White Paper

# A Glimpse of the Unobservable: Do Demographically Similar Online and RDD Recruited Panelists Behave Differently?

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## Abstract

The representativeness and coverage of online panels has been a straw man for many years. One possible correction for this coverage bias is Random Digit Dialing (RDD) panelist recruitment as a supplement to online recruitment. RDD recruitment, however, is expensive compared to online recruiting. In addition to cost differences, RDD recruits are very demographically different than their online-recruited counterparts. This paper measures the amount of question- level data differences attributable to recruitment method between RDD and Online recruited panelists. A single online research panel is used, from which identically managed panelists are split into two groups by recruitment method. This research design mitigates potential panel- level confounding factors. The data is then weighted to make demographic characteristics match across the two sample groups. A l l remaining differences are assumed to be attributable to unobservable differences between panelists due to recruitment method. If most differences can be explained by the observables, then statistical techniques such as stratified sampling, quota sampling, and data weighting can be used to adjust for the recruitment methodology. If these techniques fail to explain the differences, then recruiting panelists by RDD brings a different segment of the population into online research panels. Ultimately, better data leads to better decisions. Better decisions may justify the cost of RDD recruiting. Otherwise recruiting panelists online will offer similar data quality with substantial recruitment cost savings.

## Introduction

In 1987, Olivier Blanchard addressed a common problem with OLS regression models:

> When students run their first ordinary least squares (OLS) regression, the first problem that they usually encounter is that of multicollinearity. Many of them conclude that there is something wrong with OLS; some resort to new and often creative techniques to get around that problem. But, we tell them, this is wrong. Multicollinearity is God's will, not a problem with OLS or statistical techniques in general.

Like multicollinearity in regression models, coverage issues are ubiquitous in online research. Some researchers, like Blanchard, feel this problem is intractable and lower their expectation of data quality. Furthermore, budget, time, and supply constraints make this an easy rationalization for researchers. Poor coverage is not necessarily 'God's will'; in this paper we explore using Random Digit Dialing (RDD) to overcome or mitigate coverage bias in online research.

We used a listed RDD method of recruiting the RDD panelists starting in April of 2005. In the two years of recruiting via RDD for the panel we have observed a 2.9% response rate to the recruitment phone calls calculated by AAPOR's second definition of response rate. Of those that responded to the recruitment call, 10.0% actually signed up on the panel. Then 99.7% of the panelists who sign up via the RDD link are confirmed used third party sources or a confirmation email. These panelists are treated exactly like panelist from online sources, but they are flagged as RRD panelists.

As internet penetration rates top 73% of American adults (Madden, 2006), the 'digital divide' has shrunk, and researchers have become comfortable addressing issues of demographic representation with quota sampling and data weighting methods. However, these methods require researchers

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to ignore the unobservable differences between the average online panelist and their population counterpart.

At the root of these coverage issues lie non-probability sampling methods and the questionable representativeness of opt-in online panels. While research comparing Random Digit Dialing (RDD) telephone samples to online samples has exposed significant mode (or data collection methodology) effects, teasing out the relationship between the effects of mode and the effect of coverage is difficult. The experimental evidence that follows will measure both the observable and unobservable differences between participants in an online study who were recruited using online methods and their counterparts who were recruited using an RDD telephone sample frame.

One way to indirectly measure unobservable differences is to study recruitment method effects. For example, (how) do self-recruited panelists behave or respond differently from panelists selected by researchers for recruitment? Few people click banner-ads offering panel membership, and fewer seek out panels pro-actively (e.g., by googling relevant search terms). It's reasonable to expect such self-selected panelists hold different motivations for survey participation. But do they also respond differently? And, more importantly, can those observed differences tell us anything useful about coverage concerns in unobserved characteristics?

This paper answers these questions by drawing on a panel composed of both actively-recruited panelist and self-recruited panelist who have been treated identically since joining. This should eliminate possible panel-level confounds caused by divergent panel management procedures, incentive structure, etc. We hope this paper will make the problem of coverage bias tractable and offer a viable, creative technique to mitigate its effects.

