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Table 9: Continuous BMI effect on hospitalisations, 2013-2022.

Part 1 - Selection	(1)	(2)	(3)	(4)
BMI	1.032***	1.029***	1.017**	1.007
	(0.00515)	(0.00652)	(0.00661)	(0.0147)
BMI^2		1.000	1.000	1.000
		(0.000406)	(0.000416)	(0.000438)
Age	1.001	1.001	0.996**	0.995**
	(0.00206)	(0.00209)	(0.00219)	(0.00219)
Age^2	1.000	1.000	1.000	1.000
	(0.000125)	(0.000125)	(0.000126)	(0.000126)
Male	0.853***	0.859***	0.855***	0.853***
	(0.0429)	(0.0436)	(0.0438)	(0.0437)
Private insurance	1.230***	1.230***	1.250***	1.245***
	(0.0669)	(0.0669)	(0.0683)	(0.0682)
Hypertension			1.423***	1.424***
			(0.0862)	(0.0864)
Diabetes			1.537***	1.543***
			(0.121)	(0.121)
Stroke			1.751***	1.761***
			(0.164)	(0.166)
Part 2 - Outcome	**(1)**	**(2)**	**(3)**	**(4)**
BMI	1.004	0.988	0.987*	0.947***
	(0.00557)	(0.00745)	(0.00751)	(0.0167)
BMI^2		1.001***	1.001***	1.001*
		(0.000400)	(0.000400)	(0.000477)
Age	0.998	1.000	0.999	0.999
	(0.00255)	(0.00259)	(0.00276)	(0.00276)
Age^2	1.000	1.000	1.000	1.000
	(0.000158)	(0.000159)	(0.000159)	(0.000161)
Male	1.121*	1.131*	1.129*	1.119*
	(0.0731)	(0.0739)	(0.0740)	(0.0738)
Private insurance	0.981	0.984	0.990	0.985
	(0.0685)	(0.0687)	(0.0693)	(0.0696)
Hypertension			1.069	1.060
			(0.0791)	(0.0789)
Diabetes			1.006	1.018
			(0.0951)	(0.0967)
Stroke			1.079	1.087
			(0.120)	(0.121)
Controls	Yes	Yes	Yes	Yes
Comorbidities	No	No	No	Yes
BMI-squared	No	Yes	Yes	Yes
Interactions	No	No	Yes	Yes
AIC	20151.0	20144.5	20042.6	20057.2
BIC	20674.6	20684.5	20631.6	20809.8
Observations	26404	26404	26404	26404
Dep. var. mean	0.105	0.105	0.105	0.105

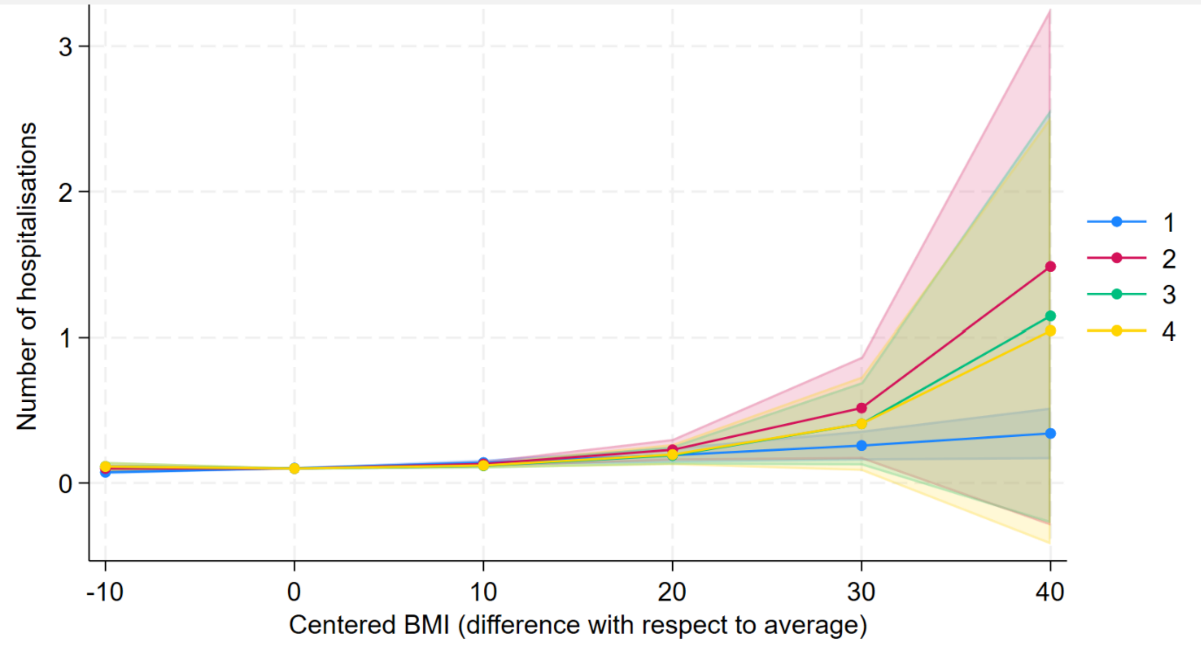
Notes: Two-part models to estimate the odds ratio of the dependent variable based on BMI. The first part of the table reports the selection model (logistic regression); the second part of the table reports the outcome model (GLM model with a negative binomial link function). Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year). All reported coefficients are odds ratios, standard errors in parentheses. Significance: *** 1%, ** 5%, *10%.

Figure 7: Expected number of emergency care visits, 2013-2022.



Notes: Expected number of visits from the outcome model (GLM model with a negative binomial link function) with 95% confidence intervals. The horizontal axis represents the centred BMI, so 0 represents the average BMI of the sample. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year).

Figure 8: Expected number of hospitalisations, 2013-2022.



Notes: Expected number of hospitalisations from the outcome model (GLM model with a negative binomial link function) with 95% confidence intervals. The horizontal axis represents the centred BMI, so 0 represents the average BMI of the sample. Model 1 includes BMI and controls (age, age squared, gender, private insurance, education, employment status, smoking status, alcohol consumption, living alone, health region, year and survey wave); Model 2 adds BMI squared; Model 3 adds comorbidities (hypertension, diabetes and heart stroke); Model 4 includes interactions (BMI and private insurance and BMI and year).