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Does panel conditioning affect data quality in ego-centered social network questions?

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ABSTRACT

This article investigates the data quality of ego-centered social network modules in web surveys. It specifically examines whether these modules are subject to the effects of the repeated measurement of the same questions known as panel conditioning effects. Ego-centered social network modules are especially at risk of panel conditioning effects because many of the components in these modules are repetitive. Based on the theories of motivated underreporting and survey satisficing, we hypothesized that respondents reduce the length of the module by underreporting their network size and/or network density. To systematically test for panel conditioning effects, we experimentally varied the treatment frequency in a longitudinal study design, which included three panel waves. The results of our study showed that we generally obtained high quality data with relatively large reported network sizes and densities, low rates of item non-response, and low non-differentiation. In contrast to our expectations, the reported average network sizes were not smaller, and the network densities were not lower when respondents were asked to answer the same social network module multiple times. We found, however, patterns of individual change in network sizes that might be due to panel conditioning. Respondents with large network sizes in a panel wave reported smaller network sizes in the subsequent wave, while respondents with small network sizes reported larger network sizes in the subsequent wave. Respondents' ability and motivation did not affect these results. Thus, we would like to encourage researchers to further explore the opportunity of implementing ego-centered social network modules in cross-sectional as well as longitudinal self-administered surveys, while being cautious that in longitudinal surveys the chance of panel conditioning effects may increase with the average network size and the response burden of the network module.

Introduction

Panel conditioning effects have been defined as changes in actual behavior, attitudes, or knowledge; or changes in response behavior as a result of previous survey participation (e.g., Sturgis et al., 2009) and are a major methodological concern of panel studies (e.g., Kroh et al., 2016; Lynn, 2009; Warren and Halpern-Manners, 2012). This concern is especially problematic because panel conditioning effects endanger one of the most important aims of longitudinal research—the valid measurement of stability and change (Halpern-Manners et al., 2014).

With respect to ego-centered social network questions, a series of studies have demonstrated the impact of panel conditioning effects on reported network size and other question characteristics in interviewer-administered modes (e.g., Eagle and Proeschold-Bell, 2015; Groves and Magilavy, 1986; Marsden, 2003; Valente et al., 2017; van Tilburg, 1998). For example, Marsden (2003) and van Tilburg (1998) found a strong impact of panel conditioning on network questions and showed that changes in the reported network size across waves could not be explained by respondents' characteristics, but were due to interviewer effects; that is effects of interviewer behavior and interviewer characteristics on respondents' answers. Valente et al. (2017) showed that both interviewer and respondent learning can occur individually or collectively as a result of interviewers or respondents communicating with each other, which, on the one hand, can lead to reducing the number of names provided and thus also the interview length or, on the other hand, can lead to interviewers gaining experience in gathering the network data thereby increasing the reported network size. The collection of social network data via an interviewer-administered survey

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mode has advantages because interviewers can guide respondents through the often rather complex modules and prompt for additional names. However, other modes of data collection, especially the online mode, are becoming more wide-spread (Couper, 2000, 2013), and therefore, a question arises as to whether this mode is similarly affected by panel conditioning effects. An additional advantage of studying panel conditioning effects in self-administered surveys compared to interviewer-administered surveys is that panel conditioning effects due to respondents are not confounded with panel conditioning effects due to interviewers.

This paper focuses on the open research question as to whether panel conditioning effects are a threat to the data quality of ego-centered social network modules when data are collected via the web. With this aim in mind, the study implemented a longitudinal study design with three waves as well as an experimental study design wherein the treatment group received the identical ego-centered social network module twice; whereas the control group first received a series of filler questions on other topics and in the second wave received the social network module for the first time.

Background and previous research

Ego-centered social networks are usually measured through a set of network generator questions, which may include a name generator question[2] (e.g., "Please tell me the names of the persons with whom you have discussed political issues during the last week."), name interpreter questions (e.g., "How old is Peter?" or "Where does Peter live?"), questions on ego-to-alter ties (e.g., "How close are you to Peter?"), and questions on alter-to-alter ties (e.g., "Do Peter and Clara know each other?"). In general, network generators can be characterized as repetitive questionnaire blocks, in which respondents have to answer the same questions over several rounds.

Data quality of ego-centered social networks in cross-sectional studies

Research has shown that name generator questions are predisposed to interviewer effects (Brüderl et al., 2013; Fischer, 1982; Groves and Magilavy, 1986; Marsden, 2003; Paik and Sanchagrin, 2013; van Tilburg, 1998). A likely source of interviewer effects is uneven prompting by interviewers (Bearman and Parigi, 2004). Some interviewers fail to follow instructions and do not ask respondents for the names they may have missed, whereas others follow the instructions correctly.

Another line of research has also shown that the answers given to name generator items depend on their placement within a survey. For instance, studies have shown that when items are placed near the end of the survey, respondents report that they have fewer friends (Paik and Sanchagrin, 2013; Yousefi-Nooraie et al., 2017). In addition, experimental studies on the use of name generators in online surveys have found that the higher the number of fields available to enter names on a web form, the higher the number of names given by respondents (Manfreda et al., 2004; Vehovar et al., 2008). Another study has shown that changes in question wording can impact the number of persons named (Bidart and Lavenu, 2005).

The evidence is scarce on the comparison of differences in data quality between self-administered and interviewer-administered data collection of ego-centered network data. A study, which included an experimental mode comparison, found that using an online mode negatively affected data quality compared with a face-to-face survey (Matzat and Snijders, 2010). Specifically, respondents of online surveys showed a higher drop-out rate (percentage of respondents who start, but do not complete a survey), more item non-response (questions left unanswered by respondents), more non-differentiation (respondents provide their answers to a series of questions in the same place of a rating scale), and a lower network density.

