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HEALTH MISPERCEPTION AND HEALTHCARE UTILISATION AMONG OLDER EUROPEANS

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Abstract

Health perception biases can have serious consequences on health. Despite their relevance, the role of such biases in determining healthcare utilisation is severely underexplored. Here we study the relationship between health misperception, doctor visits, and concomitant out-of-pocket expenditures for the population 50+ in Europe. We conceptualise health misperception as arising from either overconfidence or underconfidence, where overconfidence is measured as overestimation of health and underconfidence is measured as underestimation of health. Comparing objective performance measures and their self-reported equivalents from the Survey of Health, Ageing and Retirement in Europe, we find that individuals who overestimate their health visit the doctor 14% less often than individuals who correctly assess their health, which is crucial for preventive care such as screenings. Lower healthcare utilisation is accompanied by lower out-of-pocket spending (38% less). In contrast, individuals who underestimate their health visit the doctor more often (28% more) and have higher out-of-pocket spending (17% more). We project that underestimating health of the population 50+ will cost the average European country Intl$ 71 million in 2020 and Intl$ 81 million by 2060. Country-specific estimates based on population and demographic projections show that countries such as Germany, Denmark and The Netherlands will experience significantly large costs of such misperception. The results are robust to several sensitivity tests and, more important, to various conceptualisations of the misperception measure.

Keywords

Healthcare utilisation, health perception, overconfidence and underconfidence, doctor visits, out-of-pocket expenditures, SHARE data.

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Health Misperception and Healthcare Utilisation among Older Europeans

Sonja Spitzer and Mujaheed Shaikh

1 Introduction

Biased perception of one's own ability is a hallmark of human nature. The literature in psychology, economics, and evolutionary biology has repeatedly demonstrated this phenomenon. Zell & Krizan (2014) conducted a meta-synthesis across different scientific areas and concluded that people have only moderate knowledge of their ability. Johnson & Fowler (2011) presented an evolutionary model of one such bias, namely, overconfidence, and the conditions under which it prevails. Such biases have significant implications for education, labour market outcomes, savings, investment choices, and political decisions (Anderson et al. 2017, Ortoleva & Snowberg 2015, Reuben et al. 2017). They are particularly relevant for health, as they can directly affect risk for accident and injury (Preston & Harris 1965, Sakurai et al. 2013) and have serious long-lasting effects on wellbeing and mortality. Recent work in this domain shows that overconfidence is related to engagement in risky health behaviours (Arni et al. 2019).

Despite the relevance of biased perception for health, its role in healthcare seeking is largely unexplored. Here we study the relationship between misperception of one's own health and future healthcare utilisation and medical expenditures. We categorise misperception as arising from either overconfidence or underconfidence in one's own health. Following the literature in psychology, we measure overconfidence as the overestimation of one's actual health and measure underconfidence as the underestimation of one's actual health (Moore & Healy 2008). It is a priori ambiguous how over- or underconfidence might relate to healthcare use. On the one hand, individuals who overestimate their health may be less likely to visit the doctor when necessary, seek medical attention, or receive timely screenings because they believe their health is perfect. These individuals might also engage in more physical activity, which decreases healthcare utilisation (Rocca et al. 2015). On the other hand, the same individuals might engage in activity or behaviour detrimental to health and thus end up in the hospital more often. For example, older individuals who overestimate their mobility are more prone to fall-induced injuries (Sakurai et al. 2013). Similarly, individuals who underestimate their health may overutilise healthcare services by seeking care and purchasing relatively more medication when it is not necessary—at least in the short run. In the long run, however, they might need less care and use fewer services because of their frequent doctor visits and timely diagnoses. Assessing the relationship between health perception and healthcare utilisation thus remains an empirical task that we undertake in this study.

Measuring over- or underconfidence bias in health is anything but trivial. It requires a subjective health measure and its objective equivalent, the lack of which often dissuades researchers from engaging in such research. We use a novel indicator to measure over- and underconfidence that is derived from the objective performance measures in the Survey of Health, Ageing and Retirement (SHARE). We analyse differences between subjective and objective health based on individuals' self-reported and tested ability to stand up from a chair. Individuals who subjectively report being able to stand but objectively are unable to do so are classified as overconfident, whereas those who subjectively report being unable to stand but objectively are able to are classified as underconfident. Individuals who do not differ in their subjective report and objective assessment are classified as concordant. Prior research has shown the chair stand test to be a good predictor of overall health (Ferrer et al. 1999, Sainio et al. 2006, Pinheiro et al. 2016, Spitzer & Weber 2019). Our approach distinguishes our measure of overconfidence from overplacement and overprecision because we focus only on individual judgements of completing a task rather than on relative comparisons with others or the estimated accuracy of such judgements (Moore & Healy 2008).

To assess utilisation, we use self-reported data on the annual number of doctor visits, which includes emergency room visits and outpatient clinic visits. Using count models, a rich set of controls, and longitudinal data, we find that relative to individuals who achieve concordance (i.e., those who estimate their health accurately), individuals who underestimate their health visit the doctor more often (approximately two more visits per year). In contrast, individuals who overestimate their health visit the doctor less often. We also analyse concomitant out-of-pocket (OOP) expenditures via log-Gamma models and find that individuals who underestimate their health have higher expenses, whereas individuals who overestimate their health have lower expenses. Our results are not biased by other individual characteristics, such as education, age, employment, or marital status, nor are they a manifestation of the inverse relationship between healthcare utilisation and the estimation of one's health as already stated. The results are robust to different model specifications, estimation methods, and measures of health perception.

We use data from 15 European countries from the SHARE survey, which provides other advantages besides a measure of confidence. First, the longitudinal nature of the survey allows us to assess the relationship between confidence today and healthcare utilisation in the next wave of the survey. Thus, an important source of bias in our estimates—reverse causality—is not a first-order issue in our analyses. Second, utilising health services is conditional on having access to such services; a fair comparison of utilisation requires no significant difference in accessibility among the entities being compared. Universal coverage in European countries ensures that everyone has a certain level of access to the health system, unlike in the United States (OECD & European Commission 2018). Finally, Europe is a policy-relevant setting because of its rapidly ageing population (Lutz et al. 2003, Eurostat 2019) and fiscal pressures to reduce expenditures and unnecessary care (Christensen et al. 2009, European Commission 2018).

To quantify the public expenditure associated with health misperception, we perform a back-of-the-envelope calculation of the costs of health misperception. We project that underestimating health will cost the average European country Intl$ 71 million in 2020 and Intl$ 81 million by 2060. Although overestimating health results in negative costs due to lower numbers of doctor visits, these are in the short run only. In the long run, overestimation may result in individuals skipping timely screening and preventive care and lead to worse health, resulting in higher healthcare expenditures.

The contribution of this study is twofold. First, we introduce and advance a measure of health misperception in the health economics literature. Our measure of over- and underconfidence is simple and easy to calculate and an accurate indicator of health status. The medical literature has shown the chair stand test to be strongly correlated with physical health (Ferrer et al. 1999, Sainio et al. 2006, Pinheiro et al. 2016). Moreover, it is regularly performed in other surveys, such as the English Longitudinal Study of Ageing, which provides the opportunity to study different settings and make subsequent comparative analyses between countries.

Second, we contribute to at least two strands of the literature in health economics. The literature has repeatedly shown that individuals frequently over- or underestimate their own health status (Bago d'Uva et al. 2008, Beaudoin & Desrichard 2011, Coman & Richardson 2006, Furnham 2001, Jürges 2007). In addition, health perception differs by sociodemographic characteristics such as age (Srisurapanont et al. 2017, Crossley & Kennedy 2001), gender (Schneider et al. 2012, Merrill et al. 1997), country of residence (Spitzer & Weber 2019, Capistrant et al. 2014, Jürges 2007), education (Bago d'Uva et al. 2008, Choi & Cawley 2017), and race (Jackson et al. 2017). The difference between subjective and predicted survival probability affects healthcare utilisation (Bíró 2016*a*), and individuals with higher expected longevity are more likely to go for cancer screening (Picone et al. 2004), suggesting that health perception affects healthcare utilisation. Our paper contributes to this strand by directly studying over- and underconfidence in one's own health.

It also contributes to the literature on the determinants of healthcare use. In explaining variation in health expenditures and healthcare utilisation, this literature focuses on either the supply side (i.e., provider confidence and precision) (Baumann et al. 1991, Berner & Graber 2008, Cutler et al. 2013, Meyer et al. 2013) or easily observable demand characteristics (e.g., age, gender, income, social class, employment and education) (Bíró 2013, Cameron et al. 2010, Tavares & Zantomio 2017, Vallejo-Torres & Morris 2013, Van Doorslaer et al. 2004, Zhang et al. 2018). Our paper makes a novel contribution by extending this literature to assess a difficult-to-observe demand variable that has consistently been shown to affect health.

The remainder of this paper is structured as follows. In Section 2, we describe the data and variables. In Section 3, we introduce our methodology. Section 4 presents and discusses the results, Section 5 describes a range of robustness analyses, Section 6 provides estimates for the total public cost of health misperception, and Section 7 concludes the paper.

2 Data and Descriptive Statistics

We analyse the relationship between health misperception and healthcare utilisation based on SHARE, a representative cross-country panel study of noninstitutionalised individuals ages 50 and older as well as their younger spouses (Börsch-Supan et al. 2013).[1] The survey provides rich information on health, socioeconomic background, employment, and social networks based on about 380,000 interviews with around 140,000 individuals. It is particularly well suited for studying European countries, as the data are ex-ante harmonised. Also, because it focuses on older individuals, who generally have higher healthcare needs than the young, it is the ideal data source for our analyses. SHARE was previously used to anal-

[1]This study uses data from SHARE Waves 1, 2, 4, 5, and 6 (DOIs: 10.6103/SHARE.w1.700, 10.6103/SHARE.w2.700, 10.6103/SHARE.w4.700, 10.6103/SHARE.w5.700, 10.6103/SHARE.w6.700). SHARE data collection has been funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N211909, SHARE-LEAP: GA N227822, SHARE M4: GA N261982), and Horizon 2020 (SHARE-DEV3: GA N676536, SERISS: GA N654221) and by DG Employment, Social Affairs & Inclusion. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C), and various national funding sources is gratefully acknowledged (see www.share-project.org).

yse healthcare utilisation by, among others, Bíró (2014), Bolin et al. (2009), Paccagnella et al. (2013), and Tavares & Zantomio (2017).

2.1 Sample Construction

The chair stand test, which we use to determine our measure of over- and underconfidence, is used only in SHARE Wave 2 (2006/2007) and Wave 5 (2013). Because we are assessing the relationship between this measure of confidence and healthcare utilisation in the next wave, our dependent variables, namely, annual number of doctor visits and concomitant OOP expenditures, are taken from the next waves, that is, Wave 4 (2010–2012)[2] and Wave 6 (2015) (Börsch-Supan 2019*b*,*c*). Hence, we treat the data as pooled cross-sections by matching individuals' misperception at Waves 2 and 5 (w) with their utilisation at Waves 4 and 6 ($w+1$), respectively.

Our dependent variables are taken from wave $w+1$, which is why we drop all observations that do not provide information on doctor visits at wave $w+1$. This affects mostly respondents who participated in Wave 2 but not in the subsequent Wave 4 or respondents who participated in Wave 5 but not in the subsequent Wave 6. We also exclude all respondents younger than 50 years and all observations based on proxy respondents. Overall, this results in 58,897 observations from 15 European countries, namely, Austria, Belgium, Czechia, Denmark, Estonia, France, Germany, Italy, Luxembourg, The Netherlands, Poland, Slovenia, Spain, Sweden, and Switzerland. The sample for OOP payments is smaller (41,868 observations), as OOP payments were not captured in Wave 4 (Section 2.2.2).

Based on their results on the chair stand test, we categorise individuals into three groups: those who achieve concordance (i.e. subjectively report having no problem standing up from the chair and objectively are able to or subjectively report having problems standing up from the chair and objectively are not able to), those who are overconfident (i.e., overestimate their health; subjectively report being able to stand up but objectively are unable to), and those who are underconfident (i.e., underestimate their health; subjectively report being unable to stand up but objectively are able to). With concordance as the reference category, the sample is split into two groups: those who are overconfident and those who are underconfident. Further details are provided in Section 2.3.

For the main analysis, health misperception is based on the chair stand variables, because they are binary and therefore clearly indicate whether an individual is unimpaired or im-

[2]SHARE Wave 3 focuses on people's life histories and thus is not utilised in our analyses.

paired. For robustness, we use additional measures of health perception based on subjective cognition and walking ability and their objective counterparts. We therefore add more waves to the analyses for robustness (Section 5.5).

2.2 Outcome Variables

In line with the literature, we use the annual number of doctor visits as a proxy for healthcare utilisation (see Bago d'Uva & Jones 2009, Bíró 2016*b*, Bolin et al. 2009, Lugo-Palacios & Gannon 2017, Tavares & Zantomio 2017, Zhang et al. 2018, among others). By analysing this number, we are able to capture the effects of health perception on public expenditures, as doctor visits are frequently subsidised by the public. In addition, doctor visits are good indicators of healthcare seeking in general and preventive healthcare and screenings in particular. In addition to doctor visits, we analyse annual OOP payments for doctor visits, which allows us to analyse the effects of health perception on private healthcare expenses.

2.2.1 Annual Doctor Visits

The annual number of doctor visits, emergency room visits, and outpatient clinic visits is ascertained by answers to the following question: "Now please think about the last 12 months. About how many times in total have you seen or talked to a medical doctor or qualified/ registered nurse about your health? Please exclude dentist visits and hospital stays, but include emergency room or outpatient clinic visits." The survey question is phrased almost identically in Waves 4 and 6; however, the words "or qualified/registered nurse" are excluded in Wave 4. For this and other reasons, we run separate estimations for each wave as a sensitivity analysis (Section 5.4).

The number of doctor visits is top-coded at 98 visits per year. On average, individuals in our sample visit the doctor seven times per year. The median, however, is lower (five times), which demonstrates the variable's strong right-skewness (Table 2). Naturally, individuals who suffer from chronic diseases or activity limitations visit the doctor more frequently than healthy individuals; thus, the number of doctor visits also increases with age. Gender differences in doctor visits are clear: Women have more annual doctor visits than men. A socioeconomic gradient is also observed with respect to education: The number of doctor visits decreases as education increases. It is interesting that individuals with supplementary insurance have fewer doctor visits than those without, a finding quite contrary to the literature, which predicts moral hazard with supplemental insurance (Coulson et al. 1995, Buchmueller et al. 2004) (see Table A.1 in the Appendix).

2.2.2 OOP expenditures for doctor visits

If participants report that they have seen or talked to a doctor, they are asked, "Did you pay anything yourself for your doctor visits (in the last twelve months)? Please also include expenses for diagnostic exams, such as imaging or laboratory diagnostics." If they answer "yes", they are then asked, "Overall, how much did you pay yourself for your doctor visits (in the last twelve months), that is how much did you pay without getting reimbursed by (a health insurance/ your national health system/ a third party payer)?" The amount of OOP payments is based on the latter question; it is set to zero if the respondent did not visit a doctor at all or if he or she claims zero payments for doctor visits. All values are presented in Euros. Implausibly large values are set to missing, as suggested by SHARE (Jürges 2015). This affects 3,006 observations.

