The European Political Science Association, 2016 *doi:10.1017/psrm.2016.XX*

Misreporting social media activity: Pitfalls of Internet access panels and the impact of respondents' motivations

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By utilizing the advantages of a linked survey structure this study assesses how accuracy of self-reported social media activity (in the form of the number of recently published Tweets and the number of Twitter-subscriptions) differ between three distinct participant recruitment approaches commonly used in the social sciences (an Internet access panel, a micro-job-platform and advertisements on social media). The results suggest that immediate rewards warrant a better overall accuracy of self-reported behavior in comparison to delayed rewards and an intrinsic motivation to provide accurate estimates is related to a higher accuracy in comparison to motivations that originate from an expected monetary reward. The analyses also suggest that social media activity is generally overreported and that the tendency to over- or underreport differs along socio-demographic dimensions. This project then discusses implications for Internet access panel providers and provides further insights into the discussion about individual discrepancies between reported and observed social media activity.

Do participants in online surveys systematically misreport their social media activity? Which role does the intrinsic motivation of respondents play when it comes to response quality? Does response quality differ between Internet access panel (IAP) providers and regular micro-job-platforms (MJPs) such as e.g., Amazon's *Mechanical Turk*?

Biased self-reports and false statements have been recognized as detrimental to survey research as often self-reports are the only feasible source of information about subjects of interest. Despite a recent trend toward analyses of (big) online data (Lazer et al. 2009) some researchers caution against the sole use of digital trace data and complete neglect of survey approaches (e.g., Schober et al. 2016). As a result, scientists recently tried to provide insights into who misreports their social media activity to which degree (Guess et al. 2019; Henderson et al. 2019) and this project contributes to this strain of research. Explanations for misreports target various stages in the process of answering survey questions (Schwarz

2007). In this research note, I provide insights from a survey (n = 418) distributed via three distinct platforms – a commercial IAP, an MJP, and Twitter-ads – and elaborate on the quality of self-reported Twitter-activity by taking advantage of a linked survey structure (Stier et al. 2019). By distinguishing between the different reward structures of the platforms I elaborate on the effects of immediate vs. long term monetary reward approaches and show that participants' intrinsic motivation plays a crucial role concerning the quality of answers. Importantly, this research project employs a novel recruitment approach that utilizes Twitter advertisements and a non-monetary reward structure to determine the impact of intrinsic motivation on response quality. Additionally, individual discrepancies between reported and observed behavior pose a threat to inferences drawn from survey projects (Brady 1985). This project contributes to the scarce insights already provided by Guess et al. (2019) and Henderson et al. (2019) by showing how age, gender, and ideological self-placement affect self-reports about social media activity.

Biased self-reports

Schwarz (2007) identifies four stages in which response errors can occur: comprehension, recalling, estimating and reporting. At each stage, various mechanisms have been theorized to affect reporting such as e.g., *satisficing* if people lack the motivation to come up with valid inference strategies in the stage of estimation or recall (Krosnick 1991). Participants' motivation is – among other factors – ultimately tied to the reward structure of the survey platform where a project is distributed (Tuten, Galesic, and Bosnjak 2004). This research note contributes to the discussion about the effect of motivation on response quality by distinguishing between three platform types which are commonly used in social science: commercial IAPs, MJPs, and advertisements on social media platforms (see e.g., Guess et al. 2019; Buhrmester, Kwang, and Gosling 2011; Jäger 2017, respectively).

Commercial IAP providers curate lists of potential respondents that they contact when they field a survey. As a result, IAP providers promise a representative sample of survey participants. In contrast, MJPs allow the limitation of the reach of a task to an audience of interest. When it comes to the distribution of a survey, IAP providers offer guidance to the researcher, while MJPs leave more responsibility to the researcher. IAPs are specifically tailored to conduct market research or the distribution of social science surveys, while MJPs are designed to offer simple tasks to workers – with surveys being an exception rather than the norm. To guarantee a consistently high response quality, providers employ long term monetary incentives such as e.g., the collection of reward points that can be turned in for cash. Despite empirical findings suggesting that delayed rewards have a negative effect on response quality (e.g., Tuten, Galesic, and Bosnjak 2004), IAP providers employ long term reward strategies to discourage short term exploitation of their platform. By evaluating the response quality of participants from an IAP with the response quality of an MJP I determine whether these long term strategies have an edge over immediate rewards

(Research question 1).