Panel conditioning in ego-centered social networks

In general, the repetition of questionnaire blocks has been shown to affect respondents by producing more measurement error since respondents learn how to skip filter questions to reduce questionnaire length (Duan et al., 2007; Eckman et al., 2014) and interviewers might learn how to reduce their burden as well (Josten and Trappmann, 2016; Valente et al., 2017). Similar effects can be expected for network generator questions when information is asked about every friend named as well as the relationship between friends. This effect can be aggravated in a panel survey when respondents are repeatedly asked to provide information about their friends.

With respect to ego-centered social network questions, the evidence on panel conditioning is sparse. Struminskaya (2016) implemented an experimental study design that included a name generator question with follow-up questions—on gender, age, relationship to the respondent, closeness to the respondent, the economic situation of named friends—and found no evidence of panel conditioning. In contrast, for their network module, Eagle and Proeschold-Bell (2015) found panel conditioning effects. Specifically, they saw a decline in network size over the course of three waves of surveys with a two-year duration. However, both these studies were not designed specifically to measure panel conditioning effects. While Eagle and Proeschold-Bell (2015) did not use an experimental design with control and treatment groups to control for other factors that may have triggered the decline in network size, Struminskaya (2016) implemented an experimental design in which respondents varied in survey experience, but neither of the experimental groups had multiple exposures to the network module. Given these limitations and the contradictions of the findings, the question as to whether panel conditioning affects ego-centered social network modules remains unanswered.

Theoretical framework

Panel conditioning in network modules can be caused by motivated underreporting (e.g., Tourangeau et al., 2012) and survey satisficing (e.g., Krosnick, 1991). Some respondents tend to use previous information about the survey process to employ certain response strategies that reduce their response burden (Nancarrow and Cartwright, 2007). Specifically, respondents may show a response behavior called *motivated underreporting* by avoiding follow-up questions of the type known as loop (i.e., questions based on those answers specific questionnaire blocks are repeated), filter, and screening questions (e.g., Kreuter et al., 2011). For example, in cross-sectional studies, Eckman et al. (2014) and Kreuter et al. (2011) have shown that asking filter questions in a grouped format, in which the filters are asked in a block and the triggered follow-up questions later, produces less underreporting than asking each follow-up question immediately after the filter question. With respect to screening questions, Tourangeau et al. (2012) have shown, in a cross-sectional study, that respondents tend to underreport the number of household members eligible for survey participation.

Since respondents only learn about additional questions after they complete the name generator question of a social network module, motivated underreporting of names—due to knowledge about the additional interview burden—is impossible; although underreporting due

[2] Name generators can be based on four different types of ties between an ego and an alter (see, for example, Marin and Hampton, 2007). First, on role-relation ties, which refer to the role of a tie in a specific social domain (e.g., neighbor or colleague); second, on interaction ties, which refer to a tie with whom the ego is in contact (e.g., discussion about politics); third, on affective ties, which refer to the emotional value of a tie (e.g., an alter to whom the ego feels close); fourth, on ties based on an exchange, which refer to the supportive content between an ego and an alter (e.g., personal advice).

to a respondent's *guess* about the existence of follow-up questions is possible. The situation is different when the network module is repeated in a later panel wave. When respondents answer a network module for the second time, they may remember that every additional name triggers additional questions. Hence, respondents' answers to the name generator questions may be affected by motivated underreporting due to their knowledge about the additional interview burden associated with providing each additional name.

Survey satisficing, which is a more general concept of motivated responding, might also result in panel conditioning. The cognitive theory of survey satisficing (Krosnick, 1991; Krosnick et al., 1996) predicts that respondents may execute the four steps of the response generation process (Tourangeau et al., 2000)—comprehension of the question, retrieval of relevant information, making a judgement, and providing a response—incompletely (weak satisficing) or skip these steps entirely (strong satisficing). According to the satisficing theory, the probability of satisficing is based on three key factors: the difficulty of the answering task, respondents' motivation, and respondents' ability. Although the difficulty of the answering task in a network module is constant and a respondent's ability is unlikely to change substantially over several panel waves within a short time period, respondents' motivation when filling in a network module may differ between waves—especially, when several questions are asked about every alteri, network modules can be burdensome. When the network module is repeated, respondents might feel that they already provided the answers to these questions, and may therefore, be less motivated to put much effort into answering the module. For example, satisficing (Krosnick, 1991) could result in the provision of fewer names, non-differentiation, or item non-response.

With respect to ego-centered network modules, both theories (motivated underreporting [e.g., Tourangeau et al., 2012] and survey satisficing [e.g., Krosnick, 1991]) provide explanations about why respondents may underreport their network size and network density to avoid follow-up questions when repeatedly answering a network module.[3] These effects may be moderated by respondents' ability and motivation. With respect to answering a network module multiple times, motivated underreporting has two preconditions. First, respondents must have realized before (for example, the first time they answered the network module) that the number of questions depends on the number of friends named and that they could have saved time by filling in fewer names. Second, when answering the questions again, respondents must remember the network module and its structure. These two preconditions also apply to a possible increase in survey satisficing.

Research hypotheses

The present study examines the following research hypotheses:

H1. Repeated measurement reduces the data quality of the network module.

H2. Respondents underreport their network size when repeatedly asked the same network generator questions.

H3. Respondents underreport their network density when repeatedly asked the same network questions.

H4. A reduction in network size and network density is moderated by respondents' ability and motivation. Specifically, respondents with high ability and high motivation underreport their network size and network density.

Method and design

The data were collected with a four-wave online access panel survey from May to August 2016 (N = 554 completed interviews[4], participation rate = 29.5%). There was a one-month interval between each of the waves. A non-probability sampling method was used to select the respondents. The web survey was quota sampled by using reference distributions for gender, age, and education from the target population based on the 2014 German General Social Survey. The field time of each panel wave was one week and the average response time for each wave was approximately ten minutes. Two email reminders were sent out to the respondents before each wave. For completing each survey, respondents received a €1 incentive. The initial invitation email for the first wave informed respondents about the panel characteristics of the study.