OOP payments are available in Wave 6 but not in Wave 4; thus, we assess the association between health perception at Wave 5 (w) and OOP expenditures at Wave 6 ($w+1$) only. Consequently, the sample is smaller for analyses of OOP payments than those of doctor visits. Because potential deductibles include expenditures for not only doctor visits but also other healthcare services, such as dentist visits and hospital stays, we do not consider deductibles when calculating the OOP expenditures variable.

The mean OOP expenditure is 73 Euros per year. However, 61% of the participants have zero OOP payments at Wave 6; thus, the median is zero (Table 2). It is interesting that OOP payments do not increase with the number of chronic diseases or activity limitations, but educational attainment has a strong positive correlation with OOP expenditures. Furthermore, mean OOP payments vary substantially between countries: They are highest in Luxembourg, Switzerland, Italy, and Austria, reflecting differences in utilisation and/or cost-sharing mechanisms (Paccagnella et al. 2013) (see Table A.2 in the Appendix).

2.3 Explanatory Variable: Health Perception

Following the literature in psychology, our measure of misperception relates to the most common interpretation of over- and underconfidence, namely, over- and underestimating one's performance, actual ability, chance of success, or level of control (Moore & Healy 2008). Assuming an underlying true level of health, we group individuals according to their perception of their health status. More specifically, we differentiate among individuals who perceive their health status correctly (concordance), those who believe that they are healthier than they really are (overestimation), and those who believe that they are unhealthier than they really are (underestimation). The true level of health is proxied by objective perfor-

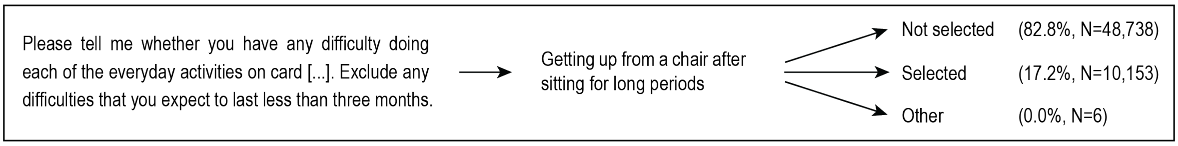


Figure 1: Survey question ascertaining subjective impairment (response category proportions in brackets)

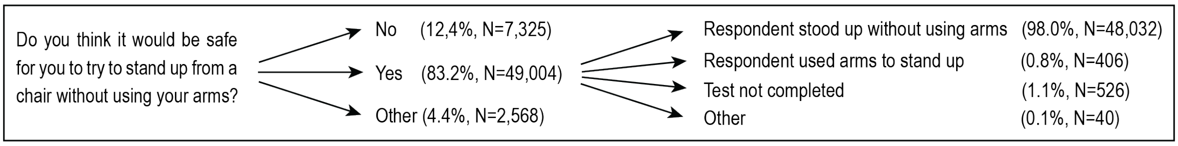


Figure 2: Sequence of questions ascertaining objective impairment (response category proportions in brackets)

mance measures data based on physical performance measures. This objective information about the respondent's health is matched with the respondent's subjective assessment of his or her health, thus revealing whether that individual's beliefs are correct or not.

SHARE provides several objective performance measures that can be utilised as proxies for true health. The measure most suited to analysing differences between objective and subjective health is the ability to stand up from a chair, as this self-assessed variable relates directly to its tested equivalent. This measure has been used previously in Spitzer & Weber (2019). In additional analyses, we also observe the differences between subjective and objective cognition as well as subjective and objective walking ability (Section 5.5).

To evaluate subjective ability to get up from a chair, survey participants are asked whether they have difficulties getting up from a chair. Figure 1 provides the detailed survey question. Individuals are considered subjectively impaired if they report difficulties getting up from a chair and subjectively unimpaired if they do not. Overall, 17.0% of the survey participants in our sample are considered subjectively impaired. Both the impaired and unimpaired groups are then subjected to the objective assessment.

In the objective assessment, individuals are asked to physically stand up from a chair.[3] The chair stand test is introduced with the interviewer saying, "The next test measures the strength and endurance in your legs. I would like you to fold your arms across your chest and sit so that your feet are on the floor; then stand up keeping your arms folded across your chest. Like this ..." The exact sequence of questions leading to the chair stand test is shown in Figure 2. Individuals are considered objectively unimpaired if they stand up

[3]It is important to note that the chair stand test in Wave 2 was only conducted among those younger than 76 years. Thus, the sample is younger than 76 for any country that participated only in Wave 2.

Table 1: Overview health perception categories

	Objectively			
Subjectively	Unimpaired		Impaired	
Unimpaired	Pos. concordance:	87.6%	Overestimating:	56.9%
Impaired	Underestimating:	12.4%	Neg. concordance:	43.1%
Total		**100.0%**		**100.0%**

Note: No weights applied

without using their arms and objectively impaired if they are not able to stand up from the chair, if they have to use their arms to stand up, or if they think it is unsafe to try to stand up from the chair.

Following the subjective report of impairment (i.e., unimpaired or impaired) and the subsequent objective test, individuals can either achieve concordance, overestimate their own health, or underestimate their own health. If they subjectively report being unimpaired but are objectively impaired, they overestimate their health. Likewise, if they subjectively report being impaired but are objectively unimpaired, they underestimate their health. Although the categorisation of over- and underestimation is straightforward, the categorisation of concordance (i.e., accurate beliefs about their health status) requires further consideration. Given true (objective) health, it is important to distinguish between two types of concordance. Individuals with a poor health status (i.e., objectively impaired) are classified as "negative concordance" if they also subjectively report being impaired. Likewise, individuals with a good health status(i.e., objectively unimpaired) are classified as "positive concordance" if they also subjectively report being unimpaired. The four health perception outcomes are shown in Table 1.

Distinguishing between the two types of concordance ensures that we use the appropriate reference category for over- and underestimation in regression analyses. Overestimation can only be measured in the group whose objective health is impaired yet who subjectively report being unimpaired. Therefore, an appropriate group of individuals to compare to are those who are also objectively impaired (i.e., negative concordance). Underestimation can only be measured in the group whose objective health is unimpaired yet subjectively report impaired. The appropriate comparator for these individuals is the group that is also objectively unimpaired. This separation of the concordance group also provides an important empirical advantage; it ensures that we compare like with like in terms of true initial health thereby ridding ourselves of an important source of endogeneity, namely variation in health that can determine utilisation.

Table 2: Summary statistics

	N	Mean	Std. Dev.	Min.	Max.	Median
Healthcare utilisation						
Annual number of doctor visits at w+1	58,764	7.332	9.423	0	98	5
Annual out-of-pocket expenditure for doctor visits at w+1	39,988	73.349	298.196	0	47,500	0
Health perception						
Positive concordance (1 = yes)	56,152	0.743	0.437	0	1	1
Underestimating (1 = yes)	56,152	0.101	0.302	0	1	0
Negative concordance (1 = yes)	56,152	0.060	0.237	0	1	0
Overestimating (1 = yes)	56,152	0.096	0.295	0	1	0
Impairment						
Subjective impairment (1 = impaired)	58,758	0.170	0.376	0	1	0
Objective impairment (1 = impaired)	56,157	0.156	0.363	0	1	0
Health variables						
Number of chronic diseases at w	58,702	1.145	1.217	0	10	1
Number of chronic diseases at w+1	58,754	1.207	1.231	0	9	1
Number of activity limitations at w	58,755	0.357	1.177	0	13	0
Number of activity limitations at w+1	58,752	0.490	1.451	0	13	0
Control variables						
Age (in number of years)	58,764	64.521	9.765	50	100	63
Gender (1 = female)	58,764	0.545	0.498	0	1	1
Low education (1 = yes)	57,979	0.430	0.495	0	1	0
Medium education (1 = yes)	57,979	0.369	0.483	0	1	0
High education (1 = yes)	57,979	0.201	0.401	0	1	0
Is retired (1 = yes)	58,471	0.509	0.500	0	1	1
Is married (1 = yes)	56,883	0.680	0.466	0	1	1
Household income (in Euros per year)	58,764	46,569.89	76,244.77	0	1,200,000	24,000
Health access (1 = difficult)	39,120	0.163	0.370	0	1	0

Note: Calibrated cross-sectional individual weights are applied. For more detailed cross-tabulations see Tables A.1 to A.3 in the Appendix.

As shown in Table 1, in the objectively impaired group, 57% overestimate their health status; in the unimpaired group, only 12% underestimate. The large number of people reporting overconfidence is not surprising, as it has been documented in psychology and evolutionary theory as being favoured by natural selection and providing adaptive gains. Individuals tend to be overconfident because it increases morale and ambition and may thus improve potential (Johnson & Fowler 2011). Furthermore, our sample consists of older people, among whom overconfidence is particularly prevalent (Idler 1993, Spitzer & Weber 2019) and is seen as a resilience strategy to maintain a positive self-image (Brandtstädter & Greve 1994).

2.4 Additional Control Variables

We control for a range of variables that might otherwise confound our results. Summary statistics for these control variables are provided in Table 2, and cross-tabulations of control variables, doctor visits, health expenditures, and health perception are provided in Tables A.1 to A.3 in the Appendix. Most important, we control for other health factors at wave

w. In particular, we include the number of chronic diseases and the number of limitations in instrumental activities of daily living (IADLs) in our model. Chronic conditions that we consider are heart problems, high blood pressure or hypertension, high blood cholesterol, stroke or cerebral vascular disease, diabetes, chronic lung diseases, cancer, stomach or duodenal ulcer, Parkinson's disease, cataracts, hip fractures, other fractures, and Alzheimer's disease. A total of 35% of the sample have no chronic diseases at wave w; the weighted mean is 1.2 diseases. IADLs that we consider are difficulties dressing, walking across a room, bathing or showering, eating and cutting up food, getting in or out of bed, using the toilet, using a map, preparing a hot meal, shopping for groceries, making a telephone call, taking medications, doing work around the house or garden, and managing money. A total of 81% of the sample have no IADLs at wave w; the weighted mean is 0.5 IADLs. We only consider chronic diseases and IADLs that are included in both Wave 2 and Wave 5.

We also control for sociodemographic characteristics, as they are expected to influence health perception as well as healthcare utilisation (Avitabile et al. 2011, Lange 2011). In particular, we include age and age squared, gender, and educational attainment according to the International Standard Classification of Education (Eurostat 2018). Because pensioners appear to have higher healthcare utilisation (Bíró 2016*b*, Zhang et al. 2018), we also consider whether an individual is retired as opposed to all other employment options (employed, self-employed, unemployed, permanently sick or disabled, homemaker, other). Also, we control for whether the survey participant is married or in a registered partnership as opposed to never married, divorced, or widowed.

The effects of economic resources on healthcare utilisation are considered via equivalised household income. Because there are many missing values for household income in SHARE, the data set comes with two additional imputed variables. We use one of these imputed variables in our model and conduct a robustness analysis with the other (Section 5.4). We equivalise household income by using the square root scale, in which household income is divided by the square root of household size. Using the Organisation for Economic Cooperation and Development equivalence scale is not feasible, as children cannot be identified unambiguously. Furthermore, we use a cube root transformation to normalise the skewed income distribution (Cox 2011). Standard log normalisation is not feasible because of the substantial number of zero values.[4] We run a robustness analysis in which we use equivalised household income that was not normalised (Section 5.4).

[4]Results are robust to dropping observations with zero values in household income.

3 Method

Ideally, we would randomly assign health perception to individuals to elicit causal effects of (mis)perception on healthcare utilisation and expenditures. In the absence of such random assignment, we rely on the panel dimension of the SHARE survey and control for a rich set of variables to account for confounding effects and bias due to reverse causation. Health perception is expected to affect healthcare utilisation, but the opposite mechanism, that healthcare utilisation precedes health perception, appears plausible too. For example, individuals who frequently visit the doctor are more likely to achieve concordance, as they receive more information about their health status. To overcome potential endogeneity, we analyse the effects of current health perception (wave w) on future healthcare utilisation (wave $w + 1$).

The main outcome variable—annual doctor visits—is strongly skewed to the right, yet without severe mass at zero. To accommodate this, we use a negative binomial model with mean dispersion, which is used frequently in the healthcare literature. We refrain from using a simple Poisson model, as the variance in the outcome variable is much larger than its mean. However, we perform robustness analyses using different models (Section 5.4). Thus, the number of doctor visits of individual i at wave $w + 1$ ($\text{DOCTOR}_{i,w+1}$) is assumed to follow a Poisson distribution but with a negative binomial specification for which each individual unit has a separate, Gamma-distributed mean. More specifically,

$$\text{DOCTOR}_{i,w+1} \sim \text{Poisson}(\mu_{i,w+1}), \tag{1}$$

where

$$\mu_{i,w+1} = \exp(\beta \times \text{HEALTH PERCEPTION}_{i,w} + \gamma \times \text{HEALTH}_{i,w} + \delta \times \text{X}_{i,w} + \nu_i), \tag{2}$$

and

$$\exp(\nu_i) \sim \text{Gamma}(1/\alpha, \alpha) \tag{3}$$

HEALTH PERCEPTION is a binary variable that indicates whether individual i achieves concordance or misperceives his or her health at wave w. The vector HEALTH includes two variables, namely the number of chronic diseases in period w as well as the number of

IADLs in period w (thus, in the same period as health perception). The vector of control variables $X_{i,w}$ includes age and age squared, the individual's gender, educational attainment, household income, and control dummies for the survey wave as well as for the country of residence. The terms β, γ, and δ represent coefficients.

As discussed earlier, the sample is split into individuals who are overconfident (i.e., overestimate their health status) and individuals who are underconfident (i.e., underestimate it). The regression coefficients are therefore interpreted relative to those who estimate their health correctly (i.e., achieve concordance). For heterogeneity analyses, we further split the sample by gender, country, and number of chronic diseases.

When analysing the effects of health perception on OOP expenditures, we use a nonlinear model with a log link and Gamma family instead of the negative binomial model to account for the continuous nature of the outcome variable as well as for the excess zeros (Deb & Norton 2018). The specification of the variables included, however, remains identical to that described in Equation 2.

A total of 32% of the survey respondents participate in Waves 2, 4, 5, and 6, which allows us to analyse how health perception varies between Wave 2 and Wave 5 for these observations. For the majority (75%), health perception does not vary with age. If health perception changes, the most common changes are from underestimating to concordance (7.6%), from concordance to overestimating (6.5%), and from concordance to underestimating (5.6%). Because there is not enough variation in health perception within individuals, we refrain from using individual fixed effects in our analyses.

In Section 5.5, we explore whether our results are robust to different specifications of health perception. In particular, we estimate Equation 2 using cognition and the ability to walk as bases for the health perception variable.

4 Results

We first present the main results for the link between health misperception and healthcare utilisation and expenditures. We then examine heterogeneity in the relationships and present the results of important robustness analyses. Finally, we provide results for alternative measures of health perception bias.

