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Abstract

Selective attrition out of longitudinal datasets is a concern for empirical researchers. This paper discusses a simple way to identify both direction and magnitude of potential sample bias in household panels. The idea is to exploit multiple types of simultaneous entries into the panel. The little known phenomenon of natural refreshments, which adds to entries through refreshments induced by data collectors, allows disentangling attrition bias from measurement errors connected to differences in participation experience (i.e. panel conditioning). A demonstrative application on subjective data from the German Socio-Economic Panel Study (SOEP) serves as an example and offers insights on health-related attrition.

JEL classification codes

C1, C8, I1

Keywords

Subjective health, refreshment samples, household survey, sample selectivity, panel effects

1. Introduction

Missing data can cause major problems for the validity of empirical results as soon as sample selectivity is not orthogonal to the variables of interest. While empirical studies on longitudinal data often leave out a proper discussion of this issue, missing-at-random assumptions are not always plausible. Unfortunately, no perfect solution to the potential problem exists. Approaches following the sample selection model by Heckman (1976) require exclusion restrictions that are typically hard to establish.[1] An alternative strategy for identification of attrition bias (AB) makes use of panel refreshments, as proposed by Hirano et al. (2001), among others. The idea is that refreshments in a longitudinal study of a population of interest are representative draws and therefore reveal to the researcher what the longer-running sample at the same point in time ideally should look like if no AB existed. Such comparisons of datasets with their supposedly ideal counterparts, however, have rarely been included in empirical studies. This might not only come from researchers' reluctance to study technical details of sample compositions but also results from a probable identification problem. In fact, fresh samples differ from longer-running ones not only because of the potential AB in the latter but also with respect to the observations' overall time in the panel. It is thus unclear whether a sample comparison showing significant differences in a variable of interest is evidence for selective attrition or just measurement effects, as e.g. first-time observations may be generally less accurate due to a lack of panel experience. The phenomenon of panel conditioning (PC) is capable of affecting the data and thereby plagues the refreshment approach, as discussed comprehensively by Das et al. (2011). This measurement phenomenon receives attention particularly in discussions on the validity of subjective survey data (see e.g. Chadi 2013, van Landeghem 2014, Wooden and Li 2014).[2]

This paper discusses the idea of using panel refreshments for identification of AB but proposes a method for solving the identification problem in the presence of PC. To tackle both forms of bias, researchers may wish to exploit a little known organizational facet of panel data, simultaneous refreshments. In contrast to refreshments that are "induced" (IndR) by survey designers from time to time to sustain high observation numbers, there are others that van Landeghem (2014) calls "natural" refreshments (NatR). These originate from several sources. First, household expansions often lead to new survey participants, as interviewers ask new household members to take part in the survey. Second, data collectors do not give up on persons

[1] Another idea is to expand estimation models with attrition indicator variables for future panel exits in order to test for significant differences between subsequent exits and stays. Assuming that the last observation reflects the situation in the subsequent exit period, this procedure yields evidence on attrition bias. A potential problem of data from future exits is that those could be susceptible to measurement error, as e.g. uncooperative survey respondents may report differently than they would in the case of high motivation (Chadi 2014).

[2] See Halpern-Manners and Warren (2012) for research on PC in objective data (i.e. labor force characteristics).

leaving households, but follow them to establish and interview the new household that may include further persons not participating in the panel so far. Third, in surveys of adults, children in the family household grow into the population of interest and enter the panel at some point in time. Finally, initial non-respondents may be converted into participants over time, for instance, by persuasion.

Studying data from the German Socio-Economic Panel Study (SOEP), natural refreshments to the longitudinal survey data turn out to be significant in numbers. While these persons may not be representative for the population of interest, they are subject to PC, just as other entries are. This paper proposes using IndR to identify the attrition bias while controlling for the lack of panel experience at the start of participation via simultaneous NatR observed in the same panel wave. Health-related attrition, as an often-debated and important empirical problem, is subject to several relevant identification issues in this context and serves as an example to illustrate the idea.

