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ORIGINAL PAPER

Redistribution through social health insurance: evidence on citizen preferences

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Abstract The extent of social health insurance (SHI) and supplementary private insurance is frequently analyzed in public choice. Most of these analyses build on the model developed by Gouveia (1997), who defines the extent of SHI as consequence of a choice by self-interested voters. In this model, an indicator reflecting individuals' relative income position and relative risk of falling ill determines the voting decision. Up to now, no empirical evidence for this key assumption has been available. We test the effect of this indicator on individuals' preferences for the extent of SHI in a setting with mandatory SHI that can be supplemented by private insurance. The data is based on a DCE conducted in the field with a representative sample of 1538 German citizens in 2012. Conditional logit and latent class models are used to analyze preference heterogeneity. Our findings strongly support the assumptions of the models. Individuals likely to benefit from public coverage show a positive marginal willingness to pay (MWTP) for both a shift away from other beneficiary groups toward the sick and an expansion of publicly financed resources, and the expected net payers have a negative MWTP and prefer lower levels of public coverage.

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Introduction

Insuring the risk of illness is fundamental for the well-being of individuals and societies. All industrial countries therefore have found ways to ensure access to at least basic healthcare. However, the degree to which the risk of illness is socialized varies substantially and typically generates debate and controversy.

In economic terms, this discussion addresses the coexistence of public and private provision of private goods and the appropriate mix of the two. Political economists have highlighted the fact that the decision on the right mix for a particular country is a political choice [e.g., 1–4]. In this context, public choice models were developed. On an abstract level, they find that the amounts of public and private health insurance resulting from a democratic process depend primarily on the characteristics risk of illness, individual income, and the distribution of these parameters within the society in combination with the voting mechanism in place. Expectations about the first two factors determine an individual's belief about whether he will be a beneficiary or a net payer under a specific regime.

An individual's risk of illness must be linked to a subjective indicator as this determines that person's expectation about future healthcare needs and thus—under the assumptions of the theoretical models—affects voting behavior. In our study, the best measure available that correlates with subjective risk of illness is self-assessed health (SAH).

Our empirical work builds on the work of Gouveia [4], who presents a theoretical model that has the virtue of accommodating varying degrees of substitutability of public and private provision of healthcare. In Gouveia's model, the main determinant of the voting behavior is the ratio between an individual's relative income position and that person's relative risk of falling ill. This ratio determines whether an individual expects to save money by purchasing some or all of his health insurance in the private market or whether the individual is favored by the redistributive characteristics of public health services. The distribution of both parameters in the population will influence the outcome of a popular vote on the extent to which healthcare is publicly provided.

While the model seems intuitive, practice has shown that reforms pertaining to questions of (social) health insurance are difficult to design and that legislators struggle to assemble the required majorities. Pauly [5] illustrates this complexity, discussing the non-existence of universal health insurance in the United States from a public-finance and public-choice perspective. However, such theoretical analyses are always subject to criticism, as they require strong assumptions regarding relevant parameters and their distribution and results often depend upon these assumptions.[1] Experimental and empirical studies are needed to test the hypotheses derived from theory.

Until now, limited empirical evidence has been available to address the core properties of the theoretical models. To the best of our knowledge, only one study explicitly addresses the link between the income-health ratio and the extent of public health insurance coverage as proposed by Gouveia: Breyer [11] contrasts the findings of the theoretical model with the health insurance systems in Germany and Switzerland. Without econometric analysis, he finds that the differences between the two systems support the theoretical results.[2]

Looking at individual-level econometric studies with a clear link to theory, the RAND experiment contributed heavily to research on topics such as the relationship between health insurance and the demand for healthcare [14] or demand for health insurance itself [15]. However, this experiment focuses primarily on different versions of private insurance contracts (e.g., with varying copayment rates), rather than the general design of the (social) health insurance system. Similarly, another group of articles, including Kerssens and Groenewegen [16], Zweifel et al. [17], and Vroomen and Zweifel [18]—generating data through discrete choice experiments (DCEs) in the field—focus on the composition of health plans, including preferences regarding benefits covered, copayment, and premiums.

Most of the experimental evidence available is based on explicit theoretical models but relates to questions such as willingness to pay for private health insurance and which factors determine this willingness [19]. Preferences for or attitudes toward particular setups of social health insurance are usually only covered indirectly when investigating the role of informal institutions, beliefs, or values such as solidarity and altruism. While experiments have contributed significantly to the understanding of individual behavior, experimental subjects usually do not represent the general public, and the settings are fairly abstract. This makes the transfer to real-world policy difficult.

Other studies, such as the ones by Sudit [20] and Martinussen [21], are closer to our topic, as they investigate attitudes—in their cases those of medical students and medical professionals, respectively—toward the welfare state and national health insurance. They find that ideology as well as self-interest significantly determine these attitudes. However, self-interest does not necessarily predominate in all cases. This finding casts at least some doubt on the relevance of income and risk of illness as determining factors, since this approach assumes self-interest as a core driver in the voting decision.[3]

The study which is closest to ours, but without an explicit link to a theoretical model, is by Loh et al. [23]. The authors analyze, in a cross-country setting, which type of health insurance system citizens would choose if they were given the opportunity to decide. The results indicate that, compared to citizens from China and the United States, Germans show the strongest support for social health insurance. However, the sample consists only of university students, which limits the results' representativeness.

We aim to contribute to the literature through a rigorous empirical strategy that is consistent with microeconomic theory. We test empirically the key property of Gouveia's model—the income-health ratio—which also undergirds more complex models. The focus is on a scenario with mandatory public health insurance that allows for supplementary private health insurance. In particular, we explore to what extent individuals' preferences comport with predictions of the model regarding the effect of their personal

[1] As an example see the controversy between Zweifel and Breuer [6], Mcguire [7], van de Ven [8], and Zweifel and Breuer [9] as well as the analysis by Kifmann and Roeder [10] regarding the efficiency of different health insurance setups.

[2] Considering the econometric analysis of OECD countries [12] in related fields such as voting on social security, aggregate level variables are difficult to interpret when linking the results to microeconomic models of voter behavior. Similar studies that cover retirement decisions are also available [13].

[3] A recent study by Victoor et al. [22] tests the suitability of the "basket method" and finds that individuals do have different attitudes regarding potential components of their insurance package.

health and income on preferences regarding public coverage.

The individual-level empirical analysis is based on a representative sample of German citizens. We focus on the 90 % of the population that is covered by the statutory health insurance system (SHI). The SHI allows users to supplement their coverage by purchasing additional private insurance, which provides an ideal context for our study. We find that an individual's income-health ratio determines preferences regarding the extent of public coverage.

The next section provides our theoretical motivation. "Discrete choice experiments and latent heterogeneity" gives background on the DCE and the analysis of heterogeneous preferences. "Implementation and survey design" explains implementation and survey design. "Empirical analysis" covers the empirical analysis, including a discussion of the results; "concluding remarks" concludes.

Theoretical motivation

Background

From a public-choice perspective, individuals' income position and risk of falling ill matter a lot when debating healthcare: expectations about these factors might influence voting behavior and thus the extent of public spending. These considerations are the basis of more elaborate microeconomic models presented, for example, by Kifmann [24], which build on the works of Gouveia [4], Epple and Romano [3], and Breyer [2]. The version presented by Gouveia [4] is the "purest." It highlights the role of the income-health nexus and explicitly addresses a scenario that fits the available data, which makes it very suitable for empirical testing. At the same time, the model's relevance remains undiminished, as more recent models still incorporate Gouveia's core assumption.