4.1 Main Results

Table 3: Annual number of doctor visits and OOP expenditures for doctor visits at w+1

	(1) Objectively Unimpaired Doctor visits	(2) Objectively Unimpaired OOP	(3) Objectively Impaired Doctor visits	(4) Objectively Impaired OOP
Health perception (ref.: concordance)				
Underestimating	0.244***	0.166*		
	(0.018)	(0.077)		
Overestimating			-0.146***	-0.378**
			(0.029)	(0.138)
Chronic diseases	0.181***	0.118***	0.149***	0.118*
	(0.005)	(0.031)	(0.009)	(0.055)
Activity limitations	0.096***	0.088	0.048***	0.031
	(0.010)	(0.045)	(0.007)	(0.030)
Age	-0.001	0.082	0.021	0.165*
	(0.011)	(0.058)	(0.018)	(0.082)
Age squared	0.000	-0.001	-0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.001)
Woman	0.042***	0.125*	0.014	0.422***
	(0.013)	(0.060)	(0.028)	(0.117)
Educ. group (ref.: low)				
Medium	0.006	0.419***	-0.006	0.112
	(0.016)	(0.072)	(0.033)	(0.126)
High	-0.003	0.881***	-0.087*	0.544***
	(0.018)	(0.093)	(0.042)	(0.152)
Retired	0.029	-0.031	0.014	0.398
	(0.017)	(0.104)	(0.033)	(0.228)
Married	-0.034*	0.029	0.019	0.405***
	(0.015)	(0.072)	(0.030)	(0.115)
Equiv. hh income (cube root)	-0.001	0.014***	-0.001	0.006
	(0.001)	(0.003)	(0.002)	(0.007)
Wave 5	-0.089***		-0.046	
	(0.015)		(0.038)	
Constant	1.507***	0.626	1.434*	-1.232
	(0.356)	(1.963)	(0.646)	(2.828)
Country dummies	Yes	Yes	Yes	Yes
N	46,067	32,564	7,801	5,603
AIC	260,957	297,483	50,545	50,035
BIC	261,202	297,684	50,740	50,194

Note: "Unimpaired" refers to the sample that is objectively unimpaired, i.e. able to stand up from the chair and "Impaired" refers to the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave w+1, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. The dependent variable "OOP" is based on annual out-of-pocket payments for doctor visits at wave w+1, i.e. Wave 6. All explanatory variables are taken from wave w, i.e. Wave 5. The coefficients are estimated based on a generalised linear model model with log link and a Gamma family. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

4.1.1 Healthcare Utilisation

Healthcare utilisation is measured by the annual number of doctor visits. Table A.1 of the Appendix shows that overall, individuals who overestimate their health have fewer doctor visits (8.6 visits) compared to their reference group (i.e., negative concordance = 11.9 visits). Similarly, those who underestimate their health have significantly more doctor visits in a year (10.1 visits) compared to their relevant reference group (i.e., positive concordance = 6.2 visits).

The table also shows cross-tabulations by other characteristics of the sample. Using number of chronic conditions and activity limitations as proxies for doctor visits provides two important insights. First, we find that as illness increases, so does the number of doctor visits irrespective of the category of perception bias. Second, at every level of illness, individuals who underestimate their health visit the doctor more often than those who are concordant. Similarly, overall, at almost each level of health (barring a few exceptions), individuals who overestimate their health visit the doctor less often. This shows that despite the same underlying health status, there is variation in doctor visits by health misperception category. Starkly similar results are observed for increasing age.

Although the picture is somewhat mixed across education categories, we observe fewer doctor visits for overestimators relative to their concordant counterparts at every level of education. Similarly, underestimators have higher healthcare utilisation than their concordant counterparts at each level of education. Accessibility to health professionals strongly determines health access; the pattern of utilisation across this variable by our misperception category remains the same as before: Overestimation shows fewer doctor visits, and underestimation shows more visits. Similar results are observed by supplementary insurance status.

These descriptive findings show that despite conditioning on individual characteristics, there is clear variation in healthcare utilisation in the form of doctor visits among the different health perception categories. In the regression analyses, we control for these and other variables such as country dummies. Table 3 shows the regression results. Columns 1 and 3 show the results for the two groups (i.e., overestimators and underestimators categorised based on the objective health status as impaired or unimpaired). All coefficients are to be interpreted relative to the concordance category.

We find a strong and significant association between health misperception and healthcare utilisation. Individuals who underestimate their health visit the doctor 27.6% more often in the subsequent period than individuals who achieve concordance. Computing marginal effects at means shows that this results in approximately two additional doctor visits per year.

We also find a strong and significant link between overestimation and the annual number of doctor visits. Individuals who overestimate their health go to the doctor less often than those who achieve concordance. Overestimating health at wave w results in 13.6% fewer doctor visits at wave $w + 1$ compared to perceiving one's health correctly. The marginal effect at means of overestimating health on healthcare utilisation is approximately 1.3 fewer doctor visits per year.

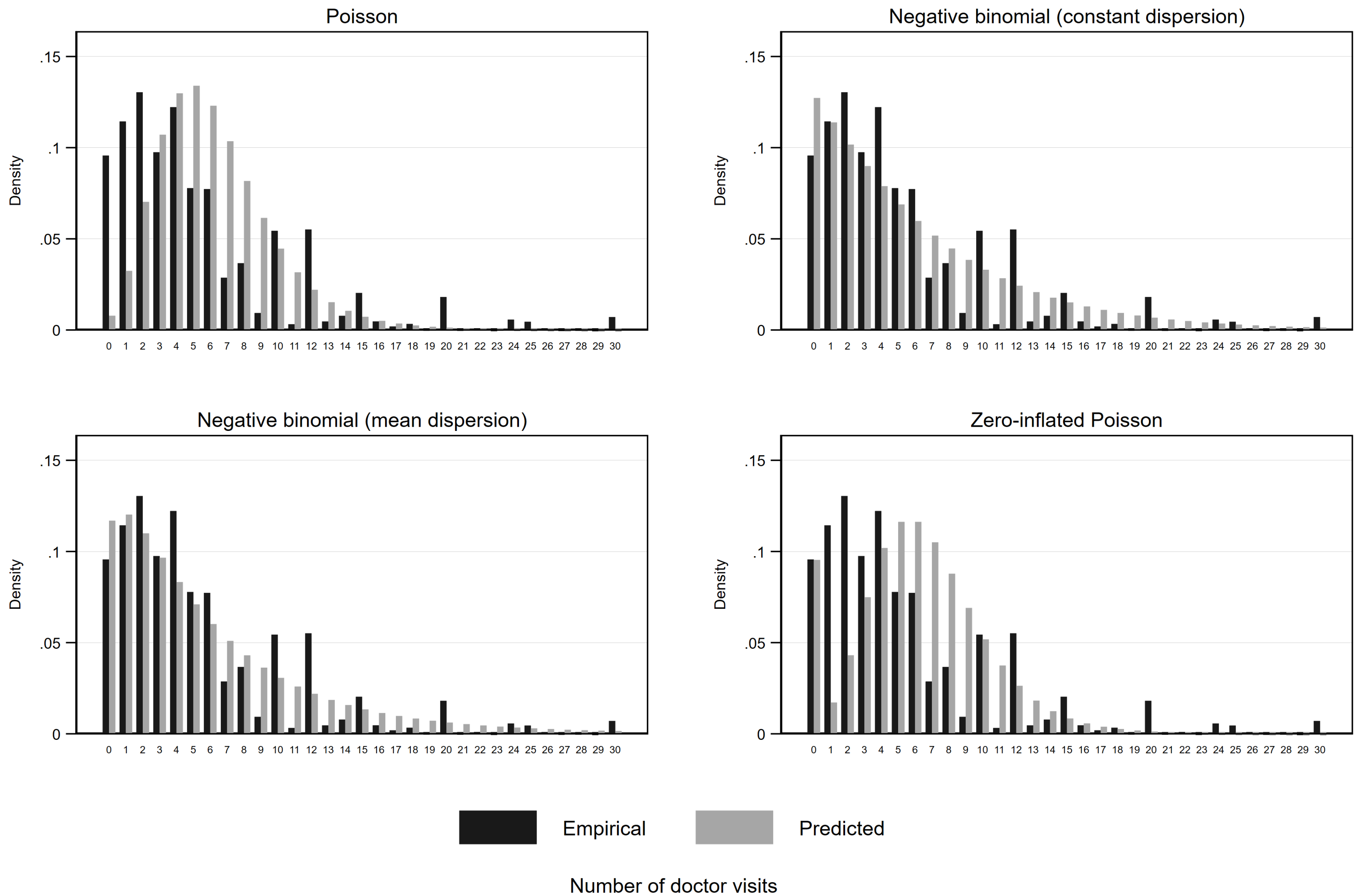
The results for doctor visits in Table 3 are based on a negative binomial model with mean dispersion. Figures 3 and 4 show that this model has the best fit among a simple Poisson model, a negative binomial model with constant dispersion, and a zero-inflated Poisson model.

4.1.2 OOP Expenditures

Individuals who visit a doctor also report OOP expenses, if any, measured in Euros. Table A.2 shows descriptive cross-tabulations of OOP expenditures incurred by other individual characteristics and by misperception category. Although no consistent pattern in OOP spending emerges by the number of chronic conditions, number of activity limitations, or increasing age, women show slightly higher expenditures than men. A clear education gradient is also observed in OOP spending, with higher education relating positively to spending. Similarly, retired individuals spend more than those who are not retired, as do married individuals compared to single ones. It is not surprising that in general individuals with supplementary insurance spend slightly less than those without it, and those with difficulty accessing healthcare spend less than those with no difficulty. Certain countries, such as Switzerland, Luxembourg, and Italy, show exceptionally high OOP expenditures, whereas others, such as France, Denmark, and Eastern European countries, show much lower OOP expenditures, which partly reflects institutional differences in user charges and the coverage of certain services.

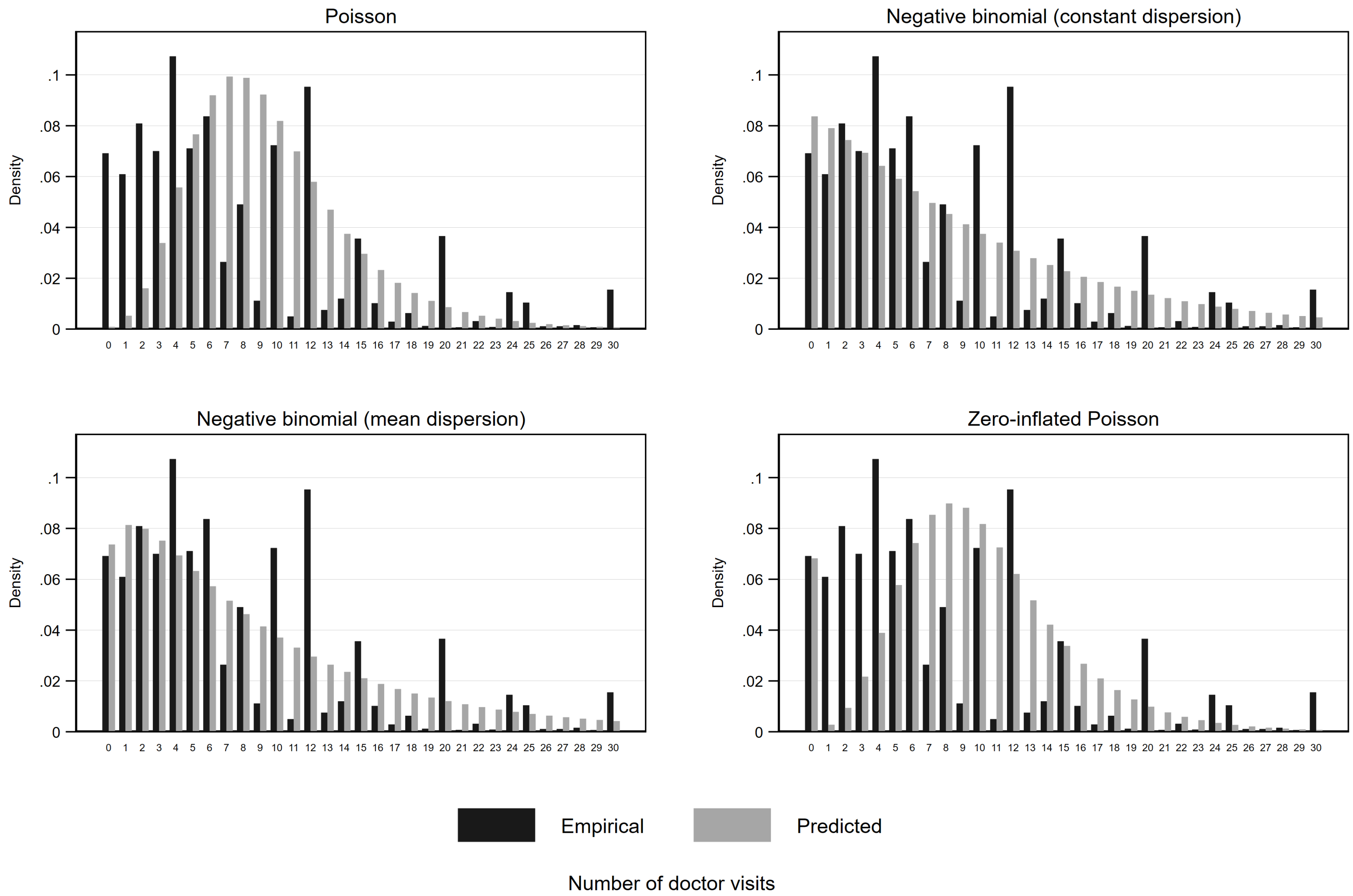
It is interesting that we observe similar patterns as for doctor visits across the misperception categories. At almost every level of chronic conditions, activity limitations, and increasing age, we find that those who underestimate their health have higher OOP spending than those who achieve concordance. The findings for overestimation are somewhat mixed. Underestimating men (women) have slightly lower (much higher) OOP spending than their concordant counterparts. Overestimating men (women) also have slightly lower (higher) OOP spending than their concordant counterparts. Although an education gradient can be seen for underestimators with higher OOP spending compared to the concordant group at

Figure 3: Count model comparison for the annual number of doctor visits in the unimpaired sample, i.e. able to stand up from the chair



Note: Doctor visits are top coded at 98 visits by year. This figure shows only the first 30 doctor visits for better visualisation. Dark bars represent the empirically observed numbers of doctor visits and light bars represent the predicted values based on the respective count model.

Figure 4: Count model comparison for the annual number of doctor visits in the impaired sample, i.e. unable to stand up from the chair



Note: Doctor visits are top coded at 98 visits by year. This figure shows only the first 30 doctor visits for better visualisation. Dark bars represent the empirically observed numbers of doctor visits and light bars represent the predicted values based on the respective count model.

each level of education, the same is not observed consistently for overestimators in the case of lower spending. Although underestimators consistently spend more OOP across the other individual characteristics, mixed findings are seen for overestimators. Regression results controlling for these characteristics in Columns 2 and 4 of Table 3 show that individuals who underestimate their health have significantly higher OOP expenses. On average, expenditures are 16.6% higher for those who underestimate their health compared to those who achieve concordance. In contrast, individuals who overestimate their health spend 37.8% less in OOP expenditures per year relative to their concordant group.