## Literature Review

At the 2006 CASRO conference, ComScore Networks suggested that 1% of the top 10 U.S. online survey panels take 34% of all online questionnaires. Previous studies have looked at the effect of using different panels for sourcing (de Gaudemar, 2006), and differences among panelists who belong to a single panel versus multiple panels (Casdas, Fine and Menictas, 2006). Other researchers have explored the difference in motivation among members, suggesting that reasonable panelist incentive manipulation rarely exerts pressure leading to statistically significant response rate differences (Taylor, 2007; Göritz, 2004). This suggests that, on average, panelists are motivated more by social exchange than by the specific incentives (Taylor, 2007). This research, however, does not explicitly address differences between panelists who self-select and those who are selected by researchers.

Because of low response rates, caller id, and other technologies, telephone sample frames have started to more closely resemble an opt-in sample frame rather than a simple or stratified random sample frame (Rivers, 2006). But do unobservable differences between panelists who opt into an online panel and those who opt into a telephone survey exist?

Dennis, Chatt, et al approached this issue by conducting a web survey and a telephone survey among active e-panel members, and a telephone survey among persons refusing to join the e-panel through RDD recruiting efforts (2005). They used the term "mode effect" to describe the method of data

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presentation to the respondent (i.e., aural versus visual). Because they called both respondents who joined the panel and those who refused, they were able to simultaneously test the magnitude of both mode effects and coverage effects. 77% of questions exhibited statistically significantly different results due to mode while 14% of questions produced statistically significant results due to sample origin effects (p. 7). Although much smaller than the mode effects, data differences attributable to coverage effects did exist.

De Wulf and Berteloot (2007) found that there are, in fact, observable differences among panelists attributable to recruitment method by using a single panel composed of actively- recruited and self-recruited panelist. Specifically, they found that panelists who were recruited online exhibited higher levels of satisficing behavior. There are also very significant demographic differences between the two groups. More research is needed to understand the unobservable differences between these panelists.

Our presentation expands De Wulf and Berteloot's work by drawing on a similar quasi- experimental design and focusing on the unobservable differences. SSI recruits panelist in two ways: (a) like most other panels through online advertising, referred to as self-recruited, and (b) over the telephone using an RDD sample frame, referred to as actively-recruited. After recruitment all panelists are treated the same (e.g., frequency and forms of communication, incentives, panelist relationship management). In short, we have access to self-recruited panelists and actively-recruited panelists who should otherwise share the same expectations for online survey panel processes. We attempt to measure how much the unobservable differences in recruitment method might bias the online collection of data.

## Experimental Design – Observing the (Un)observable

We used a stratified sampling technique to determine who would receive invitations to the study from our sampling frame of all active panelists. Our strata were determined by recruitment method: one of self-recruited panelists and one of actively-recruited panelists. Each panelist was given a random number between 1 and 1 million and the lowest 3,000 panelists in each stratum were chosen. Both samples were treated identically in all procedures. Sampled panelists were invited via email to an online survey ostensibly about website awareness and usage. The survey was open from April 23, 2007 to May 14, 2007 allowing plenty of time for panelists to respond. We hypothesized that these two types of panelists would exhibit different internet awareness and usage patterns, making it a good fit for this research because the self- recruited panelist's internet habits caused them to join our panel while the actively-recruited panelist's habits did not. We also embedded questions designed to provide several common satisficing measurements in the questionnaire. The full questionnaire can be referenced in the supplementary material. These measures include:

- Consistency of responses within the questionnaire compared to profile responses. Specifically, we compared panelist reported birth year with information given during profiling questionnaires. We chose birth year as it is static from the time the panelist completed the profiling questionnaire and the time the panelist completed the survey.

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- Report having/using very low incidence or non-existent products/services. We flagged respondents who reported owning or using fictitious products or services. These fictitious products were embedded and randomized within a larger list of actual products and services. The specific product and services are ShareTV DVR, AirLink Satellite Radio, and Part Medicare Q Plan. We also tracked respondents who reported visiting websites that do not exist. The fictional websites used were Duxbury and Republika.org.

The specific questions are as follows:

1. Which of the following products and services do you currently own or use?
2. For each web-site listed below please tell us when you last visited that web-site.

    01. Today
    02. In the past week
    03. In the past month
    04. More than a month ago
    05. I've never been to this site
    06. Item non-response and refusal. Non-response and refusal rates for the questions below were tracked. This rate was calculated in the income question by the percent of completes that choose either the "I don't know" or the "I prefer not to answer this question" options. An open ended question regarding favorite websites was checked manually for nonsense responses. The question text is reported below.