The premise is that rational, utility-maximizing individuals focus on the ratio between their relative income position and their relative risk of falling ill. Assuming a general linear income tax and disregarding the risk of falling ill, all individuals with higher than average income will oppose further taxation for the purpose of redistribution, as they will be net losers. They can obtain private insurance more cheaply. However, when also considering the risk of falling ill, this assessment may change. If their relative risk of falling ill is higher than their relative income position, they are likely to favor publicly financed insurance coverage, implying an increase in redistribution as they might benefit irrespective of their "disadvantageous" income position. So we include both parameters in our analysis, as their distribution will influence the outcome of a popular vote on the type of health insurance. Gouveia [4] analyzes different settings, ranging from exclusive mandatory public provision to purely private coverage. Due to the nature of our data, we focus on one setting, which mandates public coverage but allows private supplemental coverage. Within this setting, we examine the preferred extent of public coverage.

An assumption of all these models is that supplementary health insurance can be purchased at risk-rated premiums. If this assumption holds, then the relative income position and the relative risk of illness are decisive for an individual's voting decision. This income-health ratio reflects the tax price, i.e. the relative price to which health insurance is available under public provision compared to the private insurance market. If the ratio is larger than one, private health insurance is cheaper; persons in this position would prefer purely private coverage. In a regime without an opt-out option, a decrease in public efforts, that is any shift from public to private provision of insurance, will increase those individuals' utility level. While individuals with an income-health ratio equal to or smaller than one will generally favor some level of public provision, there may still be some who prefer a lower level than the status quo. This is true for low income individuals for whom the income effect outweighs the benefit of higher levels of public provision of health insurance [12].

Applicability of the theoretical framework to the institutional setting

About 90 % of Germans are covered by the SHI, with the rest of the population being insured privately. Civil servants with private health insurance also benefit from public healthcare allowances outside of the SHI system. Besides civil servants, the option to select exclusively private health insurance is only available for individuals above the income ceiling for compulsory SHI membership (i.e., €50,850 in 2012). We focus on the 61 million individuals (year 2012), including their dependents, for whom SHI membership is compulsory, as the number of individuals with an opt-out option is too small to be analyzed in our sample.

The SHI is financed by payroll contributions and, to a lesser extent, by general tax revenues. In the year of the survey, 2012, the contribution rate—set by the government—was 15.50 %. Contributions were capped at an income ceiling of €45,900 per annum. The income tax is progressive, including a tax-free allowance up to €8004. Thus, the marginal tax rate ranges from 0 to 45 %. Considering the tax-free allowance, it is unlikely that we can observe the reluctance of very low-income earners to agree upon an increase of taxes due to budget effects. The tax allowance protects them from this effect.

The SHI provides generous benefits but does not cover all options for diagnosis or the treatment of illnesses, which has led to an increasing demand for private supplementary insurance. In the market for private health insurance, we rarely see individually risk-rated premiums. However, when selling supplementary private health insurance in Germany (e.g., for special dental or hospital treatment, medicines, or remedies not covered by the SHI), insurers collect information regarding prior illnesses or age and do basic risk rating. The public is increasingly aware of the option to seek supplementary coverage and the typical terms. In 2013, 18 million contracts for supplementary health insurance existed in Germany, following a positive trend [25].[4]

Taking into account the theoretical model and the empirical reality, we can test key notions. Firstly, we hypothesize that individuals with an income-health ratio greater than one favor reducing the public provision of mandatory social health insurance. While the model predicts zero demand for public coverage by individuals with a favorable income-health indicator, it is unlikely that we would observe this extreme in actuality. Almost no empirical work starts with a clean slate but instead must consider the realities of the existing system. Furthermore, risk rating is not perfect, and thus risk-rated premiums are approximations. Nonetheless, we would expect that individuals with an income-health ratio higher than one prefer a lower level of public coverage than their counterparts with a ratio lower than one. Considering the fairly comprehensive coverage in the SHI system, it would not be surprising if this level was lower than the status quo. Secondly, most individuals with an income-health ratio less than one will favor public provision. As outlined above, the group of individuals who, due to income effects, favor a reduction of public coverage despite an income-health ratio smaller than one should not be relevant in our sample.

Discrete choice experiments and latent heterogeneity

The data used to estimate individuals' preferences are based on a discrete choice experiment (DCE). This approach, based on the Lancasterian demand theory [26], assumes that a utility-maximizing individual will always choose the alternative with the highest utility. Thus, an individual will choose a given alternative l only if its utility exceeds the utility derived from another alternative j [27, 28].

We cannot observe individuals' utility directly, so we treat utility as a latent construct, extending the indirect utility function of individual i to include an error term ε_{il}. According to the random utility theory [29–31], the utility function is stochastic and additively split into a deterministic observable part $V_l(\cdot)$ and a stochastic component ε_{il}:

$$U_{il} > U_{ij} \equiv V_{il} + \varepsilon_{il} > V_{ij} + \varepsilon_{ij} \qquad (1)$$

with the deterministic part V_{il} (V_{ij}) including the vector X of the k attributes $V_{il} = \sum_{k=1}^{K} \beta_k X_{ilk}$ and β_k, that is, the utility parameters. ε_{il} (ε_{ij}) captures an individual's unobserved heterogeneity. Assuming the stochastic component to be independent and identically distributed extreme value type I (i.e., $F(\varepsilon_{il}) = \exp(-\exp(-\varepsilon_{il}))$, [32]) leads to the standard conditional logit (CL) formula:

$$P_{il} = \frac{\exp(\beta' X_{il})}{\sum_{j=1}^{J} \exp(\beta' X_{ij})} \qquad (2)$$

We therefore estimate the probability P_{il} of individual i choosing alternative l rather than any other among the J alternatives [27]. The CL model is still the most common model for the analysis of discrete-choice data, leading to estimates of the mean tast of the attributes. As only utility differences matter for an individual's decisions, invariant personal characteristics will drop out of the estimation. Thus, preference heterogeneity in the CL model is typically captured by interacting socio-demographic characteristics with varying design variables [33]. However, some of the variation in preferences might be unrelated to observable personal characteristics. Neglecting this latent heterogeneity might bias estimates of the mean tast weights [34]. In combination with some basic limitations, most notably the independence of irrelevant alternatives assumption (IIA), alternative specifications such as the latent class model (LCM) are used to investigate an individual's choice behavior [35].[5]

The LCM assumes that behavior depends on observable attributes as well as on latent heterogeneity incorporated by a model of discrete parameter variation. Individuals are sorted into a set of Q discrete classes whose class membership is unknown for the researcher [38]. Following Greene and Hensher [35], the probability of individual i choosing alternative l in choice occasion t given a specific class q is given by

$$\Pr[i, t, l | \text{ class } q] = \frac{\exp(\beta_q x'_{itj})}{\sum_{j=1}^{J} \exp(\beta_q x'_{itj})} = F(i, t, j|q) \qquad (3)$$

Specify y_{it} to define a specific choice made by individual i, and the probability becomes

[4] Special insurance contracts like health insurance for travelers, etc., are not included in these figures. We refer to supplementary insurance owned by citizens insured in the SHI.