The results for OOP payments are based on a log-Gamma model. According to Akaike's information criterion and the Bayesian information criterion, the log-Gamma model has a better fit than either a log-Gaussian model or a log-Poisson model.

4.2 Heterogeneity of effects

We assess the heterogeneity of our main results in several ways. In particular, we consider gender differences, country specificities, and differences by health status.

4.2.1 Gender Differences

The literature has shown differences in health perception by individual characteristics, most important by gender (Merrill et al. 1997, Schneider et al. 2012). Gender differences in effects of health beliefs on healthcare utilisation may partly explain the well-documented differences in healthcare seeking between men and women, as men tend to have lower healthcare use (Galdas et al. 2005, Mansfield et al. 2003, Schlichthorst et al. 2016). Thus, we assess whether the relationship between health (mis)perception and utilisation also differs between men and women. As noted earlier, Table A.1 shows that, overall, women have slightly more doctor visits annually compared to men; this is true also within the misperception category, but the difference is not large. Furthermore, both under- and overestimating men and women have more doctor visits relative to their respective concordant comparators. In the case of OOP expenditures, however, whereas both under- and overestimating women have higher spending relative to their concordant group, both under- and overestimating men have lower spending relative to their concordant group. However, under- and overestimating women tend to spend more than under- or overestimating men.

Regression analyses by gender reveal that the association between health misperception and the annual number of doctor visits is slightly larger in magnitude for men than for women (Table 4). Marginal effects at means show that men who underestimate their health visit the doctor an additional 1.8 times compared to men who achieve concordance. For women, the difference is an additional 1.5 doctor visits. Men who overestimate their health have 1.5 fewer annual doctor visits compared to men who achieve concordance. For women, it is 1.3 fewer visits. A Wald test, however, reveals that the coefficients for women and men are not statistically different from each other.

4.2.2 Country Specificity

Differences in reporting behaviour by country are well documented (Capistrant et al. 2014, Jürges 2007, Spitzer & Weber 2019). To ensure that our findings are not driven by differential reporting due to cultural biases in reporting health or the oversampling of certain countries in the SHARE survey, we rerun our analyses for each country separately. By and large, we find similar results for all countries, for both under- and overestimation, with the exception of a few countries for which we do not find statistically significant results because of small sample sizes (see Tables A.4 and A.5 in the Appendix). However, it is worth noting that the magnitude of the coefficient for underestimation is much larger in certain countries, such as Denmark, Germany, and The Netherlands, than in others, perhaps reflecting differences in accessibility or other institutional differences in terms of, for example, user charges.

4.2.3 Differences by Health Status

Separating the underestimators and overestimators by objective health status allows us to overcome an important endogeneity concern related to initial health status that affects both health perception and healthcare utilisation. However, because we assess healthcare utilisation at $w+1$, we also assess heterogeneity by health status at $w+1$, which allows us to understand whether current health status drives differential utilisation in any way. Note that current utilisation at $w+1$ will not drive health misperception because we assess misperception at w.

The descriptive statistics in Table A.3 in the Appendix indicate a slight decrease in concordance as the number of chronic diseases increases; however, this trend is far from obvious and might also be due to the correlation between health and age. To disentangle these effects, we run separate regressions for those individuals who do not have any chronic diseases at wave $w+1$ (healthy) and those who report one or more chronic diseases at wave $w+1$ (unhealthy). The results are reported in Table 5. Although health perception affects the doctor visits of impaired individuals with and without chronic diseases similarly, underestimation has a bigger effect on those without chronic diseases than on those with chronic diseases—this is confirmed by a Wald test. However, marginal effects reveal no substantial difference between the healthy and the unhealthy subsamples with respect to the relationship between over- or underestimation and doctor visits. Because we categorise based on

Table 4: Annual number of doctor visits at $w + 1$ by gender

	(1) Objectively Unimpaired Men Doctor visits	(2) Objectively Impaired Men Doctor visits	(3) Objectively Unimpaired Women Doctor visits	(4) Objectively Impaired Women Doctor visits
Health perception (ref.: concordance)				
Underestimating	0.267***		0.229***	
	(0.035)		(0.021)	
Overestimating		-0.139**		-0.136***
		(0.048)		(0.034)
Chronic diseases	0.191***	0.168***	0.176***	0.143***
	(0.008)	(0.014)	(0.007)	(0.012)
Activity limitations	0.096***	0.045***	0.096***	0.050***
	(0.018)	(0.012)	(0.011)	(0.008)
Age	0.018	0.038	-0.008	0.014
	(0.017)	(0.031)	(0.013)	(0.022)
Age squared	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Educ. group (ref.: low)				
Medium	0.042	-0.074	-0.027	0.044
	(0.026)	(0.052)	(0.020)	(0.041)
High	0.017	-0.151*	-0.024	-0.055
	(0.029)	(0.061)	(0.024)	(0.057)
Retired	0.031	0.075	0.026	-0.026
	(0.031)	(0.067)	(0.021)	(0.040)
Married	-0.045	0.032	-0.047*	-0.007
	(0.025)	(0.055)	(0.018)	(0.036)
Equiv. hh income (cube root)	-0.001	0.000	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Wave 5	-0.116***	0.090	-0.066***	-0.124**
	(0.022)	(0.058)	(0.019)	(0.047)
Constant	0.654	0.604	1.983***	1.858*
	(0.583)	(1.059)	(0.441)	(0.788)
Country dummies	Yes	Yes	Yes	Yes
N	20,693	2,864	25,374	4,937
AIC	116,397	18,426	144,362	32,072
BIC	116,611	18,587	144,582	32,248

Note: "Unimpaired" refers to the sample that is objectively unimpaired, i.e. able to stand up from the chair and "Impaired" refers to the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w + 1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

health (in other words, fix health at the same level) we can conclude that the results are not driven by health differences: Both the healthy group's and the unhealthy group's healthcare utilisation is affected by their health perception in the same direction and to a similar magnitude.

Table 5: Annual number of doctor visits at $w+1$ by chronic diseases at $w+1$

	(1) Objectively Unimpaired No chronic dis. at w+1	(2) Objectively Unimpaired Chronic dis. at w+1	(3) Objectively Impaired No chronic dis. at w+1	(4) Objectively Impaired Chronic dis. at w+1
Health perception (ref.: concordance)				
Underestimating	0.351***	0.197***		
	(0.042)	(0.020)		
Overestimating			-0.259***	-0.116***
			(0.066)	(0.031)
Chronic diseases	0.185***	0.093***	0.108***	0.106***
	(0.015)	(0.006)	(0.029)	(0.010)
Activity limitations	0.142***	0.087***	0.073***	0.045***
	(0.025)	(0.010)	(0.015)	(0.007)
Age	-0.027	-0.028*	-0.019	0.006
	(0.018)	(0.012)	(0.039)	(0.020)
Age squared	0.000*	0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.155***	0.008	0.116	-0.002
	(0.024)	(0.014)	(0.063)	(0.031)
Educ. group (ref.: low)				
Medium	0.022	0.018	0.023	-0.002
	(0.030)	(0.018)	(0.075)	(0.035)
High	0.066	-0.000	0.014	-0.071
	(0.034)	(0.021)	(0.083)	(0.047)
Retired	0.023	0.020	0.094	-0.005
	(0.034)	(0.019)	(0.076)	(0.035)
Married	-0.033	-0.034*	-0.003	0.036
	(0.027)	(0.017)	(0.075)	(0.031)
Equiv. hh income (cube root)	0.002	-0.002*	0.004	-0.001
	(0.001)	(0.001)	(0.003)	(0.002)
Wave 5	-0.046	-0.067***	-0.145	-0.001
	(0.027)	(0.017)	(0.074)	(0.042)
Constant	1.835**	2.821***	1.590	2.320***
	(0.614)	(0.419)	(1.348)	(0.704)
Country dummies	Yes	Yes	Yes	Yes
N	17,362	28,696	1,827	5,973
AIC	84,631	173,306	10,120	40,020
BIC	84,849	173,537	10,274	40,207

Note: "Unimpaired" refers to the sample that is objectively unimpaired, i.e. able to stand up from the chair and "Impaired" refers to the sample that is objectively impaired, i.e. unable to stand up from the chair. The sample "No chronic dis. at $w+1$" includes those that have zero chronic diseases at wave $w+1$, whereas "Chronic dis. at $w+1$" refers to those that have one ore more chronic diseases at wave $w+1$. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w+1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

5 Robustness Tests

We conduct a range of robustness analyses to observe whether our results are sensitive to model specifications and sample composition. These results are presented in Tables A.6 and A.7 in the Appendix along with the original model specification (Column 1).

5.1 Income

First, we utilise different income variables. We exchange the first imputed income variable provided by SHARE with the second imputed income variable (Column 2), and we use income that is not normalised with the cube root method but only equivalised (Column 3). These adjustments have no effects on the results. We also replace income with wealth (Column 4), and the results remain robust.

5.2 Wave Specific Analyses

Second, we separate the sample by survey wave to explore whether the slight change in the phrasing of the survey question about doctor visits in Wave 6 (Section 2.2.1), the restriction of the chair stand test to those younger than 76 years in Wave 2 (Section 2.3), or the different time gaps between w and $w+1$ affect the results. The estimates in Table A.9 in the Appendix reveal that the effect of health misperception on healthcare utilisation is slightly stronger at Wave 5 than at Wave 2; however, the difference is not statistically significant according to a Wald test.

5.3 Response Reliability

Third, we exclude anyone diagnosed with Alzheimer's disease, dementia, or another serious memory impairment, as their survey answers might not be reliable (Column 5). The results remain robust, perhaps because the number of individuals observations with severe cognitive impairments in the survey is small.

5.4 Robustness to Further Controls

Finally, we conduct robustness analyses that are only possible for Wave 5, as they include variables only collected in this wave (see Table A.8 in the Appendix). First, we analyse whether differences in access to healthcare affect the number of doctor visits. For this, the household respondent is asked "How easy is it to get to your general practitioner or the nearest health center? Would you say it is very easy, easy, difficult or very difficult?" We dichotomise the variable by comparing the first two and the last two possible answers and add it to the model (Columns 2 and 5). The coefficients show, however, that the results do not depend on access to healthcare. Second, we investigate whether the results are robust to individuals purchasing supplementary health insurance. Although supplementary insurance increases healthcare utilisation (Moreira & Barros Pita 2010, Paccagnella et al. 2013), we find no significant changes in our results (Column 6) when controlling for this variable.

5.5 Additional Measures of Health Perception

For the main analyses, health perception is operationalised based on tested and self-reported ability to stand up from a chair. We also analyse whether the results hold for other health dimensions, in particular health perception concerning cognition and walking ability.

5.5.1 Cognition

Similar to previous work, we use the difference between subjective and objective cognition as an additional measure of health perception (Spitzer & Weber 2019). Objective cognition is operationalised based on a memory test, which is conducted in Waves 4 to 6. In particular, individuals are asked to recall a list of 10 words in any order within a minute.

Subjective cognition is based on the question "How would you rate your memory at the present time?" which is answered on a Likert scale with the categories excellent, very good, good, fair, and poor. Because the subjective cognition variable has more than 80% missing values in Wave 6, we only utilise data from Waves 4 and 5. Hence, the estimates for cognition are based on a different sample. For the main results presented in Section 4, health perception from Waves 2 and 5 is matched with healthcare utilisation from Waves 4 and 6. For the results for cognition, health perception from Waves 4 and 5 is matched with healthcare utilisation from Waves 5 and 6.

Defining cognitive impairment is not as straightforward as defining the ability to stand up from a chair. Whereas the chair stand variables are binary and therefore clearly indicate whether an individual is impaired, both the subjective and objective cognition variables are categorical. Thus, we rely on previous literature to define the threshold marking cognitive impairment. Participants are considered objectively impaired if they recall three words or fewer (Grodstein et al. 2001, Purser et al. 2005). In addition, in robustness analyses, individuals are considered impaired if they recall two words or fewer. Individuals are considered subjectively impaired if they report having a fair or poor memory (Gardner et al. 2017).

Tables 6 provides regression results for this new specification of health perception. The results confirm our earlier findings. Individuals who underestimate their cognitive ability at wave w are more likely to visit the doctor at wave $w+1$ than individuals who achieve concordance between objective and subjective measures of memory. By contrast, survey participants who overestimate their health have fewer annual doctor visits than those who achieve concordance. Modifying the threshold for objective impairment from three to two words changes the magnitude of the coefficient for overestimation but not its sign. The magnitude of the coefficient for overestimation remains virtually identical.

5.5.2 Walking Ability

We also operationalise health perception based on walking ability. Objective walking ability is based on a walking speed test in which participants have to walk a distance of 2.5 m. Individuals are considered objectively impaired if their walking speed is 0.4 m per second or slower. This threshold is in line with the previous literature (Jürges 2007, Steel et al. 2003). Because the test is only conducted in Waves 1 and 2, the analysis is restricted to those waves (Börsch-Supan 2019*a*). The walking speed test is supposed to be conducted only for individuals older than 75 years. However, the data set includes information for those 75 and younger too. The variable has many missing values (∼90%) and thus needs to be handled with caution.

Subjective walking impairment is based on the following question: "Please look at card [...]. We need to understand difficulties people may have with various activities because of a health or physical problem. Please tell me whether you have any difficulty doing each of the everyday activities on card [...]. Exclude any difficulties that you expect to last less than three months." Participants are coded as having subjectively impaired walking ability if they report difficulty walking 100 m.

When analysing health perception based on walking ability, we do not control for IADLs, as the ability to walk across a room is itself considered an IADL. Also, the second imputed income variable is used for this analysis, as the first one is not available in Wave 1. The robustness analysis in Section 5.4 shows, however, that both variables produce the same results.

Results for the effects of health perception on the annual number of doctor visits based on walking ability are provided in Table 7. The coefficients in Table 7 confirm once again that individuals who underestimate their health have more annual doctor visits than those who assess their health correctly. The results also show that those who overestimate their health have fewer doctor visits. Thus, our results are robust to different specifications of health perception.