2. Identification

The approach of using panel refreshments to identify attrition bias in longitudinal datasets appears both intuitive and easy to apply. Relying on panel organizers and their efforts to successfully refresh the panel data with a representative draw of the whole population, one need only compare data from two subsamples in terms of the information that is of interest. Data from the refreshment sample by definition cannot be subject to attrition bias (AB), if the latter is defined as the occurrence of selective panel exits over time. As soon as there are significant differences for a variable of interest between this newly established 'gold standard' of an induced refreshment (IndR) and the data collected at the same point in time but from an earlier sample that is potentially subject to attrition, the latter data appears to be biased. For several reasons, however, a simple comparison of average values between refreshment data and data from longer-participating entities does not necessarily provide a successful identification of AB. As a first conjecture, different samples may have been established using different techniques. In the case of long-running household surveys, it can be the case that individuals in earlier samples are interviewed traditionally via pencil and paper, while computer-assisted interviewing is used for members of the most recent sample. If the former is subject to particular measurement effects, it is unclear whether overall differences in the information coming from different datasets is indicative for AB or may just reflect survey mode effects.[3] Another issue is interview timing. It could be that data from one sample is collected earlier in a year, while

[3] See e.g. Conti and Pudney (2011) for evidence on how survey mode matters for subjective self-reports.

the data obtained from the other sample differs due to seasonal measurement phenomena.[4] While this discussion of technical aspects is important, it does not pose a fundamental problem to the identification of attrition bias. Instead of looking at average values of variables when comparing data from refreshment and initial samples, one could address these technical questions by running regressions and considering several issues at the same time via control variables. Such a regression model for an outcome variable of concern thus includes controls for technical aspects, like survey mode, in addition to the main binary variable for the distinction between IndR and the rest of the panel data. Arguably, however, an even more significant identification problem results from another phenomenon surrounding panel datasets, as laid out by Das et al. (2011). Data from the refreshment sample may differ from the initial sample not only in terms of representativeness but also because of individual panel experience. Panel conditioning (PC) is a phenomenon that emerges when collected information on the same question differs systematically dependent on the number of participations in a panel.[5]

[Figure 1]

Figure 1 visualizes the challenge of identifying attrition bias using induced panel refreshments in the presence of PC. The outcome variable of interest in the following is (subjectively reported) health. Previous research on health-related attrition suggests that unhealthier people are more likely to leave longitudinal surveys (e.g. Contoyannis et al. 2004, Jones et al. 2006). If correct, the expectation is that a panel refreshment sample in t=2 consists of less healthy individuals, on average, compared to a sample of individuals who started participating already in t=1. The latter sample has suffered from quantitative attrition and probably qualitative attrition in regard to health. In the absence of any significant time trend in health, however, the illustration suggests that AB goes in the other direction.[6] The picture is in line with the expectation of PC that triggers a decline in self-reported health with increasing years in panel. Consequently, identification in the case of just one source of refreshment is impossible without further assumptions, as pointed out by Das et al. (2011). In other words, we do not know

[4] See e.g. Maennig et al. (2014) and Kavetsos et al. (2014) on survey month effects in subjective data.
[5] While many empirical investigations have revealed evidence for PC, discussions on its explanation are ongoing. In addition to knowledge questions, where learning over time seems to play a role (Das et al. 2011), subjective data could be affected in a similar way. Regarding subjective well-being, first-time observations have been found to be subject to potential measurement bias as satisfaction scores are remarkably high at first and then decline over time (e.g. Chadi 2013, van Landeghem 2014). A plausible explanation is that with growing panel experience individuals learn to make better use of the scale.
[6] Note that to identify a bias in this stylized one-refreshment scenario, the comparison between refreshment sample and initial sample must take place in t=2 only. In the case of multiple IndR over time in a longitudinal survey, it is possible to conduct comparison analyses using several waves (with induced refreshments).

whether average health in the IndR sample is higher because of selective panel attrition of healthier types over time, which would counter both common belief and previous studies, or whether individuals generally report too positively on their health when being asked for the first time.

The contribution of the present paper is to offer and discuss a potential solution to the identification problem when both AB and PC are present by exploiting the phenomenon of naturally emerging entries into a longitudinal household survey. As common feature of panel surveys, natural refreshments (NatR) take place in every survey year and thereby allow identification of first-year measurement effects. Hence, the idea is to expand a regression model for a variable of concern (here: subjective health) with further control variables to allow for identification of attrition bias through IndR, while year-in-panel controls capture differences in reporting stemming from PC. This solves the identification problem that emerges out of Figure 1, thanks to the availability of multiple sources of entries into a panel. Having such a panel survey with both IndR and NatR allows disentangling AB from PC via this model for possible health-related attrition:

$$Health_{it} = \beta IndR_{it} + \gamma' YiP_{it} + \delta' SF_{it} + \chi' X_{it} + \tau_t + \varepsilon_{it} \quad (1)$$