Comparison across panel waves and randomized experiment

In the first and second wave of the online panel survey, we used a randomized experiment, including a treatment group and a control group that did not receive the treatment (Shadish et al., 2002; see Fig. 1). Respondents were randomly assigned to either the control group ($N_{wave\ 1}$ = 276) or the treatment group ($N_{wave\ 1}$ = 278). In the first wave, the respondents of the control group received a series of questions on an unrelated topic, and the respondents of the treatment group received the social network module. In the second wave, both the respondents of the control group and the treatment group received the network module. Attrition between the waves was 14.1 percent for the control group and 16.5 percent for the experimental group (χ^2 (1) = 0.74, p = .39). The χ^2-tests did not reveal any statistically significant differences between the two experimental groups with respect to socio-demographics: gender (χ^2 (1) = 2.09, p = .15), age (χ^2 (4) = 2.98, p = .56), education (χ^2 (2) = .46, p = .79), and region (χ^2 (1) = .80, p = .37). In addition, the treatment group also received the network module in the third wave ($N_{wave\ 3}$ = 190) an additional time. Attrition between the second and third wave was 18.1 percent for this group.[5]

Network module

The network module included four components (see Fig. 2). The first was the name generator question in which respondents were asked to name their closest friends (maximum 7 friends, one question; see Figures A1 to A4 in the Online Appendix). The second component (Ego-to-Alter Tie) asked respondents how close they were to each friend they had named (maximum 7 questions). Third (Alter-to-Alter Tie 1), respondents were asked whether their friends knew each other (maximum 21 questions). Finally (Alter-to-Alter Tie 2), respondents were

[3] Technically, respondents do not report or underreport their network size nor network density, but they fill in names in a name generator question and answer follow-up questions about the ties in their network. For the simplicity of the manuscript, we will use the terms respondents "report their network size" and "report their network density" throughout.

[4] Using the software package G*Power (Faul et al., 2009), we computed a power analysis in order to determine the required minimum sample size for the most complex regression model testing H4. Assuming a medium effect size f^2 = 0.15, and a statistical power set at .95, the required sample size was N = 138 (see required sample size computation in the Online Appendix). The study sample size was well above this minimum sample size, even when considering panel attrition and the experimental design, which included a random assignment of respondents to treatment and control group.

[5] In order to investigate whether attrition in the subsequent wave was related to the burden experienced from filling in the network module in a previous wave, we conducted logistic regression models using network size, item non-response in the network component, and response time as explanatory variables. The three variables showed a non-significant effect on the participation in wave 2 and 3 in the regression models.

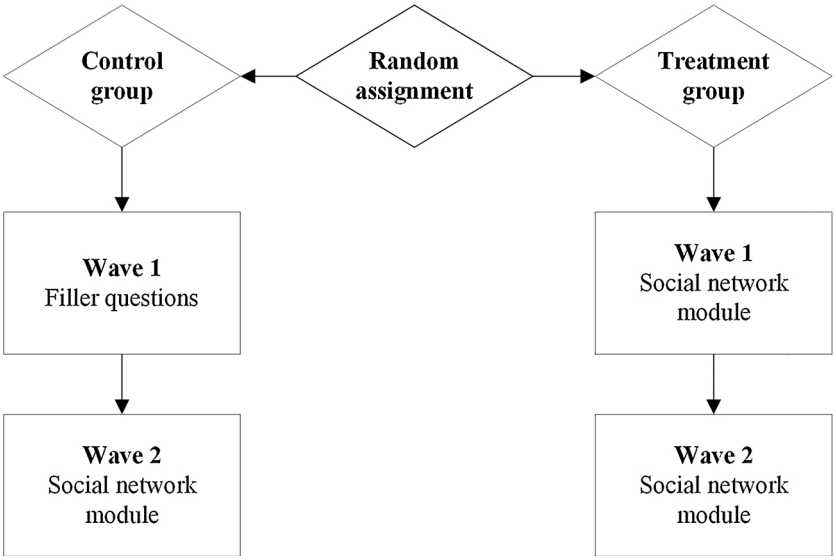

Fig. 1. Experimental design.

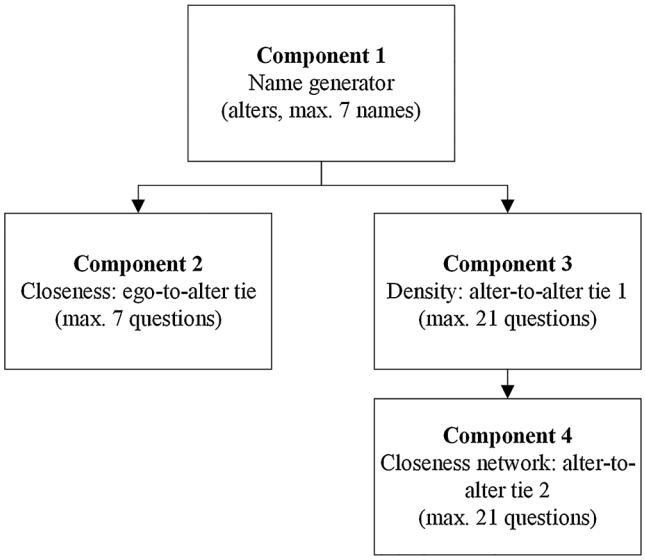

Fig. 2. Social network module.

asked about the closeness of their friends who knew each other (maximum 21 questions). In total, the network module included a maximum of 50 questions that were asked in a grouped format, which means that the respondents did not receive the follow-up questions immediately—they received them after they had completed the entire component. The average number of follow-up questions was 13.4 (treatment group) in wave 1, 12.7 (treatment group) respective 15.4 (control group) in wave 2, and 12.0 (treatment group) in wave 3. For the panel conditioning analyses, network size referred to the number of names given in component 1 and network density was calculated based on components 1 and 3 of the network module (i.e., the number of "yes" responses to the question on alter-to-alter ties in component 3 divided by the total number of alter-to-alter ties based on component 1). Components 1 and 3 were selected because respondents could actively reduce the length of the network module by underreporting the number of alter-to-alter ties in component 3.

