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Professional respondents in non-probability online panels

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10.1 Introduction

Among the concerns raised about non probability online panels is the presence of so-called "professional" respondents – well-trained or experienced survey-takers who seek out large numbers of surveys, typically for the cash and incentives offered (Baker et al., 2010, 756–757). There is accumulating evidence that there exists a large number of frequent survey-takers who participate in many different online panels. A 2006 comScore study concluded that fewer than 1% of panel members in the ten largest market research online survey panels in the United States were responsible for 34% of the completed questionnaires (Grover & Vriens, 2006). An analysis using 16 different online panels in the United States and the United Kingdom found that the average panelist belonged to four different survey panels (Gittelman & Trimarchi, 2009). Likewise, a study of 19 different panels in the Netherlands found that 62% of panelists belonged to multiple online panels (Willems, Vonk, & Ossenbruggen, 2006b). As opt-in panel surveys become more prevalent in academic research, there is a need to explore if and how frequent survey-takers affect the reliability and validity of the collected data.

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The presence of frequent survey-takers is widely recognized, but researchers are only just beginning to assess their influence on data quality. Thus far, few academic journal articles have been published on the topic, though there are a handful of marketing firm white papers and conference presentations that scrutinize the survey-taking behavior of professional respondents. Much of the existing research has focused on the concern that frequent survey-takers will be more likely to lie or rush through a survey for the incentives, jeopardizing the integrity of their responses. In their effort to complete many surveys, frequent survey-takers might be inattentive to individual surveys and thus more likely to engage in satisficing behavior that results in less reliable data. Beyond measurement error, however, we believe there is a broader question about if and how professional respondents might differ systematically from other respondents. In other words, are the attitudes, opinions, and beliefs of frequent survey-takers different from those of less experienced respondents?

In this chapter, we compare frequent and non-frequent survey-takers in a survey from the 2010 YouGov Cooperative Congressional Election Study. In contrast to the expectations of many, we do not find overwhelming and consistent evidence that frequent survey-takers are significantly more likely to satisfice. We do, however, find that professional respondents are less politically interested, engaged, and knowledgeable than other respondents in the survey. We posit that this difference might reflect the contrasting motivations of those volunteering to respond to a political survey, with professional survey-takers motivated by incentives and non-professional survey-takers motivated by interest in the survey topic. Given the well-established finding that nonprobability online surveys have overall samples that are more politically attentive and engaged on average than probability-based samples (Malhotra & Krosnick, 2007), these results suggest that eliminating professional respondents from non-probability political surveys – as some have recommended – could actually result in a *more* biased sample on these dimensions. Although the biases we identify may well not extend to other survey topics, firms, or samples, these results do suggest that measurement error might not be the only (or most) important concern when dealing with professional respondents.

10.2 Background

The term “professional respondent” is commonly used in the survey and marketing profession, but the way it is defined and operationalized varies widely. Professional respondents are typically identified as having a high level of survey-taking activity, but the specific measure might include the number of individual surveys completed in a given time frame (Garland et al., 2012), the number of online panel memberships (Comley, 2005; Baker & Downes-LeGuin, 2007), duration in a particular survey panel (Dennis, 2001), or some combination of these metrics. The specific threshold used to classify a respondent as professional based on each measure also differs; for example, some consider completion of four or more surveys per month to be excessive (Garland et al., 2012; Honda & Motokawa, 2004), while others use a threshold of 30 or more surveys a month to define professional respondents (Gittelman & Trimarchi, 2009; Frede et al., 2006). Clearly, there is no consensus about how many surveys is too many. Given these differing definitions, it is perhaps no surprise that estimates about the prevalence of professional respondents in online nonprobability samples also varies across studies and across panels. In an early study of seven prominent survey panels, Krosnick et al., (2005) found that the median number of surveys taken in the previous year ranged from six to 31. The presence of professional respondents in any given panel largely depends on the specific recruitment and management practices of the particular survey panel (Willems, Vonk,

& van Ossenbruggen, 2006a). Indeed, the prevalence of professional respondents likely stems not only from the combination of self-selection and incentives that characterizes nonprobability online panels, but also the fact that many of the online survey firms recruit panelists from the same websites (Fulgoni, 2005).

There are also two distinct conceptual frameworks for thinking about professional respondents. The most relevant line of research is focused on sample selection, with the concern that frequent survey-takers volunteer or "opt in" to answer a lot of surveys in search of monetary incentives (Gittelman & Trimarchi, 2009). A second line of research, however, is focused on panel conditioning, whereby extended duration in a panel means that respondents learn about the survey process, questionnaire, or topic. Panel conditioning is an issue not only for online, nonprobability surveys, but also longitudinal surveys of all modes, so there exists a more extensive academic literature on the topic.

These are quite different notions of professionalism – for the first, professional respondents are recruited; for the second, professional respondents are created. Panel conditioning research typically considers participation in a single survey panel (and often a single longitudinal study), while those concerned with sample selection recognize that the same respondent might participate in multiple survey panels. For some, the difference between the two types of professional respondents boils down to motivation. Toepoel et al., (2009) found that respondents who were experienced due to repeated surveying in a panel study are distinct from recruited professional respondents in that they do not necessarily participate because of the incentives offered (Mason & Watts, 2010). Despite this potential theoretical differentiation, the operationalization of professional respondents and experienced respondents is often identical. It is difficult to measure respondent motivation, so it is more common for both lines of research simply to rely on levels of survey-taking activity. The number of surveys taken – a common measure of professionalism – is also the preferred metric for assessing panel conditioning (Adams, et al., 2012; Coen, et al., 2005). Moreover, there are typically parallel concerns about the impact of professional or experienced survey-takers on the reliability and validity of the data. So, though this chapter uses the first concept of professional respondents, we reference panel conditioning literature where relevant.