QINC. What is your household's total annual income (before taxes) from all sources?

    01. Under $25,000
    02. Between $25,000 and $49,999
    03. Between $50,000 and $74,999
    04. Between $75,000 and $99,999
    05. Between $100,000 and $199,999
    06. Between $200,000 and $499,999
    07. Between $500,000 and $749,999
    08. Between $750,000 and $999,999
    09. $1,000,000 or more
    88. I don't know
    99. I prefer not to answer this question

3. We've asked you about a number of web-sites today. Please tell us the name of your favorite web-site, and then describe in as much detail as possible why that site is your favorite.

    01. Failure to follow simple attentiveness instructions. Specifically, respondents were asked the questions below to test for attentiveness. In order to capture every panelist who clicked incorrectly, once an answer was selected the respondent could not leave the row blank.

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02. For each web-site below please tell us when you last visited that web-site.
  z) For quality assurance purposes, please leave this row blank
05. Below is a list of statements some people use to describe Google. Please tell us to what extent you agree or disagree with each statement.
  z)For quality assurance purposes, please leave this row blank

We tested cross question consistency using the questions below. Respondents were allowed to choose an answer in the second question that was not in the set of answers given for the first. We flagged these respondents.

7a. Below is a list of physical places where people access the internet. Please mark all of the locations here you regularly access the internet.
7b.Now, please mark the one location where you personally access the internet most often. In other words, where do you spend the most time online?

Time to complete the questionnaire. We recorded the elapsed time to complete the survey. All respondents completing the survey in less than 3 1⁄2 minutes were flagged. This cutoff was determined by reviewing the questionnaire, determining a cutoff time that would not allow a panelist to thoughtfully answer the questions, and visually inspecting the data to make sure the cutoff was reasonable.

Next, we recorded and analyzed other observable cross-group differences (i.e., demographics) between the recruitment methods similar to De Wulf and Berteloot. Because our variables of interest are unobservable, we assumed any significant differences between recruitment methods that remained after controlling for observable differences were due to unobservable differences. We measured this by removing all satisficers (those who failed more than one of the above criteria), controlling for demographic make-up through weighting, and observing the residual effect of recruitment method on the data.

Based on previous research, our a priori hypotheses were:

1. RDD recruited panelists will be older, more educated, and wealthier than panelists recruited by online methods.
2. RDD recruited respondents will display less satisficing behavior.
3. After removing satisficing respondents from the data set, and controlling for observable demographic differences, RDD recruited panelists will consistently answer differently than online recruited panelists.

## Experimental Design

We used two methodologies to test for the existence of recruitment effects: cross tabulation (both un-weighted and weighted) and multivariate regression. First, we calculated crosstabs from the raw survey data for each question using recruitment methods as banner points to examine the demographic and satisficing differences between recruitment methods. Next, to control for differential rates of satisficing, we removed all respondents who failed more than one satisficing measure, completed the survey in 3 1⁄2 minutes or less, or gave a non/nonsense answer to the verbatim question from the data set. We then calculated crosstabs on the remaining respondents.

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We did not weight the RDD or the Online data to match the population; instead we opted to weight the RDD and Online data to match each other on all demographics collected (see Table 1 for weights). This allowed us to put the RDD and the Online data on the same demographic scale. Thus, these crosstabs may not reflect the general population, but allow us to explicitly compare the recruitment methodology. The weights used range from 0.28 for RDD recruited Caucasian males with a college degree and household income $75,000 or above to 1.92 on the high end for online recruited Caucasians with a graduate degree. We computed crosstabs from the weighted data both including and excluding satisficers. Finally, we compared the four sets of crosstabs (found in the supplemental material) to tease out the net recruitment effect from the total recruitment effect. Total recruitment effect is defined here as the effect on data due to the both the observable and unobservable group differences, while net recruitment effect is attributable to unobservable differences only. When comparing the crosstabs, we defined a ‘data difference’ as any response to a non-scaled question that was statistically different across recruitment method using a two sample proportion test. For scaled questions (the Google attitude questions), data were considered statistically different if the top three box, bottom three box, or the mean was statistically different using the appropriate test.

