Interviewer effects on onliner and offliner consent to an online survey

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1. Introduction

There is an increase of online surveys in behavioural and social science (Baker et al., 2010, p. 7; Schonlau and Couper, 2017), as the online mode is cost-effectively in terms of time, space, and labour (Greenlaw and Brown-Welty, 2009; Hardigan et al., 2012; Kaplowitz et al., 2004). In addition, social desirability bias is reduced (Kreuter et al., 2008) and interviewer effects are cancelled out (for a review see West and Blom, 2016) in online surveys. However, there are concerns regarding the generalizability of estimates from online survey data to the general population (Bethlehem, 2010; Dever et al., 2008; Mohorko et al., 2013; Schonlau and Couper, 2017), due to non-coverage of non-internet households in online surveys (Sterrett et al., 2017). To account for these selectivities many probability-based online panels are based on a random population sample necessitating a offline sampling frame to reduce self-selection into the online survey sample (for information on probability-based online surveys see Blom et al., 2016; Bosnjak et al., 2013; Revilla et al., 2016; Schonlau and Couper, 2017). During these offline recruitments the selected respondents get a request to continue the survey over the internet. Thus, respondents are pushed to the web within the recruitment to probability-based online panels. Yet, research is spares that investigates sources of error associated with pushing respondents to the web in probability-based online surveys.

The offline sampling frame of probability-based online panels can be either by mail or by an interviewer assisted mode. In case of interviewer assisted recruitments one source of error associated with pushing respondents to the web might be interviewers themselves, because the interviewers are gaining consent to further online panel continuation from respondents (see for decision stages of respondents Hoogendoorn and Daalmans, 2009). Yet, research on interviewer effects on the push to the web is sparse. Therefore, we make use of literature on interviewer effects of gaining consent to perform additional tasks, such as consent to additional data collection. In this context, research has found interviewer effects on consent variation for additional data collection or data linkage (for an overview see West and Blom, 2016). In addition, there is some evidence that interviewer experience and interviewer attitude relate to nonresponse when obtaining consent to additional tasks (for examples see Sakshaug et al., 2013, 2012). Therefore, interviewers may contribute to the explanation of consent variation and hence, interviewers might be a source of error when pushing respondents to the online survey mode in probability-based online surveys.

Gaining knowledge on interviewer effects is important for probability-based online panels, as these online panels suffer from high unit nonresponse during the transformation from the offline recruitment to the online survey (Blom et al., 2016; Hoogendoorn and Daalmans, 2009). Especially, non-internet households - so called offliners - are less likely to respond to an online panel (Blom et al., 2016), although they get the means to participate online. Differences in characteristics of onliners and offliners may introduce nonresponse bias (Blom et al., 2016). Thus, group specific interviewer effects are of great concern, as they might introduce unit nonresponse bias in probability online panels (for general information on interviewer effects on nonresponse bias see West et al., 2014; West and Olson, 2010). Consequently, this paper sets out to answer the following research questions: (1) To what extent do interviewers affect the consent to online panel continuation? (2) Is the size of interviewer effects different for onliners and offliners? (3) If so, which interviewer characteristics influence interviewer effects among onliners and offliners differentially?

2. Data

In the following we use data from a probability-based online panel, the German Internet Panel (GIP). The sample of the GIP is drawn offline by a random sample of areas (primary respondents, PSUs; for further information see Blom et al., 2015). Out of these PSUs households were randomly selected. Afterwards, the not randomly selected interviewers were assigned to PSUs (Blom et al., 2015). Here it was possible that interviewers worked in several areas, hence interviewers are sometimes cross-classified between PSUs. After interviewers made contact with the eligible households they conducted face-to-face interviews with the person present in the household. Thus, the selection of the person interviewed in the offline recruitment interview was not randomly selected. However, all age-eligible household members were invited by mail or email to participate in the online panel. Therefore, the GIP is a online panel which is based on random sample representative for the German population age 16 to 75 in which households are clustered within PSUs and interviewers.