10.3 Professional respondents and data quality

The primary concern about professional respondents has been that they will threaten data quality by providing inaccurate or fraudulent responses. Respondents introduce measurement error if they do not take a survey seriously and simply speed through the questions to get to the end. Respondents who are taking a lot of surveys might be inattentive to any one survey, and thus more likely to engage in satisficing (Krosnick, 1991). That is, they give less cognitive effort to answering the survey, as evidenced through fast response times, use of "don't know" responses, item nonresponse, random response selection, open-ended gibberish, or straight-lining responses (Baker et al., 2010).

Existing research on the extent of satisficing among frequent survey-takers is mixed, however. Many have found that frequent survey-takers complete questionnaires more quickly than those with less experience (Frede et al., 2006; Knapton & Garlick, 2007; Toepoel et al., 2008; Yan & Tourangeau, 2008), though some find no such differences (Coen et al., 2005). Less clear is whether or not speedier completion time results in more measurement error. More broadly, Toepoel et al., (2008, p. 985) conclude that experienced respondents are more likely to take "shortcuts in the response process" than fresh respondents based on higher interitem correlations for multiple-item-per-screen formats and higher likelihood of selecting first response options among the more experienced survey-takers. Garland et al. (2012) similarly found that respondents who had previously taken surveys were more likely to give a "don't know" response than fresh respondents. Others conclude that experienced respondents are more likely to answer questions strategically to avoid follow-ups (Mathiowetz & Lair, 1994; Meurs et al., 1989; Nancarrow & Cartwright, 2007). According to Miller (2007), opt-in, online panelists are more likely to satisfice than online respondents in general – in other words, the observed satisficing is not simply an issue with mode.

On the other hand, other research suggests that professional respondents are actually *less* likely to satisfice (Chang & Krosnick, 2009; Schlackman, 1984; Waterton & Lievesley, 1989). In a study of 17 online panels for the Advertising Research Foundation, Walker et al. (2009) examined the the presence of professional respondents and concluded there was "little evidence that it impacted data quality to any significant degree" despite their large numbers and some attitudinal differences. In fact, those belonging to multiple panels and taking more surveys per month were *less* likely to exhibit "bad behaviors." Likewise, even though professional respondents made up 17% of the Dutch Online Panel Comparison Study (NOPVO) sample, Matthijsse et al. (2006) concluded that there were only slight implications for data quality; any differences between professional and nonprofessional respondents disappeared after controlling for gender, income, and urbanization. Others have found that experienced panelists are less likely to answer "don't know" (Binswanger et al., 2006; Smith & Brown, 2006; Waterton & Lievesley, 1989) and have higher consistency across related survey questions, evidence of higher convergent validity (Garland et al., 2012). According to Smith and Brown (2006), frequent survey-takers are no more likely to straight-line than inexperienced survey-takers and are more likely to answer sensitive questions about income and race. Finally, De Wulf and Berteloot (2007) showed that professional respondents are more positive towards the survey process and more willing to complete subsequent surveys. Thus, the evidence is decidedly mixed as to whether professional respondents provide more or less reliable data.

Beyond measurement error, however, there is a broader question about if and how professional respondents might differ from other respondents in terms of attitudes, opinions, and beliefs. If they differ on these metrics, the presence of professional respondents could bias estimates of quantities of interest even in the (unlikely) scenario in which there was no measurement error in their responses. Here again the existing research is inconclusive. Researchers have found that frequent survey-takers are demographically different from other panelists and from probability samples; they are less likely to be employed full-time, have lower incomes, lower levels of home ownership, and belong to smaller households, for example (Casdas et al., 2006; Frede et al., 2006; Gittelman & Trimarchi, 2009). Perhaps more importantly, some have observed significant differences in the attitudes and behaviors of professional respondents, even controlling for demographic differences (Knapton & Garlick, 2007; Willems, Ossenbruggen, & Vonk 2006a; Casdas et al., 2006; Gittelman & Trimarchi, 2009; Walker et al., 2009). In a study by Casdas et al. (2006), multiple panel respondents drank less wine, invested less, smoked more, read more magazines, and owned more pets. Gittelman and Trimarchi (2010) found that frequent survey-takers exhibit different buying and media behavior than less frequent survey-takers. Miller (2007) concluded that professional respondents were less likely to be impressed by new products, while Walker et al. (2009) found that more professional respondents were more likely to report "purchase interest" in new product concepts.

In contrast, others conclude the differences are not substantial. In an analysis of 3054 different measures, Smith and Brown (2006) found that just 4.6% of items showed significant differences for respondents who were "hyperactive," defined as individuals active in two or more online panels. Interestingly, two items for which there were significant differences are relevant to the current analysis of political outcomes: signing a political petition and paying attention to the news. In another study, Frede et al. (2006) found significant differences between those answering more than 10 surveys a month and those answering fewer, but they concluded there were simply too few of the heavier responders in the Ipsos, NPD Group and TNS panels to bias the overall results. Going one step further, Coen et al. (2005) argued in an SSI White Paper that "responses from frequent responders are *more* in line with actual consumer behavior than responses from less frequent responders"(emphasis added).

