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Selectivity Processes in and Weights for the Berlin Aging Study II (BASE-II)

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Summary

Like many medical studies, the Berlin Aging Study II (BASE-II) is based on a non-random "convenience sample" of self-recruited participants. To study processes of selectivity in BASE-II, we used a questionnaire to compare BASE-II with a large, representative reference study, the German Socio-Economic Panel (SOEP), thereby allowing differences in characteristics of participants in BASE-II and SOEP to be analysed easily. Based on this selectivity analysis, we then generated propensity score weights that adjust for the selectivity in the BASE-II survey. In addition, we adjusted the weights of the BASE-II sample to statistical information from the Federal Statistical Office so that the BASE-II study has the same totals as the official statistics.

Zusammenfassung

Wie viele medizinische Studien, so basiert auch die Berliner Altersstudie (BASE-II) auf keiner Zufallsstichprobe, sondern auf einem sogenannten „Convenience Sample", also einer Stichprobe von sich selbst-rekrutierten Probanden. Die Verwendung eines Fragebogenmoduls in BASE-II, das mit wesentlichen Fragen in einer großen, für Deutschland repräsentativen Referenzstichprobe – dem Sozio-oekonomischen Panel (SOEP) – übereinstimmt, erlaubt die Analyse von Unterschieden zwischen SOEP-Befragten und BASE-II Teilnehmern, um so Selektionsprozesse unter den BASE-II Teilnehmern aufdecken zu können. Auf Basis von entsprechenden Selektivitätsanalysen werden Gewichte generiert und für Analysen bereitgestellt. Die Gewichte gleichen die Selektivität in der BASE-II Studie für deskriptive Zwecke weitgehend aus und können ggf. für die Kontrolle der Selektivität in multivariaten Modellen genutzt werden. Darüber hinaus werden Informationen des Statistischen Bundesamtes genutzt, um die Gewichte der BASE-II Studie so anzupassen, dass deren gewichtete Daten dieselben Randverteilungen aufweisen wie die offiziellen Statistiken.

Keywords: *Convenience Sample, Selectivity, Weighting, Berlin Aging Study II, BASE-II, SOEP*

JEL Classification: *C18, C23, C8, I1*

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1 Introduction

Survey data used in the social sciences are derived primarily from random samples that guarantee the representativeness of the sample and ensure the generalizability of results across a broader population. Convenience samples ("quota samples") are sometimes used, however, if random samples cannot deliver the desired quality of indicators. This is often the case, for example, in medical and psychological research in which respondents ("subjects") select themselves into a study. Because of self-selection, convenience samples are characterised by a high risk of biased data. Nevertheless, such samples are used widely, particularly in medical research, often without considering the consequences of self-selection processes on the estimates.

Given that the main components of the BASE-II study (Berlin Aging Study II) are psychological tests and medical examinations, the study population of BASE-II is based on a convenience sample. Therefore, it is a challenge (1) to describe potential biases and (2) to find an adequate weighting scheme for the socio-economic part of the BASE-II dataset (SOEP-BASE). Due to the absence of an a priori defined "gross sample" of the target population, weighting adjustments usually used in the context of nationally representative data sources such as the SOEP (German Socio-Economic Panel Study) are not applicable for BASE-II. At the same time, it is crucial to conduct bias analyses and to consider the weighting of the BASE-II data since convenience samples have a high risk of biases. Selectivity analyses and weighting are especially challenging due to the different modules and subsamples in BASE-II (Bertram et al. 2013).[1]

In section 2, this paper briefly reviews the literature on selectivity processes – sample selectivity and attrition over the course of time – in health surveys and medical studies. In section 3, the design of the BASE-II study is briefly described. Section 4 analyses selectivity processes in the BASE-II population. External datasets used for the analysis are described and the variables used in the models are specified. A description on the computation of weights follows, and it is then demonstrated how bias can be reduced through the use of those weights. The concluding section summarises the findings.

[1] The BASE-II group at the DIW provides weights for the different modules and subsamples of BASE-II.

2 Selectivity and Attrition in Health Surveys and Medical Research

Survey data are a key foundation of substantive research in the social sciences and related research fields. Schnell (2012) reports a threefold increase in research articles based on survey data from 1980 to 2010. With the growing interest in survey data, issues of data quality have come to the fore. Data quality depends upon several factors, with one of the most obvious criteria being the response rate. Low response rates are caused by unit nonresponse, which may result from sample members' noncontactability or their refusal or inability to take part in a survey. Unit nonresponse bears the risk of producing biased data if there are significant differences between non-respondents and respondents. Accordingly, studies on nonresponse or panel attrition have a long tradition in the social sciences: research articles on nonresponse due to initial sample selectivity – and attrition in the case of cohort studies and panel studies – have been published since the 1940s (Singer 2006). Special issues of journals as well as workshops on this topic appear regularly.

Please note that in an ongoing cohort study or a panel study, nonresponse due to death does not lead to issues of non-representativeness. In such studies, the event of death is defined as a neutral drop-out (e.g., Kroh et al. 2008). The underlying assumption is that – technically speaking – deceased panel members do not belong to the target population. Thus, missing observations due to death can be ignored. In fact, if panels did not reflect deaths, they would no longer be representative of the target population.

It should be noted, however, that deaths are of crucial importance in longitudinal studies because they diminish the statistical power of the active sample. Thus, the consideration of death rates is important in the design phase of the study, when the initial sample size is calculated. This is not a matter of selectivity: The initial sample must be bigger than the desired number of respondents to have sufficient numbers of survivors and to control for the loss of power due to deaths over waves.

2.1 Sample Selectivity

Health surveys are often based on non-probability samples, which encounter the problem of selectivity at the recruitment stage. But even surveys based on a probability sample face problems of selectivity due to selective unwillingness of randomly selected potential subjects (respondents) to participate in the survey. Lindenberger et al. (1999) and also Schaie et al. (1973) emphasise that initial sample selectivity has to be distinguished from selectivity due to attrition.

