Panel representativeness in the Survey of Health, Ageing and Retirement in Europe (SHARE)

Michael Bergmann[12], Tim Birkenbach[1], Sabine Friedel[1],Thorsten Kneip[1], Annette Scherpenzeel[12], Thomas Klausch[3]

1. Introduction

Response rates are common indicators for data quality. However, recent research has shown that response rates alone are insufficient to gauge survey quality (Groves, 2006). For example, response rates can inform about the number of participating respondents, but they do not necessarily inform about the extent of selective nonresponse (Groves & Peytcheva, 2008). Other concepts, such as the R-indicator by (Schouten, Cobben, & Bethlehem, 2009) have been proposed as complementary indicators to evaluate survey quality. The R-indicator, in contrast to the response rate, declines only in case of systematic drop out but remains stable otherwise.

Many studies have investigated the differences between nonrespondents and respondents with cross-sectional data, including those from initial panel waves, by R-indicators (e.g., Roberts, Vandenplas, & Ernst Stähli, 2014). However, few have looked at sample composition development over later panel waves (e.g., Bianchi & Biffignandi, 2017). Using the R-indicator approach, we investigate how the composition of the recruited panel sample develops over waves for countries that have participated in the Survey of Health, Ageing and Retirement in Europe (SHARE) from the onset. We address the following research questions:

1. To what extent do panel members drop out over waves?
2. Do panel respondents drop out systematically in SHARE?
3. Is systematic drop out different between SHARE countries?

2. Data

We use data of The Survey of Health, Ageing and Retirement in Europe (SHARE) (Börsch-Supan et al., 2013). This multidisciplinary, cross-national panel survey collects biannually micro data on health, socio-economic status, and social and family networks on individuals

[1] Munich Center for the Economics of Aging (MEA), Max Planck Institute for Social Law and Social Policy
[2] Technical University of Munich (Chair for the Economics of Aging)
[3] Department of Epidemiology and Biostatistics, VU University, Medical Center

aged 50 and older and their partners. We use all six available waves but restrict the analysis sample to countries that have been participating at least five waves. Furthermore, only respondents aged 50 or older at baseline are considered because we are interested in the main target population. These selection criteria result in 10 countries (Austria, Belgium[4], the Czech Republic, Denmark, France, Germany, Italy, Spain, Sweden, and Switzerland) with 26,701 panel respondents. The number of the observations in the result sections varies slightly due to missing information on the different variables. Another 5% of the respondents cannot be considered because they did not know or refused to report the answer to questions used in the analyses. The final analysis sample consists of 25,200 respondents. The sample size by country ranges from 898 in Switzerland to 2,848 in Sweden.

To investigate participation over time, we define participation for each wave. Participation equals 1 if the respondent did an interview and 0 if otherwise. In the first wave participation is 1 for all respondents by definition as we focus on drop out from the recruited panel sample. This approach offers the possibility to include a rich set of SHARE variables in the model. We select 27 variables to analyze the development of the composition over time. These items contain information on demographics, social embeddedness, health, economics, and respondent role in Wave 1, except for the Czech Republic where Wave 2 is the baseline (Appendix, Table 1).

We choose these variables because they are often part of research on health behavior, health care systems, retirement decisions, and social networks interactions. Data on the respondent role are considered because if more than one individual is interviewed in a household, some information is only requested from one person, such as information on the household, assets, and children. In contrast, assessing representativeness of the recruited panel sample with respect to the current population would allow including only basic information, such as gender, age, and regional information. Moreover, previous research has already shown which types of respondents are unlikely to participate in surveys (Groves & Couper, 1998). However, we want to know if panel composition, measured by SHARE survey variables that are of interest for SHARE researchers, suffers from panel drop out.

[4] The data in Belgium are collected by two agencies: one active in the French speaking part (Wallonia), the other one active in the Flemish speaking part (Flanders).