Table 6: Health perception based on cognition

	(1) Objectively Unimpaired 3 words	(2) Objectively Impaired 3 words	(3) Objectively Unimpaired 2 words	(4) Objectively Impaired 2 words
Health perception (ref.: concordance)				
Underestimating	0.079***			
	(0.013)			
Overestimating		-0.067*		
		(0.027)		
Underestimating			0.077***	
			(0.012)	
Overestimating				-0.145***
				(0.042)
Chronic diseases	0.194***	0.143***	0.189***	0.147***
	(0.004)	(0.009)	(0.004)	(0.014)
Activity limitations	0.114***	0.057***	0.106***	0.045***
	(0.005)	(0.007)	(0.005)	(0.009)
Age	0.013	0.042*	0.017*	0.055
	(0.009)	(0.021)	(0.008)	(0.031)
Age squared	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.078***	-0.003	0.072***	-0.043
	(0.011)	(0.029)	(0.011)	(0.045)
Educ. group (ref.: low)				
Medium	0.006	0.074*	0.010	0.013
	(0.014)	(0.037)	(0.013)	(0.056)
High	0.013	0.016	0.008	0.026
	(0.016)	(0.059)	(0.016)	(0.100)
Retired	0.033*	-0.046	0.022	0.010
	(0.016)	(0.035)	(0.015)	(0.052)
Married	-0.025	-0.035	-0.028*	-0.030
	(0.013)	(0.031)	(0.012)	(0.045)
Equiv. hh income (cube root)	-0.001*	-0.000	-0.001*	-0.003
	(0.001)	(0.002)	(0.001)	(0.002)
Wave 5	-0.037***	-0.054*	-0.036***	-0.100*
	(0.010)	(0.026)	(0.010)	(0.040)
Constant	1.086***	0.406	0.937**	0.245
	(0.302)	(0.750)	(0.287)	(1.114)
Control variables country	Yes	Yes	Yes	Yes
N	64,609	9,091	70,122	3,578
AIC	373,563	55,873	407,761	21,793
BIC	373,808	56,065	408,008	21,960

Note: In columns 1 and 2, individuals are considered objectively impaired if they recall 3 words or less ("3 words"), while in columns 3 and 4 the cutoff is at 2 words or less ("2 words"). The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w + 1$, i.e. Wave 5 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 4 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 7: Health perception based on walking ability

	(1) Objectively Unimpaired	(2) Objectively Impaired
Health perception (ref.: concordance)		
Underestimating	0.249**	
	(0.090)	
Overestimating		-0.328*
		(0.150)
Chronic diseases	0.129***	0.012
	(0.020)	(0.061)
Age	0.152*	0.337**
	(0.061)	(0.128)
Age squared	-0.001*	-0.002**
	(0.000)	(0.001)
Woman	-0.186**	-0.185
	(0.066)	(0.149)
Educ. group (ref.: low)		
Medium	0.189*	-0.041
	(0.075)	(0.203)
High	0.097	-0.235
	(0.088)	(0.239)
Retired	-0.040	-0.202
	(0.085)	(0.178)
Married	-0.109	0.127
	(0.066)	(0.134)
Equiv. hh income (cube root) 2	-0.007	-0.023
	(0.005)	(0.013)
Wave 2	-0.315*	-0.126
	(0.137)	(0.204)
Constant	-3.134	-9.194
	(2.197)	(4.759)
Control variables country	Yes	Yes
N	1,545	233
AIC	9,447	1,548
BIC	9,580	1,634

Note: The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w + 1$, i.e. Wave 2 or Wave 4. All explanatory variables are taken from wave w, i.e. Wave 1 or Wave 2 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

6 The Total Public Cost of Health Misperception

We perform a back-of-the-envelope calculation to estimate additional health expenditures due to health misperception. The total cost of over- or underestimating health for the population 50+ in the respective country C_t in year t is calculated as follows:

$$C_{c,t} = d_c \times m_c \times f_c \times p_{c,t} \tag{4}$$

where d_c is the predicted cost per outpatient visit in 2010 Intl$ according to the World Health Organisation for the respective country (World Health Organization 2011) and m_c denotes the marginal effect at means of over- or underestimating health on doctor visits (i.e., the difference in doctor visits between concordance and over- or underestimation according to our estimates). The term f_c denotes the fraction of individuals in the SHARE sample who over- or underestimate their health, and $p_{c,t}$ is the population older than age 50 in the respective country and year according to predictions from the Wittgenstein Centre for Demography and Global Human Capital (2018).

We project that on average across the European Union, underestimation of the population 50+ will cost Intl$ 71 million in 2020 per country and increase to Intl$ 81 million by 2060. Overestimation will result in negative healthcare costs of approximately Intl$ 37 million per country in 2020 and Intl$ 45 million in 2060. Altogether, we project a net cost of Intl$ 34 million per country in 2020. Note that although overestimation results in negative costs, these are in the short run only. In the long run, overestimation may result in individuals skipping timely screening and preventive care and lead to worse health, resulting in higher healthcare expenditures. Longer panel data will aid in evaluating the full cost of overestimation in future work.

The costs of misperception are also projected separately for each country in our sample. Figure 5 shows the total costs of underestimation in 2020, 2040, and 2060 – it is highest in Germany, Italy, and France. When dividing the total cost of underestimation by the population size, Germany, Denmark, and The Netherlands have the highest cost. Germany has a high marginal effect at means of underestimating health on doctor visits m_c along with a relatively high fraction of individuals that underestimate their health f_c. As a result, additional outpatient visits due to underestimation are predicted to cost Germany Intl$ 503 million in 2020 and Intl$ 538 million in 2060. Denmark and The Netherlands have much lower f_c, but their high cost per outpatient visit d_c along with large marginal effects m_c result in high public cost of underestimating health. Countries such as Poland and Czechia have much lower

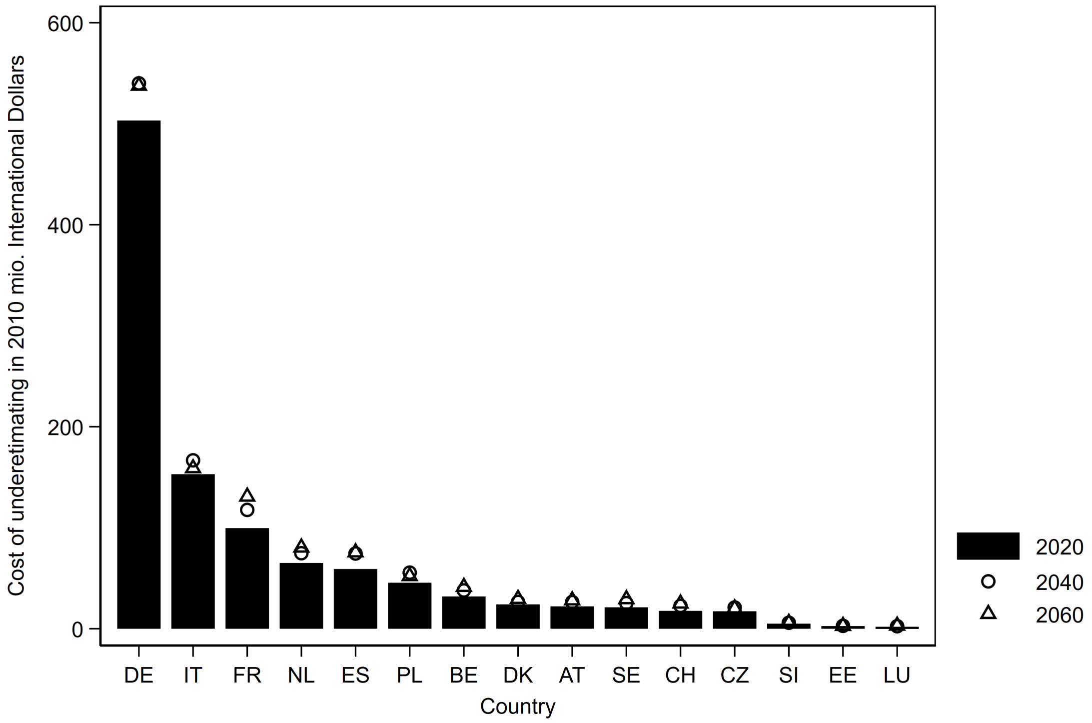


Figure 5: Projected total public cost of underestimating health for the population 50+

costs because approximately similar percentages report over- and underestimation and also much lower consultation costs. Spain has the lowest predicted cost of underestimation per capita. In total, it is Intl$ 59 million in 2020 and Intl$ 76 million in 2060. Table 8 shows projected misperception costs for all countries in 2020, 2040, and 2060.

7 Conclusion

We utilise rich longitudinal data from 15 European countries from SHARE to explore the effects of health (mis)perception on healthcare utilisation. We categorise misperception as arising due to overconfidence or underconfidence. Following the literature in psychology, overconfidence is measured as overestimation of one's health, whereas underconfidence is defined analogously as underestimation of one's own health. Healthcare utilisation is measured as the annual number of doctor visits. In addition, we assess the relationship between misperception and OOP expenditures incurred by those who visit the doctor. Our results based on count models and log-Gamma models suggest that individuals who underestimate their health visit the doctor more often and have higher OOP expenditures than those who assess their health correctly. By contrast, survey participants who overestimate their health visit the doctor less often and have lower OOP payments.

Table 8: Projected total cost of health misperception by country

Country	Year	Population 50+	Cost	Cost underestimating	Cost overestimating	Balance
		in 1,000	per visit	in mio. 2010 Intl$	in mio. 2010 Intl$	in mio. 2010 Intl$
Austria	2020	3,725.3	46.8	22.1	-30.9	-8.8
	2040	4,444.5	46.8	26.4	-36.9	-10.5
	2060	4,726.9	46.8	28.1	-39.2	-11.2
Belgium	2020	4,554.0	44.4	31.8	-16.3	15.6
	2040	5,416.9	44.4	37.9	-19.3	18.5
	2060	5,922.0	44.4	41.4	-21.1	20.3
Czechia	2020	4,137.6	31.3	17.2	-24.1	-6.8
	2040	5,038.8	31.3	21.0	-29.3	-8.3
	2060	4,829.6	31.3	20.1	-28.1	-8.0
Denmark	2020	2,324.7	47.0	24.0	0.1	24.2
	2040	2,569.4	47.0	26.5	0.2	26.7
	2060	2,859.2	47.0	29.5	0.2	29.7
Estonia	2020	519.2	25.7	2.50	-1.7	0.9
	2040	583.6	25.7	2.80	-1.9	1.0
	2060	568.9	25.7	2.80	-1.8	0.9
France	2020	26,121.9	40.8	99.5	-50.1	49.4
	2040	30,875.5	40.8	117.6	-59.2	58.4
	2060	34,332.8	40.8	130.8	-65.8	65.0
Germany	2020	37,597.6	44.0	503.1	-83.5	419.6
	2040	40,352.9	44.0	540.0	-89.6	450.3
	2060	40,176.2	44.0	537.6	-89.2	448.4
Italy	2020	27,580.7	38.4	152.9	-35.8	117.1
	2040	30,070.5	38.4	166.7	-39.0	127.7
	2060	28,662.7	38.4	158.9	-37.2	121.7
Luxembourg	2020	214.5	89.5	1.7	-2.6	-0.9
	2040	313.5	89.5	2.5	-3.7	-1.3
	2060	386.3	89.5	3.0	-4.6	-1.6
Netherlands	2020	7,082.6	48.1	65.0	-47.0	18.0
	2040	8,138.9	48.1	74.7	-54.0	20.7
	2060	8,750.5	48.1	80.4	-58.1	22.3
Poland	2020	14,398.8	25.5	45.5	-70.2	-24.7
	2040	17,587.8	25.5	55.5	-85.7	-30.2
	2060	16,498.9	25.5	52.1	-80.4	-28.3
Slovenia	2020	880.7	32.6	4.9	-4.4	0.6
	2040	1,048.1	32.6	5.9	-5.2	0.7
	2060	1,026.1	32.6	5.8	-5.1	0.7
Spain	2020	19,709.0	37.8	59.0	-186.8	-127.7
	2040	24,851.7	37.8	74.5	-235.5	-161.1
	2060	25,235.6	37.8	75.6	-239.2	-163.6
Sweden	2020	3914.8	45.8	21.1	-9.2	11.9
	2040	4703.5	45.8	25.4	-11.1	14.3
	2060	5419.9	45.8	29.2	-12.7	16.5
Switzerland	2020	3,513.4	55.2	17.6	8.7	26.2
	2040	4,516.4	55.2	22.6	11.1	33.7
	2060	4,986.1	55.2	24.9	12.3	37.2

Our results are robust to a range of sensitivity analyses with different model specifications, sample compositions, estimation methods, and health dimensions. In addition, we account for potential endogeneity by exploiting the panel structure of our data. Specifically, arguments concerning individuals' health perception improving as a result of frequent doctor visits do not apply because we focus on current misperception and future doctor visits. Descriptive cross-tabulations show that individual characteristics such as education, illnesses, age, retirement, supplementary insurance, and others do not matter for the relationship between health misperception and healthcare utilisation; regressions controlling for these variables confirm the stability of the results.

The main limitation of this study is related to panel attrition. Individuals who suffer from diseases are less likely to participate in consecutive survey waves and thus are less likely to be included in our sample. However, we address this limitation by running our analyses separately by the number of diseases that a participant is suffering from and find no difference in the results between healthy and unhealthy participants, which suggests that panel attrition is not a concern in our study. Future work could fruitfully explore the long-term effects of health misperception on healthcare utilisation, for example, exploiting national panel data collected over a longer period of time than SHARE data. Longer panels would also allow for panel regressions and thus enable researchers to control for unobserved heterogeneity between observations.

The policy implications of our results are straightforward. First, addressing rising health expenditures has been a top priority on policymakers' agenda in many countries. Excessive hospital admissions use more than 37 million bed days across the European Union every year, significantly increasing public expenditures (OECD & European Commission 2018). Containing sources of waste and inefficiency in healthcare on either the demand or supply side is important in this regard. Our paper provides new insights, highlighting demand-side misperception as a possible source of wasteful spending. Given our results, we perform a back-of-the-envelope calculation of the costs of health misperception. (see Appendix 6 for detail). We project that on average across the European Union, underestimation will cost Intl$ 71 million in 2020 per country and increase to Intl$ 81 million by 2060. While overestimating health reduces public healthcare expenditure in the short run, it is likely that in the long run it will increase cost due to forgone preventive care.

Second, if individuals' own perceptions of health are what drive healthcare demand beyond actual health and other socioeconomic characteristics, then equipping them through personalised or public health campaigns with the necessary tools and information to accurately assess their health and determine when to seek healthcare is perhaps a valuable long-term strategy for reducing unnecessary healthcare use. This is a particularly relevant measure in countries with ageing populations that suffer from cognitive dissonance and thereby increased health misperception (Brandtstädter & Greve 1994, Frieswijk et al. 2004, Henchoz et al. 2008, Idler 1993, Spitzer & Weber 2019). Reaching out to those who overestimate their health by providing information about the benefits of screening and preventive care might also improve their health and thus prevent suffering and costs in the long run. Initiatives to increase health literacy, such as the National Action Plan on Health Literacy, are already in place in Germany (Vogt et al. 2018). Other countries can follow similar approaches to evaluate health literacy levels and take strategic action to educate people.

Finally, wait time is often used as a non-price rationing measure in healthcare by policymakers (Barzel 1974, Iversen & Siciliani 2011). Identifying patients with health misperception and reducing unnecessary visits to the doctor can have important implications for the effectiveness of such rationing mechanisms. Not only will they free up physician capacity, but they can also directly ensure timely care for other patients who are in need of urgent intervention. Moreover, with the advent of artificial intelligence and technology, providing individuals with the option to use online physician chatbots and telephone consultations will further reduce the burden of unnecessary doctor visits due to misperception rather than true health need.