The relevant panel conditioning research is similarly mixed. Chang and Krosnick (2009, p. 14) conclude that "accumulating experience at doing surveys makes panel members less and less like the general public they are intended to represent." Others, however, find little evidence that panel experience biases outcomes of interest (Kruse et al., 2010; Toepoel et al., 2009). For example, Pineau et al. (2005) found in an analysis of 30 different survey outcomes that less than 10% of items showed differences in attitudes and behaviors based on tenure in the panel. Clearly, the existing research does not offer a clear picture of the impact of professional respondents on data quality.

10.4 Approaches to handling professional respondents

Even if there is no consensus about the impact of professional respondents on the reliability and validity of the data, the concerns remain widespread. Panel companies have adopted a variety of procedures and management practices to try to eliminate professional respondents, reduce over-surveying, and validate respondents are who they say they are (Baker et al., 2010). Panels actively search for false identities and routinely embed trap or "red herring" questions (Conrad et al., 2005; Kapelner & Chandler, 2010; Miller, 2007; Oppenheimer et al., 2009). For example, Downes-Le Guin et al. (2006) found that 14% of panelists in his study reported owning a Segway (which has less than 0.1 incidence in population), whereas telephone surveys had no such overreporting. Others limit the number of surveys a panelist takes within a specified time period (Dennis, 2001).

In addition to such efforts to avoid including professional respondents in the sample in the first place, companies frequently toss out data from "undesirable" respondents after data collection (Knapton & Garlick, 2007; Rogers & Richarme, 2009). Some firms collect more than the target number of respondents with the expectation that some will be eliminated. Peruzzi (2010, July 8) advises that "between 1 and 5% of survey data from panel sample is garbage. Garbage – throw it out; don't bring it into your final dataset to analyze." Others, however, caution that it is inadequate to attempt correction through purging problematic respondents (Harlow, 2010) or demographic weighting (Casdas et al., 2006).

In sum, panel companies and clients are obviously concerned about the quality of the data that professional respondents will provide, but it remains unclear how they might affect the data or what can be done about it. In this chapter, we offer to this growing body of research one more analysis of professional respondents. We examine the data quality implications of frequent survey-taking and multiple panel participation among respondents in the 2010 Cooperative Congressional Election Study. Admittedly, our analysis is limited to a single sample from a single survey firm on the topic of political attitudes and behaviors. But given the prominence of political surveys in the polling field, we believe this analysis is of interest even if any patterns observed here cannot be generalizable to other survey topics or panels.

10.5 Research hypotheses

Given the topic of the survey and the timing during the 2010 congressional campaigns, we hypothesize that professional respondents might differ from other respondents in their political attitudes and behaviors, reflecting differences in motivation to participate in the study. It is well established that people with more interest in the survey topic respond at higher levels than those less interested in the topic (Goyder, 1987; Groves et al., 2000, 2004). This effect might be amplified in opt-in online panels where the number of survey invitations is large. As the 2010 American Association of Public Opinion Researchers (AAPOR) report notes,

> People who join panels voluntarily can differ from a target population in a number of ways (e.g., they may have less concern about their privacy, be more interested in expressing their opinions, be more technologically interested or experienced, or be more involved in the community or political issues). For a specific study sample, this may be especially true when the topic of the survey is related to how the sample differs from the population

(Baker et al., 2010, p. 746). Although Yan and Tourangeau (2008) found no evidence that survey topic matters, others have found such biases, especially in online political surveys, where online panelists have been found to be more politically engaged, interested, and knowledgeable than the general population (Malhotra & Krosnick, 2007).

By contrast, we expect professional respondents are more likely to be motivated by the incentives being offered. Research consistently finds that those participating in more surveys are more likely to be doing so for monetary reasons (Frede et al., 2006; Sparrow, 2007). Paolacci et al. (2010) reported that more than 61% of respondents in a Mechanical Turk sample said that earning additional money was the primary reason they participated, and almost 14% said it was their primary source of income. These statistics might seem surprising since the incentives offered for completing online surveys are often very small amounts of money – sometimes less than a dollar per survey – but that is precisely why professional respondents complete large numbers of surveys. Online message boards routinely recommend signing up for dozens of panels at a time to maximize cash and prizes, and a Google search for the terms “online surveys for money” yields more than 300 million hits.

Of course, researchers have long pointed out that there are many different reasons why respondents join panels (see Dillman et al. (2009) for a thorough discussion of motivation theory). Comley (2005), for example, identifies four groups of respondents: the helpers, the opinionated, the incentivized, and the professionals. Less clear, however, is how motivation, frequency of survey-taking, and data quality all interact. This is clearly a topic that deserves further study, not only for panel research, but across all longitudinal studies that use respondent incentives. Unfortunately, the survey used in our analysis does not include a measure of motivation for participation (indeed, motivation is a notoriously tricky notion to measure). In a separate Mechanical Turk survey, however, we did find support for the assumption that frequent survey-takers were significantly more likely to say their primary reason for taking the survey was the monetary incentive, confirming the conclusions of earlier research. It thus seems reasonable to assume that professional respondents may differ from nonprofessional respondents in how the survey topic factors into their motivation and decision to take part in the survey. If professional respondents choose to participate in a survey because of the incentives offered, the survey topic is likely of less consequence. Thus, the pattern we expect to find in a political survey is that more frequent survey-takers will be less politically informed, engaged, and knowledgeable than less frequent survey-takers.

It is worth noting that this expectation contrasts with the findings for respondents "trained" through panel conditioning. Previous research has found that long-term participation in longitudinal political studies results in a sample that is *more* politically interested on average. Political knowledge questions, in particular, are sensitive to panel conditioning effects (Battaglia et al., 1996; Das et al., 2011; Kruse et al., 2010; Nancarrow & Cartwright, 2007; Toepoel et al., 2009). It is thought that participation in repeated political studies might induce respondents to pay attention to the campaign (Bartels, 1999). In contrast, professional respondents in our analysis have participated in a large number of surveys of varying topics and foci. Indeed, participation in a large number of surveys might actually mean that any one survey leaves less of a lasting impression on the respondent.