3. Concept of representativeness

Representativeness of a panel can be measured in different ways (Bethlehem, Cobben, & Schouten, 2011). Representativeness, or in other words stability of the panel sample, here means that the participation propensity over waves is equal for different respondent subgroups. To assess SHARE's panel stability, we compare the sample composition of the initial panel sample to the sample composition of subsequent waves. This comparison allows us to detect systematic drop out from the panel with respect to SHARE survey variables. To quantify panel sample stability over waves, we use the R-indicator concept introduced by Schouten et al. (2009)[5]. The R-indicator ranges between 1 and 0, where 1 means full stability of the wave 1 sample and 0 no stability of the wave 1 sample composition.

Particularly in surveys of older population, such as SHARE, some respondents are likely to drop out because they die. While this drop out is likely to be systematic (e.g., with regard to health), this loss is rather natural and reflects the target population development. Accordingly, we would consider this type of nonresponse appropriate and necessary to preserve the proper representation of the target population. We use mortality information[6] to distinguish between those who died from those who dropped out for other reasons and calculate R-indicators for two samples. One sample includes all respondents recruited in the first wave and the other excludes respondents who have reportedly died over the course of the panel.

4. Results

The retention rate declines almost linear over the waves from 69% to 43% (Figure 1), with a kink at the first follow-up interview.

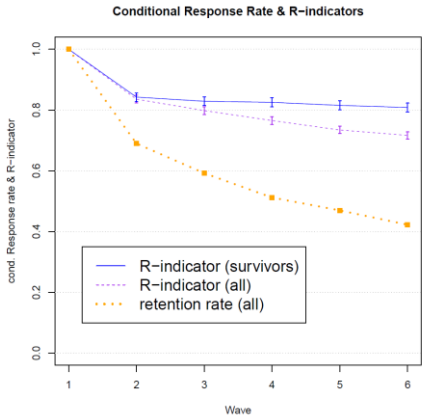

Figure 1 Comparison of pooled retention rates for the selected SHARE countries and the two versions of the R-indicators

[5] The analyses were conducted in R; using software and documentation provided by the RISQ project (http://www.risq-project.eu).
[6] Quality of information differs between countries.

The majority of the respondents drop out after their first interview (about 30%). In contrast to the retention rate, the R-indicator for all panel respondents decreases weakly over time. After six waves, the sample reaches an R-indicator score of 0.72. The largest systematic loss is observed from the first to the second wave (- 0.16 points). The R-indicator of the survivors differs significantly from the R-indicator of all respondents after the second wave. After six waves, survivors represent the Wave 1 recruited panel respondents by over 80%.

To address the question whether panel sample stability differs between countries, we calculated retention rates and R-indicators for each country separately. Overall, the same pattern of declining retention rates and the stabilizing R-indicators after the second wave is observed (Figure 2).