In the following we use pooled data of the recruitments in 2012 and 2014 with an indicator for the year of the recruitment round to account for possible differences in the recruitments (for sensitive analysis on the data used see Blom et al., 2016). In total 5238 age-eligible respondents were interviewed face-to-face. Out of these respondents, 3842 respondents gave consent to online panel continuation of whom 2970 were classified as onliners and 872 were classified as offliners. In addition, the composition of offliners and onliners differs significantly with regard to socio-demographic characteristics, general health, and political attitude.

This study benefits from an interviewer survey which was conducted prior to the field phase of the GIP with paper-and-pencil questionnaires during the interviewer training (survey based on Blom and Korbmacher, 2013). All interviewers were asked to fill out a questionnaire on topics concerning interviewers' own behaviour, interviewers' experience with measurements, interviewers' expectations, interviewers' computer and internet usage and interviewers' socio-demographic characteristics. As we cannot link the information of the interviewer questionnaires between recruitments we deleted all interviewers who worked in both recruitments of the GIP. In addition, some interviewers did not answer the interviewer questionnaire, hence we ended up with 214 interviewers.

3. Analytic approach

Most investigations of interviewer effects on response behaviour have fitted a two-level multilevel model (respondents nested within interviewers) or a three-level multilevel model (respondents nested within PSUs nested within interviewers), because multilevel models account for a hierarchical structure of the data and hence adjust for dependencies between levels by extended error terms (for a statistical formulation Bryk and Raudenbush, 1992; Hox, 2002; Maas and Hox, 2004). In the GIP data the hierarchical structure is reflected by groups of respondents who can be allocated to the same interviewer, hence respondents are nested within interviewers.

Because no substantially relevant differences in consent rate were detected among PSUs, we decided to omit this source of variation from the models, and prefer a two-level model over three-level or cross-classified models. As we neglect the estimation of area effects an overestimation of area characteristics can occur. However, we account for regional clusters in the sampling design weights by means of jackknife variance estimation (for details see Gould, 1995; Quenouille, 1956).

This organization of the models lead to the question on the dependencies whether respondents who were recruited by the same interviewer have similar probability of online panel continuation compared to respondents who were interviewed by different interviewers? In addition, we argue that interviewer effects vary depending on the equipment status of respondents – being online or being offline. Therefore, we extend our multilevel model by including random slopes.

For this purpose we estimate a multilevel regression analysis and we denote our dependent variable π_{ij} as consent to online panel continuation of respondent i who was interviewed by interviewer j.

$$\pi_{ij} = \begin{cases} 0 & \text{no consent to online panel continuation,} \\ 1 & \text{consent to online panel continuation.} \end{cases}$$

To estimate the between-interviewer variation in the probability to give consent to online panel continuation we estimate a multilevel logistic model with two levels (respondents nested within interviewers). As in single-level logistic regressions, the probability π of observing the value 1 in dichotomous variable π_{ij} is modelled as an logistic transformation. Therefore,

$$logit(\pi_{ij}) = ln(\frac{\pi_{ij}}{1 - \pi_{ij}})$$

with π_{ij} being the probability of that respondent i contacted by interviewer j gives consent to online panel continuation. Being an offliner versus onliner is introduced as a key dummy predictor affecting the probability to consent. The dummy is coded as

$$OFF = \begin{cases} 0 & \text{being onliner,} \\ 1 & \text{being offliner.} \end{cases}$$

Because the difference in consent rate between offliner and onliners can vary across interviewers, we additionally include a random slope for the dummy identifying offliners. The resulting multilevel model is written in equations (1) to (3). By substituting equations (2) and (3) into (1), we obtain the model in reduced form – see equation (4).