10.6 Data and methods

We examine the relationship between survey-taking frequency and political attitudes and behaviors using a survey of 1000 American adults conducted as part of the 2010 Cooperative Congressional Election Study (CCES). The survey was administered over the Internet by YouGov, with respondents drawn from their opt-in panel using a stratified (by age, race, gender, and education) sample that is then matched to a random sample from the 2008 American Community Survey on a set of demographic and (imputed) political variables.

The CCES had two waves, pre and post election, with the pre-election phase conducted in October and the post-election phase conducted in November. The study was a collaboration between 40 research teams; half of the questionnaire consisted of Common Content asked of all respondents, and half of the questionnaire consisted of Team Content designed by each individual participating team and asked of a subset of 1000 people. Overall, the CCES had a final matched sample size of 55400 respondents answering the Common Content questions in the pre- and post-election waves. The sample used 196235 email addresses for the study, of which 9262 were determined to be ineligible, 79723 did not respond, and 27155 had partial responses. The study had 75450 completed interviews (Ansolabehere, 2012, August 10). YouGov recruits respondents for their panel by advertising short surveys about entertaining topics on popular websites and then inviting those who respond to join the panel.[1]

The Duke University team questionnaire included questions about the number of surveys completed in the past four weeks and the number of survey panels to which the respondent belongs. Detailed question wording for all questions in the analysis can be found in Appendix 10.A. The mean number of self-reported surveys in the past four weeks is 4.54, with about one-quarter of respondents reporting participation in more than one survey per week. The mean number of self-reported panels is 2.25, with 53% reporting participation in more than one online panel and 36.5% in 3 or more online panels. The full distribution of responses are shown in Figure 10.1. To avoid applying arbitrary thresholds to define "professional" respondents, our analysis uses these continuous measures in the analysis that follows.

[1] The invitation sent to respondents did not explicitly mention it was a political survey, instead calling it "a survey on national and community affairs conducted by PollingPoint in conjunction with 35 of the nation's leading universities and research institutes." Arguably, however, such national affairs in October of election year might be thought to be about politics. Moreover, we might expect that the large number of partial responses came disproportionately from individuals who were either not politically interested or not as motivated by the compensation.

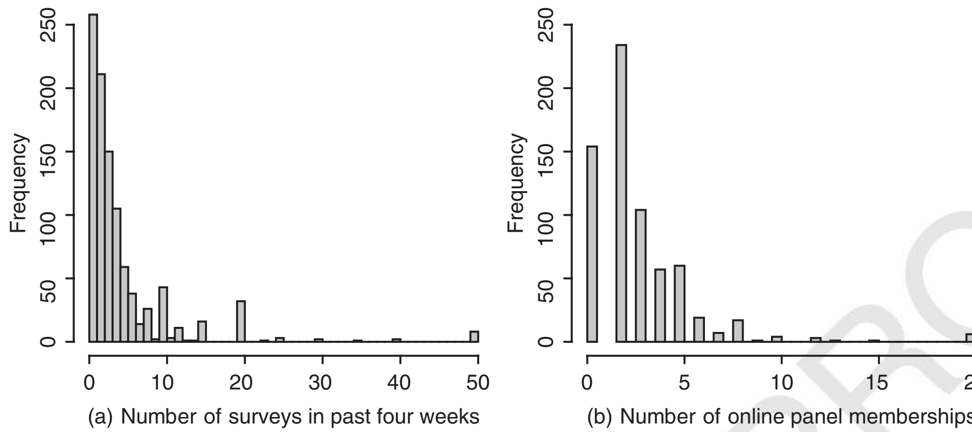

Figure 10.1 Self-reported survey-taking behavior in CCES.

One obvious weakness of these self-report measures is that they they could be subject to overreporting or underreporting. While this would not be a problem if such error were random, we might expect there to be systematic underreporting since some panel companies have procedures to discourage frequent survey-taking. As a robustness check, we replicated our results excluding those individuals who answered that they completed "0" other surveys, on the assumption this response may have been the most clearly dishonest response. In almost every case, the results provide even stronger support for our expectations. Although we did not have access to the number of surveys each respondent has completed for YouGov, the self-report measure has the advantage that it captures survey-taking in all online panels. Not surprisingly, those who belong to multiple panels report a higher number of surveys completed in the previous month (correlation of .615).

We examine the relationship between these survey frequency measures and a variety of different political attitudes and behaviors, including political knowledge, interest, turnout, engagement, and ideological extremism. We estimate a series of multivariable models that include either the number of surveys completed in the last four weeks or the number of panel memberships as the key independent variable. For the ease of presentation, OLS regression models are estimated except in the case of binary outcome variables, in which logit models are estimated. Results hold if we instead use ordered logit for outcomes with fewer than seven response options. In all models, we control for age, race, gender, income, marital status, education, and full-time work status. Analyses were conducted on unweighted data, though the model results are similar when weighted using the provided weight variable. We also replicated the models using the unmatched sample with nearly identical results.

10.7 Results

The full set of empirical results are reported in Table 10.1 for online panel membership and Table 10.2 for number of surveys completed.[2] Overall, our analysis finds that individuals who participate in more surveys and on more survey panels have consistently lower levels

[2] All reported predicted probabilities in the text are calculated holding all indicators at their mode and other variables at their means.

Table 10.1 Model results for self-reported panel membership.