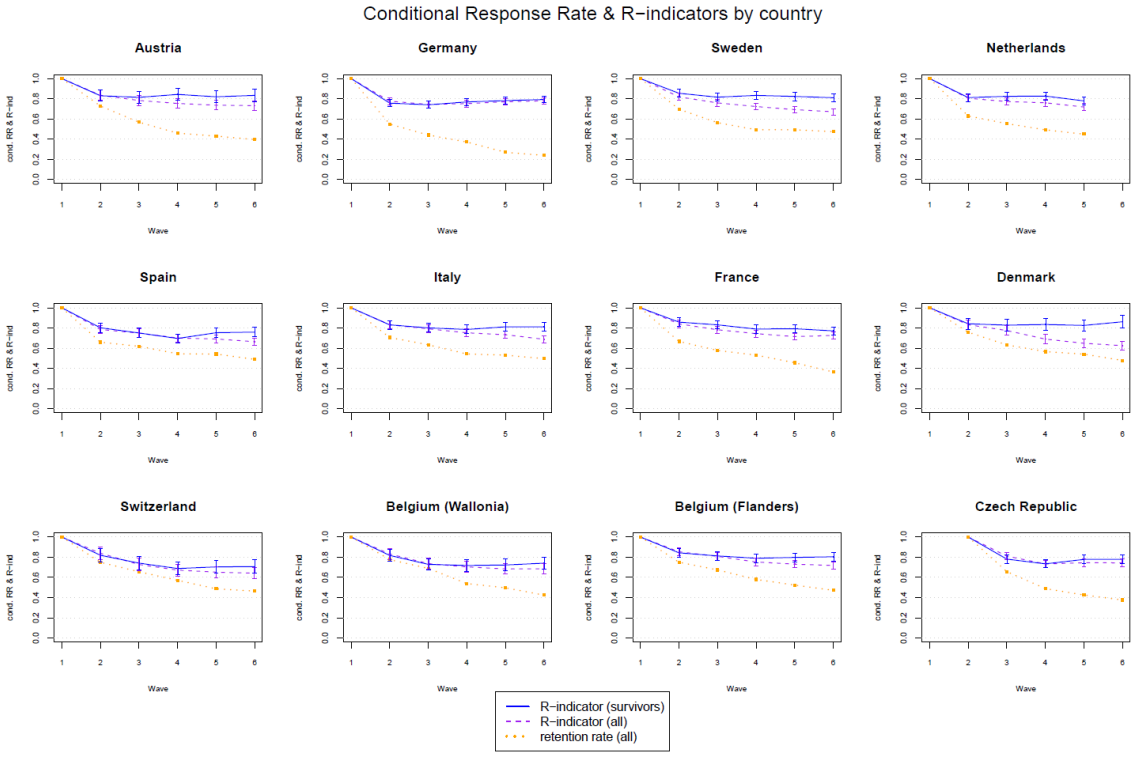

Figure 2 Comparison of pooled retention rates and the two versions of the R-indicators by selected SHARE countries

All countries reach an R-indicator score of about 0.65. or higher in the last wave. However, the gap between retention rates and R-indicators varies across countries. For example, only a small number of panel respondents in Germany remains until Wave 6 (about 25%), whereas in Switzerland more than half of the initial sample remained. However, both reach an R-indicator score over 0.75 in the sixth wave. When excluding the deceased, panel sample stability raises in all countries. The largest differences can be observed in Italy, Sweden, and Denmark. In contrast, in some other countries the R-indicators with and without the deceased

in Wave 6 do not differ significantly from each other. The smallest differences are found in Germany and the Czech Republic.

5. Conclusion and Discussion

The aim was to assess the extent of panel respondents' drop out of SHARE and relate it to the development of the panel sample over waves, focusing in particularly on survey variables of interest rather than only on basic demographics. A notable loss of recruited panel members over time was observed, varying over countries. This observation is in line with other panel studies (e.g., Banks, Muriel, & Smith, 2011). However, the sample stability in terms of survey variables was rather high. After Wave 6, the panel sample composition still represents well the recruited panel sample in Wave 1. A substantial systematic change in sample composition was observed from the first to the second wave. Overall, results indicate that panel drop out since SHARE's second wave is rather non-systematic with regard to the chosen SHARE survey variables.

Furthermore, and in contrast to retention, the overall R-indicator, used here as indicator of panel sample stability over time, differed only weakly between countries. Overall, all countries represent their recruited sample well over waves, even though they differed in their retention rates. This result leads to conclude that other measurements than retention rates need to be advocated to inform researchers and funders about survey data quality.

In this study, we chose not to study any survey errors that were introduced prior to the start of the panel. This study was set out to compare SHARE's panel sample composition over waves with the recruited Wave 1 sample with regard to SHARE survey variables. Any comparison with the current population or gross sample would allow comparing only basic characteristics, such as gender, age and regional information. However ideally, any study of panel drop out should also investigate the relationship between initial nonresponse and panel participation.

References

Banks, J., Muriel, A., & Smith, J. P. (2011). Attrition and health in ageing studies: Evidence from ELSA and HRS. *Longitudinal and life course studies, 2*(2), 10.14301/llcs.v14302i14302.14115. doi:10.14301/llcs.v2i2.115

Bethlehem, J., Cobben, F., & Schouten, B. (2011). Nonresponse and Representativity. In *Handbook of Nonresponse in Household Surveys* (pp. 178-208): John Wiley & Sons, Inc.