Why does initial sample selectivity occur? According to Kranke et al. (2008), the trade-off between sufficient numbers of participants and the cost-effectiveness of the study leads to an array of potential problems with the data from clinical studies: Because such studies are typically limited to a small number of participants, findings are often difficult to generalize (Kranke et al. 2008: 114). The authors therefore suggest determining the necessary sample size by means of a “power calculation”. Yet they do not mention the problems of self-selection biases, which are potentially serious in (health) surveys if respondents and non-respondents differ with respect to specific outcomes, and which may thereby impair the generalizability of findings.

Although the (social science) literature reports severe selectivity problems resulting from low participation rates, this is not necessarily always the case (Weisberg 2005; Groves 2006; Groves et al. 2009). Conversely, it is also possible that high response rates can result in stronger nonresponse biases (Stang and Jöckel 2004) if, for instance, response rates were increased through additional recruitment efforts and/or if errors occurred in the additional recruitment phase. When reluctant respondents are recruited by means of strong incentives, they may differ substantially from the target population at large. Moreover, reluctant respondents for whom a greater recruitment effort is needed may give answers that are more error-prone.

Additionally, health surveys often exclude potential respondents from the study for practical reasons (as is the case in BASE-II; Böckenhoff et al. 2013). The exclusion of nursing home residents from population studies, for instance, causes underestimations of the prevalence of neurological dysfunctions (Hättich 1994: 64).

The literature on response rates in health surveys has addressed several factors that affect the willingness to participate. Broadly speaking, two types of factors are decisive: health-related factors and socio-demographic factors.

In a meta-analysis of nonresponse mechanisms in health studies, Hättich (1994) summarised differences between non-respondents and respondents according to a variety of health-related outcomes. In this analysis, he included prior studies that used external data for nonresponse bias adjustments. His findings showed that healthy persons are less likely to respond to health surveys due to the low relevance of the topic for them personally, to their low awareness of the problem, or their fear that they might be diagnosed with diseases (Hättich 1994: 298). Accordingly, respondents to health surveys are more likely to be individuals seeking to obtain early diagnosis of diseases or to prevent diseases in the first place (Hättich 1994: 300). This corresponds to findings from a study conducted by the Robert Koch Institute on the death rates of children after vaccination (Schlaudet al. 2011): Higher participation rates were observed among parents whose children had died after being vaccinated, resulting in probable overestimation of the risk of death after vaccination by the study. This again indicates the risk of overestimation due to self-selection into medical surveys.

With reference to socio-demographic characteristics, Hättich (1994) found that in 27% of health studies, older people were less likely and women more likely to participate. This finding contradicts the study by Lynn and Clarke (2001) who analysed response rates in three British surveys and concluded that “women are more likely to be reluctant to take part in a health survey” (Lynn and Clarke 2001: 19-20).

Regarding socio-economic status, Hättich (1994) found that participants held higher school degrees than non-respondents in 56% of the studies, higher social status in 37%, higher income in 35% and higher employment status in 46% of the studies. Ten percent of the studies revealed that non-respondents were more likely to live in areas with high unemployment but lower levels of education and income. In 35% of the studies, married persons were more likely to participate than non-married persons. Hättich (1994: 288) explains that marriage is sometimes related to higher health status. Additionally, non-married persons are likely to have fewer preventive medical check-ups but a higher risk of mortality. Few studies have examined psychological differences in Hättich’s meta-analysis (1994: 293). Only two studies revealed higher scores on depression scales among non-respondents, one of which found that female non-respondents scored lower in depression than female respondents.

Although there is not much literature on sample selectivity in health surveys (Lindenberger et al. 1990), it can be concluded that unhealthy persons tend to respond more positively to invitations to participate in health surveys. In contrast, selective attrition occurs mainly in the opposite direction, since unhealthy individuals are more likely to drop out (see section 2.2 below).

2.2 Attrition over the Course of Time

Having summarised the state of the research on sample selectivity in health surveys above, we now turn to studies on attrition processes in health surveys. Our summaries provide an overview of factors related to biases in health surveys that should be considered in weighting adjustments.

In many cohort studies, refusals are among the least important reasons for drop-outs, while mortality has the strongest effect on selectivity, in particular in health surveys (Norris 1985, Badawi et al. 1999, de Graaf et al. 2000). This finding contradicts research findings on nonresponse in the social sciences, where, in samples of the general population (with a large number of young and very young respondents), mortality is low (and in fact not a problem as long as it reflects actual mortality processes), whereas refusals pose the major threat to data quality. The following review reveals that mortality is strongly associated with health-related factors, which in turn correspond to specific socio-demographic characteristics.

Norris (1985) discusses different reasons for drop-outs from a probability sample of older adults and compares respondents with attriters who had died, become disabled, were difficult to find, or had refused to take part. The deceased and disabled were older and had more symptoms of psychological and physical problems than respondents (Norris 1985). Hard-to-find persons had poorer psychological health than respondents (Norris 1985). Refusers did not differ significantly from respondents.

In distinguishing among deceased persons, noncontacted persons, and refusers in the Netherlands Mental Health Survey and Incidence Study, de Graaf et al. (2000) observed that psychopathological factors had only moderate effects on attrition. Psychopathology did not affect refusals, but morbidity and non-contactability as well as mortality did (de Graaf et al. 2000). Those who could not be located for the first follow-up interview were more likely to be suffering from alcohol abuse, substance use, agoraphobia, or eating disorders (de Graaf et al. 2000). Mortality and morbidity were associated with agoraphobia, dysthymia, anxiety disorders, and obsessive-compulsive disorders (de Graaf et al. 2000).

Badawi et al. (1999) delivered similar results based on an analysis of nonresponse in a follow-up survey. A broad database from the initial survey conducted in 1981 served as starting point for the nonresponse analysis in the follow-up survey conducted in 1996. Of the initial 3,841 participants, 848 had died during the 15 years between the two surveys. When examining the effects of various health factors, mortality was associated with mental disorders, drug and alcohol abuse, antisocial personality profiles, and cognitive impairments. Again, refusals turned out to be of minor importance for the evaluation of a possible bias in this follow-up survey.

While the studies reviewed above distinguish among different causes for attrition, there are also a number of studies that consider the various potential causes together, without differentiating them. The aim of such studies is to reveal the impact of health-related characteristics of sample members on attrition. For instance, Radler and Ryff (2010) analysed panel attrition in a national survey (MIDUS) carried out by the MacArthur Midlife Research Network from 1995 to 1996. Of the 7,108 participants aged 25 to 75, those with better subjective health, lower functional health limitations, and a higher BMI score proved more likely to participate in the second wave of the panel than others (Radler and Ryff 2010).