$$logit(\pi_{ij}) = \beta_{0j} + \beta_{1j}OFF_{ij} \tag{1}$$
$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{2}$$
$$\beta_{1j} = \gamma_{10} + u_{1j} \tag{3}$$
$$logit(\pi_{ij}) = \gamma_{00} + \gamma_{10}OFF_{ij} + u_{1j}OFF_{ij} + u_{0j} \tag{4}$$

with

$$u_{0j} \sim N(0, \sigma^2_{u_0}), u_{1j} \sim N(0, \sigma^2_{u_1}),$$

In this model, parameters γ_{00} and γ_{10} are the fixed effects. γ_{00} is the grand intercept, representing the logit of consent for onliners across all interviewers. γ_{10} captures how the logit of consent differs for offliners compared to onliners, again on average across all interviewers. The variation across interviewers is incorporated in the random part of the model. Random intercept u_{0j} denotes how the level of onliner' consent deviates from the average for interviewer j. Consequently, the random intercept variance $\sigma^2_{u_0}$ represents the cross-interviewer variation in the success of recruiting onliners. Random slope variance $\sigma^2_{u_1}$ is less intuitive to interpret, and refers to how the difference in consent rate between offliners and onliners varies between interviewers.

In the parameterization used above, the random part is hard to interpret. The random slope variation does show how the gap in consent between offliners and onliners is different per interviewer, and thus yields insight in whether there are interviewers who 'specialize' in convincing offliners or rather onliners. However, our research questions are with regard to the different size and nature of interviewer effects among offliners and onliners. To be able to answer these questions, the parameterization of the model needs to be changed. Concretely, we switch from dummy coding (or contrast coding) to a model that uses contrast coding in the fixed part and separate coding in the random part of the model (Jones, 2013, p. 136 ff.). Separate coding means that the intercept is omitted, and that the two dummies for onliners and offliners are introduced separately. Therefore, we included the additional dummy predictor

$$ON = \begin{cases} 0 & \text{being offliner,} \\ 1 & \text{being onliner.} \end{cases}$$

Rather than using the onliners as reference category and estimating the contrast with offliners, the consent rates are modelled separately for both groups. The model with contrast coding in the fixed part and separate coding in the random part is summarized in equation (5). This model has no random intercept, but has a random slope for onliners and a second random slope for offliners. The two variance components represent the amount of interviewer difference for each group separately, which is exactly what we need to answer the research questions at hand. Note that the fixed part of equation (5) and the interpretation of the fixed effects are identical as in equation (4).

$$logit(\pi_{ij}) = \gamma_{00} + \gamma_{10}OFF_{ij} + u_{1j}OFF_{ij} + u_{2j}ON_{ij} \tag{5}$$

with

$$u_{1j} \sim N(0, \sigma^2_{u_1}), u_{2j} \sim N(0, \sigma^2_{u_2})$$

Essentially, the equation (5) with separate coding in the random part is statistically equivalent as equation (4), and the random components of equation (5) can be expressed in terms of equation (4). However, statistical equivalence between the models only holds if the covariance matrix of the random effects is specified as unstructured, and a covariance between both random effects at the interviewer level is specified (for more detail see Rabe-Hesketh and Skrondal, 2008, pp.303). Therefore, the resulting covariance matrix for the random slopes u_{1j}, u_{2j} is given by

$$Var \begin{bmatrix} u_{1j} \\ u_{2j} \end{bmatrix} = \begin{bmatrix} \sigma^2_{1j} & \sigma_{21} \\ \sigma_{12} & \sigma^2_{2j} \end{bmatrix}$$

A positive (negative) covariance between the random slopes for offliners and onliners would mean that interviewers who are good in recruiting one group are more (less) successful in convincing the other group to participate in the panel.

This basic model can be augmented by including interactions between offliner status and interviewer status. Conceptually, these cross-level interactions allow us to evaluate which interviewer characteristics determine the propensity to consent for offliners and onliners separately. The extended model can be written as follows:

$$logit(\pi_{ij}) = \gamma_{00} + \gamma_{10} OFF_{ij} + \gamma_{11} OFF_{ij} Z_j + \gamma_{01} Z_j + u_{1j} OFF_{ij} + u_{2j} ON_{ij} \tag{6}$$

with

$$u_{1j} \sim N(0, \sigma^2_{u_1}), u_{2j} \sim N(0, \sigma^2_{u_2})$$

with $\gamma_{11} OFF_{ij} Z_j$ reflecting the slope γ_{11} of the interaction of the respondent characteristics of being offline OFF_{ij} and the interviewer characteristics Z_j.