The model builds upon the basic idea of the panel-refreshment approach, which is to test for differences between data of an induced refreshment sample $IndR_{it}$ and the rest of the panel data at the point in time when the IndR is implemented. As its novelty, the analysis here considers the year that an individual is in the panel (YiP_{it}), i.e. whether it is the individual's first participation, the second, etc. To capture potential effects related to PC, a large set of dummy variables is used in the baseline specification. Recall that if only IndR enter the panel, it is obviously not possible to identify first-participation measurement bias and attrition bias simultaneously (Das et al. 2011). This is a particular problem if the first-participation effect is severe, which can happen, for instance, when learning improves the data quality over time. As soon as NatR enter the panel in every wave of the panel, PC can be measured directly, as the first-year-in-panel variable is equal to one, not only for induced but also for natural refreshers. In the absence of the latter, the key variable for the (induced) refreshment sample $IndR_{it}$ would determine the total bias, consisting of AB and PC (see Figure 1). To learn more about the role of PC, it is informative to inspect how results change when YiP_{it} is included or excluded in the specification.

Additionally, the model considers survey factors (SF_{it}) as controls, expecting that both survey

mode and timing may affect responses and are not necessarily the same across samples.[7] In line with the features of the panel survey analysed in the following application, the model allows considering multiple induced refreshments. In this case, the number of panel waves used for the comparison analysis increases by the number of IndR. In addition, a time effect τ_t can be included to capture changes in the outcome variable over time using wave dummies. The model also includes an error term ε_{it}.

Finally, to learn more about what is behind the AB once it has been identified, the model can be expanded by further variables (X_{it}) on individual characteristics, such as age. A possible explanation for health-related AB in panel surveys could be that a sample's age composition changes over time, so that, by controlling for it, differences between initial and refreshment sample may vanish. As a further step, covariates identifying groups of individuals may be interacted with the $IndR_{it}$ dummy to check whether there is group-specific heterogeneity in attrition bias. As an example, for a longitudinal analysis of the effect of temporary employment on health, there might not be a problem if health-related AB is present but orthogonal to the group distinction of interest, in contrast to a situation in which an attrition of e.g. the unhealthy differs significantly between the two groups of temporary and permanent workers.

3. Empirical application

The SOEP is Europe's longest running representative panel survey of households (Wagner et al. 2007). Over several months in each year, participants are questioned about their lives either directly by interviewers or via questionnaires that people can fill out on their own. Over the years, the SOEP has implemented several (induced) panel refreshments. Three representative IndR in 1998, 2000 and 2006 are in the center of the following analysis and part of the dataset shown in Table 1.[8] As in every other year, NatR enter the panel in significant numbers, allowing for a distinction between different groups of simultaneous panel entrants (shown in brackets).

[Table 1]

The main variable of interest is health satisfaction, observed on a scale ranging from 0 ("completely dissatisfied") to 10 ("completely satisfied") via this question: "How satisfied are you with your health?" Another SOEP variable captures subjective health on a 5-point scale.

[7] Note that differences in the data across interview months might also emerge when people with specific characteristics select themselves into later interview dates, which is reason to compare results with and without consideration of this survey factor.

[8] A non-representative add-on sample (implemented in 2002) on households with high income is excluded from the analysis here.

Findings are very similar for both variables, but to allow for an easy application, the 11-point variable is preferred here and interpreted as a continuous measure of health while standard linear regressions are used.[9]

[Table 2]

The lower panel in Table 2 presents the main results from applying the empirical model (1) and a step-by-step inclusion of survey and time control variables. A comparison with the results in the upper panel, where PC effects are disregarded, demonstrates that panel experience plays a large role in the application of the refreshment approach onto subjective health data. Without consideration of individual time-in-panel effects, the results suggest a positive health-related AB and an underrepresentation of healthy people in the SOEP data. The IndR dummy, however, at first reflects the total bias containing both PC and AB (see Figure 1), i.e. both lacking panel experience in the IndR sample and potential attrition bias in the rest of the data. Disentangling the two forms of bias is possible because of the existence of natural refreshers, which ensures that each time-in-panel dummy is identified. Considering the positive bias in self-reports by people at the start of their survey career turns the IndR effect into a significantly negative one, as the lower panel supports the notion of unhealthier individuals being underrepresented in the rest of the panel data.