[5] Mixed logit models also can overcome the limitations of the CL model. However, specific assumptions about the distribution of the parameters among the respondents are required [36, 37]. In this paper, we apply LCMs to investigate preferences for social health insurance.

$$P_{it|q}(l) = \Pr(y_{it} = l | class = q). \quad (4)$$

The T_i choice situations are assumed to be uncorrelated given a certain class q. Thus, the joint probability given a specific class assignment is:

$$P_{i|q} = \prod_{t=1}^{T} P_{it|q} \quad (5)$$

As long as individual class assignment is unknown, H_{iq} denotes the probability for individual i to be in class q:

$$H_{iq} = \frac{\exp(z_i'\theta_q)}{\sum_{q=1}^{Q} \exp(z_i'\theta_q)}, \quad q = 1, \ldots, Q; \quad \theta_Q = 0 \quad (6)$$

The probability H_{iq} is affected by z_i, that is, a vector of observable personal characteristics and a constant. If no covariates are considered, the vector reduces to the constant terms that sum to one. Thus, the likelihood and the log-likelihood for individual i over Q classes are given by

$$\begin{aligned} P_i &= \sum_{q=1}^{Q} H_{iq} P_{i|q} \\ \ln L &= \sum_{i=1}^{N} \ln P_i = \sum_{i=1}^{N} \ln\left[\sum_{q=1}^{Q} H_{iq}\left(\prod_{t=1}^{T} P_{it|q}\right)\right]. \end{aligned} \quad (7)$$

The log-likelihood function is maximized with respect to the parameter β_q and θ_q [35]. Finally, a crucial issue in the estimation of an LCM is the choice of the number of classes Q, which will be discussed in "Estimation strategy".

Implementation and survey design

Following Bateman et al. [39], the development of the DCE requires special attention. The key steps are identifying and explaining relevant attributes and levels, applying an experimental design to create a statistically meaningful but still manageable number of choice sets, conducting the experiment, and analyzing the data. To account for the hypothetical nature and the complexity of the topic, extensive preparation was done, including intensive literature reviews, expert interviews, group discussions, and paper-based pretests involving a total of 629 students and faculty members. Additionally, three independently conducted pretests, with about 40 (nonstudent) participants each, helped to eliminate ambiguous wording and finalize the explanatory text.

The starting point for the selection of attributes was the annual financial statement of the Federal Ministry of Labor and Social Affairs (Sozialbudget), which summarizes all social spending, including public and social insurance spending. Based on this and additional literature, we preselected a number of potential attributes, which were then condensed during the process described above.

The result was a set of 10 attributes: personal tax and social insurance contributions, the amount of redistribution as a percentage of the GDP, the socio-demographic status of beneficiaries (sick persons and persons in need of care, families with children, retirees, unemployed, working poor) as well as the nationality of recipients (German, West European, other). These were grouped together in four diagrams to make the substitutive character and the trade-offs explicit (see Fig. 1 in the Appendix). In the context of the aforementioned model, the price attribute (personal tax and social insurance contributions), the attribute introducing the redistributive component (redistribution as a percentage of the GDP), and the attribute referring to sick persons and persons in need of care, are of particular importance. As outlined in more detail below, these attributes are used to approximate the individuals' preferences for an expansion of redistribution per se and for a shift of resources toward or away from the healthcare sector.

In a second step, the levels of the attributes were defined. While being within a realistic range, they should be spaced enough to make respondents "jump" between the status quo and an alternative redistributive scheme. That is, respondents should be forced to overcome trade-offs [39, 40]. The levels of the status quo were defined on the basis of official statistics such as the Sozialbudget. Table 1 represents the final selection of attributes and their respective levels. Again referring to Fig. 1, in all choice situations, the left side (framed in blue) represents the status quo of redistribution in Germany. The varying alternatives were placed on the right and framed in red.

The complete factorial design, containing all possible combinations of attributes and their levels, results in a total of 129,600 combinations (alternatives). By using the program gosset to apply a D-optimal design [41–43],[6] we could restrict the number of alternatives to 49. As this number exceeds the mental burden individuals can handle, design was blocked into seven sets of seven choice sets.[7] Each respondent was confronted with only one of these groups. To control for errors in decision-making, one

[6] While the D-optimality was primarily developed for linear estimation models, Carson et al. [44] suggest that the application for nonlinear models such as probit or logit is also possible.

[7] Bech et al. [45] show that the cognitive burden increases in the number of choice sets. Nevertheless, exposing respondents to up to 17 choice-sets is manageable, and respondents can handle it without problems. The blocking was based on the principle that each individual should be challenged with a balanced set of decisions, i.e., each block should contain a similar number of cases in which taxes/contributions and redistributive level were increased or decreased.

Table 1 Attributes, labels and levels

Attribute	Level				
			Status quo		
Personal tax and social insurance contributions					
Tax and contribution	15 %	25 %	30 %	35 %	45 %
Total amount of redistribution as a percentage of GDP					
Redistribution	20 %	25 %	30 %	35 %	45 %
Socio-demographic status of beneficiaries					
Retirees		30 %	40 %	45 %	
Sick persons and persons in need of care		30 %	35 %	40 %	
Unemployed		5 %	10 %	15 %	
Families with children		5 %	10 %	15 %	20 %
Working poor			5 %	10 %	
Nationality of recipients					
German	75 %	80 %	85 %	90 %	
West European			5 %	10 %	
Other		5 %	10 %	15 %	

alternative was included twice in each of the seven groups, resulting in eight binary choices per respondent.[8]

The DCE and an accompanying questionnaire were administered in the field by the market research institute GfK Nuremberg with computer assistance, recruiting a national quota sample[9] from the German voting-age population. The use of computer-based presentation techniques by the interviewers increased the level of control over the process—respondents, for example, were not allowed to go back and forth between choice tasks—and helped to reduce complexity by presenting clearly structured decision scenarios on the screen.

The first part of the interview was dedicated to socio-demographic characteristics and attitudes toward redistribution. This was followed by a comprehensive description of the current structure and volume of the German welfare system (see supplementary material for online publication). This step ensured that all respondents had similar knowledge of the status quo. A significant amount of interview time was invested in this. The attributes and the respective levels were then introduced. Participants were instructed that the alternative scenarios were possible redistribution systems that might be implemented in the future. After giving the chance to clarify any open questions, the eight binary choice situations were presented, and the interviewee made choices one after another. The interview closed with more sensitive questions, such as individuals' income, and questions for further robustness checks, such as those regarding the perceived complexity of the experiment.

The average interview lasted 36 min. Upon completion, the interviewee received a small in-kind acknowledgement. While typical laboratory experiments include real financial payoffs, this is usually not the case in field experiments. This may increase the risk of respondents overstating their true willingness-to-pay, as they do not feel a direct financial effect. Recent literature, however, suggests that willingness-to-pay estimates are not sensitive to whether payoffs are involved [49, 50].

Empirical analysis

Data

Our data is drawn from a representative cross-sectional survey of 1538 Germans conducted in February 2012. Table 2 presents selected items from the unrestricted dataset and compares mean values to data from official statistics (Destatis). For all items, the mean values in the sample and those from official statistics do not differ significantly, indicating that the dataset is indeed representative of the German population.

Of these, 1345 individuals are covered by SHI, 97 have a full private health insurance, 94 are covered by a mix of private and public insurance (civil servants), and two claim

[8] Only 13.3 % of the respondents failed the test on consistency—compared to other studies this is a fairly low number [46]. Numerous robustness tests show that results do not change regardless of whether these observations are included; results are available from the authors upon request. Furthermore, we find no link between socio-demographic characteristics, such as education and income, and the probability of choosing inconsistently. Following Lancsar and Louviere [47], we include the individuals who behaved inconsistently in all our analyses.

[9] Quota samples are a common approach in social-science research and are an alternative to random sampling [48]. The sample is stratified by age, gender, education, federal state, household size, location indicator, and household net income. Due to the sampling procedure in place, no take-up rates can be reported.