Lindén-Boström and Persson (2012) analysed the nonresponse bias regarding self-rated health in a follow-up study performed on non-respondents to a postal questionnaire of the public health survey Life and Health conducted in Sweden. Besides non-respondents, new sample members were selected for the follow-up as control group. The survey addressed persons aged 18 to 84. The response rate in the follow-up was 49%. The initial non-respondents were compared with the newly selected sample members and it was revealed – in line with the findings of Radler and Ryff (2010) – that initial non-respondents were significantly more likely to report poor health than respondents (Lindén-Boström and Persson 2012: 3).

Dahlhamer and Simile (2009) analysed nonresponse in the American National Health Interview Survey (NHIS). Since the response rates in that survey had dropped to under 70%, the researchers worried that biases in critical health information could have emerged. Paradata from 2007 were used to assess the nonresponse bias, and it turned out that sample members were more likely to participate if their self-rated health was above average. Accordingly, Streib (1966) observed higher retention rates among individuals who reported better health. The findings were based on data from the Cornell Study of Occupational Retirement, for which persons aged approximately 64 years were surveyed. Their health status was measured based on a five-point scale measuring the subjective perception of one’s own health.

Vink et al. (2004) used information provided by proxy respondents in a twin family study and were able to show that siblings are very appropriate proxy respondents for their twins, as they often have a similar general state of health. Non-respondents turned out to have a less healthy lifestyle than respondents, with smokers appearing significantly more frequently among the non-respondents (Vink et al. 2004, Stang et al. 2005). Nevertheless, the analysis showed relatively small differences in health status between respondents and non-respondents.

This finding is in line with that of Lindenberger et al. (1999), who analysed attrition in the BASE-I study, a probability sample of the elderly aged 74 and older in West Berlin. No health-related selectivity was found in the BASE-I study, except in regard to BMI.

In addition, no health-related attrition could be observed by Ekholm et al. (2010), who analysed determinants of nonresponse in the Danish Health Interview Survey 2000, which is conducted by face-to-face interviews, and the Funen County Health Survey 2000/2001, which is conducted by telephone interviews. Both surveys represent a general population health interview survey in which data from administrative registers was linked to survey data. Proxy indicators for health were hospital admission costs and dispensed prescription medicine costs. For both studies, it turned out that health was not a predicative factor for nonresponse. The socio-economic status was a much stronger predictor: those with a lower status refused to participate significantly more often.

Goudy (1985) explored effects of attrition in the Social Security Administration's Retirement History Study, which surveyed 11,153 individuals aged 58 to 63 in 1969. The strongest effects were found for race, city size, and education. Those who were less educated, non-white, and lived in rural areas were more likely to respond in subsequent waves of the panel (Goudy 1985). While the city size effect corresponds to recent findings from the nonresponse research, the race and education effects run counter to those findings (see, e.g., Groves and Couper 1998). Health-related indicators did not affect attrition. However, Goudy's (1985) finding might be traced back to the fact that only subjective health measures were used. Although medical contacts were also surveyed, this information was based on self-reports and could therefore be biased. Moreover, the frequency of medical visits does not necessarily indicate the health status, as hypochondriac tendencies might affect the number of visits as well. A specific feature of the sample is that, although a probability sample selection was conducted, women were only included if they lived alone. This sample specificity may also affect the results of the attrition analysis.

The study by Badawi et al. (1999) revealed that demographic characteristics are also decisive in the attrition process. They found that married couples, living in a household without children, having a low household income, being unemployed, being widowed or single, being 65 years old or older, being male, and having no high school education are all associated with a higher risk of mortality. In a population-based cohort study, Stang et al. (2005) were able to partly confirm these findings, as they observed lower response probabilities among persons from lower social classes and among singles.

Schaie et al. (1973) found that participants in subsequent waves of a longitudinal study were positively selected based on cognitive abilities as compared to nonparticipants. Furthermore, this effect increased with increasing age. This suggests that attrition effects become more powerful in older age groups (Schaie et al. 1973).

Siegler and Botwinick (1979) examined attrition in a sample of individuals aged 60 to 94 and found that intellectual ability was positively related to retention in the panel. Furthermore, those panel members who stayed in the panel showed less change in their intellectual abilities over time (Siegler and Botwinick 1979). Winefield et al. (1990: 83) argue: "In the case of older people it is likely that those who are aware of declining cognitive power are more likely to drop out. They are also likely to be in poorer physical health and therefore more likely to drop out for reasons of ill-health or through death." Powell et al. (1990) also examined attriters from studies on aging and found them to be characterised by a higher rate of lower physical health.

The literature review shows that attrition as well as sample selectivity is associated with those characteristics typically under study in health surveys. Thus, the risk of biased data has to be compensated for by a weighting scheme that takes into account the factors which promote attrition and sample selectivity in health surveys. Accordingly, the BASE-II weighting scheme considers the factors that turned out to be influential.

3 The BASE-II Study

Conceptualised as a follow-up to the Berlin Aging Study, which started 1990 (Baltes and Mayer 1999), the Berlin Aging Study II (BASE-II) is a joint project of five research institutions: the Max Planck Institute for Human Development (MPIB), Max Planck Institute for Molecular Genetics, the Research Group Geriatrics at the Charité Berlin, the Ageing and Tumour Immunology Group (TATI) of the University of Tubingen, and the SOEP group at DIW Berlin. BASE-II is funded by the German Federal Ministry of Education and Research (BMBF) and the participating institutes (Bertram et al., 2013).

The BASE-II target population consists of elderly persons between the ages of 60 and 80. For the purpose of comparability, a reference group of young persons aged 20 to 35 is also included in the study as the second target population. 1,600 older and 600 younger residents from the Berlin greater metropolitan area (and some from Brandenburg) were recruited for the study (Böckenhoff et al. 2013). Information on age and location relate to the point in time of recruitment. Consequently, some BASE-II participants were older than 80 at time of the first assessment. Additionally, some may have moved to another region in the meantime – an aspect that is true in particular of the younger age group, which generally has a higher tendency to relocate.