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A Appendix

Table A.1: Crosstable mean doctor visits at $w+1$ (weighted)

	Health perception				
	Pos. concordance	**Underestimating**	**Neg. concordance**	**Overestimating**	**Total**
	Mean doctor visits				
No. chronic diseases at w					
0	4.6	7.2	10.5	6.1	5.1
1	6.3	9.5	10.5	8.0	7.0
2	8.1	10.6	12.1	11.0	9.0
3	8.8	11.3	11.7	12.4	10.0
4	11.0	16.2	13.8	15.5	13.1
5	13.5	13.5	16.2	11.3	13.9
6	11.7	18.9	14.8	17.2	14.6
7	11.0	14.1	26.9	32.1	21.1
8	11.3	19.5	15.0	14.9	13.2
9	20.0				20.0
10	11.7				11.7
Total	6.2	10.1	11.9	8.6	7.2
No. activity limitations at w					
0	6.0	9.0	11.1	7.8	6.5
1	8.3	10.3	10.8	9.8	9.3
2	9.8	14.0	11.6	13.9	12.0
3	11.7	11.5	11.9	15.1	12.2
4	10.2	31.1	11.6	12.3	15.5
5	7.8	11.7	12.3	18.6	12.8
6	5.2	11.4	14.7	12.4	13.2
7	8.8	15.8	13.4	15.6	13.8
8	4.7	8.6	15.3	9.8	13.6
9	7.6	9.6	20.2	11.5	18.9
10		30.0	20.5	6.7	19.4
11		9.1	9.8	6.0	9.7
12		6.2	16.6	30.6	16.4
13	5.5	8.6	14.5	98.0	10.3
Total	6.2	10.1	11.8	8.6	7.2
5-year age groups					
50-54	5.2	10.6	11.7	6.8	5.9
55-59	5.4	10.9	13.8	7.2	6.4
60-64	6.0	9.1	10.5	8.9	6.8
65-69	6.8	9.5	13.5	9.4	7.7
70-74	7.7	10.8	10.9	9.1	8.5
75-79	8.1	9.0	12.0	12.1	9.1
80-84	8.0	11.4	10.4	9.0	9.0
85-89	6.4	9.4	12.8	9.3	8.7
90+	5.5	7.8	9.2	13.9	9.0
Total	6.2	10.1	11.8	8.6	7.2
Gender					
Men	6.0	10.0	11.8	8.1	6.7
Women	6.4	10.1	11.9	9.1	7.5
Total	6.2	10.1	11.8	8.6	7.2
Education					
Low	6.6	10.1	11.8	9.2	7.7
Medium	6.2	9.7	12.1	8.2	7.0
High	5.7	10.8	11.3	7.5	6.4
Total	6.2	10.1	11.8	8.6	7.2

Note: Calibrated cross-sectional individual weights are applied.

Table A.1, continued: Crosstable mean doctor visits at $w+1$ (weighted)

	Health perception				
	Pos. concordance	**Underestimating**	**Neg. concordance**	**Overestimating**	**Total**
			Mean doctor visits		
Is retired					
No	5.5	10.2	11.6	7.9	6.4
Yes	7.0	10.0	11.9	9.3	7.9
Total	6.2	10.1	11.8	8.6	7.2
Is married					
No	6.4	9.9	11.5	9.2	7.5
Yes	6.1	10.2	12.0	8.5	7.0
Total	6.2	10.1	11.8	8.7	7.2
Healt access					
Not difficult	5.9	10.2	11.0	8.4	6.7
Difficult	6.5	10.0	12.0	10.6	8.3
Total	6.0	10.1	11.3	8.9	7.0
Supplementary insurance					
No	6.1	10.4	11.7	9.7	7.3
Yes	5.7	9.4	10.6	7.1	6.4
Total	6.0	10.0	11.4	8.9	7.0
Has children					
No	6.1	10.8	12.0	10.1	7.3
Yes	6.2	10.0	11.8	8.5	7.2
Total	6.2	10.1	11.8	8.7	7.2
Country					
Austria	6.1	8.8	11.4	8.9	7.0
Germany	6.9	11.2	13.4	10.1	8.0
Sweden	3.8	5.7	10.6	5.4	4.3
Netherlands	5.0	7.4	9.8	8.6	5.5
Spain	5.2	8.6	10.2	7.5	6.2
Italy	7.3	13.1	13.8	10.2	8.6
France	5.6	7.7	9.3	6.7	6.1
Denmark	4.3	8.2	10.6	6.4	4.9
Switzerland	4.4	7.2	8.6	8.0	5.0
Belgium	7.0	10.3	16.4	9.5	8.0
Czechia	6.5	9.7	11.2	9.1	7.5
Poland	6.7	9.9	10.2	6.8	7.5
Luxembourg	7.7	10.5	17.3	12.1	9.0
Slovenia	4.5	7.4	9.0	7.5	5.5
Estonia	4.9	7.6	8.4	6.2	5.9
Total	6.2	10.1	11.8	8.6	7.2
Survey wave					
Wave 2	6.5	10.1	12.6	8.3	7.4
Wave 5	6.0	10.0	11.4	8.9	7.0
Total	6.2	10.1	11.8	8.6	7.2

Note: Calibrated cross-sectional individual weights are applied.

Table A.2: Crosstable mean OOP expenditures in Euros at $w+1$ (weighted)

	Health perception				
	Pos. concordance Mean OOP	**Underestimating** Mean OOP	**Neg. concordance** Mean OOP	**Overestimating** Mean OOP	**Total** Mean OOP
No. chronic diseases at w					
0	64.1	98.9	65.0	73.5	66.7
1	73.9	100.4	56.3	66.5	75.2
2	75.2	79.6	65.8	79.0	75.3
3	80.4	76.5	94.4	102.0	83.6
4	79.4	76.9	58.8	83.3	74.8
5	81.1	158.1	95.0	41.3	98.1
6	71.7	181.6	352.4	6.4	156.3
7	38.3	95.1	9.0	67.7	40.2
8	23.2	334.6	50.7	8.8	40.6
10	0.0				0.0
Total	70.8	92.4	74.6	74.6	73.6
No. activity limitations at w					
0	71.8	90.5	75.7	73.7	73.5
1	62.5	96.5	72.9	61.7	71.3
2	53.6	50.9	52.3	108.2	60.7
3	44.8	140.5	160.1	103.2	121.3
4	35.6	86.4	34.0	34.6	46.9
5	38.1	57.9	75.4	57.3	64.6
6	9.8	54.0	90.8	42.6	73.3
7	0.0	123.1	18.7	527.8	60.6
8	34.2	0.0	47.2	59.3	39.9
9	163.4	19.0	15.6	0.0	16.7
10		0.0	219.9	0.0	197.9
11		352.6	28.2	0.0	60.5
12		289.9	46.6	8.6	100.2
13	2.2	298.1	141.1		240.2
Total	70.8	92.4	74.5	74.4	73.5
5-year age groups					
50-54	60.8	147.3	57.4	46.8	65.8
55-59	67.4	80.9	72.5	103.9	71.0
60-64	70.6	78.8	86.0	68.4	71.8
65-69	73.9	80.6	110.8	89.8	77.6
70-74	89.7	99.7	86.3	58.6	88.1
75-79	76.2	96.6	102.2	81.5	82.7
80-84	67.5	74.3	42.5	86.9	67.1
85-89	48.3	70.0	45.3	52.9	51.5
90+	49.0	15.4	10.8	47.2	35.1
Total	70.8	92.4	74.5	74.4	73.5
Gender					
Men	74.5	70.4	62.2	60.9	72.7
Women	67.1	104.2	79.6	84.6	74.2
Total	70.8	92.4	74.5	74.4	73.5
Education					
Low	62.0	89.3	78.5	64.3	66.8
Medium	71.1	92.0	71.0	70.6	73.3
High	85.4	108.5	55.7	120.8	88.4
Total	71.1	93.7	74.3	74.1	73.9

Note: Calibrated cross-sectional individual weights are applied.

Table A.2, continued: Crosstable mean OOP expenditures in Euros at $w+1$ (weighted)

	Health perception				
	Pos. concordance Mean OOP	**Underestimating** Mean OOP	**Neg. concordance** Mean OOP	**Overestimating** Mean OOP	**Total** Mean OOP
Is retired					
No	64.8	101.1	54.4	81.8	68.5
Yes	77.0	87.4	88.7	70.0	78.5
Total	70.7	92.8	75.4	75.0	73.6
Is married					
No	69.5	72.9	42.0	68.5	67.2
Yes	72.5	100.8	103.1	81.5	77.5
Total	71.6	90.8	74.8	76.2	74.1
Healt access					
Not difficult	71.5	98.6	78.2	84.0	75.4
Difficult	67.7	81.4	66.7	43.8	66.6
Total	71.0	95.0	74.1	74.5	73.9
Supplementary insurance					
No	70.5	101.1	73.0	75.8	74.3
Yes	71.2	76.6	80.2	71.3	72.2
Total	70.7	92.5	74.6	74.5	73.5
Has children					
No	89.3	131.7	92.9	73.9	91.6
Yes	68.3	88.9	72.7	74.8	71.3
Total	70.8	92.8	75.0	74.7	73.6
Country					
Austria	123.9	141.1	124.0	58.3	121.0
Germany	55.8	45.6	30.7	75.9	54.2
Sweden	67.9	75.2	75.6	66.9	68.9
Spain	10.1	33.4	64.2	16.5	18.0
Italy	139.7	270.5	135.8	132.5	149.2
France	28.6	37.3	27.2	29.8	29.5
Denmark	5.5	2.9	4.9	1.5	5.1
Switzerland	386.5	442.0	636.0	380.6	397.0
Belgium	90.6	183.0	155.2	90.9	105.1
Czechia	7.3	11.2	9.6	10.9	8.3
Luxembourg	171.3	209.6	292.1	206.8	185.3
Slovenia	13.9	20.2	9.9	2.8	13.2
Estonia	14.8	12.0	14.6	13.9	14.3
Total	70.8	92.4	74.5	74.4	73.5
Survey wave					
Wave 5	70.8	92.4	74.5	74.4	73.5
Total	70.8	92.4	74.5	74.4	73.5

Note: Calibrated cross-sectional individual weights are applied.

Table A.3: Crosstable health perception (weighted)

	Health perception								
	Pos. concordance		**Underestimating**		**Neg. concordance**		**Overestimating**		**Total**
	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %
Objective impairment									
Unimpaired (n=47,913)	88.0	[87.5,88.5]	12.0	[11.5,12.5]	0.0		0.0		100.0
Impaired (n=8,239)	0.0		0.0		38.3	[36.6,40.0]	61.7	[60.0,63.4]	100.0
Total (n=56,152)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(3) =	5.62e+04								
Design-based F(2.77, 155429.77) =	7984.2277	Pr =	0.000						
No. chronic diseases at w									
0 (n=20,630)	82.1	[81.2,82.9]	5.7	[5.2,6.2]	3.1	[2.7,3.5]	9.1	[8.5,9.9]	100.0
1 (n=17,715)	76.2	[75.1,77.3]	10.2	[9.5,11.0]	4.4	[3.9,4.9]	9.2	[8.5,10.0]	100.0
2 (n=10,246)	67.8	[66.2,69.3]	13.9	[12.8,15.1]	8.2	[7.4,9.1]	10.1	[9.1,11.2]	100.0
3 (n=4,712)	60.4	[58.0,62.7]	16.2	[14.6,18.0]	11.7	[10.3,13.4]	11.6	[10.1,13.3]	100.0
4 (n=1,889)	48.2	[44.4,51.9]	20.4	[17.4,23.8]	20.1	[17.2,23.3]	11.4	[9.1,14.1]	100.0
5 (n=650)	39.5	[32.7,46.8]	25.7	[19.9,32.5]	24.1	[18.8,30.4]	10.7	[7.3,15.3]	100.0
6 (n=180)	39.9	[29.2,51.8]	16.3	[10.0,25.4]	28.5	[19.2,40.2]	15.2	[8.2,26.5]	100.0
7 (n=51)	22.1	[10.0,41.8]	19.9	[7.7,42.6]	53.0	[30.4,74.5]	5.0	[1.7,13.8]	100.0
8 (n=18)	50.9	[17.5,83.5]	3.7	[0.5,22.2]	36.6	[9.0,77.1]	8.8	[1.5,38.2]	100.0
9 (n=1)	100.0		0.0		0.0		0.0		100.0
10 (n=2)	100.0		0.0		0.0		0.0		100.0
Total (n=56,094)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(30) =	3717.8201								
Design-based F(24.19, 1.36e+06) =	56.8893	Pr =	0.000						
No. activity limitations at w									
0 (n=47,381)	80.6	[80.0,81.2]	7.9	[7.5,8.3]	2.6	[2.3,2.8]	8.9	[8.5,9.4]	100.0
1 (n=4,717)	50.3	[47.9,52.7]	22.7	[20.8,24.9]	12.8	[11.3,14.5]	14.2	[12.5,16.0]	100.0
2 (n=1,683)	30.2	[26.6,34.0]	26.5	[23.2,30.0]	29.9	[26.3,33.8]	13.5	[11.1,16.4]	100.0
3 (n=851)	21.3	[16.7,26.6]	25.7	[21.2,30.7]	38.9	[33.5,44.6]	14.2	[10.4,19.0]	100.0
4 (n=485)	15.4	[10.4,22.2]	20.9	[14.4,29.3]	48.6	[40.4,56.8]	15.2	[10.9,20.7]	100.0
5 (n=340)	11.4	[6.9,18.2]	19.3	[13.3,27.2]	52.0	[43.0,60.9]	17.3	[11.0,26.1]	100.0
6 (n=224)	7.0	[2.5,18.1]	13.9	[8.4,22.1]	63.1	[51.7,73.2]	16.0	[9.3,26.1]	100.0
7 (n=159)	4.6	[1.6,12.6]	20.0	[10.5,34.7]	69.9	[55.8,81.1]	5.4	[2.2,12.9]	100.0
8 (n=93)	3.5	[0.8,13.2]	17.0	[7.8,33.0]	75.0	[59.6,85.9]	4.5	[1.8,10.8]	100.0
9 (n=71)	0.7	[0.2,3.4]	9.3	[3.0,25.7]	87.6	[71.8,95.1]	2.4	[0.4,12.7]	100.0
10 (n=42)	0.0		6.5	[0.9,34.1]	81.1	[58.6,92.9]	12.4	[4.0,32.4]	100.0
11 (n=27)	0.0		7.4	[1.7,26.5]	91.6	[73.2,97.7]	1.1	[0.1,7.6]	100.0
12 (n=26)	0.0		22.8	[8.5,48.3]	61.8	[36.9,81.7]	15.4	[4.2,43.0]	100.0
13 (n=49)	4.4	[0.9,19.7]	66.2	[49.3,79.8]	29.2	[16.8,45.7]	0.1	[0.0,0.8]	100.0
Total (n=56,148)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(39) =	1.49e+04								
Design-based F(33.61, 1.89e+06) =	177.1679	Pr =	0.000						
5-year age groups									
50-54 (n=7,593)	81.7	[80.1,83.2]	7.0	[6.1,8.0]	2.8	[2.3,3.5]	8.5	[7.4,9.7]	100.0
55-59 (n=10,672)	78.6	[77.3,80.0]	8.7	[7.9,9.7]	4.0	[3.4,4.7]	8.6	[7.7,9.6]	100.0
60-64 (n=11,137)	77.0	[75.7,78.2]	10.6	[9.7,11.6]	4.2	[3.7,4.8]	8.2	[7.4,9.0]	100.0
65-69 (n=10,290)	73.6	[72.2,74.9]	10.7	[9.8,11.6]	5.4	[4.8,6.2]	10.3	[9.4,11.3]	100.0
70-74 (n=8,143)	68.7	[67.0,70.3]	12.5	[11.3,13.8]	8.3	[7.4,9.3]	10.5	[9.5,11.7]	100.0
75-79 (n=4,390)	63.7	[61.2,66.1]	13.9	[12.3,15.8]	11.8	[10.2,13.5]	10.6	[9.2,12.3]	100.0
80-84 (n=2,645)	55.7	[52.4,59.0]	13.2	[11.1,15.6]	16.5	[14.1,19.2]	14.6	[12.3,17.2]	100.0
85-89 (n=1,047)	47.4	[42.3,52.5]	13.8	[10.7,17.7]	20.6	[16.8,25.1]	18.1	[14.6,22.2]	100.0
90+ (n=235)	38.2	[28.3,49.1]	7.3	[4.1,12.6]	27.5	[18.9,38.2]	27.0	[18.4,37.8]	100.0
Total (n=56,152)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(24) =	2476.8374								
Design-based F(22.74, 1.28e+06) =	37.9231	Pr =	0.000						

Note: Calibrated cross-sectional individual weights are applied.