Table 2 Comparison of sample and official statistics

	Sample	Official statistics
Female	0.516	0.509
East German	0.214	0.197
Age		
18–29	0.169	0.171
30–39	0.141	0.143
40–49	0.203	0.201
50–59	0.171	0.171
60+	0.316	0.314
Monthly gross income from employment	2172 €	2150 €[a]
Proportion of SHI insured	87.12 %	86.81 %

Weighted data of the sample

[a] The value is based on measures from 2005 and extrapolated to 2012 using the general wage development

that they do not have any health insurance. Of the SHI-covered individuals, 139 did not provide information on income.[10] These individuals as well as all nonmandatory members of the SHI system—that is, those with an individual monthly gross income of more than €4125—were excluded from the analysis. Thus, the final sample of mandatory SHI members consists of 1172 individuals.[11]

The dependent variable is choice, indicating whether the individual opted for the alternative. Derived from the theoretical models, the income-health indicator is the central variable for the analysis. The indicator equals one if the ratio of relative income position and the relative health status is larger than one and zero otherwise. Instead of focusing on the ratio, we use the binary indicator for our analyses because, according to theory, the value of one is pivotal for the individuals' decision-making.[12] In the context of choosing a future system, expectations about the future development of these indicators is important. We have no means to account for this directly and must rely on current assessments as a proxy for expectations. For income, we use the individual's monthly gross personal income in euros. The relative income position is the individual's income in

Table 3 Variable description

Variable name	Label
Dependent variable	
Choice	1 = if decision for hypothetical alternative
	0 = if decision for status quo
Basis variables	
Income-health indicator	1 = the ratio on the basis of the relative individual income and the relative SAH is larger than one
Income-health ratio	Linear ratio on the basis of the relative individual income and the relative SAH
Individual income	Monthly gross personal income in euros (wages or pensions)
SAH	Would you say that your health status is
	1 = very good
	2 = good
	3 = ok
	4 = bad
	5 = very bad
Socio-demographic controls	
Female	=1 if female, = 0 if male
Age	Age of the respondents in years
East Germany	=1 if respondent is from East Germany, 0 otherwise
Secondary school	=1 if highest educational degree is secondary school, 0 otherwise
Vocational training	=1 if highest educational degree is vocational training, 0 otherwise
A-level	=1 if highest educational degree is A-level, 0 otherwise
University degree	=1 if highest educational degree is university, 0 otherwise
Married	=1 if married, 0 otherwise
Widowed	=1 if widowed, 0 otherwise
Divorced	=1 if divorced, 0 otherwise
Number of children	Number of children within the household

relation to the sample average. Self-assessed health (SAH) is the proxy for the expectations about the risk of falling ill. SAH is measured on a five-point scale, ranging from 1 = very good to 5 = very bad. Again, the ratio puts the individual SAH in relation to the sample average (see Table 3). For both components of the indicator, uncertainty plays an important role. Future studies may be able to collect more complementary data to account also for this aspect.

Table 4 column [1] summarizes descriptive statistics for the sample of all mandatory SHI members. For the binary dependent variable choice, the sample mean of 0.35 indicates that of the 9376 observed choices, in 35 % of the cases the alternative was chosen. Examining columns [2]

[10] Income variables are typically prone to missing values; however, the share of missing values is, compared to other surveys, relatively small within this dataset [51].

[11] The data has been collected on the basis of the German population eligible to vote. We see that the proportion of SHI insureds in the sample is very close to the administrative data, and it is very plausible that the restricted sample also representatively reflects the underlying population.

[12] See the robustness checks in "Robustness checks", which show that using the ratio as well as accounting for individuals' uncertainty on their concrete position, do not change the results.

Table 4 Descriptive statistics

	[1] All observations SHI mandatory		[2] Indicator = 0		[3] Indicator = 1	
	Mean	SD	Mean	SD	Mean	SD
Dependent variable						
Choice	0.35	0.48	0.34	0.47	0.36	0.48
N	9376		4960		4416	
Basis variables						
Individual income	1407.54	1008.07	685	585.44	2219.00	726.38
Relative income position	1.00	0.72	0.49	0.42	1.59	0.52
SAH	2.27	0.86	2.61	0.89	1.88	0.63
Relative health status	1.00	0.38	1.15	0.39	0.83	0.28
Income-health ratio	1.22	1.15	0.41	0.34	2.13	1.07
Income-health indicator	0.47	0.50	0.00	0.00	1.00	0.00
Socio-demographic controls						
Female	0.55	0.50	0.67	0.47	0.42	0.49
Age	49.23	17.11	51.85	17.97	46.29	15.59
East Germany	0.33	0.47	0.37	0.48	0.29	0.45
Secondary school	0.33	0.47	0.31	0.46	0.35	0.48
Vocational training	0.21	0.41	0.20	0.40	0.22	0.42
A-Level	0.12	0.33	0.12	0.32	0.13	0.34
University degree	0.10	0.30	0.07	0.25	0.14	0.35
Married	0.52	0.50	0.52	0.50	0.53	0.50
Widowed	0.07	0.25	0.09	0.29	0.04	0.20
Divorced	0.12	0.32	0.12	0.33	0.12	0.32
Number of children	1.23	1.15	1.33	1.19	1.11	1.10
N	1172		620		552	

and [3], representing individuals with an income-health indicator equal to 0 and 1, respectively, this value remains stable. Compared to other DCEs, 0.35 is a rather high value [52, 53]. Furthermore, only 8 % of respondents never chose an alternative. This gives rise to the expectation that the MRS and MWTP values can be estimated with sufficient precision.

The descriptive statistics of the indicator and the respective basis variables are based on the 1172 aforementioned individuals. With the sample being capped at an income of €4125, the resulting average income is €1407. Self-assessed health is somewhere between good and OK. On average, the income-health ratio is at 1.22. As only 47 % of the sample ($N = 522$) have an indicator equal to one, this means that the distribution is slightly right skewed. Comparing columns [2] and [3], one can see that, as expected, average income and average SAH is lower—respectively worse—for the individuals with an indicator equal to zero. This carries over to the relative income position and the relative health status, resulting in an average income-health ratio of 0.41 vs. 2.31 (for a graphical presentation of the income-health indicator components, see also Fig. 2 in the Appendix).

Estimation strategy

As both the beneficiary groups and the nationalities add up to 100 %, we have to omit one reference category for each of them to avoid perfect collinearity. In this case, we opt for unemployed and German. Thus, the basic linear additive utility function of the model is given by

$$U_{itj} = \beta_0 + \beta' \Delta X_{itj} + \varepsilon_{itj}, \quad j = 1, 2. \tag{8}$$

The systematic part of the utility function includes an alternative specific constant (ASC) for the status quo alternative (β_0) and a vector of the design attributes X. To allow for a meaningful interpretation of the welfare measures, the analyses must be related to one specified point of the individuals' utility function. The status quo is the natural anchoring point. Thus, for the econometric analysis, we specify the design attributes to reflect the difference between the value of the status quo alternative and the hypothetical alternative, that is, ΔX.[13] The results describe a deviation from the status quo.

[13] The quadratic terms are generated in the same way [e.g., $\Delta \text{Redistribution}^2 = (\text{Redistribution}_{\text{status quo}} - \text{Redistribution}_{\text{alternative}})^2$] to adequately reflect the quadratic deviation from the status quo.