It should be noted that one distinctive characteristic of the BASE-II study is that the target population has not been randomly sampled. Instead, participants in BASE-II were recruited from the MPIB on the basis of stored address files from three studies conducted previously by the MPIB focusing on neuro-cognition. Therefore, the BASE-II population consists of three subgroups (in the following referred to as laboratory samples I, II, and III), which differ by study provenance. A differentiation between these three subgroups is important, as they also differ with regard to their entrance date into the BASE-II study and, as a further consequence, also with regard to the number of waves of participation in the BASE-II study. While laboratory sample I (L1) was transferred into the SOEP-BASE study in 2008, laboratory sample II (L2) was included in 2009 and laboratory sample III (L3) participated for the first time in 2012 (and the recruitment process for L3 is still ongoing in 2013) (Böckenhoff et al. 2013).

Participants in these three studies had been recruited by means of advertisements in local newspapers and the Berlin public transport system, and they received a substantial expense allowance from the MPIB that far exceeded incentives commonly given to respondents in social surveys. Participants were paid 70 Euros for spending 7 hours to take cognitive tests and to complete a questionnaire at the MPIB. Respondents who underwent medical examinations at Charité hospital were paid 60 Euros, and each respondent also received a detailed description of his or her diagnosis. The diagnosis seems to have been a crucial motivator for the majority of BASE-II participants to take part in the study. Thus, not only did the BASE-II participants select themselves into the study; they also can be assumed to represent a very specific subpopulation of the Berlin (and Brandenburg) population.

Moreover, the studies at the MPIB are subject to certain requirements for participation. For example, it is necessary that participants do not suffer from claustrophobia and do not have any tattoos, walking disabilities, or implants.

Although the BASE-II target population represents an individual sample, the SOEP-specific part of BASE-II (called SOEP-BASE) includes all members of households in which BASE-II participants live. This additional information on household members enables highly detailed analysis of the impact of living conditions and social surroundings on BASE-II participants' health status. Moreover, the transformation from an individual sample to a household sample offers a sample structure that is comparable to that of the core SOEP study.

All these distinctive characteristics have to be considered in selectivity and attrition analyses and in the design of the weighting scheme. Selectivity, attrition, and weighting will be discussed in the next section.

4 Description of Data and Variables

Siedler and Sonnenberg (2010) suggest combining convenience samples with representative surveys, and highlight the possibility to assess potential biases in convenience samples as one of the primary benefits of such an approach. They also note that this can provide insight into the generalizability of findings derived from convenience samples (Siedler and Sonnenberg 2010: 7-8). In line with these recommendations, the SOEP is used in the present analysis as a representative survey (Siedler et al. 2009) for comparison of BASE-II participants with the same age groups in the larger German population that is surveyed in the SOEP. This comparison serves as the basis for selectivity analysis. The research question of this paper is whether and in which direction BASE-II participants differ from randomly sampled SOEP participants. Based on these findings, differences with regard to neighbourhood characteristics (provided by the so-called "microm data") were considered. The microm data have been used to optimise the selectivity analysis. In addition, regional information provided by the Federal Statistical Office is used for demographic post-stratification.

4.1 BASE-II Basic Data

As discussed in section 3 above, different subsamples of BASE-II participants can be distinguished. For clarity, it should be noted that cross-sectional weights are calculated on the basis of the waves 2009 and 2012. The generated weights based on the 2009 and 2012 data are then transferred to the 2008 and

2010 data, so that weights are available for these years and datasets as well. In addition, the 2008 data are used to fill in missing values in 2009, and the 2010 data are used to fill in missing values in 2012[2].

Since the BASE-II study consists of a sample of individual respondents, the generation of weights is based on the individuals who actually participated in the BASE-II study. The weights are then transferred from the given “anchor person” to the entire household of that BASE-II participant. Weights are therefore available for both the individual level and the household level. In generating weights on the individual level, only BASE-II participants are considered.

4.2 SOEP-BASE Data

The SOEP data for the years in which the BASE-II study took place serve as a reference dataset. That means the selectivity analysis conducted below focuses on differences between SOEP participants and BASE-II participants. First, the two age groups covered in the BASE-II sample are also covered in the SOEP reference sample. Second, it is possible to choose one person from each SOEP household to represent the reference group, because in most of the BASE-II households, there is only one person participating in the BASE-II study. We chose the reference persons from each SOEP household randomly: first, we selected a person who represents one of the two age groups in the BASE-II study. If more than one member of a household represents one of the two age groups, we choose the person who is most closely related to the head of the household.[3] If a decision for a reference person cannot be made in step 2, the decision is made by a random selection. This was the case if, for instance, two or more same-aged children of the household head lived in the household.

Additionally, it can be assumed that not all SOEP participants who meet the requirements of the two dimensions above should serve as reference group, since the SOEP is a representative sample for the whole of Germany, while the BASE-II study is restricted mainly to Berlin. Therefore, we only include SOEP households from Berlin, nearby Brandenburg, and from one of Germany’s large cities.

[2] Only those missing outcomes coded -1 were imputed with data from the prior wave.

[3] The hierarchical order is as follows: head of the household, partner of household head, child of household head, foster child of household head, son-in-law or daughter-in-law, parents of household head, father-in-law or mother-in-law, siblings of household head, brother-in-law or sister-in-law, grandchild of household head, other persons related to the household head, other persons not related to household head, child of partner of household head.

4.3 Microm Data

The microm data provided by the private firm "microm GmbH" contain neighbourhood information such as type of residential area, purchasing power, social structure of the neighbourhood, number of vehicle registrations, residential mobility, consumer behaviour, and social milieu (Goebel et al. 2007).

The dataset enables linkage of data from BASE-II and SOEP with this neighbourhood information at three different aggregation levels: household cells (groupings of about eight households), market cells (groupings of about 470 households), and eight-digit postal codes (groupings of about 500 households). This regional information makes it possible to describe the neighbourhood surroundings of survey participants systematically. The microm variables used in the analysis are: social status, vehicle registration density, purchasing power, and risk of defaulting on mortgage loans, affinity for the internet and personal computers, unemployment rate, mobility, share of females, seniors, and immigrants in the neighbourhood.