In line with previous studies on PC in subjective data, the detailed results in Appendix Table A1 demonstrate a significant reporting bias related to a dearth of panel experience, as the first-participation effect in health satisfaction is strongly positive. Furthermore, this positivity bias declines in magnitude as years in panel increase.[10] The results also suggest that interview mode and time effects are to some extent relevant for measuring subjective health but do not strongly affect the identification of health-related AB, as the finding does not change much throughout the specifications. Note that to maximize power and precision, the analysis exploits the availability of all three IndR together, allowing the use of one single dummy variable that identifies all randomly drawn fresh starters in the years 1998, 2000 and 2006. Using separate dummies, one for each IndR, shows robustness of the main results across the three waves (see Appendix Table A2), which empirically supports the notion of a time-invariant AB.[11]

[9] Note that all results mentioned but not presented in tables are available from the author upon request.
[10] Alternative specifications, varying the set of year-in-panel controls (i.e. using the maximum number of dummies for all possible participation years), yield the same finding, just like when differences in participation experience are considered via a linear year-in-panel variable.
[11] Additional interaction terms between wave and year-in-panel dummies allow considering potential variations of PC over time, which does not lead to any other findings on health-related AB.

[Table 3]

Having identified health-related AB in the SOEP data, the analysis continues by discussing potential explanations for it. To do so, Table 3 presents results when variables on people's individual characteristics are added to the empirical model. The first column shows that females generally report worse health, but the AB does not stem from a particular unbalance in the data between the sexes, as the IndR coefficient remains significantly negative. In contrast, another socio-demographic characteristic appears to be very relevant here. Adding a linear age variable to the model shows how health deteriorates with age and that the negative AB effect becomes insignificant when age-related differences in the sample composition are considered.[12] Adding further individual characteristics of respondents does not lead to other insights.

A final step demonstrates how to check group-specific heterogeneity in health-related AB by addressing the question of whether unhealthy individuals are more likely to leave the panel dependent on their gender. Investigations on gender differences in health are an important research objective, which would be subject to a problem in case of sex-specifics in AB. The panel-refreshment approach allows checking such concerns in a simple fashion via an interaction term between the IndR dummy and a group indicator.

The interaction term in column (4) of Table 3 does not support the notion of gender differences in health-related AB. Inclusion of further variables to the empirical model does not change this finding. The interpretation of the insignificant interaction effect between gender and the AB identifier is that there is evidence for a health-related AB in the SOEP data, as long as differences in age are not considered, but there is no indication that AB plagues the investigation of gender differences in health.

4. Conclusion and discussion

This paper discusses the concern of health-related attrition and uses this particular example to demonstrate how attrition bias can be identified by empirical researchers. A little known design feature of longitudinal household surveys provides an intuitive and easy-to-implement option to assess both direction and magnitude of the problem, even if panel conditioning plays a strong role. The existence of multiple sources of panel refreshments allows distinguishing panel effects from attrition bias. In another step, interactions between the identifier of the attrition bias and a variable of interest show whether an attrition-phenomenon (e.g. linked to ill-health) is more or

[12] Using additional polynomials for age does not alter the finding.

less pronounced for the group a researcher wants to study, which would frustrate the empirical analysis.

Limitations of the approach are reflected in some more or less strong assumptions. Panel conditioning as well as attrition bias are time-invariant, in the ideal case, which, given multiple induced refreshments over time, can be more closely examined. While the assumption of constant panel conditioning across types of refreshments cannot be tested easily, a closer look at the data allows discussing potential differences between natural refreshers and other observations in the panel data. Whereas survey organizers typically treat natural refreshers as a regular part of the main dataset, empirical researchers have, thus far, largely ignored this aspect of the data. In the context of health, a difference in age sticks out, as natural refreshers are on average younger than other respondents are. One way to inspect this point further is to run regressions with a dummy indicator for all respondents having once entered the panel as natural refresher.[13] Certainly, more research on this type of survey participant seems promising, given that the present paper is one of the first to address this panel phenomenon.

As a final assumption of importance, the initial non-response resulting from refusals to the first invitation has to be assumed as similar over time or, at least, orthogonal to the factors of interest. Missing data from those who never participate in the data collection process certainly remains a problem that cannot be solved with any type of panel refreshment.

[13] The finding on gender-interactions does not change when doing so. As a likely consequence of differences in age, the growing group of (former) natural entries (see last column in Table 1) appears to be generally healthier than earlier entries from official SOEP samples. Adding age as a variable to the regression model, no significant differences between natural and earlier entries in terms of health status remain.