Additionally, researchers discussed the impact of participant motivation on data quality (Deci 1976) with the overall assumption that intrinsic motivation leads to better item response (Jäckle and Lynn 2008). Following their logic, I expect intrinsically motivated participants to provide more accurate estimates of their behavior than monetarily motivated participants (RQ2). As monetary rewards are currently the most common form of compensation for participants, this research note presents the results of an alternative approach that attempts to comply with respondents' interests and, thus, outlines the potential impact of intrinsic motivation on response quality.

Research about misreports and data quality has long been limited to comparisons between response rates or the length of answers given to open-ended questions but rarely focused on arguably more important aspects such as e.g., the reliability of answers (Singer and Ye 2013). Deviating projects focused on the accuracy of self-reports about television consumption and television news exposure (e.g., Prior 2009), smartphone and mobile phone usage (e.g., Boase and Ling 2013), video games (e.g., Kahn, Ratan, and Williams 2014), Internet use (e.g., Revilla, Ochoa, and Loewe 2017), and social media exposure (e.g., Junco 2013). Activity and media consumption are being over- as well as underreported depending on the subject and device. At the same time, misreporting is often not constant among respondents and socio-demographic factors seem to play a role in whether or not subjects accurately answer questions about their media consumption (e.g. Prior 2009).

Thus, another aspect this research note investigates is systematic patterns that may occur when respondents misreport on their social media activity. Research on misreporting patterns for social media activity is scarce. Two exceptions are Guess et al. (2019) and Henderson et al. (2019), who analyzed the accuracy of statements regarding (political) social media use focusing on Twitter activity (Guess et al. also analyzed Facebook activity) from participants in two distinct IAPs (*YouGov* and *Qualtrics* respectively). On an aggregate level, both papers find meaningful self-reports of social media usage, while also detecting considerable differences between self-reporting and observed behavior on the individual level. While Guess et al. find a higher likelihood for older respondents and politically interested respondents to overreport their Facebook activity it remains unclear whether these predictors "will always be correlated with overreporting" (Guess et al. 2019, p. 14). Contrarily, Henderson et al. find a higher probability for older respondents and women to underreport their Twitter activity. Overall, Henderson et al. conclude that tendencies to over- and underreport on average cancel each other out while Guess et al. also find corresponding values between reported and observed behavior on average. This study proceeds from Guess et al.'s and Henderson et al.'s findings by complementing their results with insights gained from other platforms. Specifically, I determine whether social media activity on average is being over- or underreported in other contexts than those of Guess et al. and Henderson et al., (RQ3). Additionally, I evaluate whether their findings of systematic misreporting patterns of Twitter-activity are also occurring when recruiting participants from other platforms (RQ4).[1]

Empirical approach

To estimate respondent's awareness about their social media activity, I fielded an online survey among U.S. and German Twitter-users on three distinct platforms during the period between December 1st, 2018 and January 31st, 2020. A majority of interviews were completed by respondents contacted by a commercial IAP provider (*respondi*), while I collected complementary interviews via the MJP *JobBoy* (Table 1). To determine whether IAPs or MJPs (i.e., long term or immediate monetary rewards') guarantee a better response quality (RQ1), I exploit differences in the reward structure of the platforms. As for *respondi*, participants received a comparably low immediate monetary reward (0.25 Cents) for a completed interview but were presumably compensated on a long term basis if they adhered to certain quality standards throughout multiple interviews. In contrast, on the MJP (*JobBoy*) participants were compensated immediately after a manual approval of the completion of the interview (1$) and there was not any subsequent contact after the interview.

Additionally, to make comparisons to presumably intrinsically motivated participants I advertised the survey via Twitter-ads[2] and offered participants the possibility to receive an evaluation of the ideological direction of their Twitter-network by presenting the polished results of the procedure by Barberá et al. (2015) (see section S3 in the online appendix). Importantly, respondents recruited via this last channel did not receive any monetary reward. I expect this last group of participants to be more invested and committed as they should expect their answers to influence their evaluation of their accounts. Respondents were either asked about their Twitter handle in the survey (*respondi*) or were requested to authorize an app (*JobBoy*, Twitter-Ads) to subsequently retrieve Twitter-profile information via the Twitter application programming interface (API).