4.4 Regional Information from the Federal Statistical Office

For the purpose of post-stratification, the weights calculated on the basis of the selectivity analyses were then adjusted to the proportions of the respective age, gender, household size, and German citizenship in the population of Berlin.

4.5 Data Preparation

Some data preparation was necessary, as missing observations occurred in some of the BASE-II variables used for the weighting scheme. We therefore decided to impute missing observations in weighting variables that originate from item nonresponse in order not to lose observations. Otherwise, no weights could be generated for participants with at least one missing observation in the variables used in the weighting scheme.

We applied the approach of "multiple imputation of chained equations" (White et al. 2011): This required that a dummy variable for BASE-II participation be generated and used as a dependent variable. First, all missing values were filled in by random draws from observed values. Second, all variables were regressed on each other in a step-by-step process. Missing values were then imputed as a random draw from the conditional distribution of the regression and used in regressions for other variables with missing values. To account for imputation uncertainty, five different predictions were made. The entire procedure was implemented twenty times with different starting points. As a result, five different complete datasets are available for analysis, taking the uncertainty of multiple imputation into account (see also White et al. 2011; Horton and Lipsitz 2001).

Table 1 Overview of Variables used in the Selectivity Analyses

Variable	Source	Type	Values	Level	Year	Expected Effect
Socio-Demographics						
German	SOEP	binary	0= not German	individual	2009 & 2012	Positive
Male	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Negative
Married	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Multi-person household	SOEP	binary	0= single hh	household	2009 &2012	Positive
Education: high degree	SOEP	binary	0= low education level	individual	2009 & 2012	Positive
Paid work last 7 days	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Employment	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Retirement	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Health						
Number of medical consultations	SOEP	metric	-	individual	2009 & 2012	Positive
Hospital stay	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Compulsory health insurance	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	-
Disabled	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Health status	SOEP	binary	0= fair to poor, 1= good	individual	2009 & 2012	Negative
Body mass index	SOEP	metric	-	individual	2012	-
Smoking	SOEP	binary	0= no, 1= yes	individual	2012	Negative
Healthy nutrition	SOEP	binary		Individual	2012	Positive
Diabetes	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Asthma	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Heart disease	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Cancer	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Migraine	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Hypertension	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Depression	SOEP	binary	0= no, 1= yes	individual	2009	Positive
No diseases	SOEP	binary	0= no, 1= yes	individual	2009	Negative
Chronic illness	SOEP	binary	0= no, 1= yes	individual	2009	Positive
Personality & Attitudes						
Political interest	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Party identity	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Optimism	SOEP	binary	0= no 1= yes	individual	2009	Positive
Major concerns	SOEP	binary	0= no 1= yes	individual	2009 & 2012	Positive
Satisfaction (health, sleep, apartment, leisure, life)	SOEP	binary	0= low, 1= high	individual	2009 & 2012	-
Participation in cultural events	SOEP	binary	0 = less often than once a month 1= at least once per month	individual	2009	positive
Trust in strangers	SOEP	binary	0= low, 1= high	individual	2009	Positive
Risk affinity	SOEP	binary	0= no, 1= yes	individual	2009 & 2012	Positive
Big 5 – Dummy coding (openness, neuroticism, conscientiousness, extraversion, agreeableness)	SOEP	Dummy coding	1 = low, 2= medium, 3= high	individual	2009	Negative for neuroticism, else positive

Microm Data						
Social status	Microm	Dummy coding	1 = low, 2= medium, 3= high	house cells	2009 & 2012	Positive
Vehicle registration density	Microm	Dummy coding	1 = low, 2= medium, 3= high	house cells	2009 & 2012	Positive
risk of defaulting on mortgage loans	Microm	Dummy coding	1 = low, 2= medium, 3= high	house cells	2009 & 2012	Negative
Internet affinity	Microm	Dummy coding	1 = low, 2= medium, 3= high	house cells	2009 & 2012	Positive
Computer affinity	Microm	Dummy coding	1 = low, 2= medium, 3= high	house cells	2009 & 2012	Positive
Mobility	Microm	Dummy coding	1 = low, 2= medium, 3= high	house cells	2009 & 2012	Negative
Share of females	Microm	Dummy coding	1 = low, 2= medium, 3= high	market cell	2009 & 2012	Positive
Share of seniors	Microm	Dummy coding	1 = low, 2= medium, 3= high	market cell	2009 & 2012	Positive
Share of immigrants	Microm	Dummy coding	1 = low, 2= medium, 3= high	market cell	2009 & 2012	Negative
Unemployment rate	Microm	Dummy coding	1 = low, 2= medium, 3= high	market cell	2009 & 2012	Negative
Purchasing power	Microm	Dummy coding	1 = low, 2= medium, 3= high	market cell	2009 & 2012	Positive

For imputation and selectivity analyses, variables were transformed by dichotomising or collapsing continuous variables and ordinal variables with multiple categories into three categories, with the middle category serving as a reference group. These transformations make it possible to 1) control for non-linear effects, 2) interpret the coefficients more easily, and 3) control for outliers on variables that could otherwise result in the estimation of extreme probabilities. Since outliers can still affect the estimates of probabilities, we adjusted the estimates of the outliers to the remaining estimates. This procedure is important because extreme probabilities might inflate the estimated weights inappropriately (Spieß 2010; Valliant and Dever 2011).

5 Analysis

Although the BASE-II sample represents a convenience sample, it is possible that some sample members refused to participate in the SOEP-BASE survey. This is because subjects were first contacted and assessed by MPIB and could then change their minds when asked to participate in the SOEP-BASE survey.

There are several possible reasons for these refusals. Some participants were not aware that the questionnaires that were provided by TNS Infratest and which resembled the SOEP questionnaire were part of the BASE-II study, although information materials were sent to participants thoroughly describing the relationship between TNS Infratest and BASE-II. Another reason might be that individuals were strongly motivated to participate in the medical and psychological modules of BASE-II out of an interest in their own health. Since the questionnaire for the SOEP-BASE survey includes questions on a number of topics, participants might not perceive a strong relationship – and possibly not any relationship at all – to health. Lastly, some participants decided to end their participation in the study altogether. They have therefore been defined as “hard refusers” and cannot be contacted again by any institution involved in the BASE-II study.