Bianchi, A., & Biffignandi, S. (2017). Representativeness in panel surveys. *Mathematical Population Studies, 24*(2), 126-143. doi:10.1080/08898480.2016.1271650

Börsch-Supan, A., Brandt, M., Hunkler, C., Kneip, T., Korbmacher, J., Malter, F., . . . Zuber, S. (2013). Data Resource Profile: The Survey of Health, Ageing and Retirement in Europe (SHARE). *International Journal of Epidemiology, 42*(4), 992-1001. doi:10.1093/ije/dyt088

Groves, R. M. (2006). Nonresponse Rates and Nonresponse Bias in Household Surveys. *The Public Opinion Quarterly, 70*(5), 646-675.

Groves, R. M., & Couper, M. P. (1998). Influences of Household Characteristics on Survey Cooperation. In *Nonresponse in Household Interview Surveys* (pp. 119-154): John Wiley & Sons, Inc.

Groves, R. M., & Peytcheva, E. (2008). The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis. *The Public Opinion Quarterly, 72*(2), 167-189.

Roberts, C., Vandenplas, C., & Ernst Stähli, M. (2014). Evaluating the impact of response enhancement methods on the risk of nonresponse bias and survey costs. *Survey Research Methods, 8*(2), 14. doi:10.18148/srm/2014.v8i2.5459

Schouten, B., Cobben, F., & Bethlehem, J. (2009). Indicators for the representativeness of survey response. *Survey Methodology, 35*(1), 13.

Appendix

Table 1: Variables used in the R-Indicator Response Model

Variable	based on SHARE Variable	Categorisation
Demographics		
Age	dn002, dn003, int_year, int_month	(50-59; 60-69; 70-79; 80+)
Gender	gender	(1: "male"; 2: "female")
Born in country of interview	dn004	(1: "yes"; 5: "no")
Education	isced1997_r	(0-2: "low"; 3,95,97: "medium & other"; 4-6: "high")
Household type	ch001, ch007, partnerinhh	("single"; "single+child(ren)"; "couple"; "couple+child(ren)")
Household size	hhsize	(1; 2; 3+)
Living with partner in same household	partnerinhh	(1: "yes"; 5: "no")
Urbanization	areabldgi	(1-3: "city/large town"; 4: "small town"; 5: "rural village")
Social embeddedness variables		
Residential proximity of (closest) child(ren)	ch007	("no child"; " in HH"; "< 1km"; ">1km")
Number of social activities	ac002d1-ac002d7	(0; 1+)
Received social support	sp002	(1: "yes"; 5: "no")
Given social support	sp008	(1: "yes"; 5: "no")
Health variables		
Health (US version)	sphus	(1-3: "good or better "; 4-5: "fair or poor")
Number of chronic diseases	chronic	(0; 1+)
Depression (Euro-D)	eurod	(0; 4+)
Grip strength	maxgrip	quartiles + "no measurement category"
Verbal memory score	cf008tot + cf016tot	(0-9: "low"; 10-20: "high")
Hospital visit in last 12 month	hc012	(1: "yes"; 5: "no")
Currently smoking	br002	(1: "yes"; 5: "no")
Currently drinking	br010	(1: "daily"; 2-4; 5-6; 7: "never")
Limitation of Instrumental Activities of Daily Living	iadl2	(0; 1+)
Economic variables		
Current job situation	ep005	(1: "retired"; 2: "working"; 3-97: "not working & other")
Does household face difficulties to make ends meet	co007	(1-2: "yes"; 3-4: "no")
Household income	thinc	quartiles
Technical Variables		
Financial respondent	fin_resp	(1: "yes"; 0: "no")
Family respondent	fam_resp	(1: "yes"; 0: "no")
Household respondent	hou_resp	(1: "yes"; 0: "no")