Social media activity

Social media activity was collected in two ways. Participants were requested to provide (a) their estimate of the number of Tweets published by them in the month leading up

[1]Note that Guess et al. (2019) did not find any systematic misreporting patterns for self-reported Twitter-activity.

[2]`ads.twitter.com`, *Last accessed August 27, 2019*. To improve the participation rate on Twitter, I targeted an U.S. audience that interacted with relevant keywords – i.e., *Partisannews*, *newsbias*, *echochamber*, *Partisan* and/or *polarization* – and was interested in politics and current events.

to the survey and (b) their estimate of the number of accounts they are *following* on Twitter (subsequently called *Twitter-subscriptions*). Respondents indicated their activity on a categorized five-point Likert-scale ranging between clearly defined intervals.[3] I then compare these self-reported estimates with measured estimates retrieved via the API and can, thus, conclude whether a respondent over- or underreported the amount of Twitter-subscriptions or the number of recently published Tweets.

Results

First, the accuracy of self-reported social media activity varies between platforms and the measured concepts with Internet access panelists (subsequently called *panelists*) generally providing the lowest quality answers (Table 1). Second, Tweets are being recalled less accurately than the number of subscriptions. 51.5 % of the time, respondents were correct about their number of Twitter-subscriptions, while they accurately recalled their number of recently published Tweets Twitter-subscriptions only in 37.1 % of the cases. Third, – and with regards to the fourth research question – overreports on average outweigh underreports for both measures (Tweets and subscriptions). Nevertheless, this tendency is heavily dependent on the context as e.g., overreports of both Tweets and subscriptions hardly occurred by participants recruited via Twitter-Ads (2.9 %; 5.6 %) but were more common among monetarily rewarded respondents. Concerning the first research question – are long term monetary rewards advantageous with regards to response quality in comparison to immediate rewards? – I find that micro-jobbers, in general, have better accuracy than panelists when it comes to providing estimates about the number of recently published Tweets (50.0 % vs. 34.0 %; Fisher's exact test p-value (p_{Fisher}) = 0.03). This seems to be caused by a weaker tendency to overreport (19.2 % vs. 45.8 %; p_{Fisher} < 0.001). However, this general tendency does not translate to misreports of the number of subscriptions where I do not find meaningful differences between micro-jobbers and panelists.

[3]The exact question concerning the recent Tweets was: "How many Tweets did you publish last month?" and respondents had the possibility to chose one of the following categories: (i) "None", (ii) "1-5", (iii) "6-20", (iv) "21-100", (v) "More than 100". The exact question was concerning the Twitter-subscription number was: "How many people do you follow on Twitter?" and respondents had the possibility to choose one of the following categories: (i) "None", (ii) "1-5", (iii) "6-20", (iv) "21-100", (v) "More than 100". Nevertheless, we filtered persons who provided category *i* or *ii* as answers to the question concerning the number of subscriptions due to data quality reasons.

Impact of motivation

Concerning the second research question – does intrinsic motivation improve response quality? –, I compare in table 1 the accuracy of self-reports about subscription-numbers of presumably motivated respondents recruited via Twitter-Ads with monetarily rewarded respondents (micro-jobbers and panelists) and expect motivation to have a positive effect on accuracy. Non-monetarily rewarded respondents seem to more accurately estimate their Twitter-subscription numbers as compared to others (79.4 % vs. 48.9 %; p_{Fisher} = 0.001). I attribute this tendency to the smaller chance of these respondents to overreport their subscriptions (2.9 % vs. 30.3 %; $p_{Fisher} < 0.001$). Although this weaker tendency to overreport for motivated participants translates to the accuracy of self-reports about the number of recently published Tweets (motivated respondents only overreported in 3.0 % of cases while monetarily rewarded participants overreported in 42.18 % of cases; $p_{Fisher} < 0.001$), I also find significantly more underreports of intrinsically motivated participants (51.5 % vs. 21.6 %; $p_{Fisher} < 0.001$). This ambivalence results on average in no significant difference between the overall accuracy of self-reports about the Tweeting activity of intrinsically motivated and monetarily rewarded respondents (p_{Fisher} = 0.348).