Data quality indicators

Data quality was measured using four indicators: item non-response, non-differentiation, response time, and validity.[6]

Item non-response

Item non-response refers to a question (respective item) left unanswered by a respondent. The percentage of questions with item non-response was calculated separately for each of the four components of the network module (0–100%).

Non-differentiation

Non-differentiation refers to the responses that do not vary within a set of items. For example, a respondent who provided the same answer "I slightly disagree with the statement" six times to a set of six items was considered a non-differentiating respondent with respect to this particular set of six items. We used the non-differentiation indicator proposed by Roßmann et al. (2017), which takes the value 1 if all the responses excluding missing values have an identical value when answering all the questions of the component; the indicator equals 0 if at least one response has another value (see also Roßmann, 2017).

Response time

Response time for the network module was measured in seconds-per-name needed for answering. We calculated two indicators for response time: the first response time indicator measured the time use for the name generator component only and a second indicator measured the time use for the entire network module.

Validity

With respect to validity, we compared the correlations of network size with other measures (e.g., education, age, and employment) in our study to correlations based on other data and studies.

Other measures

Ability

In line with previous research (e.g., Holbrook et al., 2007; Krosnick et al., 1996), respondents' level of formal education was used as a proxy

[6] Although we consider the drop-out rate as another informative data quality indicator, we decided against adding it to our list of indicators because respondents did not drop-out of the survey, while answering the social network module, during any of the three waves. A possible reason for these zero drop-out rates might be that respondents received the monetary incentive only if they completed the entire survey.

to measure respondents' cognitive ability (see Online Appendix Table A1 for the question wording). Respondents without a school-leaving certificate or with intermediary secondary qualification were coded as having low education, and respondents who were entitled to study at a college or university were assigned to high education.

Motivation

Also in line with previous research (Krosnick, 1991; Krosnick et al., 1996), respondents' need for cognition (low, high) was used as a proxy to measure respondents' motivation. The need for cognition indicator was based on a German short scale with four items (Beissert et al., 2014; Cacioppo and Petty, 1982; see Online Appendix Table A1 for the question wording).

Results

Data quality of the network module

We compared the data quality of our network module with benchmarks from previous studies to gain a better understanding of its data quality. The analyses in this part are based on all the respondents who received the network question for the first time. Therefore, we combined the respondents from both experimental groups to increase the sample size and statistical power.

With respect to network size, our study resulted in an average of 3.4 names per respondent (maximum 7 names). This number was above the number of friends reported in the 2010 German General Social Survey (Allbus), which had an average of 2.6 names per respondent (maximum 5 names) and the 2010 General Social Survey (GSS) in the United States, which had an average of 2.4 names per respondent (maximum 6 names).

When considering item non-response, our study showed an item non-response rate below 5 percent for all four components of the social network module. This rate was below the item non-response rates found in previous studies on ego-centered network questions (e.g., Vehovar et al., 2008; Yousefi-Nooraie et al., 2017), which reported item non-response rates that ranged between 4 and 30 percent for the name generator questions.

With respect to non-differentiation, we examined the responses to the questions of component 2 (Closeness: Ego-to-Alter Tie) and 4 (Alter-to-Alter Tie 2) because component 3 (Alter-to-Alter Tie 1) had a dichotomous response scale, and therefore, insufficient variance. For component 2, non-differentiation equaled 30.5 percent, and for component 4, it equaled 14.5 percent.[7]

Concerning validity, our network module replicated the positive correlation of high extraversion with network size ($p < .001$ see Table 1; Asendorpf and Wilpers, 1998; Selfhout et al., 2010; Swickert et al., 2010), and the greater network size of women compared to men ($p < .10$ see Table 1; e.g., Hill and Dunbar, 2003; McLaughlin et al., 2010). Our own analyses based on samples of the national population in Germany and the United States (Allbus 2010, GSS 2010) also showed positive correlations of education and employment[8] on network size. For both education and employment, our study showed a non-significant correlation in the expected direction (see Table 1). In addition, we found a marginally significant positive correlation of age to network size, with respect to which previous studies have shown mixed findings (see Table 1). Taking these results together, all correlations with other variables were in the expected direction, and four out of six correlations were significant or marginally significant.

Altogether, the social network module performed well on all four data quality indicators; especially, in the areas of network size, item non-response, and validity. With respect to non-differentiation, our findings are not straightforward, and future studies will need to determine the size of the effect of non-differentiation on the data quality of a social network module.

Panel conditioning across waves

With respect to the stability of repeated measurements, we compared three consecutive waves of the panel. In this section, we present analyses comparing each wave with the next consecutive wave.[9][10] To avoid misleading results due to panel attrition, we limited these analyses to the respondents who answered all three panel waves.

Even though the average network size became slightly smaller over the course of the panel (difference between wave 1 and wave 3 = .14 names), the network sizes stayed considerably high, and the differences were non-significant (see Table 2). We also investigated the moderation effects[11] of ability measured by the level of education of a respondent and of motivation measured by a respondent's need for cognition. However, in contrast to our expectations, both interaction effects were not significant (see Table 2). This finding suggests that respondents with high ability or high motivation were not more likely to underreport their network size or network density when asked the questions in our network module three times within two months. We observed a similar pattern with respect to network density, non-differentiation, item non-response, and response time. None of these indicators showed substantive differences over time (see Table 2).

By taking a closer look at the changes of network size over the panel waves, we observed that 40.2 percent of respondents reported the same number of names in the first and second waves, 33.2 percent reported a smaller network size, and 26.6 percent reported a larger network size (see Fig. 3). The percentage of the same number of names was higher than those reported in previous findings on identical network sizes of name generator questions. For example, Wolf (2006) has noted that about one-third of respondents reported exactly the same network size, and the test-retest reliability of name generators measured by Cronbach's α was between 0.77 and 0.65. Compared to these findings, the test-retest reliability of our study was α = .84 between waves 1 and 2,

[7] When thinking about these percentages, it is important to remember that respondents were asked to name their closest friends and it is very likely that they feel "close" or "very close" to each of them. Therefore, the question design did not allow us to distinguish between non-differentiation due to similar substantive responses and non-differentiation due to shortcutting the response process. However, our main research interest was the change in non-differentiation when respondents were repeatedly asked. Thus, the indicator will be more informative in the following sections when examining changes across waves and when comparing the treatment to the control group.