4. Results

In order to investigate whether interviewers contribute to an explanation of consent to online panel continuation, we use a multilevel logistic model with two levels (respondents are nested within interviewers). In our null model (not presented) we have an intra-class correlation of 25.3% indicating an considerable variance located at the interviewer level.

In the first model of table 1 we extend our null model of the multilevel logistic regression by including respondent and interviewer characteristics (intercept model). Looking at the fixed part of the model, we do not find any association of interviewer characteristic on gaining consent to online panel continuation to be significant. However, we find that the propensity to give consent to panel continuation significantly increases with the age of the respondent. Furthermore, the coefficient for age-squared is negative and significant, suggesting as respondents get older the effect on giving consent gets stronger. Moreover, households with two or three and more household members are more likely to give consent to the online panel than single households. Respondents with a medium educational level are more likely to give consent compared to respondents with a low educational level. Respondents who are not at work are significantly more likely to give consent to online panel continuation compared to respondents who work full time. Respondents that use the internet on a daily basis are significantly more likely to give consent to online panel continuation compared to any other group of internet users. In case of voting behaviour, we find a significant negative association of respondents who are not eligible to vote and respondents who refused to answer this question compared to voters. Finally, being an offliner reduces the propensity of giving consent significantly. When we look at the random part of the multilevel model, we find a significant interviewer term, indicating a significant interviewer effect on consent.

In the second model of table 1 we extend our analysis by one random slope which was contrast coded (being offline). We find no differences in the fixed effects part compared to the first model. However, the variance decomposition changed a bit. There is a significant random slope of being offline indicating that there is a variation between interviewers in case of gaining consent from offliners compared to onliners.

In the third model of table 2 we use contrast coding in the fixed part and separate coding in the random part. As the second and the third model are statistically the same we do not find any differences in the coefficient estimations of the fixed part. However, the variance decomposition yields different insights. First, we detect a significant random slope effect for onliners. This means that there is variation across interviewers in gaining consent from onliners. For offliners, we find significant interviewer effects. Interestingly, the size of the variance component for offliners is considerably smaller than the interviewer variance for onliners. Thus, there is much less variation between interviewers when recruiting offliners compared to onliners. In addition, the difference in size of interviewer effects is significantly different between onliners and offliners. Finally, there is a significantly positive covariance of the random slope coefficients, indicating interviewers who are good in gaining consent from offliners are, relatively speaking, good in gaining consent from onliners and vice versa.

In the fourth model of table 2 we extend our analysis by cross-level interactions. Only the interaction with how much a interviewer adapts to the respondent during the interview, in terms of adjusting to dialects or the rate of speaking, is significant. The positive interaction effect means that the adaptation to the respondent is more relevant when obtaining consent from offliners than when recruiting onliners.

5. Discussion

Based in our results, we conclude that interviewers have an impact on consent to online panel continuation; however, the low response rates of offliners are not associated with interviewer effects. Consequently, it is not the interviewers who introduce low response rates for offliners. This result was not expected as research shows that interviewers have an impact on gaining consent for the collection of biomarkers and external data linkage (Sakshaug et al., 2012, 2013; West and Blom, 2016).

Table 1. Multilevel logistic regression for interviewer effects on consent to online panel continuation with 95% confidence intervals