TABLE 1 *Accuracy of statements about the number of recent Tweets and the number of Twitter-subscriptions.*

Recent Tweets	n	Accurate	Overr.	Underr.
Ads	33	45.5 %	3.0 %	51.5 %
MJP	52	50.0 %	19.2 %	30.8 %
IAP	332	34.0 %	45.8 %	20.2 %
Overall	418	37.1 %	39.0 %	23.9 %
Fisher's exact tests (p-values)				
RQ1: MJP vs. IAP		0.03	0	0.102
RQ2: Ads vs. MJP & IAP		0.348	0	0

Subscriptions	n	Accurate	Overr.	Underr.
Ads	34	79.4 %	2.9 %	17.6 %
MJP	65	56.9 %	30.8 %	12.3 %
IAP	311	47.3 %	30.2 %	22.5 %
Overall	412	51.5 %	28.2 %	20.4 %
Fisher's exact tests (p-values)				
RQ1: MJP vs. IAP		0.174	1	0.067
RQ2: Ads vs. MJP & IAP		0.001	0	0.826

Noteworthy, both tendencies – effects of the timing of rewards and the motivation on the average accuracy of self-reports – were significant when controlling for other demographic information (see table 2) and are, thus, not likely to be due to different distributions in the sample.

Systematic misreports

Finally, I briefly elaborate on logistic regression models fitted on the tendency to mis-, over-, or underreport either recently published Tweets or the Twitter-subscription-number (Table 2).[4] As mentioned above, Guess et al. (2019) find that older respondents are more likely to provide inflated self-reports on Facebook activity, while Henderson et al. (2019) find a contrary tendency. In this sample, a higher age is related to fewer occurrences of overreports and more occurrences of underreports of the number of Twitter-subscriptions (Table 2), thus, confirming the findings of Henderson et al. Additionally, I find that respondents who claim to be conservatives have a stronger tendency to overreport both the number of recently published Tweets and their subscription-numbers. As a side note, in contrast to Guess et al. who found that female respondents significantly underreport their political Facebook use and to Henderson et al. who found that female participants are more likely to underreport their Twitter activity, in this sample women seemed to less frequently misreport their Twitter-subscriptions than men.

Conclusions

In a data collection effort spanning various platforms used to recruit participants for social science projects (an Internet access panel, a micro-job-platform, and social media advertisements), I showed that social media activity on average is being overreported. Additionally, inflated self-reports about Twitter-activity are more frequently observed when it comes to activity that is not directly observable upon the first inspection of one's own Twitter profile: the number of recently published Tweets was more often estimated wrongly and more often being overreported than the number of Twitter-subscriptions. Although the accuracy of panelists might be very low (e.g., only 34.0 % of the estimates of recently published Tweets were correct), these differences signal that respondents do not provide wrong answers intentionally but might have problems to properly recall previous behavior or choosing an appropriate estimation strategy. Speaking of IAPs, the

[4] I included socio-demographic information such as the person's age, gender, the self-reported ideology, and whether a person has at least a college degree in these models. Additionally, I checked whether accounts who – upon manual inspection of their Twitter profile – display frequent participation in online lotteries. Further, I distinguish between the regional setting – U.S.A. or Germany – and controlled for the platform where the survey was distributed on.

accuracy of participants recruited via a commercial provider (*respondi*) was generally lowest when comparing the response quality with participants recruited via an MJP (*JobBoy*) and interested participants gathered through Twitter-ads. This last insight is particularly worrisome as commercial IAPs represent an attractive opportunity for social science research. In fact, researchers argue in favor of survey research in the light of recent developments of social science research (Jungherr 2019) and established institutions such as the German longitudinal election study (GLES) utilizes these providers to conduct research projects.