	Political knowledge	Political interest	Turnout	Political activity	Ideological strength
(Intercept)	1.15*	1.91*	−2.93*	−0.77*	0.87*
	(0.23)	(0.13)	(0.65)	(0.20)	(0.20)
Panel Membership	−0.11*	−0.04*	−0.15*	−0.05*	−0.05*
	(0.02)	(0.01)	(0.05)	(0.02)	(0.02)
Age	0.02*	0.02*	0.06*	0.02*	0.01*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Female	−0.39*	−0.27*	−0.50†	−0.09	−0.19*
	(0.09)	(0.05)	(0.26)	(0.08)	(0.08)
White	0.21*	0.25*	−0.07	0.16†	0.26*
	(0.09)	(0.05)	(0.26)	(0.08)	(0.08)
Income	0.05*	0.04*	0.09*	0.01	0.02
	(0.02)	(0.01)	(0.04)	(0.01)	(0.01)
Education	0.14*	0.05*	0.36*	0.12*	0.03
	(0.03)	(0.02)	(0.10)	(0.03)	(0.03)
Married	0.08	−0.01	0.56*	0.14†	0.07
	(0.09)	(0.05)	(0.25)	(0.08)	(0.08)
Work Full-Time	0.12	0.04	0.09	0.07	0.02
	(0.09)	(0.05)	(0.26)	(0.08)	(0.08)
N	840	842	691	853	843
Adj. R^2	0.21	0.33	0.18	0.13	0.07

Notes: Standard errors in parentheses.
†$p < .10$
*$p < .05$
All models OLS regression except Turnout, which is logit with Nagelkerke R^2 reported.
Panel membership range is 0–12, all higher values top-coded as 12.

of political interest and engagement. That is, we find a negative and statistically significant relationship between our professionalism measures and the political outcome variables.

Looking first at the relationship between panel membership and political knowledge in the first column in Table 10.1 finds that each additional panel membership is associated with a .11 *lower* score on the political knowledge scale (0–4 scale). The model predicts that, holding all else constant, the most active respondents – those belonging to 10+ panels – have a knowledge level nearly a full point lower than those belonging to a single online panel. It is also worth noting that the political knowledge level of respondents in this survey is substantially higher than what is found in probability samples. For example, a probability-based telephone survey from March 2011 by the Pew Research Center finds that 38% of Americans knew which party holds the majority in the House of Representatives. In contrast, the same question in the CCES survey (one component of the knowledge scale) finds that 91% of those belonging to a single online panel answered correctly, compared to 74% of those belonging to three or more panels. Both groups are more knowledgeable than the telephone sample, but the frequent survey-takers are less biased in this measure than those with less experience. It is worth noting that this finding is counter to the idea that respondents in web surveys might

Table 10.2 Model results for self-reported number of surveys in past four weeks.

	Political knowledge	Political interest	Turnout	Political activity	Ideological strength
(Intercept)	0.99*	1.86*	−2.89*	−0.88*	0.77*
	(0.23)	(0.13)	(0.65)	(0.20)	(0.20)
Survey Number	−0.03*	−0.01*	−0.06*	−0.01	−0.01*
	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)
Age	0.02*	0.02*	0.06*	0.02*	0.01*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Female	−0.46*	−0.29*	−0.59†	−0.10	−0.21*
	(0.09)	(0.05)	(0.25)	(0.07)	(0.08)
White	0.20*	0.25*	−0.02	0.17*	0.27*
	(0.09)	(0.05)	(0.26)	(0.08)	(0.08)
Income	0.05*	0.04*	0.09*	0.01	0.02
	(0.02)	(0.01)	(0.04)	(0.01)	(0.01)
Education	0.14*	0.05*	0.38*	0.12*	0.03
	(0.03)	(0.02)	(0.10)	(0.03)	(0.03)
Married	0.04	−0.02	0.53*	0.12	0.06
	(0.09)	(0.05)	(0.25)	(0.08)	(0.08)
Work Full-Time	0.11	0.04	0.07	0.05	0.03
	(0.09)	(0.05)	(0.26)	(0.08)	(0.08)
N	843	847	692	858	847
Adj. R^2	0.20	0.33	0.18	0.12	0.07

Notes: Standard errors in parentheses.
† $p < .10$
* $p < .05$
All models use OLS regression except Turnout, which is a logit with Nagelkerke R^2 reported.
Survey number range is 0–30, all higher values top-coded as 30.

look up the answers on political knowledge questions, though previous research has similarly found little evidence of this behavior (Ansolabehere & Schaffner, 2011; Prior & Lupia, 2008).

The effects are similar, but smaller, for political interest. Those who belong to more survey panels report lower levels of political interest. The model predicts that those belonging to 10 or more online panels are, on average, about one half a point less interested in politics on the 4-point scale than those belonging to a single panel. A simple bivariate comparison, for instance, shows that 73% of those belonging to a single online panel were interested in politics "most of the time," compared to 48% of those belonging to three or more online panels.

A similar pattern is found for more specific political behaviors, including voter turnout in the 2010 congressional election and participation in other political activities, such as attending a local political meeting, displaying a yard sign or bumper sticker, or working for a political campaign. For example, the model predicts that, holding all else constant, those belonging to 10 or more panels are 15 percentage points less likely to vote and they participate in an average of 0.50 fewer political activities (0–3 scale) than those belonging to a single panel. Turnout is one of the few variables for which we have an especially strong external benchmark. The 2010 Current Population Survey (CPS) finds that 45.5% of eligible citizens reported voting in the 2010 congressional election. In contrast, in the CCES sample (unweighted), those belonging to three more online panels had a self-reported turnout rate of 74%, compared to 89% among those in a single online panel. Thus, once again, we find somewhat less bias in the estimate for the professional respondents.