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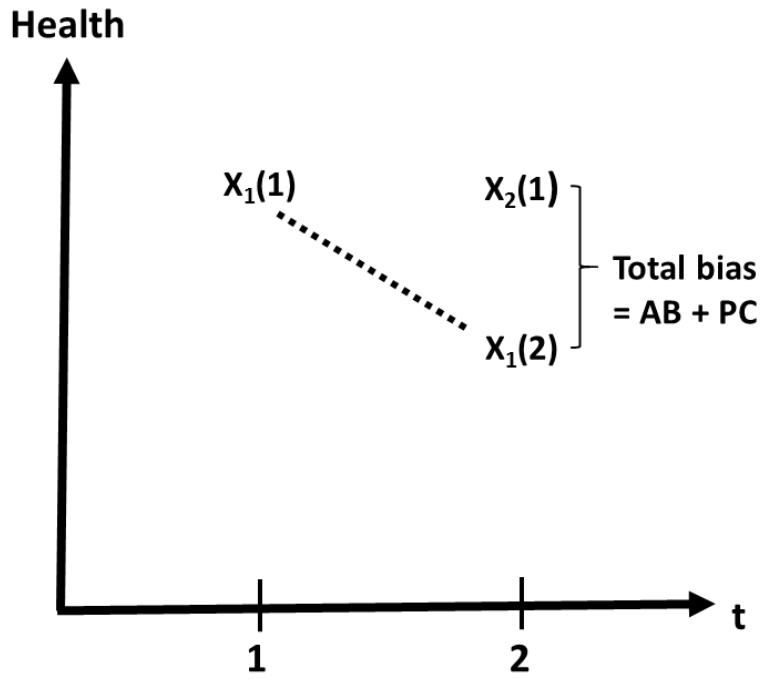
Figure 1 Identification problem for single-refreshment case



Notes: $X_s(y)$ stands for the average health in sample s observed in year y that the sample is in the panel. Sample 1 starts in t=1. Sample 2 is an induced refreshment sample, starting in t=2.

Table 1 Data structure and panel entries

	All	Induced refreshments			Main dataset		
		IndR 1998	IndR 2000	IndR 2006	*= All earlier and natural entries*	*All earlier entries*	*All natural entries*
Wave of 1998	14132	1849			12283	*7987*	*4296*
	[2042]	[1849]			[193]		*[193]*
Wave of 2000	23934	1413	10607		11914	*7291*	*4623*
	[10845]		[10607]		[238]		*[238]*
Wave of 2006	20406	959	5775	2584	11088	*5270*	*5818*
	[2775]			[2584]	[191]		*[191]*
Total sum	58472						

Notes: Observation numbers for fresh first-time panel participants are in brackets.

Table 2 Main regression results on health-related attrition bias

Panel A

Dependent variable:	Health satisfaction			
Specification:	(1)	(2)	(3)	(4)
Induced refreshment (of 1998/2000/2006)	0.349*** (0.022)	0.305*** (0.023)	0.148*** (0.029)	0.081*** (0.031)
N	58472	58472	58472	58472
adjusted R^2	0.005	0.005	0.008	0.008
Survey mode		X	X	X
Interview month			X	X
Year effects				X
Year-in-panel controls				

Panel B

Dependent variable:	Health satisfaction			
Specification:	(1)	(2)	(3)	(4)
Induced refreshment (of 1998/2000/2006)	-0.569*** (0.078)	-0.624*** (0.078)	-0.730*** (0.080)	-0.759*** (0.080)
N	58472	58472	58472	58472
adjusted R^2	0.027	0.028	0.030	0.030
Survey mode		X	X	X
Interview month			X	X
Year effects				X
Year-in-panel controls	X	X	X	X

Source: SOEP waves from 1998, 2000, and 2006.