	Model 1 base model				Model 2 contrast coding			
	β	Std. err.	Min 95%	Max 95%	β	Std. err.	Min 95%	Max 95%
Fixed part								
Respondent characteristics								
Age	0.07	0.03	[0.01	0.12]	0.07	0.03	[0.01	0.12]
Age^2	-0.00	0.00	[-0.00	-0.00]	-0.00	0.00	[-0.00	-0.00]
Being male	-0.07	0.12	[-0.31	0.16]	-0.07	0.12	[-0.31	0.17]
Ref. Single household								
Two hh members	0.28	0.13	[0.02	0.54]	0.30	0.13	[0.04	0.57]
Three and more hh members	0.46	0.16	[0.14	0.77]	0.47	0.17	[0.15	0.80]
Ref. Low educational level								
Medium educational level	0.40	0.14	[0.12	0.68]	0.40	0.14	[0.12	0.68]
High educational level	0.28	0.16	[-0.04	0.59]	0.29	0.16	[-0.03	0.61]
Ref. Work full time								
Part time	0.27	0.20	[-0.12	0.65]	0.23	0.20	[-0.16	0.61]
No regular work	0.26	0.22	[-0.17	0.69]	0.26	0.22	[-0.17	0.69]
Retired	0.39	0.21	[-0.02	0.80]	0.40	0.21	[-0.01	0.81]
Not at work	0.93	0.24	[0.45	1.41]	0.94	0.24	[0.46	1.42]
Ref. Never use the internet								
$<$ once a month to once a week	1.09	0.20	[0.69	1.48]	1.06	0.21	[0.66	1.46]
$>$ once a week	1.35	0.20	[0.96	1.73]	1.29	0.20	[0.90	1.69]
Daily	1.98	0.19	[1.60	2.35]	1.95	0.20	[1.56	2.33]
Ref. Never,media consumption								
$< \frac{1}{2}$ hour	0.34	0.21	[-0.08	0.76]	0.34	0.22	[-0.09	0.77]
$> \frac{1}{2} - 1$ hour	0.73	0.22	[0.29	1.17]	0.73	0.23	[0.29	1.17]
$> 1 - 1\frac{1}{2}$ hours	0.73	0.26	[0.22	1.25]	0.68	0.26	[0.17	1.20]
$> 1\frac{1}{2}$ hours	0.89	0.29	[0.32	1.45]	0.85	0.29	[0.28	1.42]
Ref. Voters								
Nonvoters	-0.39	0.22	[-0.83	0.05]	-0.38	0.22	[-0.81	0.06]
Not eligible	-0.87	0.32	[-1.50	-0.25]	-0.91	0.32	[-1.54	-0.28]
Don't know	-0.13	0.16	[-0.44	0.18]	-0.16	0.16	[-0.47	0.15]
Refused to answer	-1.04	0.21	[-1.45	-0.63]	-1.07	0.21	[-1.49	-0.65]
Being offline	-0.66	0.15	[-0.95	-0.37]	-0.94	0.18	[-1.30	-0.58]
Interviewer characteristics								
Age	-0.06	0.11	[-0.28	0.15]	-0.08	0.11	[-0.29	0.14]
Age^2	0.00	0.00	[-0.00	0.00]	0.00	0.00	[-0.00	0.00]
Being male	-0.27	0.21	[-0.68	0.13]	-0.15	0.20	[-0.55	0.25]
Ref. Low educational level								
Medium educational level	0.05	0.28	[-0.49	0.59]	-0.03	0.27	[-0.57	0.50]
High educational level	-0.30	0.22	[-0.73	0.12]	-0.36	0.21	[-0.77	0.05]
Intercept	0.49	3.17	[-5.72	6.70]	0.97	3.13	[-5.18	7.11]
Random part								
$\text{Variance}_{\text{interviewer}}$	1.05	0.20	[0.65	1.45]	1.81	0.39	[1.06	2.57]
$\text{Variance}_{\text{offline}}$					0.71	0.33	[0.06	1.37]
$\text{Covariance}_{\text{interviewer,offline}}$					-1.00	0.32	[-1.63	-0.36]
N interviewer	214				214			
N respondents	3719				3719			

Table 2. Multilevel logistic regression for interviewer effects on consent to online panel continuation with 95% confidence intervals with random slopes