We do not provide any design weights for the BASE-II population and did not analyse nonresponse in the initial wave, as no sampling design was used for the selection of participants. As the BASE-II population represents a convenience sample, we are much more interested in possible selectivity processes. To this end, we compared the participants in the SOEP-BASE survey with the participants in the SOEP. The weights were then calculated on the basis of selectivity analyses and are used to compensate for self-selection processes.

On that basis, we generated weights that adjust for selectivity processes in analogy to nonresponse weights. “Nonresponse weights adjust for nonresponse bias by weighting by the inverse of a sample unit’s response propensity” (Blom 2009: 139). While nonresponse weights are mostly based on demographic information, we were able to utilize a multitude of characteristics of the respondents in our selectivity analyses. This was possible since the questions in the SOEP and the BASE-II study are largely overlapping. After having done the sample weighting adjustments (see Kalton and Flores-Cervantes 2003: 83), we conducted population weighting adjustments (Kalton and Flores-Cervantes 2003: 83) based on data from the Mikrozensus (a 1 percent sample of the German population, who are obligated to respond to this survey). The population weighting adjustments are based on a raking (see Kalton and Flores-Cervantes 2003: 86-87) used because the population distributions on gender, household size, and German citizenship are each cross-classified by age (see also Blom 2009: 149). A complete cross-classification would have led to too-small cell frequencies in the old age groups.

5.1 Selectivity Analysis

It is important to analyze the two age groups in BASE-II separately to model the different selectivity processes. We conducted several logistic regression models to reveal possible selectivity processes in the SOEP-BASE survey. Therefore, the dependent variable is binary with 0 = SOEP respondent and 1 = BASE-II respondent. For the two years 2009 and 2012, we estimated three models for both age groups (see Tables 2 and 3). Model 1 considers all SOEP participants as the universe, while model 2 is restricted to inhabitants of Berlin/Brandenburg, and model 3 includes only those respondents who live in large cities (with at least 100,000 inhabitants).

The variables used in the models differ, because we first ran models that included all variables displayed in table 1 that were provided for the corresponding year. We then dropped all variables from our models that do not reach the 5% level of significance. The difference in the variable list used demonstrates the difference in the selectivity processes between young and old respondents.

Model 1 for both years reveals that the share of older inhabitants in an area where BASE-II respondents live has a significant effect only for the older cohort. The higher the share of older inhabitants in an area, the higher the overrepresentation of the older cohort living in that area. The multivariate comparison of the characteristics of respondents in SOEP and BASE reveals several differences. Male respondents are overrepresented in BASE-II if they belong to the younger cohort, but underrepresented if they belong to the older cohort. For the older cohort, the finding is not surprising in light of the difficulties often encountered in recruiting older male respondents. Multi-person households have a stronger self-selectivity tendency than single households among older cohorts. Retirement is also a strong predictor for overrepresentation in BASE-II. Having paid work in the last 7 days has a positive effect on overrepresentation of older respondents in model 1 in 2009.

Diabetes and heart diseases have effects only in the models for the older cohort. Depression has a positive effect across age groups in all models for 2009, which indicates that BASE-II participants suffer from depression more often than SOEP participants. According to the “topic salience theory” (Dillman et al. 2002), individuals are more willing to participate in a survey if they are interested in the survey topic. Thus, it can be expected that BASE-II participants are more health-conscious and also more likely to be directly affected by illness. Contrary to such expectations about topic salience, the presence of the aforementioned diseases (diabetes, heart disease, depression) is associated with a *lower* probability of belonging to the BASE-II study. This effect of health status on participation might be mediated by education: BASE-II participants tend to have significantly higher educational degrees, which in turn are associated with better health behavior and thus better health status.

Effects of chronic illness and no illness appear in the expected directions: If respondents were never diagnosed with a serious illness, they are less likely to belong to BASE-II, while those who suffer from chronic illnesses are more likely to be BASE-II respondents. However, these two effects are valid only for the old cohort. In contrast, disability has a positive effect on self-selection into the BASE-II study for the young cohort. Thus, topic salience seems to promote self-selection in both the older and younger cohort. Body mass index has a negative effect on BASE-II participation, which can be explained by the fact that very high body mass index values are a criterion for exclusion from the MPI studies. This selectivity is observed only in the younger cohort.

A good self-reported subjective health status has a positive effect on self-selection into the BASE-II study among the elderly. This might be associated with the positive effect of an optimistic view regarding the future on self-selection into the study, which was observed for the elderly in 2009. In addition, satisfaction with health has a positive effect for the older cohort. For the younger cohort, satisfaction with life in general is lower for BASE-II- than for SOEP respondents. Satisfaction sleep has a positive effect for the young cohort, but a negative effect for the older cohort. Political interest has an effect only for the elderly. Those older respondents who are interested in politics and have a high level of trust in strangers are more likely to select themselves into the BASE-II study. This corresponds to previous findings on the positive relationship between political interest and trust and survey participation. While the positive effect of political interest can be explained by the “social isolation hypothesis” (Groves and Couper 1998), while the positive effect of trust in others is formulated in the “social exchange hypothesis” (Dillman 1978; Goyder 1987).

Risk affinity has a positive effect on self-selection into BASE-II for the older cohort, but a negative effect for the younger cohort. Regarding personality traits, neuroticism has a positive effect on self-selection in the older cohort, while extraversion has a negative effect in younger respondents. Both effects contradict our expectations. It may be argued that neuroticism leads to low cooperation, whereas the other four traits enhance cooperation (see Saßenroth 2013). Likewise, the observed effects for conscientiousness and agreeableness run counter out expectations since neither shows effect on self-selection. Only the effects of openness on self-selection appear in the assumed direction, since the effects for both age groups are positive.

There are also some differences between the models. Model 2 (residents of Berlin/Brandenburg only) differs especially strongly from the other two models. In this model, the positive effect of regional unemployment rates on self-selection into BASE-II does not exert the same effect in 2009. In the same year, the positive effect of computer affinity on self-selection is also not significant in model 2. The share of immigrants has a positive effect on self-selection into the BASE-II study for models 1 and 3. In the model for Berlin/Brandenburg, the share of immigrants has no effect in 2009 and an inverse effect in

2012. The effect of the local risk of defaulting on mortgage loans is positive in 2009 for model 1 and 3 but not significant for model 2. In 2012, the effect occurs only for the old cohort in the models 2 and 3.