Notes: Dependent variable is health satisfaction on a 0 to 10 scale. Control variables are for survey mode (oral interview with paper and pencil, oral interview with computer assistance, self-written with interviewer presence, self-written without interviewer presence, and partly oral, partly self-written), interview month (eight dummies), year (waves of 2000 and 2006), and year-in-panel controls (dummies for the first to eighth participation in the SOEP). See Appendix Table A1 for a complete set of results on all variables used. Robust standard errors are in parentheses. Levels of statistical significance are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 Health-related attrition bias, individual characteristics and interaction with gender

Dependent variable:	Health satisfaction					
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Induced refreshment (of 1998/2000/2006)	-0.758*** (0.080)	0.032 (0.078)	-0.011 (0.084)	-0.771*** (0.083)	0.012 (0.081)	-0.038 (0.087)
Female	-0.134*** (0.018)	-0.106*** (0.017)	-0.021 (0.020)	-0.140*** (0.021)	-0.115*** (0.020)	-0.033 (0.022)
Age		-0.047*** (0.001)	-0.042*** (0.001)		-0.047*** (0.001)	-0.042*** (0.001)
Interaction: Female X Induced refreshment				0.024 (0.044)	0.038 (0.041)	0.054 (0.044)
N	58472	58472	52620	58472	58472	52620
adjusted R^2	0.031	0.136	0.155	0.031	0.136	0.155
Survey mode	X	X	X	X	X	X
Interview month	X	X	X	X	X	X
Year effects	X	X	X	X	X	X
Year-in-panel	X	X	X	X	X	X
Additional controls			X			X

Source: SOEP waves from 1998, 2000, and 2006.

Notes: Dependent variable is health satisfaction on a 0 to 10 scale. Survey-related control variables are in line with those in Table 2. Additional controls are variables for education status, employment status, unemployment, number of persons in household, recent move, no children in household, family status, partnership, (log equalized real) income and federal state. See Appendix Table A3 for a complete set of results on all variables used. Both age and income variables are de-meaned. Robust standard errors are in parentheses. Levels of statistical significance are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table A1 Main regression results on health-related attrition bias (complete)

Dependent variable:	Health satisfaction			
Specification:	(1)	(2)	(3)	(4)
Induced refreshment	-0.569***	-0.624***	-0.730***	-0.759***
(of 1998/2000/2006)	(0.078)	(0.078)	(0.080)	(0.080)
Year-in-panel controls		*Reference: 9th year in panel and beyond*		
1st year in panel	1.189***	1.205***	1.170***	1.161***
	(0.076)	(0.076)	(0.076)	(0.076)
2nd year in panel	1.354***	1.354***	1.344***	1.344***
	(0.053)	(0.053)	(0.052)	(0.053)
3rd year in panel	0.844***	0.823***	0.834***	0.812***
	(0.044)	(0.045)	(0.045)	(0.045)
4th year in panel	0.972***	0.975***	0.955***	0.951***
	(0.054)	(0.054)	(0.054)	(0.055)
5th year in panel	0.912***	0.916***	0.891***	0.888***
	(0.056)	(0.056)	(0.056)	(0.056)
6th year in panel	0.643***	0.649***	0.642***	0.650***
	(0.053)	(0.053)	(0.053)	(0.053)
7th year in panel	0.296***	0.274***	0.239***	0.278***
	(0.031)	(0.031)	(0.031)	(0.033)
8th year in panel	0.589***	0.607***	0.608***	0.604***
	(0.063)	(0.063)	(0.063)	(0.063)
Survey mode		*Reference: Self-written by mail*		
Oral interview with paper and pencil		0.146***	0.172***	0.163***
		(0.032)	(0.032)	(0.032)
Oral interview with computer assistance		0.200***	0.244***	0.266***
		(0.035)	(0.036)	(0.036)
Self-written with interviewer Presence		0.228***	0.269***	0.263***
		(0.051)	(0.051)	(0.051)
Self-written without interviewer presence		0.135***	0.155***	0.151***
		(0.032)	(0.033)	(0.033)
Partly oral, partly self-written		0.048	0.071	0.066
		(0.052)	(0.052)	(0.052)
Interview month			*Reference: Interview in September or beyond*	
January			-0.539***	-0.573***
			(0.057)	(0.057)
February			-0.403***	-0.396***
			(0.053)	(0.053)
March			-0.398***	-0.375***
			(0.054)	(0.054)
April			-0.282***	-0.268***
			(0.054)	(0.055)
May			-0.249***	-0.235***
			(0.057)	(0.057)
June			-0.376***	-0.364***
			(0.058)	(0.059)
July			-0.159**	-0.152**
			(0.064)	(0.064)

(To be continued on the next page)

August			-0.263***	-0.253***
			(0.068)	(0.069)
Year effects		*Reference: Wave 1998*		
Wave 2000				0.017
				(0.025)
Wave 2006				-0.091***
				(0.027)
Constant	6.297***	6.171***	6.543***	6.567***
	(0.013)	(0.028)	(0.057)	(0.059)
N	58472	58472	58472	58472
adjusted R^2	0.027	0.028	0.030	0.030

Source: SOEP waves from 1998, 2000, and 2006.