[8] Employment was measured by asking respondents the question "What is your current work status? Work status refers to any work that is paid or related to income" with the four response categories ("full-time work," "part-time work," "work occasionally, (e.g., €450 job)," "do not work"). In order to ensure comparability with other surveys the variable was dichotomized in (1) "do work" (including "full-time work," "part-time work," and "work occasionally") and (0) "do not work."

[9] We omitted the comparison of wave 1 to wave 3 because they did not add anything substantive to the conclusions. Thus, omitting this comparison simplified the presentation of the results.

[10] In order to investigate whether having taken the social network module multiple times would increase the likelihood of showing panel conditioning effects, we pooled the data of the three waves and tested the variable "number of times the network module was taken" (0 = not taken before, 1 = taken once, 2 = take twice). The result showed a non-significant effect of this variable and thus did not provide support for the assumption (see Table A2).

[11] Moderation effects were tested by using fixed-effects panel regression models. We ran one model that included the interaction of "wave 3" and "ability" and the interaction of "wave 3" and "motivation," as well as the main effects of these variables. If, for instance, the interaction term of "wave 3" and "motivation" was significant, the effect of the repeated measurement of network size was moderated by the respondents' level of motivation.

Table 1
Validity Comparison: Correlations of Network Size with Other Measures in Different Data.

	Allbus 2010[a]	Allbus 2000[a]	GSS 2010[a]	Our Study[a]	Asendorpf and Wilpers, (1998)[b]	Selfhout et al. (2010)[b]	Swickert et al., (2010)[b]
Education	.25***	.14***	.20***	.02			
Female	.07*	.00	.06*	.07^{+}			
Age	−.23***	−.13***	.05+	.07^{+}			
Employment	.17***	.08***	.04	.05			
Extraversion				.20***	.34***	.10***	.46**
Need for cognition				.12**			
Mean (number of friends)	2.63	2.15	2.41	3.29			
Maximum number of friends	5	3	6	7			
N	1,337	3,804	1,272	554	132	205	366

Note. ***$p < .001$ **$p < .01$ *$p < .05$ +$p < .10$, a) correlations are based on our own calculations, b) correlations reported in previous studies. See Online Appendix Table A1 for the question wordings.

Table 2
Panel Conditioning Across Waves.

Indicators	Wave			Wave 1 vs. wave 2		Wave 2 vs. wave 3	
	Wave 1	Wave 2	Wave 3	*t*	*p*	*t*	*p*
Network size	3.37	3.32	3.23	0.47	ns	0.83	ns
Moderation by ability				0.06 [a]	ns	−0.27 [a]	ns
Moderation by motivation				−0.29 [a]	ns	0.29 [a]	ns
Network density	66.2%	62.8%	63.5%	0.83	ns	−0.16	ns
Moderation by ability				0.03 [a]	ns	−0.02 [a]	ns
Moderation by motivation				−0.03 [a]	ns	0.03 [a]	ns
Item Non-Response							
C1: Name Generator	3.7%	3.2%	1.6%	0.38	ns	1.13	ns
C2: Ego-to-Alter Tie	0.0%	2.1%	2.1%	−1.64	ns	0.00	ns
C3: Alter-to-Alter Tie 1	4.7%	2.6%	4.2%	0.63	ns	−0.65	ns
C4: Alter-to-Alter Tie 2	1.6%	1.6%	0.0%	0.00	ns	1.74	$p < .10$
Non-differentiation							
C2: Ego-to-Alter Tie	32.6%	27.6%	30.3%	0.93	ns	−0.52	ns
C4: Alter-to-Alter Tie 2	22.7%	27.4%	24.2%	−0.75	ns	0.50	ns
Response time (per name)							
C1: Mean	11.0s	10.6s	10.5s	0.42	ns	0.13	ns
C1: Median	8.4s	8.3s	7.9s				
C1-4: Mean	26.9s	27.2s	25.2s	−0.17	ns	1.10	ns
C1-4: Median	25.6s	24.0s	22.4s				
N	190	190	190				

Note. a) These coefficients and the related *t*-tests are based on fixed-effects panel regression models with wave X ability/motivation interaction terms (see Table A3 and Table A4 for the full panel regression models). "C" refers to "component." The sample size *N* can slightly vary in individual cells due to item non-response.

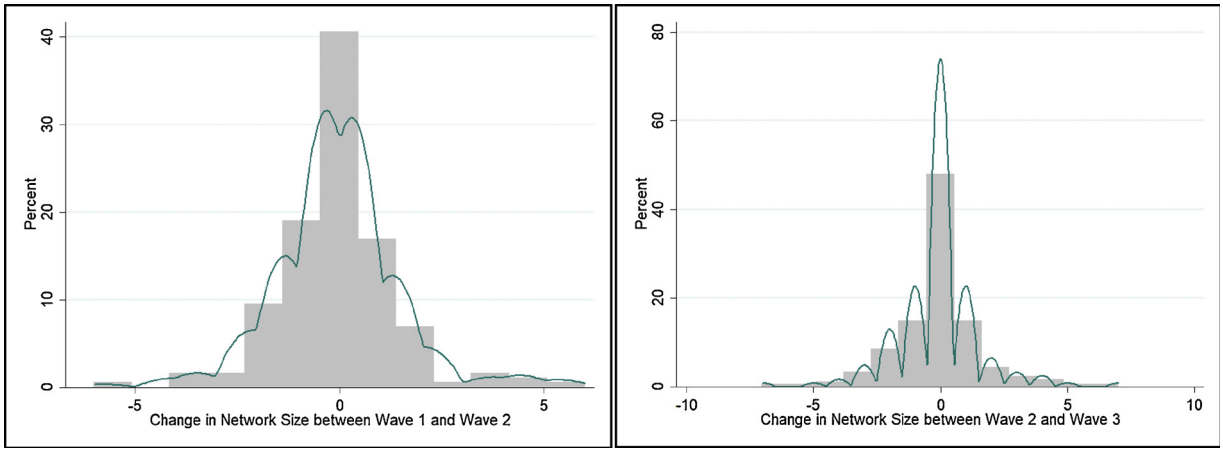

Fig. 3. Change in the reported network size over time: wave 1 to wave 2, and wave 2 to wave 3.