Table 5 Basic model comparison

Choice	[1] All linear	[2] Linear and redistribution^2	[3] Linear and redistribution^2, tax and contrib.^{2}	[4] Linear and redistribution^2, tax and contrib.^{2}, sick and persons in need of care^2	[5] Linear and redistribution^2, tax and contrib^2, sick and persons in need of care^2, other nationalities^2
Log likelihood	−5477.23	−5470.35	−5435.52	−5430.59	−5426.10
McFadden Adj. R^2	0.089	0.090	0.095	0.096	0.097
AIC	10,974.46	10,962.69	10,895.04	10,887.18	10,880.19
BIC	11,045.92	11,041.29	10,980.79	10,980.07	10,980.24
LR-test		13.77***	69.65***	9.86***	8.98***
MWTP redist[a]	0.452***	0.542***	0.542***	0.549***	0.548***
N	9376	9376	9376	9376	9376

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a] All MWTP standard errors were calculated using the delta method

As a linear specification of the indirect utility function imposes the restrictive assumption of a constant marginal utility [54, 55], we identify relevant quadratic terms using several specification procedures that systematically test all potential combinations of quadratic and linear terms. Primarily we rely on the forward-selection and backward-elimination procedure in combination with standard likelihood ratio tests suggested by Hosmer and Lemeshow [56] and Sennhauser [57]. Table 5 summarizes the statistical measures for some of the tested specifications. Model [1] includes only linear terms. From model [2] to model [5] successively all other squared terms that were identified as being statistically relevant are added. Model [5] featuring squared terms for redistribution, tax and contributions, sick, and other nationalities clearly outperforms all alternatives. Thus, vector X_{itj} in Eq. (8) is extended to include all design attributes in linear terms and the attributes redistribution, tax and contribution, sick and persons in need of care, and other nationalities in squared terms.

To allow for a meaningful interpretation of the results, after the estimation, MTWP values are calculated. Slightly simplifying, the MWTP is equal to the MRS, that is, the ratio of the partial derivatives pertaining to the design attribute of interest and the price attribute tax and contribution.[14] The status quo being the reference category in all choices, we calculate the MWTP at the status quo values, that is, $\Delta\text{Redistribution} = \Delta\text{Tax and contribution} = 0$, making the quadratic terms cancel out of the equation. Calculating the MWTP redist, that is, the MWPT with regard to an expansion of the general redistributive budget, the equation reads

$$MWTP_{TC}^{RE} = -\frac{\partial V_{ilj}(\bullet)/\partial \Delta\text{Redistribution}}{\partial V_{ilj}(\bullet)/\partial \Delta\text{Tax and contribution}} = -\frac{\beta_{\text{Redistribution}} + \beta_{\text{Redistribution}^2} * 2 * \Delta\text{Redistribution}}{\beta_{\text{Tax and contribution}} + \beta_{\text{Tax and contribution}^2} * 2 * \Delta\text{Tax and contribution}} = -\frac{\partial V_{ilj}(\bullet)/\partial \Delta\text{Redistribution}}{\partial V_{ilj}(\bullet)/\partial \Delta\text{Tax and contribution}}\Bigg|_{\substack{\Delta\text{Tax and contribution}=0;\\ \Delta\text{Redistribution}=0;}} = -\frac{\beta_{\text{Redistribution}}}{\beta_{\text{Tax and contribution}}} = -\frac{0.0314}{-0.0573} = 0.5479 \quad (9)$$

This means that, taking the estimation results of model [5] in Table 5 (see full estimation results in the Appendix), the individuals in our sample on average would be willing to cede 0.548 additional percentage points of their income in return for an increase of the overall redistributive budget by 1 percentage point. To obtain MWTP sick, that is, the MWTP to increase the share that is dedicated to the sick, the enumerator of Eq. (9) is replaced by the partial derivative with regard to the attribute sick.

In the CL version of the utility function, preference heterogeneity is considered by interacting personal

[14] Based on Roy's identity, the price parameter tax and contribution can be interpreted as the marginal utility of income. For the formal proof see [58] or [59].

characteristics, such as the income-health indicator, with varying design attributes. Thus, Eq. (8) changes to

$$U_{itj} = \beta_0 + \beta' X_{itj} + \eta' Z_i X_{itj} + \varepsilon_{itj} \quad j = 1, 2, \tag{10}$$

with the person-specific interaction term $Z_i X_{itj}$, that is, an interaction between the income-health indicator and the design attributes in *X*. Accordingly, the MWTP values can be calculated for each of the two instances of the income-health indicator, the partial derivatives then including the coefficients of the respective interaction terms.

The LCM accounts for preference heterogeneity through a set of *Q* discrete classes. In our approach, the number of classes is derived from theory. As outlined before, theory suggests that there exist two distinct classes within the sample of mandatorily insured individuals. Class membership may be determined by the income-health indicator—one class with individuals whose indicator is zero and one class with individuals having an income-health indicator of one or greater. Following this, the vector Z_i in Eq. (6) consists of a constant and the income-health indicator in the two-class LCM.

Results

Looking first at the results of the conditional logit model (Table 6), one can see that all attributes besides working poor are highly significant. Most interestingly, the income-health indicator has a highly significant negative impact on tax and contribution as well as on redist. For a meaningful interpretation of these coefficients, the MWTP is calculated.[15] While MWTP redist captures the MWTP for an expansion of the overall budget for redistribution beyond the current status quo, *MWTP sick* captures the MWTP for shifting resources away from the other groups (i.e., in this case, away from the unemployed) to individuals sick or in need of long-term care. Individuals with an indicator equal to zero, that is, the expected beneficiaries of an extension of the public provision of health care, indeed have a highly significant positive willingness to pay not only for a shift towards the sick but also for a general extension of the budget for redistribution. On average, they would be willing to cede 0.74 % points of their income to obtain a 1 % point of GDP increase of the overall budget.

Examining the expected net losers of the public setup, they prefer a lower overall level of redistribution, the (negative) MWTP again being highly significant. Thus, to accept a further expansion of public coverage, they would demand compensation. Despite leaning towards the expected negative sign, the MWTP regarding a shift to or away from the sick is not significantly different to zero. Nonetheless, even if the share of redistribution dedicated to the sick remains stable, the general preference for a reduction in the overall level of redistribution implies that the amount of money available for the sick shrinks. The differences in MWTP redist and MWTP sick respectively between the two groups are significant at the 5 % (MWTP sick) and the 1 % (MWTP redist) levels.

Our empirical results corroborate the assumptions and predictions of the theoretical models: in a setting that

Table 6 Estimation results of CL model for MWTP for redistribution

Choice		[1] CL	
		Coeff	SE
Tax and contribution		−0.081	0.004***
Tax and contribution^2		−0.002	0.000***
Redistribution		0.059	0.005***
Redistribution^2		−0.002	0.000***
Sick persons and persons in need of care		0.031	0.009***
Sick persons and persons in need of care^2		0.005	0.002**
Retirees		0.048	0.007***
Families with children		0.043	0.008***
Working poor		0.004	0.010
West Europeans		−0.057	0.010***
Other nationalities		−0.061	0.006***
Other nationalities^2		0.007	0.002***
ASC		0.332	0.070***
Income-Health Indicator			
×Tax and contribution		−0.017	0.006***
×Tax and contribution^2		0.000	0.000
×Redistribution		−0.024	0.008***
×Redistribution^2		0.002	0.001***
×Sick persons and persons in need of care		−0.011	0.012
×Sick persons and persons in need of care^2		−0.002	0.003
MWTP sick[a]	Income-health Indicator = 1	−0.146	0.154
MWTP sick[a]	Income-health Indicator = 0	0.388	0.118***
MWTP redist[a]	Income-health Indicator = 1	−0.337	0.095***
MWTP redist[a]	Income-health Indicator = 0	0.736	0.058***
Number of observations			9376
Number of respondents			1172
LL			−5486
McFadden Adj. R^2			0.095
AIC			11,009
BIC			11,145

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

[a] All MWTP standard errors were calculated using the delta method

[15] Ai and Norton [60] point to the fact that the full interaction effect in a nonlinear model should rather be calculated using the "cross derivative of the expected value of *y* […]." However, in a nonlinear model, the expected value of *y* depends on the unobserved error term. This renders an exact calculation almost impossible. Thus, we have tested whether the results prove robust when using a traditional OLS specification. We find that the magnitude does not change significantly.

features mandatory public coverage but allows for supplementary private insurance, expected beneficiaries of public provision strongly support an extension of public coverage, while expected net payers strongly object. As suggested by the theory, the latter group would favor even a reduction below the status quo.