The final column reports results for a measure of ideological extremism. The negative and significant relationship indicates that those participating in more online survey panels are more ideologically moderate than those belonging to fewer online panels. The model predicts that, holding all else constant, those participating in 10+ panels were about one half point less extreme on a 0–3 scale than those belonging to a single panel. Looking descriptively at the bivariate data, for instance, shows that 21% of those belonging to a single panel call themselves moderate compared to 31% of those belonging to 3 or more panels.

As shown in Table 10.2, we find similar results when using the number of surveys completed in the past four weeks rather than number of panel memberships. For example, the models predict that those who answered surveys on at least a daily basis (30+ surveys in the past four weeks) were, on average, 20% less knowledgeable, 8% less interested, and 8% less ideologically extreme than those who answered no other surveys. These frequent survey-takers were also predicted to be 19 percentage points less likely to have voted in the 2010 congressional election. The relationship between number of surveys completed and number of other political activities is in the expected negative direction but does not reach the expected level of statistical significance ($p = .16$, one-tailed). It is again perhaps easiest to visualize the magnitude of these relationships with a simple descriptive look at the data. The "professional" respondents (5+ surveys in past four weeks) were less likely than nonprofessional respondents to get all four political knowledge questions correct (31% vs. 51%), less likely to say they are interested "most of the time" (53% vs. 70%), less likely to have reported voting (76% vs 95%), less likely to have participated in at least one other political activity (38% vs. 51%), and more likely to report being ideologically "moderate" (30% vs. 20%). In sum, then, even though the overall sample seems to be more politically knowledgeable and engaged than the general population, the presence of professional respondents actually reduced the extent of the bias in the survey.

10.8 Satisficing behavior

We next consider the possibility that professional respondents reduce data quality due to higher levels of satisficing. That is, do they speed through the survey without giving adequate cognitive attention to answering the questions in a thoughtful manner? Researchers have used a variety of different indicators of satisificing that we explore here: self-reported survey effort, interview duration, attrition after the pre-election wave, response straight-lining, percentage of skipped questions, and percentage of "don't know" responses. See Appendix 10.A for detailed information about question wording and variable construction. The results are shown in Table 10.3 for online panel membership and Table 10.4 for surveys completed. In contrast to the expectations of many (including us), we did not find consistent evidence that frequent participation in surveys or multiple survey panel participation was related to bad survey-taking behavior.

The first columns in Table 10.3 and Table 10.4 report the results for self-reported survey effort. As one of the final questions on the questionnaire, we asked each respondent how much effort they had put into answering the survey. Not surprisingly, all respondents were more likely to say "a lot" than "a little," but we also find that those belonging to more panels and completing more surveys report more effort than the less frequent survey-takers. Holding all

Table 10.3 Quality measures: self-reported panel membership.

	Survey effort	Interview duration	Attrited	Straight-line	Percent missing	Percent DK	Open junk
(Intercept)	5.73*	36.39*	−0.78	−0.15	6.69*	27.41*	0.95†
	(0.29)	(5.72)	(0.52)	(1.12)	(0.55)	(1.93)	(0.54)
Panel	0.06*	0.81	−0.06	0.01	0.10*	0.57*	0.10*
Membership	(0.03)	(0.50)	(0.05)	(0.10)	(0.05)	(0.17)	(0.05)
Age	−0.001	0.11	−0.01	−0.03†	−0.01	−0.22*	−0.04*
	(0.00)	(0.08)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Female	0.08	−0.82	0.32	0.74	−0.16	2.71*	0.51*
	(0.11)	(2.16)	(0.21)	(0.54)	(0.21)	(0.73)	(0.24)
White	−0.27*	−2.08	−0.62*	−1.19*	0.45*	−2.12*	−0.26
	(0.12)	(2.28)	(0.21)	(0.49)	(0.22)	(0.77)	(0.23)
Income	−0.05*	−0.25	−0.03	−0.19*	0.005	−0.33*	−0.04
	(0.02)	(0.38)	(0.04)	(0.09)	(0.04)	(0.13)	(0.04)
Education	−0.01	−0.30	−0.003	−0.22	−0.1	−0.98*	−0.24*
	(0.04)	(0.81)	(0.08)	(0.19)	(0.08)	(0.27)	(0.09)
Married	0.32*	2.48	0.19	−0.08	−0.54*	−1.87*	−0.25
	(0.12)	(2.29)	(0.22)	(0.50)	(0.22)	(0.77)	(0.23)
Work	0.07	1.42	−0.26	0.55	0.28	−1.58*	−0.54*
Full-Time	(0.12)	(2.31)	(0.22)	(0.51)	(0.22)	(0.78)	(0.25)
N	851	853	853	853	853	853	853
Adj. R^2	0.02	0.00	0.04	0.18	0.01	0.23	0.17

Notes: Standard errors in parentheses.
$^\dagger p < .10$
$^* p < .05$
All models use OLS regression except Straightline, Open-Ended Junk, and Attrited which are logits with Nagelkerke R^2 reported.
Panel membership range is 0–12, all higher values top-coded as 12.

else constant, the model finds that those who belonged to 10+ panels report 6% more effort than those belonging to a single panel. Table 10.4 similarly shows that those taking more surveys in the past four weeks were significantly more likely to report higher levels of survey effort.