Notes: Dependent variable is health satisfaction on a 0 to 10 scale. Robust standard errors are in parentheses. Levels of statistical significance are: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A2 Time-variant health-related attrition bias

Dependent variable:	Health satisfaction			
Specification:	(1)	(2)	(3)	(4)
Induced refreshment of 1998	-0.504***	-0.556***	-0.672***	-0.690***
	(0.094)	(0.094)	(0.096)	(0.098)
Induced refreshment of 2000	-0.592***	-0.638***	-0.757***	-0.847***
	(0.079)	(0.079)	(0.081)	(0.083)
Induced refreshment of 2006	-0.524***	-0.608***	-0.653***	-0.577***
	(0.088)	(0.091)	(0.091)	(0.092)
N	58472	58472	58472	58472
adjusted R^2	0.027	0.028	0.030	0.031
Survey mode		X	X	X
Interview month			X	X
Year effects				X
Year-in-panel controls	X	X	X	X

Source: SOEP waves from 1998, 2000, and 2006.

Notes: Dependent variable is health satisfaction on a 0 to 10 scale. Control variables are for survey mode (oral interview with paper and pencil, oral interview with computer assistance, self-written with interviewer presence, self-written without interviewer presence, and partly oral, partly self-written), interview month (eight dummies), year (waves of 2000 and 2006), and year-in-panel controls (dummies for the first to eighth participation in the SOEP). Robust standard errors are in parentheses. Levels of statistical significance are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 Health-related attrition bias, individual characteristics and interaction with gender (complete)

Dependent variable:	Health satisfaction					
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Induced refreshment	-0.758***	0.032	-0.011	-0.771***	0.012	-0.038
(of 1998/2000/2006)	(0.080)	(0.078)	(0.084)	(0.083)	(0.081)	(0.087)
Year-in-panel	*Reference: 9th year in panel and beyond*					
1st year in panel	1.161***	0.299***	0.370***	1.161***	0.299***	0.370***
	(0.076)	(0.075)	(0.080)	(0.076)	(0.075)	(0.080)
2nd year in panel	1.338***	0.204***	0.355***	1.338***	0.204***	0.354***
	(0.052)	(0.052)	(0.063)	(0.052)	(0.052)	(0.063)
3rd year in panel	0.809***	0.209***	0.234***	0.809***	0.209***	0.234***
	(0.045)	(0.043)	(0.047)	(0.045)	(0.043)	(0.047)
4th year in panel	0.946***	0.068	0.168***	0.946***	0.068	0.167***
	(0.054)	(0.052)	(0.056)	(0.054)	(0.052)	(0.056)
5th year in panel	0.887***	0.068	0.145***	0.887***	0.068	0.145***
	(0.056)	(0.053)	(0.056)	(0.056)	(0.053)	(0.056)
6th year in panel	0.647***	0.034	0.024	0.646***	0.034	0.024
	(0.053)	(0.051)	(0.053)	(0.053)	(0.051)	(0.053)
7th year in panel	0.278***	0.189***	0.159***	0.278***	0.189***	0.159***
	(0.033)	(0.031)	(0.032)	(0.033)	(0.031)	(0.032)
8th year in panel	0.601***	-0.021	0.050	0.601***	-0.021	0.050
	(0.063)	(0.061)	(0.064)	(0.063)	(0.061)	(0.064)
Survey mode	*Reference: Self-written by mail*					
Oral interview with	0.163***	0.368***	0.431***	0.163***	0.368***	0.431***
paper and pencil	(0.032)	(0.031)	(0.033)	(0.032)	(0.031)	(0.033)
Oral interview with	0.266***	0.474***	0.476***	0.266***	0.474***	0.476***
computer assistance	(0.036)	(0.034)	(0.037)	(0.036)	(0.034)	(0.037)
Self-written with	0.261***	0.153***	0.122**	0.261***	0.153***	0.121**
interviewer presence	(0.051)	(0.050)	(0.052)	(0.051)	(0.050)	(0.052)
Self-written without	0.147***	0.047	-0.011	0.147***	0.047	-0.012
interviewer presence	(0.033)	(0.031)	(0.033)	(0.033)	(0.031)	(0.033)
Partly oral, partly	0.065	0.051	0.083	0.065	0.051	0.083
self-written	(0.052)	(0.051)	(0.053)	(0.052)	(0.051)	(0.053)
Interview month	*Reference: Interview in September or beyond*					
January	-0.571***	-0.184***	0.029	-0.571***	-0.183***	0.030
	(0.057)	(0.055)	(0.059)	(0.057)	(0.055)	(0.059)
February	-0.397***	-0.054	0.055	-0.397***	-0.054	0.055
	(0.053)	(0.051)	(0.054)	(0.053)	(0.051)	(0.054)
March	-0.376***	-0.128**	-0.052	-0.376***	-0.128**	-0.052
	(0.054)	(0.052)	(0.055)	(0.054)	(0.052)	(0.055)
April	-0.270***	-0.064	-0.004	-0.270***	-0.064	-0.004
	(0.055)	(0.052)	(0.055)	(0.055)	(0.052)	(0.055)
May	-0.235***	-0.035	0.010	-0.235***	-0.035	0.010
	(0.057)	(0.055)	(0.058)	(0.057)	(0.055)	(0.058)
June	-0.365***	-0.104*	-0.060	-0.365***	-0.104*	-0.060
	(0.059)	(0.056)	(0.059)	(0.059)	(0.056)	(0.059)
July	-0.154**	0.086	0.098	-0.154**	0.086	0.098
	(0.065)	(0.062)	(0.065)	(0.064)	(0.062)	(0.065)