The expectation that the measures employed by panel providers (e.g., in the form of long term reward structures) should lead to higher response quality were contradicted in the presented analyses. Response quality of workers of MJPs outperformed the response quality of panelists, thus, providing support for theoretical considerations that expect immediate rewards to outperform delayed rewards in terms of data quality (Tuten, Galesic, and Bosnjak 2004). Alternative explanations include misleading incentives on the side of IAPs that nudge respondents to lie about their behavior in order to proceed with a questionnaire or long term conditioning that goes along with frequent exposure to social science surveys (Singer and Ye 2013). Further, the fact that interest in the topic and intrinsic motivation to provide an accurate estimate of one's behavior made a tremendous difference in the response accuracy, showcases the potential of alternative reward structures. Despite the obvious problems of lower response rates (Jäckle and Lynn 2008) and its dependency on the context, appealing to respondent's intrinsic motivation may be a path worth further exploration for researchers aiming to improve response quality.

Nevertheless, this work has some limitations to its conclusions. The analyses are based on a non-probability sample in the case of an IAP, while they are presumably also biased by non-random participation motivation in the case of an MJP and the Twitter-ads approach. As a result, our sample differs from population characteristics (see online appendix for a more extensive discussion) and we, thus, should be careful with generalizations of the presented findings. It is noteworthy, however, that these drawbacks are inherent to other research conducted in this field (Guess et al. 2019; Henderson et al. 2019) and future research may proceed by using probability samples and alternative reward approaches.

Finally, this work contributed to methodological research by evaluating systematic misreporting patterns and showing that a respondent's ideological self-placement, age, and gender might play a role. Systematic individual differences are problematic as they might bias inferential conclusions drawn from models which were fitted on this data (Brady 1985). To provide more clarity, future research needs to investigate individual discrepancies of misreports for larger samples and other platforms to further solidify the general expectations as the presented results are to parts at odds with the findings of previous research in this field.

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TABLE 2 *Logistic regression results on the tendency to (1) misreport, (2) overreport or (3) underreport (a) the number of recently published Tweets and (b) the number of Twitter-subscriptions.*

	(a) Recently published Tweets			(b) Number of Subscriptions		
	Misrep.	Overrep.	Underrep.	Misrep.	Overrep.	Underrep.
	(1)	(2)	(3)	(1)	(2)	(3)
Partisan	−0.20	−0.16	−0.08	0.24	0.35	−0.05
	(0.23)	(0.24)	(0.27)	(0.23)	(0.25)	(0.28)
Conserv.	0.32	0.74^{***}	-0.58^{*}	0.36	0.70^{***}	−0.29
	(0.25)	(0.25)	(0.30)	(0.24)	(0.26)	(0.30)
Age	−0.003	−0.01	0.004	−0.01	-0.03^{***}	0.02^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	0.10	−0.21	0.35	-0.50^{**}	−0.28	-0.44^{*}
	(0.21)	(0.22)	(0.24)	(0.21)	(0.24)	(0.26)
College	0.25	0.36	−0.09	0.22	0.42^{*}	−0.12
	(0.22)	(0.23)	(0.26)	(0.22)	(0.24)	(0.27)
Lotteries	0.24	0.67^{*}	−0.61	−0.02	0.22	−0.33
	(0.36)	(0.37)	(0.46)	(0.34)	(0.37)	(0.45)
USA	0.44	0.53^{*}	−0.25	−0.07	−0.15	0.06
	(0.30)	(0.28)	(0.36)	(0.28)	(0.31)	(0.34)
MJP	-1.07^{***}	-1.94^{***}	0.96^{**}	−0.44	−0.20	−0.53
	(0.40)	(0.45)	(0.45)	(0.36)	(0.40)	(0.49)
Ads	-0.77^{*}	-3.78^{***}	1.73^{***}	-1.72^{***}	-2.64^{**}	−0.81
	(0.46)	(1.05)	(0.49)	(0.53)	(1.06)	(0.59)
Constant	0.49	−0.19	-1.43^{***}	0.34	0.09	-1.87^{***}
	(0.35)	(0.38)	(0.41)	(0.36)	(0.41)	(0.44)
N	415	415	415	408	408	408
Log Likelih.	−266.7	−246.8	−214.9	−269.3	−223.3	−198.8
AIC	553.4	513.7	449.7	558.7	466.6	417.7

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$