Of course, it is also possible that the more professional respondents are simply more likely to lie in response to this question. One alternative metric for survey effort could be the amount of time spent completing the interview. Previous research has found that professional respondents are more likely to speed through surveys (Toepoel et al., 2008). However, in this sample, the more professional respondents took slightly longer to complete the survey – a mean of 39 minutes among those answering fewer than five surveys a week, and 44 minutes for those taking five or more. Once we control for other factors, we find that the relationship between duration and panel memberships or surveys completed is positive, but not statistically significant. If we look just at excessive speeding (completion in less than 20 minutes – one half the average time), we likewise find that professional respondents were slightly less likely to speed through the questionnaire.

Table 10.4 Quality measures: number of completed surveys.

	Survey effort	Interview duration	Attrited	Straight-line	Percent missing	Percent DK	Open junk
(Intercept)	5.66*	37.42*	−0.34	0.53	6.63*	28.40*	1.05*
	(0.28)	(5.57)	(0.51)	(1.15)	(0.54)	(1.90)	(0.54)
Number of	0.03*	0.17	−0.10*	−0.21*	0.06*	0.12†	0.03†
Surveys	(0.01)	(0.19)	(0.03)	(0.10)	(0.02)	(0.06)	(0.02)
Age	0.0002	0.12	−0.01	−0.03†	−0.01	−0.22*	−0.04*
	(0.00)	(0.07)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Female	0.12	0.04	0.31	0.83	−0.19	3.14*	0.57*
	(0.11)	(2.12)	(0.20)	(0.55)	(0.20)	(0.72)	(0.23)
White	−0.30*	−1.85	−0.58*	−1.17*	0.41†	−2.14*	−0.23
	(0.11)	(2.25)	(0.21)	(0.50)	(0.22)	(0.77)	(0.23)
Income	−0.05*	−0.35	−0.05	−0.23*	0.004	−0.38*	−0.05
	(0.02)	(0.38)	(0.04)	(0.10)	(0.04)	(0.13)	(0.04)
Education	−0.01	−0.44	−0.003	−0.21	−0.09	−1.04*	−0.25*
	(0.04)	(0.80)	(0.08)	(0.19)	(0.08)	(0.27)	(0.09)
Married	0.33*	2.73	0.18*	0.1	−0.54*	−1.69*	−0.25
	(0.11)	(2.26)	(0.22)	(0.52)	(0.22)	(0.77)	(0.23)
Work	0.07	1.44	−0.26	0.7	0.27	−1.51†	−0.58*
Full-Time	(0.12)	(2.29)	(0.22)	(0.53)	(0.22)	(0.78)	(0.25)
N	856	858	858	858	858	858	858
Adj. R^2	0.03	0.00	0.07	0.22	0.02	0.22	0.17

Notes: Standard errors in parentheses.
$^{\dagger}p < .10$
$^{*}p < .05$
All models use OLS regression except Straight-line, Open-Ended Junk, and Attrited which are logits with Nagelkerke R^2 reported.
Survey number range is 0–30, all higher values top-coded as 30.

Column 3 in Tables 10.3 and 10.4 shows that more professional respondents are also less likely to attrite – that is, drop out before the post-election wave – though the difference is statistically significant only for the survey measure. The model predicts that, holding all else constant, those answering just one survey in the last month had a 15% probability of attriting, compared to a less than 1% probability of dropping out among those answering 30 surveys in the last month. Likewise, professional respondents were no more likely to straight-line, that is, select the same response for an entire battery.

While the measures thus far find no support for the hypothesis that professional respondents are more likely to satisfice, we do find they are more likely to skip individual questions, give junk answers to open-ended questions, and give "don't know" responses. Overall, many of these behaviors are rare – the average percentage of "don't know" responses through the questionnaire was just 9%, the average percentage of missing responses was 6%, and 13% gave junk responses to the open-ended questions – but the analysis does find that professional respondents are more likely to engage in these bad behaviors. For example, column 5 of Table 10.3 and Table 10.4 shows that, holding all else constant, those belonging to more online panels and answering more surveys in the past four weeks had a higher percentage of missing responses. Likewise, column 6 shows a positive and significant relationship with the percentage of "don't know" responses. The model predicts that those with 10+ panel memberships gave an average of 5.7% "don't know" responses, compared to less than 1% among those belonging to a single panel. And in the final column, we find that more frequent survey-takers are more likely to give junk responses to two open-ended questions in the survey; that is, they gave no answer, volunteered a "don't know" or "no opinion" answer, or simply typed in gibberish.

It will likely be noted that the adjusted R^2 is very small for many of these models, suggesting we do not do a very good job predicting variation in these bad behaviors. Although this is not problematic given the purpose of our analysis – to evaluate if there was a significant relationship between these outcomes and our measures of professionalism – it does suggest that our ability to more generally predict satisficing behaviors in this survey is quite limited.[3] A more comprehensive analysis of satisficing behavior in the CCES and other online panels is a topic worthy of further study.

Indeed, while the items considered here are commonly used measures of satisficing, we want to raise the possibility of an alternative explanation for the observed patterns. It could be that the failure to give a substantive response to many of these items reflects a lack of ability rather than a lack of motivation. In other words, less politically knowledgeable professional respondents might be more likely to sincerely answer "don't know" (or skip an individual question) because they were not sure how to answer, despite giving the question adequate thought and consideration. As a test of this alternative hypothesis, we re-estimated these models including a control for political knowledge. Doing so finds that the professionalism measures are no longer statistically significant in 5 out of 6 cases. The relationship remains significant between number of surveys completed and percentage missing, but not in any other case once we control for political knowledge. This suggests that the bad behaviors could be attributable to respondent competencies rather than respondent laziness.