	Model 3 contrast and separate coding				Model 4 cross-level interactions			
	β	Std. err.	Min 95%	Max 95%	β	Std. err.	Min 95%	Max 95%
Fixed part								
Respondent characteristics								
Age	0.07	0.03	[0.01	0.12]	0.07	0.03	[0.01	0.12]
Age^2	-0.00	0.00	[-0.00	-0.00]	0.00	-0.00	[-0.00	0.00]
Being male	-0.07	0.12	[-0.30	0.17]	-0.07	0.12	[-0.31	0.16]
Ref. Single household								
Two hh members	0.30	0.13	[0.04	0.57]	0.30	0.13	[0.04	0.56]
Three and more hh members	0.47	0.17	[0.15	0.80]	0.46	0.16	[0.14	0.79]
Ref. Low educational level								
Medium educational level	0.40	0.14	[0.12	0.68]	0.41	0.14	[0.13	0.69]
High educational level	0.29	0.16	[-0.03	0.61]	0.29	0.16	[-0.02	0.61]
Ref. Work full time								
Part time	0.23	0.20	[-0.16	0.61]	0.22	0.20	[-0.17	0.60]
No regular work	0.26	0.22	[-0.17	0.69]	0.26	0.22	[-0.17	0.69]
Retired	0.40	0.21	[-0.01	0.81]	0.38	0.21	[-0.03	0.79]
Not at work	0.94	0.24	[0.46	1.42]	0.92	0.24	[0.44	1.40]
Ref. Never use the internet								
$<$ once a month to once a week	1.06	0.21	[0.66	1.46]	1.06	0.20	[0.66	1.46]
$>$ once a week	1.29	0.20	[0.90	1.69]	1.30	0.20	[0.90	1.69]
Daily	1.95	0.20	[1.56	2.33]	1.95	0.20	[1.57	2.34]
Ref. Never,media consumption								
$< \frac{1}{2}$ hour	0.34	0.22	[-0.09	0.77]	0.35	0.22	[-0.07	0.78]
$> \frac{1}{2} - 1$ hour	0.73	0.23	[0.29	1.17]	0.74	0.23	[0.30	1.18]
$> 1 - 1\frac{1}{2}$ hours	0.68	0.26	[0.17	1.20]	0.70	0.26	[0.18	1.21]
$> 1\frac{1}{2}$ hours	0.85	0.29	[0.28	1.42]	0.89	0.29	[0.32	1.45]
Ref. Voters								
Nonvoters	-0.38	0.22	[-0.81	0.06]	-0.37	0.22	[-0.81	0.07]
Not eligible	-0.91	0.32	[-1.54	-0.28]	-0.91	0.32	[-1.54	-0.28]
Don't know	-0.16	0.16	[-0.47	0.15]	-0.17	0.16	[-0.47	0.14]
Refused to answer	-1.07	0.21	[-1.49	-0.65]	-1.07	0.21	[-1.49	-0.65]
Being offline	-0.94	0.18	[-1.30	-0.58]	-3.16	0.87	[-4.87	-1.46]
Interviewer characteristics								
Age	-0.08	0.11	[-0.29	0.14]	-0.07	0.11	[-0.28	0.14]
Age^2	0.00	0.00	[-0.00	0.00]	0.00	0.00	[-0.00	0.00]
Being male	-0.15	0.20	[-0.55	0.25]	-0.16	0.20	[-0.55	0.23]
Ref. Low educational level								
Medium educational level	-0.03	0.27	[-0.57	0.50]	-0.05	0.27	[-0.58	0.48]
High educational level	-0.36	0.21	[-0.77	0.05]	-0.34	0.21	[-0.75	0.06]
Adaption to respondent					-0.40	0.25	[-0.89	0.09]
Being offline and adapt to respondent					0.66	0.25	[0.17	1.15]
Intercept	1.03	3.13	[-5.10	7.16]	2.30	3.22	[-4.00	8.61]
Random part								
Variance$_{\text{online}}$	1.82	0.39	[1.06	2.58]	1.79	0.38	[1.04	2.54]
Variance$_{\text{offline}}$	0.53	0.22	[0.11	0.96]	0.45	0.21	[0.05	0.86]
Covariance$_{\text{online,offline}}$	0.82	0.20	[0.42	1.22]	0.85	0.20	[0.46	1.24]
N interviewer	214				214			
N respondents	3719				3719			

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