In addition, some differences occur across survey years. While strong worries in general have a positive effect for all respondents in 2012, they have a negative effect for old respondents in model 2 for 2009 only. For 2012, the effects of a high educational degree and employment are positive for both age cohorts. However, in 2009, the effects are negative for the older cohort.

However, many findings are stable across models, years, and age cohorts. German nationality has a very strong effect on self-selection into the BASE-II study. This finding can be traced back directly to the exclusion criteria used by the MPI, which exclude persons who do not speak German. Individuals who select themselves into the BASE-II study are more likely to possess a specific party preference. In addition, attendance of cultural events, which is included in the models in 2009, is also associated with a higher probability of self-selection. These findings on cultural and political involvement correspond to prior findings in the context of theoretical work on social isolation vs. integration. According to this theory, people should be more likely to participate in a survey if they are socially integrated.

Additionally, the share of females has an inverted u-shaped effect on BASE-II participation. Lower and higher shares have lower probabilities compared to a medium share of female inhabitants. The affinity for the internet has a positive effect on BASE-II participation.

Table 2 Estimates on Selectivity in 2009

	Model 1 old	Model 1 Young	Model 2 Old	Model 2 young	Model 3 old	Model 3 young
Microm Data						
Share of females: low	0.401***	0.127***	0.614*	0.246***	0.918	0.198***
Share of females: high	0.016***	0.034***	0.143***	0.408*	0.021***	0.036***
Share of seniors: low	0.905				0.730	
Share of seniors: high	2.429***				1.377	
Unemployment: low	0.299***	0.215***			0.383***	0.238***
Unemployment: high	1.788***	2.482***			1.035	2.181**
Share of immigrants: low	0.488***	0.473**			0.464***	0.332***
Share of immigrants: high	0.982	1.243			1.884**	1.500
Risk of defaulting on mortgage loans: low	0.596**	1.016			0.449***	1.118
Risk of defaulting on mortgage loans: high	0.955	1.720*			0.803	2.145**
Status: low	0.937					
Status: high	1.446+					
Vehicle density: low	1.594**	1.710*				

Vehicle density: high	0.538***	0.643				
Internet affinity: low	0.711+	0.347**	1.009		1.112	0.355***
Internet affinity: high	2.069***	0.826	1.709+		1.849**	1.074
Computer affinity: low	0.476***	0.811	0.702		0.485**	
Computer affinity: high	1.388+	2.005**	1.545		1.274	
Purchasing power: low	1.638*	1.861*		0.791	2.357***	
Purchasing power: high	1.037	1.351		1.708	1.118	
Socio-demographics						
German	10.421**	6.206*	14.663**		21.574***	
Male	0.409***		0.326***	1.571+	0.424***	
High educational degree	0.735+	5.948***	0.467**	3.976***		5.547***
Employment	0.525*					
Multi-person household	2.272***		2.576***		2.635***	
Paid work last 7 days	2.180**					
Retirement	1.634*		2.322**			
Health						
Diabetes	0.529***				0.524**	
Heart disease	0.539***		0.420***		0.561**	
Depression	2.890***	3.428**	5.739***	4.425**	2.476**	3.226**
No illness	0.486***				0.542**	
Chronic illness	1.505**					
Health status	1.883***					
Compulsory health insurance			0.323**			
Personality & Attitudes						
Interest in Politics	1.304*				1.383*	
Party identification	1.557***		1.455+		1.327+	
Optimism	1.279+		1.708**		1.378+	
Attendance of cultural events	3.238***	2.354***	4.107***	2.559**	2.364***	2.434***
Trust in strangers	1.376*				1.635**	
Risk affinity	1.405*		2.130***			
Conscientiousness: low	1.265+		1.627*		1.212	
Conscientiousness: high	0.873		0.956		0.755	
Openness: low	0.584***	0.500**	0.634+	0.534+	0.572**	0.463**
Openness: high	1.448*	1.116	1.517+	0.850	1.487*	1.031
Agreeableness: low	1.758***	1.805*	1.516		1.629*	1.694*
Agreeableness: high	1.127	1.207	0.851		0.938	1.164
Neuroticism: low	1.021		1.051		1.112	
Neuroticism: high	1.378*		1.920*		1.704*	
Extraversion: low		1.688*		1.885+		1.819*
Extraversion: high		0.933		1.074		1.067
Satisfaction: health	2.170***		2.261***		2.919***	
Satisfaction: sleep		1.600*				1.793**
Satisfaction: apartment		0.574*				0.467**
Satisfaction: life		0.626*				0.577*
Often worried			0.568**			
Observations	4678	2976	1421	581	2197	1271

Exponentiated coefficients, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 Estimates on Selectivity in 2012

	Model 1 old	Model 1 Young	Model 2 Old	Model 2 young	Model3 old	Model 3 young
Microm Data						
Share of females: low	0.438***	0.275***	0.422***		0.743+	0.296***
Share of females: high	0.036***	0.148***	0.294***		0.042***	0.132***
Share of seniors: low	0.894	0.625*			0.770	0.670
Share of seniors: high	1.429**	0.822			1.118	0.909
Unemployment: low	0.467***	0.443*	1.647		0.580**	
Unemployment: high	2.321***	3.226***	0.700		1.458*	
Share of immigrants: low	0.779+		1.376	1.496	0.681*	0.745
Share of immigrants: high	1.414*		0.627*	0.424*	2.144***	1.116
Risk of defaulting on mortgage loans: low			0.651+		0.566***	
Risk of defaulting on mortgage loans: high			0.881		1.007	
Status: low	0.811			0.471**		
Status: high	1.440*			0.727		
Vehicle density: low	1.857***	2.571**		1.509		
Vehicle density: high	0.308***	0.742		0.694		
Internet affinity: low	0.648*	0.665	0.563**		0.697	0.622+
Internet affinity: high	2.017***	1.003	1.734*		1.801*	1.010
Computer affinity: low	0.527**	0.607+			0.596*	
Computer affinity: high	1.455*	1.300			1.484+	
Purchasing power: low	1.188	1.806*	0.594*		1.164	2.970***
Purchasing power: high	0.546***	1.156	0.766		0.475***	0.672
Socio-demographics						
German	22.432***		18.486***		34.457***	3.892**
Male	0.438***	1.529*	0.334***	2.055**	0.508***	1.690**
High educational degree	3.334***	8.579***	3.059***	5.887***	3.061***	5.589***
Employment	1.903***	1.985*	1.710+	2.217**	1.976**	2.324***
Multi-person household	2.088***		1.810*		2.333***	1.561*
Retirement	2.695***	5.614***		3.827+	2.520**	5.307**
Health						
Health status	2.081***		1.832*		2.148***	
Disability				4.913**		2.611*
Body mass index		0.921***				0.908***
Smoking	3.233***	2.201***	5.192***	2.585***	3.609***	2.432***
Personality & Attitudes						
Interest in politics	1.486**		1.482*			
Party identity	1.458**	1.559*	1.469*	2.192**	1.541**	1.496*
Risk affinity	1.272*			0.619+		
Satisfaction: health	1.516**		1.941**	2.035*	1.722**	
Satisfaction: sleep	0.648***		0.679+		0.699*	
Satisfaction: leisure time	0.657**					
Satisfaction: life	1.689***	0.501***		0.394**		0.421***
Often Worried	2.426***	2.011***	2.442***	1.632*	2.300***	2.176***
Observations	5309	3247	1553	566	2425	1384