However, considering the median voter, finding a majority for the extension of coverage is a rather close call. For 53 % of voters in our sample, the indicator equals zero. Acknowledging that, in real life, the indicator is very likely one of many factors influencing the decision, further analysis is warranted. We do this by applying a latent class

Table 7 Estimation results from the latent class model

Choice	[1]				[2]			
	Class 1		Class 2		Class 1		Class 2	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Tax and contribution	−0.028	0.005***	−0.351	0.038***	−0.032	0.006***	−0.247	0.021***
Tax and contribution^2	−0.003	0.000***	−0.008	0.003***	−0.003	0.001***	0.000	0.001
Redistribution	0.044	0.006***	0.091	0.012***	0.053	0.006***	0.071	0.011***
Redistribution^2	−0.002	0.001***	−0.002	0.001**	−0.002	0.001***	−0.002	0.001**
Sick persons and persons in need of care	0.027	0.010***	0.036	0.022	0.028	0.011***	0.013	0.020
Sick persons and persons in need of care^2	−0.009	0.003***	0.013	0.006**	−0.009	0.003***	−0.004	0.006
Retirees	0.041	0.009***	0.112	0.024***	0.048	0.009***	0.052	0.019***
Families with children	0.039	0.010***	0.078	0.024***	0.031	0.011***	0.073	0.019***
Working poor	0.005	0.014	0.030	0.026	−0.010	0.015	0.068	0.025***
West Europeans	−0.036	0.013***	−0.112	0.025***	−0.038	0.014***	−0.115	0.024***
Other nationalities	−0.090	0.008***	−0.033	0.017*	−0.099	0.009***	−0.025	0.016
Other nationalities^2	0.007	0.003**	−0.006	0.006	0.006	0.003*	0.002	0.005
ASC	0.465	0.097***	−0.005	0.191	0.446	0.100***	−0.034	0.178
Class probabilities								
Constant					−0.692	0.400*	–	
Income-health indicator					−0.624	0.167***	–	
Female					−0.211	0.168	–	
Age					0.039	0.007***	–	
East Germany					0.001	0.001	–	
Secondary school					0.235	0.214	–	
Vocational training					0.003	0.234	–	
A-level					0.316	0.272	–	
University degree					0.773	0.315**	–	
Married					−0.314	0.243	–	
Widowed					−0.422	0.429	–	
Divorced					−0.184	0.322	–	
Number of children					−0.132	0.088	–	
Average class probability	0.647		0.353		0.640		0.360	
MWTP sick[a]	0.964	0.399**	0.102	0.066	0.882	0.363**	0.052	0.083
MWTP redist[a]	1.572	0.283***	0.258	0.029***	1.664	0.291***	0.288	0.039***
Number of observations			9376				9376	
Number of respondents			1172				1172	
LL			−5219				−5191	
McFadden Adj. R^2			0.195				0.198	
AIC			10,492				10,460	
BIC			10,685				10,739	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

[a] All MWTP standard errors were calculated using the delta method

model, as outlined in "Discrete choice experiments and latent heterogeneity". This has the virtue of allowing for latent and unobservable variables that may influence a voter's stance on public or private provision of healthcare. Table 7 summarizes the results. Model [1] represents the baseline two-class model, and model [2] tests whether the income-health indicator can explain class membership when also controlling for other socio-demographic characteristics. MWTP values are calculated according to equation (9) for each of the two classes.[16]

In Model [1], class one comprises about 65 % of the population—the clear majority. While in class one the coefficient of sick persons and persons in need of care is now positive and highly significant, this is not true for class two. The difference in the coefficients for tax and contribution is also very marked. Thus, class one exhibits a significant positive willingness to pay for a shift towards the sick (MWTP sick = 0.964). Furthermore, members of the class want the overall budget for redistribution to be considerably expanded (MWTP redist = 1.572). In contrast, on average the members of class two are not willing to pay for a shift in favor of the sick. Although there is a small but significant willingness to pay for an increase in the budget for redistribution, this willingness to pay (MWTP redist = 0.258) is much lower than the respective willingness to pay of class one.

Once we include the income-health indicator (among other socio-demographic control variables) to explain class membership, we see that this variable has a highly significant effect. The probability of being a member of class one—that is, the class with the high levels of willingness to pay—is much lower if the indicator equals one (−0.624). Thus, the expected net beneficiaries are primarily in this group. While the statistical criteria slightly improve, coefficients, willingness to pay, and overall size of the two classes change only marginally between the two models. Besides the effect of our income-health indicator, only age and university degree exhibit statistical significance. Older individuals as well as those with a higher education are more likely to be in class one; they are more likely to have a higher preference for redistribution and sick people or people in need of care. Other socio-demographic characteristics do not affect class membership.

In summary, the latent class model supports the findings of the conditional logit model regarding individuals with an income-health indicator equal to zero. Contrary to the conditional logit model, we see a slight positive willingness to pay in a group of individuals that is positively correlated with an indicator equal to one. Acknowledging that in real life the income-health indicator never solely determines favoring an extension of public or private provision, this seems to be very plausible. In both classes, individuals of both types are present. But there is a strong majority in favor of increasing redistribution, with a special focus on the sick, and the income-health indicator is a good predictor for group membership.

Robustness checks

As individuals are unlikely to know their exact relative positioning on both scales, we test for robustness and apply different empirical specifications.[17] In particular, the classification of the individuals into the two income-health indicator groups according to their income-health ratio is crucial. The cutoff value of one might be questionable: individuals close to that value may not differ significantly from persons in the other group. However, the lack of perfect information is not a fundamental concern from an empirical perspective, as this is also true for real world votes and reflects individuals' behavior.

The following analysis presents results of conditional logit and latent class models for subsets of the sample. In this specification, individuals with an income-health ratio between 0.95 and 1.05 are excluded, resulting in a loss of 52 observations.

Results of the CL model [1] are the same compared to the estimation using the full sample (Table 8). MWTP Sick and MWTP Redist do not change. Individuals with an income-health indicator of one show no significant MWTP for sick persons, while individuals with an indicator of zero exhibit a strong positive MWTP. The same holds true when examining MWTP for redistribution.

Turning to the results of the LCM (Table 8; column [2]), the findings prove robust, and class membership is significantly affected by individuals' income-health indicator. The results suggest that individuals with an income-health indicator of one are less likely to be in class one (the class with a strong positive and significant MWTP for redistribution and sick). Likewise, individuals with an indicator of zero are more likely to have preferences for an increasing amount of redistribution devoted to the sick and persons in need of care.

We also test whether using the income-health ratio itself rather than the binary indicator applied in most formal microeconomic models has an impact on individuals' preferences for redistribution using a CL model [3] and a LCM [4]. The results presented in Table 8 show that the MWTP values change neither for the sick nor for redistribution. Class membership within the LCM still

[16] This means for class 1 in model [1]: MWTPsick = − (0.027/-0.028) = 0.964. MWTP values for redistribution as well as for the second class are calculated equivalently.