α = .82 between waves 2 and 3, and α = .82 between waves 1 and 3, which further strengthens the finding of strong reliability and high data quality.

The change in the reported network size between waves 1 and 2 was especially likely for respondents with a network size of 3–6 friends in wave 1 (*percentage* $_{change}$ = 68.2 percent to 82.9 percent), and the change between waves 2 and 3 was especially likely for respondents with a network size of 0 friends and 3–6 friends in wave 2 (*percentage* $_{change}$ = 59.3 percent to 83.3 percent). Between waves 1 and 2, respondents with a network size of 1 in the first wave (*percentage* $_{change}$ = 40.0 percent) were particularly stable in the reported network size. And between waves 2 and 3, particularly stable in the reported network size were respondents with a reported network size of 1 in the second wave (*percentage* $_{change}$ = 30.8 percent).

Table 3
Change in the Number of Friends Between Wave 1 and Wave 2 by Number of Friends in Wave 1.

Number of friends		Difference	*t*	*p*	*N*[a]
Wave 1	Wave 2				
0	0.67	0.67	2.00	ns	6
1	1.55	0.55	2.56	$p < .05$	40
2	2.48	0.48	2.05	$p < .05$	31
3	3.43	0.43	1.57	ns	35
4	3.27	−0.73	−2.59	$p < .05$	22
5	4.57	−0.43	−1.69	ns	21
6	5.00	−1.00	−2.45	$p < .10$	4
7	5.81	−1.19	−4.26	$p < .01$	31

Note. a) The *t*-test is only reliable when $N > 30$ (Kühnel and Krebs, 2012). We included the test for smaller sample sizes nonetheless to display the tendency of larger network sizes in wave 2 for network sizes from 0 to 3 in wave 1 and smaller network sizes in wave 2 for network sizes of 4 to 7 in wave 1.

Table 4
Change in the Number of Friends Between Wave 2 and Wave 3 by Number of Friends in Wave 2.

Number of friends		Difference	*t*	*p*	*N*[a]
Wave 2	Wave 3				
0	2.00	2.00	1.94	ns	6
1	1.64	0.64	3.39	$p < .01$	39
2	1.97	−0.03	−0.22	.ns	34
3	3.30	0.30	0.35	ns	27
4	3.68	−0.32	−0.32	ns	31
5	4.15	−0.85	−2.60	$p < .05$	20
6	5.50	−0.50	−1.20	ns	12
7	5.62	−1.38	−3.07	$p < .01$	21

Note. a) The *t*-test is only reliable when $N > 30$ (Kühnel and Krebs, 2012). We included the test for smaller sample sizes nonetheless to display the tendency of larger network sizes in wave 3 for network sizes from 0 to 3 in wave 2 and smaller network sizes in wave 3 for network sizes of 4 to 7 in wave 2.

We further explored the finding that network sizes of respondents with small and large network sizes are especially subject to change. For that purpose, we looked at average changes in the network size by network size in the previous wave. When considering changes between waves 1 and 2 (see Table 3)[12], the respondents with a network size below 4 in the first wave, reported, on average, a larger network size in the second wave, and the respondents with a network size above 3 in the first wave, reported, on average, a smaller network size in the second wave. These differences between waves 1 and 2 were significant for respondents who reported 1, 2, 4, or 7 friends in the first wave ($p < .05$, see Table 3).

Between waves 2 and 3 (see Table 4)[13], the respondents with a network size below 4 in the second wave (except respondents with a network size of 2), reported on average a larger network size in the third wave, and the respondents with a network above 3 reported on average a smaller network size in the third wave. These differences between waves 2 and 3 were significant for respondents who reported 1, 5, or 7 friends in the second wave ($p < .05$, see Table 4).

Considering the absence of substantive changes in the average network size between waves 1 and 2 and between waves 2 and 3 (see Table 2), the changes of persons with smaller and larger network sizes displayed in Tables 3 and 4 could hint at an effect known as a "regression toward the mean" (e.g., Galton, 1886), which refers to the fact that if a random variable is measured twice, unities with extreme values in the first measurement tend to have values closer toward the mean in the second measurement. In line with this interpretation, the standard errors of the network sizes of the full sample are not significantly different across the three waves ($SE_{wave\ 1} = 0.15$, $SE_{wave\ 2} = 0.15$, $SE_{wave\ 3} = 0.14$).

Panel conditioning experiment

In this section, we focus on comparing the two experimental groups in wave 2. With respect to the results for network size, the treatment group reported a slightly smaller network than the control group (see Table 5); however, this difference was not significant. The network density was slightly smaller for the treatment group than the control group; this difference also was non-significant.

Considering the moderation effects[14], ability showed only a marginally significant negative effect on the reported network size ($p = .09$; see Table 5), and motivation was non-significant ($p = .14$; see Table 5). This finding was in contrast to our expectation based on the satisficing theory (Krosnick, 1991; Krosnick et al., 1996), which suggests that respondents who remember the question mechanism and who were motivated in the first place will show a panel conditioning effect. With respect to network density, we did not find a moderation of the panel conditioning effect by respondents' ability and motivation.

Finally, we also looked at scores of various data quality indicators for the two groups (see Table 5). Item non-response was generally very low, and we observed only one marginally significant difference between the two groups. As previously described, non-differentiation was generally high, and the differences between the experimental groups were non-significant for component 2 (Ego-to-Alter Tie) but significant with respect to the treatment group for component 4 (Alter-to-Alter Tie 2). With respect to response time—measured in seconds-per-name when respondents answered the network module—the results did not show significant differences between the two groups.