Exponentiated coefficients, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Computation of Weights

5.2.1 Cross-Sectional Weights

In the next step, we generate weights on the basis of the selectivity analyses. The selectivity weights are calculated as inverse propensities for self-selection into the BASE-II study. They include information on both age cohorts although we analyzed the two age cohorts separately. The choice of the SOEP reference group for the selectivity analyses is of central importance as the divergent results of the different logistic regression models presented in 6.1 have shown. Major differences occur in particular for model 2, which includes only inhabitants of Berlin and Brandenburg. However, the correlation coefficients between weights are of appropriate size (see tables 4 & 5).

Table 4 Correlation of Selectivity Weights 2009

	Weights model 1	Weights model 2
Weights model 1	1.0000	
Weights model 2	0.5954	1.0000
Weights model 3	0.9171	0.6348

Table 5 Correlation of Selectivity Weights 2012

	Weights model 1	Weights model 2
Weights model 1	1.0000	
Weights model 2	0.6777	1.0000
Weights model 3	0.8810	0.7307

In the next step, we used the weights based on the selectivity analyses that included the whole German population and adjusted them by raking to population distributions of gender, German citizenship and household size, all cross-classified with age.

The tables 6 and 7 display the effects of the generated cross-sectional weights on the representativity of the BASE-II sample. Obviously, the mean estimates are closer to the SOEP means after weighting. Those weights that were calculated for BASE-II participants only were then applied to other participating household members. Household members, who participated although the corresponding BASE-II participants from the same household did not participate in that wave, received a weight of the value zero.

Table 6 Comparison of Weighted and Unweighted Estimates 2009

	Desired mean (SOEP, weighted)	BASE-II mean, unweighted	BASE-II mean, weighted
Male	0.48	0.40***	0.49
German Citizenship	0.91	1.00***	0.91
HH-Size	2.42	1.66***	2.20
Employed	0.57	0.32***	0.44

Note: Significance levels are: * = 0.1, **=0.5, ***=0.01.
Significance levels are based on regression estimates

Table 7 Comparison of Weighted and Unweighted Estimates 2012

	Desired mean (SOEP, weighted)	BASE-II mean, unweighted	BASE-II mean, weighted
Male	0.48	0.51*	0.48
German Citizenship	0.91	1.00***	0.91
HH-Size	2.40	1.71***	2.16
Employed	0.57	0.31***	0.48

Note: Significance levels are: * = 0.1, **=0.5, ***=0.01.
Significance levels are based on regression estimates

5.2.2 Longitudinal Weights

Longitudinal weights are generated for wave 2012 on the basis of an attrition model. The model included all variables used in the selectivity analyses measured in 2009. The dependent variable used indicates whether 2009 participants were re-interviewed in 2012.

As displayed in table 8, attrition processes differ substantially between the two age cohorts. Neighborhood information is a good predictor of panel attrition among the younger cohort, while personality and attitudes are more predictive for panel attrition among the older cohort. Only one factor from the health block is significant: the number of doctor visits. The effect is negative for the older cohort. Notably, socio-demographic variables are not relevant in the attrition process.

The longitudinal weight delivered with the BASE-II data is the inverse probability of participation in 2012 multiplied by the cross-sectional weight from 2009. Longitudinal weights were only calculated for those sample members who participated in both years.

Table 8 Estimates on Attrition in 2012 conditional on Participation in 2009

	Older Cohort	Young Cohort
Microm data		
Share of seniors: low		0.305**
Share of seniors: high		0.612
Share of immigrants: low		1.778+
Share of immigrants: high		0.784
Risk of defaulting on mortgage loans: low		0.641
Risk of defaulting on mortgage loans: high		0.437*
Computer affinity: low		0.666
Computer affinity: high		1.618
Purchasing power: low		1.069
Purchasing power: high		0.394+
Mobility: low		1.603
Mobility: high		1.728
Health		
Number of medical visits	0.957*	
Personality & Attitudes		
Interest in politics		0.501**
Risk affinity	0.631**	
Openness low	1.496	
Openness high	0.809	
Satisfaction: sleep	0.670*	
Attendance of cultural events		1.980*
Observations	1062	313

6 Conclusion

The paper aims to describe selectivity processes in the Berlin Aging Study II (BASE-II), which is based on a convenience sample of 2,200 participants aged 60 to 80 or 20 to 35 who live in Berlin or the surrounding area. For this purpose, the sample of BASE-II participants was compared with the SOEP sample from the same survey year, but restricted to the two age groups represented in the BASE-II study. The SOEP sample was utilized for this comparison as it represents the entire resident population of Germany. Selectivity analyses were conducted for two survey years: 2009 and 2012. Predictors of selectivity fall into four groups: socio-demographics, health, personality & attitudes, and neighborhood characteristics. It turned out that information from all four areas could be used to predict selectivity. The results therefore indicate that self-selection in medical studies is driven by personality factors, health-related factors, socio-demography, and neighborhood surroundings.

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