(To be continued on the next page)

August	-0.253***	-0.047	-0.001	-0.253***	-0.047	-0.001
	(0.069)	(0.066)	(0.069)	(0.069)	(0.066)	(0.069)
Year effects			*Reference: Wave 1998*			
Wave 2000	0.017	0.028	-0.026	0.017	0.028	-0.026
	(0.025)	(0.024)	(0.025)	(0.025)	(0.024)	(0.025)
Wave 2006	-0.090***	0.043*	0.025	-0.090***	0.043*	0.025
	(0.027)	(0.025)	(0.027)	(0.027)	(0.025)	(0.027)
Female	-0.134***	-0.106***	-0.021	-0.140***	-0.115***	-0.033
	(0.018)	(0.017)	(0.020)	(0.021)	(0.020)	(0.022)
Age		-0.047***	-0.042***		-0.047***	-0.042***
		(0.001)	(0.001)		(0.001)	(0.001)
Education status			*Reference: Secondary education*			
Primary education			-0.197***			-0.197***
			(0.025)			(0.025)
Tertiary education			0.223***			0.223***
			(0.025)			(0.025)
Employment status			*Reference: Full-time employment*			
Regular part-time employment			-0.016			-0.017
			(0.033)			(0.033)
Irregular part-time employment			0.045			0.045
			(0.052)			(0.052)
Other forms of employment			-0.102*			-0.101*
			(0.059)			(0.059)
Out of labor force			-0.203***			-0.203***
			(0.026)			(0.026)
Unemployed			-0.306***			-0.306***
			(0.040)			(0.040)
Recent move			0.027			0.027
			(0.030)			(0.030)
Number of persons in household			0.025**			0.025**
			(0.010)			(0.010)
No children in household			-0.138***			-0.138***
			(0.028)			(0.028)
Family status			*Reference: Single*			
Married			-0.069**			-0.069**
			(0.034)			(0.034)
Separated			-0.141*			-0.141*
			(0.075)			(0.075)
Divorced			-0.210***			-0.210***
			(0.047)			(0.047)
Widowed			-0.062			-0.062
			(0.057)			(0.057)
Partnership			-0.005			-0.004
			(0.032)			(0.032)

(To be continued on the next page)

Log equalized real income			0.396*** (0.024)			0.396*** (0.024)
Interaction: Female X Induced refreshment				0.024 (0.044)	0.038 (0.041)	0.054 (0.044)
Constant	6.638*** (0.060)	6.384*** (0.058)	6.747*** (0.095)	6.641*** (0.060)	6.389*** (0.058)	6.754*** (0.096)
N	58472	58472	52620	58472	58472	52620
adjusted R^2	0.031	0.136	0.155	0.031	0.136	0.155
Federal state controls			X			X

Source: SOEP waves from 1998, 2000, and 2006.

Notes: Dependent variable is health satisfaction on a 0 to 10 scale. Federal state controls are 15 dummy variables. Both age and income variables are de-meaned. Robust standard errors are in parentheses. Levels of statistical significance are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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