In summary, the experiment did not show panel conditioning main effects of network size and network density. A respondent's ability and motivation did not moderate the effect of answering the network module for the second time on reported network size and the reported network density, and substantive differences were not found in the data quality indicators of item non-response, non-differentiation, and response time.

Sensitivity analysis

To gain additional information on the subgroup of respondents, which had comparatively high response effort when answering the social network module in the first wave, we conducted a sensitivity analysis (see Table 6) wherein we replicated the analyses across panel waves for respondents with a network size above the median of three friends in wave 1 (see Table 2). Again, we limited our analyses to respondents who answered all three panel waves. This resulted in 78 respondents, who reported 4 or more friends in the first panel wave. The sensitivity analysis showed a significant decline in network size between wave 1 and wave 2, which is in line with the results of Tables 3 and 4. However, the difference in the reported network size between

[12] Some of the *t*-tests in Table 3 and 4 should be interpreted with caution because the *t*-test is only reliable when $N > 30$ (Kühnel and Krebs, 2012). Therefore, we repeated the analysis when combining respondents who had less than four friends in wave 1 (group one) and respondents who had more than three friends in wave 1 (group two). The differences in the number of friends between waves 1 and 2 were significant for both groups ($p < .001$).

[13] We also repeated the analysis when combining respondents who had less than four friends in wave 2 (group one) and respondents who had more than three friends in wave 2 (group two). The differences in the number of friends between waves 2 and 3 were significant for both groups ($p < .001$).

[14] Moderation effects were tested by using linear regression models. We ran one model that included the interaction effect of "treatment" and "ability" and the interaction effect of "treatment" and "motivation," as well as the main effects of these variables.

Table 5
Panel Conditioning: An Experimental Comparison Between Treatment and Control Group.

Indicators	Control group	Treatment group	Difference	*t*	*p*
Network size (NS)	3.65	3.32	0.33	1.55	ns
Moderation by ability			−0.39[a]	−1.68[a]	$p < .10$
Moderation by motivation			−0.57[a]	−1.47[a]	ns
Network density (ND)	65.8%	62.8%	3.0%	0.72	ns
Moderation by ability			−0.02[a]	−0.39[a]	ns
Moderation by motivation			.004[a]	0.05[a]	ns
Item Non-Response					
C1: Name Generator	0.5%	3.2%	−2.6%	−1.90	$p < .10$
C2: Ego-to-Alter Tie	1.6%	2.1%	−0.5%	−0.29	ns
C3: Alter-to-Alter Tie 1	7.4%	2.6%	4.8%	1.26	ns
C4: Alter-to-Alter Tie 2	1.6%	1.6%	0.0%	0.01	ns
Non-differentiation					
C2: Ego-to-Alter Tie	26.2%	27.6%	−1.4%	−0.26	ns
C4: Alter-to-Alter Tie 2	15.5%	27.4%	−11.9%	−2.10	$p < .05$
Response time (per name)					
C1: Mean	11.8s	10.6s	1.2s	1.02	ns
C1: Median	8.2s	8.3s	−0.1s		
C1-4: Mean	32.3s	27.2s	5.1s	1.57	ns
C1-4: Median	25.1s	24.0s			
N	188	190			

Note. a) These coefficients and the related *t*-tests are based on linear regression models with treatment X ability/motivation interaction terms (see Table A5 for the full regression models). The sample size *N* can slightly vary in individual cells due to item non-response.

Table 6
Sensitivity Analysis: Panel Conditioning Across Waves for Respondents With a Network Size Above the Median in Wave 1 (Network Size Wave 1 > Three Friends).

Indicators	Wave			Wave 1 vs. wave 2		Wave 2 vs. wave 3	
	Wave 1	Wave 2	Wave 3	*t*	*p*	*t*	*p*
Network size	5.56	4.72	4.63	5.42	$p < .01$	0.48	ns
Moderation by ability				0.12[a]	ns	−0.91[a]	$p < 0.10$
Moderation by motivation				−0.42[a]	ns	0.30[a]	ns
Network density	60.3%	61.0%	64.0%	−0.15	ns	−0.60	ns
Moderation by ability				0.01[a]	ns	0.03[a]	ns
Moderation by motivation				0.06[a]	ns	−0.05[a]	ns
Item Non-Response							
C1: Name Generator	0.0%	0.0%	0.0%	0.00	ns	0.00	ns
C2: Ego-to-Alter Tie	0.0%	5.1%	5.1%	−1.65	ns	0.00	ns
C3: Alter-to-Alter Tie 1	9.0%	6.4%	10.2%	0.63	ns	−0.65	ns
C4: Alter-to-Alter Tie 2	3.8%	3.8%	0.0%	0.00	ns	1.76	$p < .10$
Non-differentiation							
C2: Ego-to-Alter Tie	19.2%	16.2%	21.6%	0.48	ns	−0.81	ns
C4: Alter-to-Alter Tie 2	15.1%	22.2%	19.4%	−0.99	ns	0.35	ns
Response time (per name)							
C1: Mean	8.0s	9.4s	10.1s	−1.78	$p < .10$	−0.68	ns
C1: Median	7.4s	8.0s	7.9s				
C1-4: Mean	27.5s	31.5s	27.5s	−1.74	$p < .10$	0.71	ns
C1-4: Median	28.1s	26.1s	26.6s				
N	78	78	78				

Note. a) These coefficients and the related *t*-tests are based on fixed-effects panel regression models with wave X ability/motivation interaction terms (see Tables A6 and A7 for the full panel regression models). “C” refers to “component”. The sample size *N* can slightly vary in individual cells due to item non-response.

wave 2 and wave 3 was non-significant. Of the other indicators—network density, item non-response, non-differentiation, and response time—only the fourth item non-response indicator (C4: Alter-to-Alter Tie) showed a marginally significant decline between waves 2 and 3, and both response time indicators (C1: Name Generator and C1-C4: Complete Network Module) showed a marginally significant increase between wave 1 and wave 2.