Table A.3, continued: Crosstable health perception (weighted)

	Health perception								
	Pos. concordance		**Underestimating**		**Neg. concordance**		**Overestimating**		**Total**
	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %
Gender									
Men (n=24,503)	79.4	[78.5,80.2]	7.3	[6.8,7.8]	3.8	[3.5,4.2]	9.5	[8.9,10.2]	100.0
Women (n=31,649)	69.9	[69.0,70.7]	12.5	[11.9,13.2]	7.8	[7.3,8.3]	9.8	[9.2,10.4]	100.0
Total (n=56,152)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(3) =	922.0913								
Design-based F(2.99, 167664.12) =	107.2160	Pr =	0.000						
Education									
Low (n=21,346)	68.2	[67.2,69.2]	11.0	[10.4,11.7]	8.8	[8.3,9.5]	12.0	[11.3,12.7]	100.0
Medium (n=21,228)	76.1	[75.0,77.1]	10.3	[9.6,11.0]	4.8	[4.3,5.3]	8.8	[8.1,9.6]	100.0
High (n=12,833)	83.2	[82.0,84.3]	7.8	[7.1,8.6]	2.5	[2.1,3.0]	6.5	[5.7,7.3]	100.0
Total (n=55,407)	74.3	[73.7,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(6) =	1177.9308								
Design-based F(5.94, 329109.56) =	68.3745	Pr =	0.000						
Is retired									
No (n=25,298)	77.6	[76.7,78.5]	8.7	[8.2,9.3]	4.8	[4.4,5.3]	8.8	[8.2,9.5]	100.0
Yes (n=30,601)	71.0	[70.1,71.8]	11.6	[11.0,12.2]	7.0	[6.6,7.5]	10.5	[9.9,11.1]	100.0
Total (n=55,899)	74.4	[73.8,75.0]	10.1	[9.7,10.5]	5.9	[5.6,6.2]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(3) =	344.7396								
Design-based F(2.99, 167064.47) =	39.5269	Pr =	0.000						
Is married									
No (n=14,874)	69.8	[68.5,71.1]	11.4	[10.6,12.4]	8.1	[7.4,8.9]	10.7	[9.8,11.6]	100.0
Yes (n=39,474)	76.1	[75.4,76.7]	9.6	[9.2,10.1]	5.1	[4.8,5.5]	9.2	[8.8,9.7]	100.0
Total (n=54,348)	74.2	[73.5,74.8]	10.2	[9.7,10.6]	6.0	[5.7,6.3]	9.7	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(3) =	290.4041								
Design-based F(2.98, 162037.55) =	30.4726	Pr =	0.000						
Healt access									
Not difficult (n=32,586)	78.2	[77.4,78.9]	9.7	[9.2,10.3]	5.0	[4.6,5.4]	7.2	[6.7,7.7]	100.0
Difficult (n=6,341)	60.8	[58.5,63.0]	13.1	[11.7,14.7]	14.6	[13.1,16.4]	11.5	[10.1,13.0]	100.0
Total (n=38,927)	75.3	[74.6,76.1]	10.3	[9.7,10.8]	6.5	[6.1,7.0]	7.9	[7.4,8.4]	100.0
Pearson: Uncorrected chi2(3) =	1158.8844								
Design-based F(2.99, 116441.54) =	116.8392	Pr =	0.000						

Note: Calibrated cross-sectional individual weights are applied.

Table A.3, continued: Crosstable health perception (weighted)

	Health perception								
	Pos. concordance		Underestimating		Neg. concordance		Overestimating		Total
	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %
Supplementary insurance									
No (n=26,149)	73.0	[72.1,74.0]	10.3	[9.6,10.9]	7.8	[7.3,8.4]	8.9	[8.3,9.5]	100.0
Yes (n=15,280)	78.8	[77.6,79.9]	10.4	[9.6,11.2]	4.4	[3.8,4.9]	6.5	[5.9,7.2]	100.0
Total (n=41,429)	75.1	[74.4,75.8]	10.3	[9.8,10.8]	6.6	[6.2,7.0]	8.0	[7.6,8.5]	100.0
Pearson: Uncorrected chi2(3) =	282.3894								
Design-based F(2.99, 123937.16) =	31.5801	Pr =	0.000						
Has children									
No (n=5,121)	74.2	[72.1,76.1]	9.3	[8.0,10.7]	6.0	[5.0,7.2]	10.5	[9.2,12.1]	100.0
Yes (n=50,336)	74.2	[73.6,74.9]	10.2	[9.8,10.7]	6.0	[5.7,6.3]	9.5	[9.1,10.0]	100.0
Total (n=55,457)	74.2	[73.6,74.8]	10.1	[9.7,10.6]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(3) =	10.8682								
Design-based F(2.99, 165995.64) =	1.0866	Pr =	0.353						
Country									
Austria (n=3,241)	72.7	[70.7,74.6]	11.5	[10.1,12.9]	7.1	[6.1,8.3]	8.7	[7.5,10.0]	100.0
Germany (n=5,222)	75.8	[74.4,77.2]	12.7	[11.6,13.8]	5.1	[4.4,5.8]	6.4	[5.7,7.2]	100.0
Sweden (n=4,722)	80.3	[78.9,81.6]	9.6	[8.6,10.5]	3.9	[3.3,4.7]	6.2	[5.4,7.1]	100.0
Netherlands (n=1,376)	84.2	[82.1,86.2]	8.5	[7.1,10.1]	2.9	[2.1,4.0]	4.4	[3.4,5.7]	100.0
Spain (n=5,384)	71.7	[69.8,73.5]	8.6	[7.5,9.7]	8.7	[7.7,9.8]	11.0	[9.8,12.4]	100.0
Italy (n=4,868)	70.3	[68.7,71.8]	8.3	[7.4,9.2]	6.9	[6.1,7.8]	14.5	[13.4,15.8]	100.0
France (n=4,311)	76.6	[75.1,78.1]	9.0	[8.1,10.0]	4.5	[3.8,5.2]	9.9	[8.8,11.0]	100.0
Denmark (n=4,475)	86.1	[85.0,87.1]	7.9	[7.1,8.8]	2.6	[2.2,3.2]	3.4	[2.8,4.0]	100.0
Switzerland (n=3,344)	83.9	[82.5,85.2]	7.4	[6.6,8.4]	2.6	[2.1,3.3]	6.1	[5.2,7.0]	100.0
Belgium (n=5,599)	77.0	[75.7,78.2]	11.5	[10.6,12.5]	5.2	[4.6,5.9]	6.4	[5.6,7.1]	100.0
Czechia (n=5,147)	71.6	[69.6,73.5]	10.2	[9.1,11.5]	8.3	[7.3,9.5]	9.9	[8.5,11.4]	100.0
Poland (n=1,222)	61.4	[58.5,64.3]	14.1	[12.2,16.3]	9.7	[8.1,11.6]	14.7	[12.7,17.0]	100.0
Luxembourg (n=1,013)	73.4	[70.3,76.2]	12.5	[10.5,14.8]	6.3	[4.9,8.2]	7.8	[6.1,9.9]	100.0
Slovenia (n=2,222)	72.0	[69.8,74.2]	10.8	[9.5,12.4]	7.3	[6.2,8.6]	9.9	[8.4,11.5]	100.0
Estonia (n=4,006)	64.9	[63.3,66.5]	13.8	[12.7,15.0]	12.6	[11.5,13.7]	8.7	[7.8,9.7]	100.0
Total (n=56,152)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(42) =	1357.8340								
Design-based F(20.44, 1.15e+06) =	26.8724	Pr =	0.000						
Survey wave									
Wave 2 (n=14,623)	73.1	[72.0,74.1]	9.9	[9.2,10.6]	5.1	[4.7,5.7]	11.9	[11.2,12.7]	100.0
Wave 5 (n=41,529)	75.1	[74.3,75.8]	10.3	[9.8,10.8]	6.6	[6.2,7.0]	8.0	[7.6,8.5]	100.0
Total (n=56,152)	74.3	[73.6,74.9]	10.1	[9.7,10.5]	6.0	[5.7,6.3]	9.6	[9.2,10.1]	100.0
Pearson: Uncorrected chi2(3) =	272.0734								
Design-based F(3.00, 168272.56) =	30.3672	Pr =	0.000						

Note: Calibrated cross-sectional individual weights are applied.

Table A.4: Underestimating health and annual number of doctor visits at $w + 1$ by country

	(1) Austria	(2) Belgium	(3) Czechia	(4) Denmark	(5) Estonia	(6) France	(7) Germany	(8) Italy
Health perception (ref.: concordance)								
Underestimating	0.157*	0.180***	0.171***	0.510***	0.241***	0.173***	0.306***	0.211***
	(0.063)	(0.051)	(0.045)	(0.090)	(0.072)	(0.048)	(0.053)	(0.063)
Chronic diseases	0.166***	0.171***	0.181***	0.206***	0.226***	0.177***	0.188***	0.218***
	(0.021)	(0.016)	(0.014)	(0.019)	(0.021)	(0.014)	(0.016)	(0.018)
Activity limitations	0.072*	0.163***	0.060*	0.075*	0.128***	0.045**	0.132***	0.030
	(0.032)	(0.029)	(0.028)	(0.036)	(0.026)	(0.017)	(0.036)	(0.017)
Age	0.006	-0.035	0.036	0.004	0.006	-0.048	-0.045	0.081*
	(0.041)	(0.028)	(0.035)	(0.036)	(0.040)	(0.029)	(0.028)	(0.037)
Age squared	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.094	0.134***	0.054	0.003	-0.061	0.069	0.058	0.161***
	(0.053)	(0.038)	(0.035)	(0.047)	(0.049)	(0.036)	(0.036)	(0.042)
Educ. group (ref.: low)								
Medium	0.035	-0.051	0.012	-0.007	0.033	-0.035	0.040	-0.047
	(0.063)	(0.047)	(0.037)	(0.071)	(0.058)	(0.041)	(0.060)	(0.057)
High	0.050	-0.039	0.014	-0.016	0.073	-0.001	0.015	-0.178*
	(0.070)	(0.045)	(0.052)	(0.073)	(0.074)	(0.052)	(0.065)	(0.084)
Retired	0.074	0.056	-0.025	0.045	0.038	0.001	0.097	-0.003
	(0.065)	(0.046)	(0.067)	(0.065)	(0.067)	(0.049)	(0.054)	(0.060)
Married	-0.053	-0.082	0.065	-0.120*	-0.042	-0.016	-0.013	0.007
	(0.053)	(0.042)	(0.038)	(0.050)	(0.050)	(0.039)	(0.044)	(0.059)
Equiv. hh income (cube root)	-0.000	-0.001	-0.002	-0.004	0.011	-0.002	-0.001	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.002)	(0.002)	(0.002)
Constant	0.867	2.702**	0.172	1.307	0.893	3.183**	3.161***	-1.246
	(1.392)	(0.925)	(1.161)	(1.249)	(1.334)	(0.969)	(0.908)	(1.214)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,593	4,666	3,991	4,082	3,048	3,530	4,587	3,757
AIC	15,395	28,098	23,833	21,083	16,761	19,215	27,479	23,323
BIC	15,478	28,188	23,921	21,171	16,839	19,301	27,570	23,410

Note: The coefficients are based on the sample that is objectively unimpaired, i.e. able to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w + 1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.4, continued: Underestimating health and annual number of doctor visits at $w+1$ by country

	(1) Luxembourg	(2) Netherlands	(3) Poland	(4) Slovenia	(5) Spain	(6) Sweden	(7) Switzerland
Health perception (ref.: concordance)							
Underestimating	0.088	0.370*	0.120	0.302***	0.172**	0.277***	0.240**
	(0.105)	(0.174)	(0.079)	(0.079)	(0.057)	(0.066)	(0.079)
Chronic diseases	0.107***	0.162***	0.255***	0.222***	0.181***	0.123***	0.204***
	(0.031)	(0.043)	(0.026)	(0.028)	(0.018)	(0.022)	(0.025)
Activity limitations	0.266***	0.028	0.045	-0.002	0.038	0.159***	0.222**
	(0.063)	(0.071)	(0.029)	(0.051)	(0.023)	(0.040)	(0.072)
Age	-0.098	-0.003	0.149	0.010	0.007	0.026	0.026
	(0.073)	(0.129)	(0.103)	(0.058)	(0.034)	(0.040)	(0.046)
Age squared	0.001	0.000	-0.001	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.091	-0.054	0.038	-0.076	0.085	-0.087	-0.011
	(0.093)	(0.086)	(0.071)	(0.062)	(0.046)	(0.050)	(0.057)
Educ. group (ref.: low)							
Medium	0.228*	-0.253*	0.035	0.009	-0.043	0.103	0.007
	(0.098)	(0.099)	(0.074)	(0.069)	(0.075)	(0.068)	(0.076)
High	-0.143	0.004	-0.045	-0.053	0.049	0.080	0.031
	(0.113)	(0.112)	(0.105)	(0.090)	(0.079)	(0.069)	(0.094)
Retired	0.044	-0.236*	0.086	0.019	0.040	0.082	0.153*
	(0.104)	(0.102)	(0.086)	(0.088)	(0.050)	(0.090)	(0.077)
Married	-0.161	-0.003	0.131	0.054	0.075	-0.065	-0.147*
	(0.111)	(0.108)	(0.094)	(0.072)	(0.051)	(0.061)	(0.070)
Equiv. hh income (cube root)	0.006	-0.001	0.005	0.004	-0.001	-0.008	-0.003
	(0.003)	(0.005)	(0.007)	(0.005)	(0.003)	(0.005)	(0.002)
Constant	5.093*	1.545	-3.495	0.431	0.966	-0.038	0.578
	(2.391)	(4.046)	(3.186)	(1.906)	(1.160)	(1.388)	(1.575)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	878	1,196	911	1,810	3,948	4,130	2,940
AIC	5,424	6,581	5,525	9,590	21,252	20,692	15,472
BIC	5,486	6,647	5,588	9,661	21,340	20,780	15,556