10.9 Discussion

Our analysis finds that higher levels of participation in surveys and online panels are associated with lower levels of political knowledge, interest, engagement, and ideological extremism in the 2010 CCES. Our analysis does not explicitly test why that is the case, but we suspect it reflects differences in the initial motivation to participate between professional and nonprofessional respondents. Frequent survey-takers may have been motivated to participate in the survey for the compensation offered, while the less frequent survey-takers were interested in the survey topic. Certainly, this hypothesis is worthy of further study.

These conclusions are based on the analysis of a single political survey so we cannot assume these patterns will hold in other nonprobability samples. For one, the CCES was an especially lengthy political survey taken in the midst of a heated midterm election. As such, it may have been more likely to attract some politically-interested respondents. Second, these results might be specific to this survey company or specific study, reflecting, say, the panel management procedures of YouGov or the academic source of the survey. Third, as with any non-probability sample, the observed sample may differ in unknown ways from the broader target population. Thus, we cannot necessarily generalize our findings here to other non-probability samples. Nonetheless, these findings offer a somewhat different take

[3] For a more thorough discussion of the appropriateness of R-squared, see King (1990).

on the potential biases in non-probability samples. These results make clear that assessing a non-probability sample as a whole could mask countervailing biases within the sample. In this survey, professional respondents actually reduce bias by lowering the average level of political interest, knowledge, and engagement in the sample. This means that eliminating professional respondents from this nonprobability political surveys, as some have recommended, would have resulted in a *more* biased sample along these dimensions.

In contrast to some expectations, we did not find consistent evidence that more professional respondents gave less thoughtful responses to the questionnaire. On the contrary, frequent survey-takers spent more time completing the questionnaire, were less likely to attrite, were less likely to straight-line, and reported putting more effort into answering the survey. While panel memberships and number of surveys completed were related to skipping questions, answering “don’t know,” or giving junk responses to open-ended questions, these relationships did not hold once political knowledge was accounted for. In some respects, then, the findings are reassuring for those concerned about professional respondents. Indeed, deleting professional respondents from a sample from an online nonprobability survey could decrease both the validity *and* reliability of the data.

In sum, the results here offer one more analysis about the consequences of having a growing class of professional respondents participating in non-probability online panels. As the prevalence of online survey research grows, so too does the need to learn more about who is “opting-in” to these samples and why they are doing so. Our analysis suggests the problem may not be so much with the number of surveys completed, but an individual’s reason for completing them. It is inherently difficult to measure motivation – in no small part because respondents might not be conscious of their motivations – but it would nonetheless be worthwhile for future research to consider how motivation to participate interacts with the survey topic to shape the content and quality of survey responses.

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Appendix 10.A

10.A.1 Detailed variable information

Survey Frequency: "About how many online surveys (on all topics) have you completed in the past 4 weeks?"

Panel Memberships: "How many survey panels do you belong to?"

Political Interest: "How often are you interested in news and public affairs? Most of the time (4) Some of the time (3) Only now and then (2) Hardly at all (1)"

Turnout: "Which of the following statements best describes you? I did not vote in the election this November (0) I thought about voting this time - but didn't (0) I usually vote, but didn't this time (0) I attempted to vote but did not or could not (0) I definitely voted in the General Election on November 2 (1)"

The *Political Activity* scale is a sum of "yes" responses to three items (0–3): "During the past year, did you … attend local political meetings (such as school board or city council)? (1); put up a political sign (such as a lawn sign or bumper sticker)? (1); work for a candidate or campaign? (1)"

The *Political Knowledge* scale is the sum of correct responses to four separate questions (0–4): "Please indicate whether youve heard of this person and if so which party he or she is affiliated with." The Governor, US Senators, and US House member for each respondent based on residency as listed.

Ideological strength is calculated by folding the standard 7-point strongly liberal to strongly conservative question. "How would you rate each of the following individuals and groups? Yourself. Very Liberal (3), Liberal (2), Somewhat Liberal (1), Moderate (0), Somewhat Conservative (1), Conservative (2), Very Conservative (3), Not Sure (0)."

Survey effort: "Finally, we are interested in your survey experience. Overall, how much effort would you say that you put into answering the question on scale that ranges from 1–7, where 1 means very little effort and 7 means a lot of effort?"

The *Percent Don't Know* measure is calculated as the percent of "don't know" responses to 81 questions asked of all respondents for which this response was not a substantive response (e.g., knowledge items were not included).

Percent Missing is calculated as the percent of 301 questions asked of all respondents that were skipped.

The *Straight-line* variable is an indicator if a respondent gave an identical response to each of 13 items in a grid that asked "How would you rate each of the following individuals and groups? very liberal, liberal, somewhat liberal, middle of the road, somewhat conservative, conservative, very conservative, not sure." The items to rate were: yourself, governor of respondents' state, Barack Obama, Democratic Party, Republican Party, Senator 1, Senator 2, U.S. Senate candidate 1 (if up for election in 2010), U.S. Senate candidate 2 (if in election), U.S. House candidate 1, U.S. House candidate 2, U.S. House Member (if retiring and candidates are both new), Tea Party Movement.

Open-ended Junk is an indicator if a respondent gave a "don't know," gibberish, or no response to either of two open-ended questions: (1) "What do you think is the most important problem facing the country today?" and (2) "What policy issue do you think is most at stake in this election?"

Interview Duration is calculated by subtracting the end time from the start time. Times that exceeded 2 hours were coded as 2 hours to try to account for respondents who might have walked away from the computer or were distracted by other activities.

Attrition is an indicator that a respondent completed the pre-election wave but failed to complete the post-election wave.