Overall, the results of the sensitivity analysis for the group of respondents with four or more friends revealed that only the network size between waves 1 and 2 of the network module was substantially affected by repeatedly asking the network module. When comparing the results of the sensitivity analysis to the analysis with the full sample, we note that the described negative effect on the reported network size for respondents with a large network size in the previous wave (see Tables 3 and 4) was also observed between waves 1 and 2, but it was not observed between waves 2 and 3. Therefore, the sensitivity analysis supported the assumption that there might be a regression toward the mean in the network size; which would suggest that respondents with extreme values in the network size in the first measurement, had, on average, values which were closer toward the mean in the second and third measurements (e.g., Galton, 1886). However, the significant decrease of the network size between waves 1 and 2 also raises caution to a possible threat of underreporting of respondents with large network sizes for whom the network module requires more response effort than for respondents with small network sizes.

Discussion

The present study investigated panel conditioning effects of ego-centered social networks in web surveys. To this end, we employed a longitudinal study design and a randomized experiment. We investigated four research questions on the repeated measurement of a

network module: first, does panel conditioning lead to a decrease in data quality; second, does panel conditioning lead to an underreporting of network size; third, does panel conditioning lead to an underreporting of network density; and fourth, is panel conditioning moderated by respondents' ability and motivation.

With respect to data quality, repeated measurement did not substantively reduce the overall data quality of the network module for most of the data quality indicators. The indicators item non-response, non-differentiation, and response time were not substantially affected, nor was the network density affected by panel conditioning. With regard to network size, we did not find a panel conditioning effect when looking solely at the mean network size. Also, the comparison with other studies did not indicate that the network size in the present study suffered from underreporting due to panel conditioning. In fact, the network size was remarkably high in comparison with studies, such as the German General Social Survey (Allbus) and the General Social Survey (GSS) in the United States. More detailed analyses showed, however, patterns of change across waves for specific network sizes and the sensitivity analysis for respondents with a network size above the median in the first wave revealed that respondents with large network sizes tended to report fewer friends in the subsequent wave, while respondents with small network sizes tended to report more friends. These specific patterns of change across the waves are most likely due to regression to the mean and panel conditioning. This interesting phenomenon should receive special attention in follow-up studies.

The randomized experiment did not reveal any moderation effects—related to the ability and motivation of a respondent—on reported network size or network density. Likewise, the comparison across panel waves did not show a moderation effect related to ability or motivation. This result contradicted our expectations based on the theory of survey satisficing (Krosnick, 1991; Krosnick et al., 1996). Thus, it seems that the underlying mechanisms of underreporting are not activated when answering the questions in ego-centered social network modules.

Our mixed results, without a panel conditioning effect for most indicators but a possible panel conditioning effect for the reported network size, build upon previous research, which indicated that panel conditioning is predominantly a threat to knowledge questions, while other questions are affected only under specific circumstances, such as very difficult questions (e.g., Binswanger et al., 2013; Struminskaya, 2016).

The present research has certain limitations and avenues for future research. First, even though our network module required quite some effort on the part of the respondents by starting with an open name generator question, a question type that is generally considered challenging for respondents (see Singer and Couper, 2017), and a maximum of 49 follow-up questions, it is relatively short compared to many other more detailed network modules. Future studies should explore whether our findings can be generalized to studies that include larger network modules, multiple name generator questions (see Marin and Hampton, 2007), and more follow-up questions. Those follow-up questions could be on more cognitively demanding topics, where respondents must retrieve specific information from memory (e.g., about political parties of the alteri, knowledge about political views of alteri, or other details about the persons in their network such as age or education).

Second, each survey wave had an average response time of about ten minutes, which is relatively short. Future studies could explore whether respondents are more prone to panel conditioning effects if the social network module and the complete survey requires a longer response time.

Third, the reported average network size in our study was smaller than in many other network studies. Therefore, studies with larger average network sizes could be more strongly affected by panel conditioning, especially because we found a decrease in the network size for respondents with large network sizes in the preceding wave. Stronger panel conditioning effects could thus be expected in larger network sizes, more burdensome network modules, and surveys with longer durations.

Fourth, our conclusions are limited to the online mode. It would be particularly interesting if future studies would replicate our experimental study design in a mixed-mode survey to compare interviewer-administered and self-administered network modules.

Fifth, panel conditioning is more likely to arise after many repetitions (Warren and Halpern-Manners, 2012). The repetitive nature of the follow-up questions after the name generator question mitigated this problem, and our study did not reveal any strong evidence for panel conditioning across waves when the same module was administered three times within two months, which is a relatively high frequency compared to panel studies that implement network generators and usually have one-year intervals between the waves. However, future studies could further explore whether panel conditioning effects occur when a network module is repeated more often.

Sixth, our respondents were experienced survey participants, and inexperienced respondents might be affected differently by a repeated measurement due to their lack of survey experience (Toepoel et al., 2008, 2009). Therefore, to test this open question empirically, we would encourage replications of our study design with fresh respondents.

Irrespective of these limitations, our study indicated that panel conditioning has only minor negative implications for short ego-centered network modules in web surveys. Researchers can probably safely assume that data on closeness and other alter characteristics are not substantially affected by panel conditioning. This result is in line with the findings of previous studies that investigated panel conditioning effects on other survey questions (e.g., Dennis, 2001; Struminskaya, 2016). However, structural measures such as network sizes are more likely to be affected by panel conditioning and these structural measures might be particularly subject to panel conditioning effects when ego-centered network modules of medium or large sizes are employed. Based on our findings, we would like to encourage researchers to explore the opportunity that self-administered surveys and especially web surveys could provide, by implementing ego-centered social network modules in the online mode, and further testing the possibilities of optimal visualization (e.g., Stark and Krosnick, 2017), as a method of reducing the response burden.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.socnet.2018.08.003.

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