Note: The coefficients are based on the sample that is objectively unimpaired, i.e. able to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w+1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.5: Overestimating health and annual number of doctor visits at $w+1$ by country

	(1) Austria	(2) Belgium	(3) Czechia	(4) Denmark	(5) Estonia	(6) France	(7) Germany	(8) Italy
Health perception (ref.: concordance)								
Overestimating	-0.205	-0.112	-0.190**	0.006	-0.192**	-0.062	-0.068	-0.022
	(0.122)	(0.084)	(0.060)	(0.157)	(0.074)	(0.085)	(0.106)	(0.090)
Chronic diseases	0.183***	0.142***	0.138***	0.203***	0.162***	0.058	0.123***	0.237***
	(0.040)	(0.027)	(0.022)	(0.038)	(0.025)	(0.029)	(0.034)	(0.031)
Activity limitations	0.044	0.110***	0.022	0.099**	0.022	0.073**	0.049*	0.048**
	(0.024)	(0.021)	(0.016)	(0.034)	(0.021)	(0.027)	(0.022)	(0.015)
Age	0.034	0.013	0.087*	-0.185*	0.146*	-0.010	-0.110	0.065
	(0.074)	(0.055)	(0.042)	(0.081)	(0.060)	(0.056)	(0.073)	(0.051)
Age squared	-0.000	-0.000	-0.001*	0.001*	-0.001**	0.000	0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Woman	-0.085	0.151	-0.077	0.176	-0.043	0.016	0.014	0.210**
	(0.135)	(0.087)	(0.064)	(0.154)	(0.073)	(0.083)	(0.109)	(0.073)
Educ. group (ref.: low)								
Medium	-0.185	-0.128	0.013	0.093	0.018	0.013	0.107	-0.149
	(0.121)	(0.100)	(0.060)	(0.194)	(0.082)	(0.093)	(0.154)	(0.109)
High	0.139	-0.110	0.066	-0.210	-0.091	0.083	-0.047	0.014
	(0.171)	(0.094)	(0.120)	(0.181)	(0.104)	(0.126)	(0.175)	(0.146)
Retired	0.061	-0.017	-0.098	-0.014	-0.109	0.100	0.306*	-0.008
	(0.141)	(0.097)	(0.101)	(0.193)	(0.121)	(0.100)	(0.132)	(0.082)
Married	-0.004	0.150	0.055	0.171	0.185**	0.001	-0.014	-0.065
	(0.115)	(0.083)	(0.064)	(0.158)	(0.072)	(0.094)	(0.123)	(0.084)
Equiv. hh income (cube root)	-0.004	-0.013**	-0.004	-0.015	0.004	-0.001	0.005	-0.001
	(0.005)	(0.004)	(0.004)	(0.009)	(0.006)	(0.005)	(0.005)	(0.003)
Constant	1.124	1.677	-0.796	8.084**	-3.010	2.221	5.848*	-0.460
	(2.636)	(1.944)	(1.450)	(2.863)	(2.078)	(1.986)	(2.437)	(1.746)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	423	591	964	236	834	554	532	950
AIC	2,857	4,062	6,325	1,471	5,144	3,355	3,734	6,501
BIC	2,913	4,124	6,393	1,520	5,205	3,416	3,793	6,569

Note: The coefficients are based on the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w+1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.5, continued: Overestimating health and annual number of doctor visits at $w+1$ by country

	(1) Luxembourg	(2) Netherlands	(3) Poland	(4) Slovenia	(5) Spain	(6) Sweden	(7) Switzerland
Health perception (ref.: concordance)							
Overestimating	-0.134	-0.346	-0.160	-0.207	-0.298***	-0.135	0.096
	(0.166)	(0.271)	(0.112)	(0.113)	(0.071)	(0.166)	(0.149)
Chronic diseases	0.112*	0.274**	0.136***	0.073*	0.142***	0.107**	0.150*
	(0.055)	(0.102)	(0.035)	(0.035)	(0.024)	(0.040)	(0.072)
Activity limitations	0.122***	-0.065	0.054	-0.019	0.017	0.066*	0.118*
	(0.032)	(0.058)	(0.034)	(0.021)	(0.018)	(0.031)	(0.055)
Age	0.373**	0.603	0.072	0.070	-0.006	-0.155	0.166
	(0.130)	(0.345)	(0.130)	(0.076)	(0.043)	(0.115)	(0.104)
Age squared	-0.003**	-0.005	-0.001	-0.001	0.000	0.001	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Woman	-0.057	-0.059	-0.138	0.221*	-0.125	-0.003	-0.001
	(0.180)	(0.242)	(0.117)	(0.094)	(0.087)	(0.154)	(0.157)
Educ. group (ref.: low)							
Medium	0.164	0.476	0.005	-0.083	-0.130	0.290	-0.018
	(0.168)	(0.324)	(0.110)	(0.105)	(0.149)	(0.217)	(0.192)
High	-0.428	-0.294	0.238	-0.409*	-0.179	-0.197	-0.146
	(0.409)	(0.274)	(0.240)	(0.184)	(0.184)	(0.161)	(0.227)
Retired	-0.630**	-0.329	0.183	0.134	0.049	0.496*	0.122
	(0.214)	(0.331)	(0.122)	(0.121)	(0.079)	(0.238)	(0.225)
Married	-0.083	-0.179	0.044	-0.044	0.056	-0.032	-0.302
	(0.173)	(0.274)	(0.118)	(0.115)	(0.087)	(0.177)	(0.175)
Equiv. hh income (cube root)	-0.011**	0.030*	-0.003	0.002	-0.001	0.005	-0.004
	(0.004)	(0.012)	(0.012)	(0.008)	(0.005)	(0.010)	(0.005)
Constant	-9.187*	-17.679	-0.059	0.432	2.510	6.492	-4.023
	(4.345)	(10.819)	(4.064)	(2.540)	(1.525)	(4.365)	(3.622)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	120	87	305	377	1,151	417	260
AIC	868	587	1,928	2,315	7,028	2,430	1,652
BIC	904	619	1,976	2,366	7,099	2,486	1,702

Note: The coefficients are based on the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w+1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.6: Robustness analyses for annual doctor visits of the unimpaired sample

	(1) Main	(2) Income 1	(3) Income 2	(4) Wealth	(5) Alzheimer dropped
Health perception (ref.: concordance)					
Underestimating	0.244***	0.244***	0.244***	0.240***	0.243***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Chronic diseases	0.181***	0.181***	0.181***	0.179***	0.182***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Activity limitations	0.096***	0.096***	0.096***	0.095***	0.097***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	-0.001	-0.000	-0.001	0.004	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age squared	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.042***	0.042***	0.042***	0.042***	0.042***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Educ. group (ref.: low)					
Medium	0.006	0.008	0.005	0.018	0.007
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
High	-0.003	0.002	-0.004	0.020	-0.003
	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)
Retired	0.029	0.031	0.029	0.030	0.028
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Married	-0.034*	-0.031*	-0.035*	-0.018	-0.035*
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Equiv. hh income (cube root)	-0.001				-0.001
	(0.001)				(0.001)
Wave 5	-0.089***	-0.085***	-0.089***	-0.092***	-0.089***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Equiv. hh income (cube root) 2		-0.002			
		(0.001)			
Equiv. hh income not normalised			-0.000		
			(0.000)		
Wealth quintile (ref.: 1st)					
2nd				-0.058**	
				(0.022)	
3rd				-0.103***	
				(0.021)	
4th				-0.110***	
				(0.022)	
5th				-0.130***	
				(0.022)	
Constant	1.507***	1.499***	1.485***	1.381***	1.491***
	(0.356)	(0.357)	(0.356)	(0.356)	(0.358)
Country dummies	Yes	Yes	Yes	Yes	Yes
N	46,067	46,067	46,067	46,067	45,917
AIC	260,957	260,954	260,958	260,875	259,975
BIC	261,202	261,199	261,203	261,146	260,219

Note: The coefficients are based on the sample that is objectively unimpaired, i.e. able to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w + 1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.7: Robustness analyses for annual doctor visits of the impaired sample

	(1) Main	(2) Income 1	(3) Income 2	(4) Wealth	(5) Alzheimer dropped
Health perception (ref.: concordance)					
Overestimating	-0.146***	-0.146***	-0.146***	-0.145***	-0.144***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Chronic diseases	0.149***	0.149***	0.149***	0.146***	0.152***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Activity limitations	0.048***	0.048***	0.048***	0.047***	0.049***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	0.021	0.022	0.021	0.023	0.024
	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)
Age squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.014	0.014	0.014	0.015	0.009
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Educ. group (ref.: low)					
Medium	-0.006	-0.005	-0.007	0.006	-0.007
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
High	-0.087*	-0.084*	-0.088*	-0.069	-0.084*
	(0.042)	(0.043)	(0.042)	(0.043)	(0.042)
Retired	0.014	0.016	0.014	0.019	0.011
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Married	0.019	0.023	0.019	0.034	0.012
	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)
Equiv. hh income (cube root)	-0.001				-0.001
	(0.002)				(0.002)
Wave 5	-0.046	-0.042	-0.046	-0.047	-0.045
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Equiv. hh income (cube root) 2		-0.001			
		(0.002)			
Equiv. hh income not normalised			-0.000		
			(0.000)		
Wealth quintile (ref.: 1st)					
2nd				-0.050	
				(0.038)	
3rd				-0.110**	
				(0.039)	
4th				-0.119**	
				(0.040)	
5th				-0.086	
				(0.045)	
Constant	1.434*	1.434*	1.421*	1.382*	1.338*
	(0.646)	(0.645)	(0.643)	(0.645)	(0.645)
Country dummies	Yes	Yes	Yes	Yes	Yes
N	7,801	7,801	7,801	7,801	7,709
AIC	50,545	50,544	50,545	50,534	49,893
BIC	50,740	50,739	50,740	50,749	50,088

Note: The coefficients are based on the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w + 1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.8: Robustness analyses for Wave 5

	(1) Objectively Unimpaired Main	(2) Objectively Unimpaired Access	(3) Objectively Unimpaired Insurance	(4) Objectively Impaired Main	(5) Objectively Impaired Access	(6) Objectively Impaired Insurance
Health perception (ref.: concordance)						
Underestimating	0.259***	0.261***	0.259***			
	(0.021)	(0.022)	(0.021)			
Chronic diseases	0.176***	0.173***	0.176***	0.143***	0.140***	0.143***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.011)	(0.010)
Activity limitations	0.093***	0.095***	0.094***	0.048***	0.052***	0.049***
	(0.011)	(0.011)	(0.011)	(0.007)	(0.007)	(0.007)
Age	0.004	0.006	0.003	0.028	0.026	0.028
	(0.012)	(0.012)	(0.012)	(0.021)	(0.022)	(0.021)
Age squared	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.038**	0.038**	0.039**	-0.036	-0.034	-0.036
	(0.014)	(0.015)	(0.014)	(0.032)	(0.033)	(0.032)
Educ. group (ref.: low)						
Medium	0.022	0.026	0.022	-0.005	-0.003	-0.006
	(0.018)	(0.018)	(0.018)	(0.036)	(0.038)	(0.036)
High	0.007	0.009	0.004	-0.091	-0.080	-0.089
	(0.021)	(0.022)	(0.021)	(0.048)	(0.049)	(0.048)
Retired	0.026	0.025	0.026	-0.012	-0.023	-0.013
	(0.021)	(0.021)	(0.021)	(0.038)	(0.040)	(0.038)
Married	-0.037*	-0.040*	-0.038*	0.046	0.055	0.046
	(0.016)	(0.017)	(0.016)	(0.031)	(0.032)	(0.031)
Equiv. hh income (cube root)	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Health access		0.020			0.021	
		(0.023)			(0.033)	
Supplementary insurance			0.019			-0.046
			(0.021)			(0.050)
Overestimating				-0.147***	-0.142***	-0.149***
				(0.032)	(0.033)	(0.032)
Constant	1.306**	1.226**	1.324***	1.168	1.183	1.171
	(0.398)	(0.407)	(0.398)	(0.714)	(0.753)	(0.715)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	33,984	32,023	33,921	5,840	5,417	5,812
AIC	192,107	180,867	191,768	37,858	35,136	37,681
BIC	192,317	181,084	191,987	38,025	35,308	37,855

Note: "Unimpaired" refers to the sample that is objectively unimpaired, i.e. able to stand up from the chair and "Impaired" refers to the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w+1$, i.e. Wave 6. All explanatory variables are taken from Wave 5. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.9: Robustness analysis: Annual number of doctor visits at $w+1$ by survey wave

	(1) Objectively Unimpaired Wave 2	(2) Objectively Unimpaired Wave 5	(3) Objectively Impaired Wave 2	(4) Objectively Impaired Wave 5
Health perception (ref.: concordance)				
Underestimating	0.189***	0.259***		
	(0.037)	(0.021)		
Overestimating			-0.129*	-0.147***
			(0.062)	(0.032)
Chronic diseases	0.201***	0.176***	0.166***	0.143***
	(0.011)	(0.006)	(0.022)	(0.010)
Activity limitations	0.114***	0.093***	0.045*	0.048***
	(0.021)	(0.011)	(0.019)	(0.007)
Age	-0.077*	0.004	0.011	0.028
	(0.036)	(0.012)	(0.076)	(0.021)
Age squared	0.001*	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Woman	0.050*	0.038**	0.173***	-0.036
	(0.023)	(0.014)	(0.052)	(0.032)
Educ. group (ref.: low)				
Medium	-0.048	0.022	-0.014	-0.005
	(0.029)	(0.018)	(0.067)	(0.036)
High	-0.032	0.007	-0.065	-0.091
	(0.033)	(0.021)	(0.079)	(0.048)
Retired	0.023	0.026	0.067	-0.012
	(0.029)	(0.021)	(0.058)	(0.038)
Married	-0.012	-0.037*	-0.103	0.046
	(0.028)	(0.016)	(0.071)	(0.031)
Equiv. hh income (cube root)	-0.002	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.003)	(0.002)
Constant	3.622**	1.306**	1.876	1.168
	(1.118)	(0.398)	(2.440)	(0.714)
Country dummies	Yes	Yes	Yes	Yes
N	12,083	33,984	1,961	5,840
AIC	68,559	192,107	12,603	37,858
BIC	68,736	192,317	12,737	38,025

Note: "Unimpaired" refers to the sample that is objectively unimpaired, i.e. able to stand up from the chair and "Impaired" refers to the sample that is objectively impaired, i.e. unable to stand up from the chair. The dependent variable "doctor visits" is based on the annual number of doctor visits, visits to emergency rooms and outpatient clinic visits at wave $w+1$, i.e. Wave 4 or Wave 6. All explanatory variables are taken from wave w, i.e. Wave 2 or Wave 5 respectively. The estimated coefficients are based on a negative binomial regression model with mean dispersion. Standard errors are clustered at the household level and presented in parentheses. * p<0.05, ** p<0.01, *** p<0.001

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