[17] Full estimation results from the conditional logit and latent class models are available upon request.

Table 8 Robustness tests—subsample and income-health ratio

Choice	Income-health indicator			Income-health ratio		
	[1] CL 0.95–1.05	[2] LCM 0.95–1.05		[3] CL	[4] LCM	
		Class 1	Class 2		Class 1	Class 2
	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)
Class probabilities						
Constant		0.962 (0.139)***			0.802 (0.130)***	
Income-health indicator		−0.610 (0.155)***				
Income health ratio					−0.146 (0.062)**	
Average class probability		0.658	0.342		0.650	0.350
MWTP sick[a]		0.697 (0.339)**	0.102 (0.071)		0.933 (0.386)***	0.106 (0.067)
Income-health indicator = 1	−0.100 (0.154)			0.039 (0.072)		
Income-health indicator = 0	0.334 (0.120)***			0.267 (0.125)**		
MWTP redist[a]		1.440 (0.240)***	0.257 (0.032)***		1.559 (0.276)***	0.260 (0.030)***
Income-health indicator = 1	−0.317 (0.098)***			−0.110 (0.045)**		
Income-health indicator = 0	0.715 (0.061)***			0.685 (0.061)***		
Number of observations	8960		8960	9376		9376
Number of respondents	1120		1120	1172		1172
LL	−5248		−4895	−5495		−5216
McFadden Adj. R^2	0.096		0.195	0.093		0.195
AIC	10,533		10,025	11,027		10,488
BIC	10,668		10,224	11,163		10,688

Full estimation results are available upon request

$p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

[a] All MWTP standard errors were calculated using the delta method

significantly depends on an individual's income-health ratio. However, the magnitude of the effect has decreased compared to the binary indicator.

Finally, we perform a test of the two components of the income-health ratio themselves—relative income position and relative health status—and thus check whether using the indicator or the ratio entails a loss of information. Both ratios are assumed to determine class membership in the LCM separately. As can be seen from Table 9, both variables exhibit a significant effect on the probability of belonging to a certain class. While individuals who have worse health status compared to the average are more likely to belong to class one, those with an above average income are less likely to be found in the class. Turning to the MWTP values, MWTP for redistribution and sick is significantly higher in class one, that is, the group of individuals who would be net losers from increased redistribution or who would gain from increased redistribution to sick persons. In contrast, MWTP for sick persons is insignificant in class two. Again, our main result proves robust even when controlling for the components of the income-health ratio.

Table 9 Robustness test—estimation results from the latent class model for separate ratios

Choice	Components of the ratio			
	[1] LCM			
	Class 1		Class 2	
	Coeff	SE	Coeff	SE
Class probabilities				
Constant	0.271	0.266		
Relative health status	0.566	0.209***		
Relative income position	−0.186	0.105**		
Average class probability	0.655		0.345	
MWTP sick[a]	0.909	0.371**	0.101	0.068
MWTP redist[a]	1.533	0.260***	0.259	0.031***
Number of observations			9376	
Number of respondents			1172	
LL			−5213	
McFadden Adj. R^2			0.195	
AIC			10,483	
BIC			10,690	

Full estimation results are available upon request

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

[a] All MWTP standard errors were calculated using the delta method

To sum up, the exclusion of individuals close to the cutoff value of one, the use of the income-health ratio instead of the binary indicator or even the components of the income-health ratio does not affect the overall results. Our findings remain robust. Evaluating the different models with respect to goodness of fit, we find that the LCM model outperforms the traditional CL model in every specification. The LCM of the indicator (Table 7; [2]), the model without individuals close to the cutoff value of one (Table 8; [2]) and the LCM of the income-health ratio (Table 8; [4]) are superior to the respective CL models regarding AIC, BIC, and LL value. We also find that using the income-health indicator does not entail a loss in goodness of fit when contrasted with a specification that includes the components of the indicator separately. The AIC and LL is lower when using the indicator rather than the ratio or the components of the ratio between the CL models and the LCM.[18]

[18] We have also checked whether the inclusion of individuals claiming to have a gross income of zero bias our results. However, results from CL models and LCM of the indicator and the ratio itself prove robust. In fact, the coefficients increase and standard errors decrease. Thus, results would be even stronger when excluding individuals with no income from our analysis. More information is available upon request.

Concluding remarks

Our aim is to test the relationship between income, risk of illness, and preferences for redistribution in favor of sick persons. The analysis, which employs a unique dataset, is based on a discrete choice experiment (DCE) that was conducted in the field with more than 1500 individuals. Our results underscore the relevance of the income-health indicator suggested by the theory. Persons who benefit from public coverage exhibit a positive willingness to pay for an extension of the coverage beyond the status quo. The others are not willing to contribute to this end. In the conditional logit model, we even find negative MWTP—that is, these individuals would prefer a lower level of coverage. These findings support the notion of the prior theoretical works and are robust to a number of different specifications. While the conditional logit model is more closely linked to the theoretical model, the latent class model may provide more practical information for policymakers. We find that, within the group of mandatorily insured, there is a solid majority exhibiting a positive MWTP for extension of the welfare state and a shift of resources into the healthcare sector. However, we cannot predict the outcome of a popular vote on this topic, as individuals with full private health insurance or a mix of private health insurance and public allowances were excluded from the analysis. As these two groups are largely exempt from the redistributive system within the SHI, it is difficult to predict their voting behavior.

The advantage of the DCE is that respondents are forced to overcome trade-offs and consider explicit budget effects, giving a much clearer picture of citizens' preferences. We argue that, especially from an economic perspective, these results are superior to pure attitudinal measures, though we concede that the results are an approximation of preferences, subject to limitations, such as the hypothetical nature of the decision task. Using real financial incentives could help to make the decision task more realistic, but this is simply not feasible in the setting of a large and representative field study. The highly significant results for the price attribute underscore that participants took the budget effects into account when making their decisions. Generally, the framing of the price attribute is critical. In this study, the price attribute summarizes taxes and contributions to social insurance systems as a proportion of income. For technical and methodological reasons, this cannot be adjusted for participants' individual income levels. We addressed this issue through various robustness checks and found that the results endured. The same is true regarding concerns that the very general framing of the decision task may weaken its applicability for questions explicitly addressing social health insurance. However, the attributes referring to the sick turned out to be an important factor in the decision-making. We are confident that the advantages mentioned above as well as the chance to capture preferences that are not revealed in real economic markets outweigh the potential limitations.

On a more general level, other potential limitations do have to be considered. First, only the effect of one specific factor was analyzed. Future research should also consider determinants such as risk aversion, altruism, and culture. Second, survey data always refer to a point in time and cover the current economic and social situation in the country in which the survey was administered. Finally, we cannot directly control the correctness of the respondents' self-assessment compared to the average. The model implies that individuals know their income-health ratio, which is a rather strong assumption. Objective measures might be preferable. However, this paper concentrates on subjective perceptions and preferences. Individuals will opt for or against an alternative depending on their perceived, rather than their objective, position. In addition, comparing individuals' equivalent household net income with their subjective self-positioning on a social distance scale suggests that individuals are fairly realistic when assessing their status in relation to fellow citizens.

Besides strengthening the empirical underpinning of a very broadly used theoretical model, some practical implications can be derived from our results. The data based on a DCE administered in the field, combined with latent class models, provides insights into the preference structure of citizens. Thus, this seems to be a promising approach also for analyzing the potential acceptance of health reform, including changes to the financing of healthcare coverage. As basically all developed countries have some sort of combination between mandatory and voluntary components as well as varying degrees and forms of public subsidization, this particular question is applicable to a wide range of healthcare systems.

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Conflict of interest No potential conflicts of interest exist.

Appendix

See Table 10 and Figs. 1,2.

Table 10 Full estimation results of specification tests

Choice	[1] All linear	[2] Linear and redistribution^2	[3] Linear and redistribution^2, tax and contribution^2	[4] Linear and redistribution^2, tax and contribution^2, sick and persons in need of care^2	[5] Linear and redistribution^2, tax and contribution^2, sick and persons in need of care^2, other nationalities^2
Tax and contribution	−0.056 (0.002)***	−0.056 (0.002)***	−0.057 (0.002)***	−0.057 (0.002)***	−0.057 (0.002)***
Tax and contribution^2			−0.001 (0.000)***	−0.001 (0.000)***	−0.001 (0.000)***
Redistribution	0.025 (0.002)***	0.030 (0.003)***	0.031 (0.003)***	0.032 (0.003)***	0.031 (0.003)***
Redistribution^2		−0.001 (0.000)***	−0.001 (0.000)***	−0.001 (0.000)***	−0.001 (0.000)***
Sick persons and persons in need of care	0.019 (0.005)***	0.017 (0.005)***	0.015 (0.005)***	0.015 (0.005)***	0.017 (0.005)***
Sick persons and persons in need of care^2				−0.004 (0.001)***	−0.004 (0.001)***
Retirees	0.039 (0.004)***	0.035 (0.004)***	0.034 (0.004)***	0.033 (0.004)***	0.032 (0.004)***

Table 10 continued

Choice	[1] All linear	[2] Linear and redistribution²	[3] Linear and redistribution², tax and contribution²	[4] Linear and redistribution², tax and contribution², sick and persons in need of care²	[5] Linear and redistribution², tax and contribution², sick and persons in need of care², other nationalities²
Families with children	0.037 (0.005)***	0.034 (0.005)***	0.031 (0.005)***	0.029 (0.005)***	0.028 (0.005)***
Working poor	0.005 (0.006)	0.010 (0.006)	0.010 (0.006)	0.007 (0.006)	0.003 (0.007)
West Europeans	−0.052 (0.006)***	−0.048 (0.006)***	−0.042 (0.006)***	−0.040 (0.006)***	−0.037 (0.006)***
Other nationalities	−0.040 (0.004)***	−0.043 (0.004)***	−0.042 (0.004)***	−0.041 (0.004)***	−0.039 (0.004)***
Other nationalities²					0.004 (0.001)***
ASC	−0.338 (0.029)***	−0.305 (0.030)***	−0.217 (0.032)***	−0.142 (0.040)***	−0.216 (0.047)***
Log Likelihood	−5477.23	−5470.35	−5435.52	−5430.59	−5426.10
McFadden Adj. R^2	0.089	0.090	0.095	0.096	0.097
AIC	10,974.46	10,962.69	10,895.04	10,887.18	10,880.19
BIC	11,045.92	11,041.29	10,980.79	10,980.07	10,980.24
LR-test		13.77***	69.65***	9.86***	8.98***
MWTP	0.452***	0.542***	0.542***	0.549***	0.549***
N	9376	9376	9376	9376	9376

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

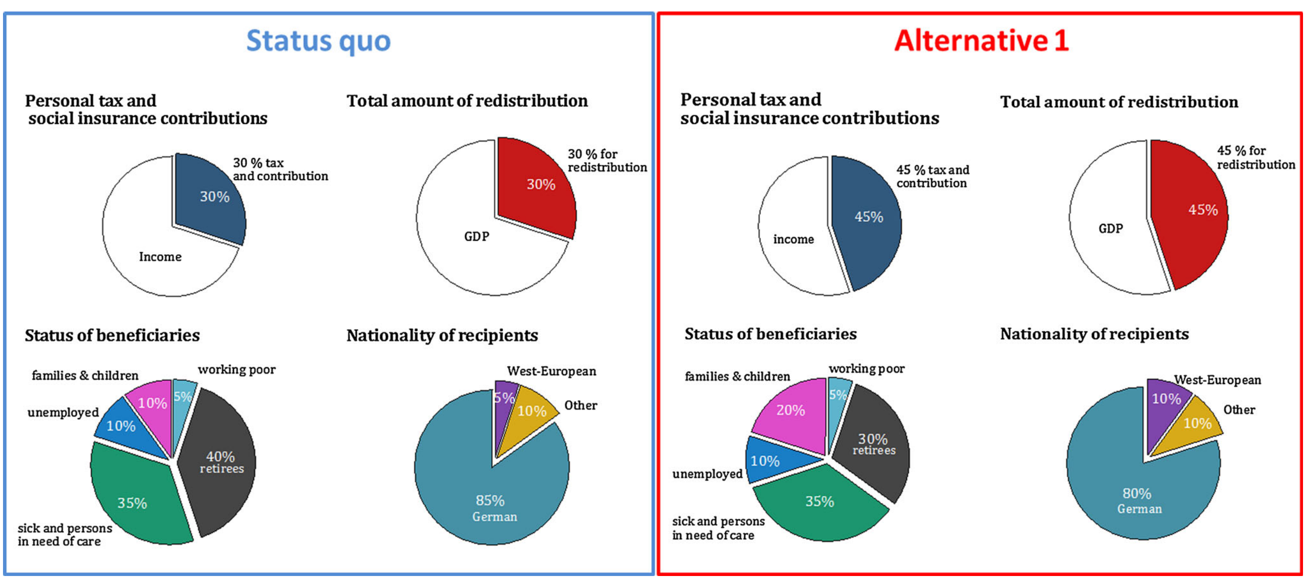

Fig. 1 Choice situation

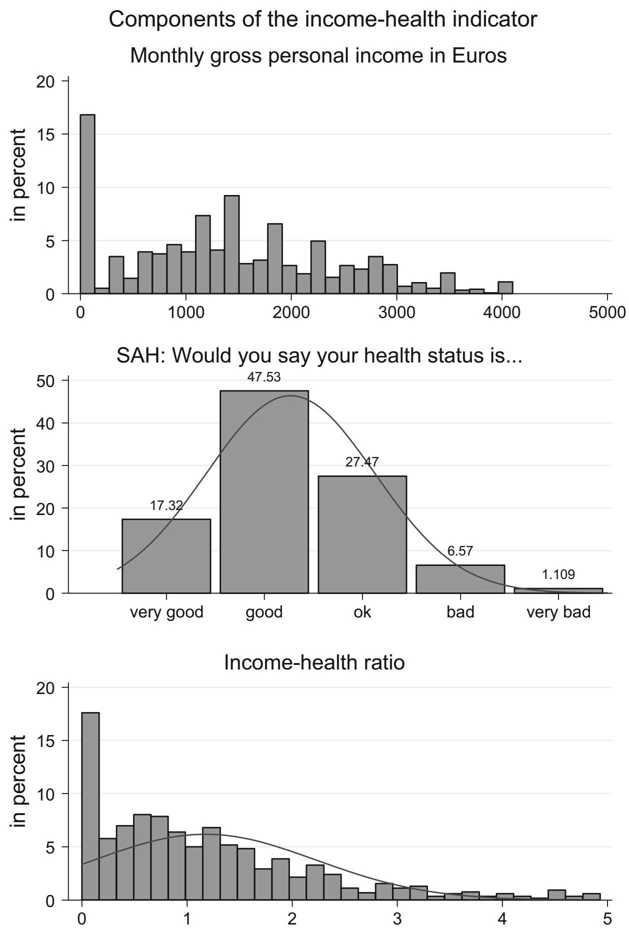

Fig. 2 Income-health indicator and its components

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