In order to ensure the robustness of our findings, we conducted multivariate regression analysis for all the questions with a numeric scale using PROC REG in SAS. This analysis accounted for the correlation between the dependent variables (responses of the questions). The independent variables used were the demographic variables and the recruitment method variable. Overall F-statistics and the Type III Sums of Squares t- test were used to separate out the net recruitment effect from the total recruitment effect.

The questions were:

5. Below is a list of statements some people use to describe Google. Please tell us to what extent you agree or disagree with each statement. Use a scale from 0 to 10, where 0 means “Completely Disagree with the Statement,” a 5 means “Neither Agree Nor Disagree,” and 10 means “Completely Agree with the Statement.”

    a. Google is the single best internet search tool available
    b. Other internet search tools are much better than Google
    c. Google offers the single best internet amp tool
    d. Other internet map tools are much better than Google’s
    e. Besides the internet search tool, Google is the leader in internet technology innovation
    f. Google doesn’t seem to be developing any new services or tools these days
    g. Google’s home page is too crowded with advertisements
    h. I regularly use the word “google” as a verb
    i. Google is an environmentally conscious company
    j. Google gives back to the community
    k. Google only cares about generating profits

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## Experimental Results

We calculated response rate in each group according to AAPOR's standard second definition (RR2). The RDD panelists responded at about double the rate of online recruited panelists (24.6% versus 14.7%). These response rates led to a striking difference in sample size: 709 completes from the RDD sample and 408 completes from the online sample. The demographic differences between RDD recruited panelists and their online recruited counterparts are also striking (see Table 2). Generally, the online recruitment methodology produced more females and African Americans than RDD. RDD recruited respondents are also more likely to have a higher level of education, and belong to a higher income bracket. The cross group differences in the distribution of age exhibit a small trend with RDD respondents being younger overall. The magnitude of these observable differences suggests that, although the digital divide is diminishing, there are very real differences between individuals who actively seek panel membership and those who are familiar enough with the web to join when approached by phone.

With a single exception, satisficing measures are uniformly higher among online recruited respondents (see Table 3). In addition to the differential failure rates for satisficing measures embedded in the questionnaire, online recruited respondents tend to complete the survey much faster than the RDD recruits (see Table 4). One difference of note is that RDD panelists were more likely to report ownership of non-existent products. Similarly, RDD panelists reported owning more products than online panelists overall, suggesting the difference in satisficing rate could be attributed to this general tendency. In fact, online panelists reported a higher rate of ownership for only one item: VOIP home telephone service. Online recruited panelists also belong to more panels (median=5 versus median=2) and take more online surveys (median=10 versus median=4) on average than the RDD recruits (Table 3).

Figure 1 summarizes the bulk of our results by separating out total recruitment effect, net recruitment effect, and the masked recruitment effect from the crosstabs. In order to capture only meaningful differences in internet habits, we excluded all demographics and satisficing questions because they are used to weight the data and remove panelists. A little less than half (47%) of the questions had no statistically significant ($\alpha = 0.05$) recruitment effect before adjusting the data for satisficing and demographics. Of this 47%, 7% of the questions revealed net effects that were masked by the demographic differences. These differences would have lead to Type II errors if the adjustments were not made. This leaves 40% of the questions that had no net or total recruitment effects.

The remaining 53 percent of the questions had a statistically significant recruitment effect before adjusting for satisficing and demographics. Only 28% of the total questions show a statistically significant net recruitment effect and total recruitment effect. Some questions (14%) had no statistically significant net recruitment effect after only adjusting for the different demographic compositions. Many other questions (12%) had no statistically significant effect after adjusting for either satisficing or for demographic differences. Thus, after adjusting for demographics and satisficing, only 35% of the questions still had net recruiting effects. The largest differences between RDD and online recruited respondents were exposed in ownership and use patterns of the included goods and services (Question 1); and in fundamental attitudes towards Google (Question 5). Generally, the probability of receiving the daily newspaper, investing in mutual funds, using a home equity loan, etc. is higher for RDD recruited panelists. RDD panelists also tend to have a systematically higher opinion of Google than their online recruited counterparts.

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The practical significance of these findings, however, depends heavily on the magnitude of business or policy decisions based upon the data. With 28% of questions exhibiting a statistically significant net recruitment effect, though, researchers should be careful when selecting what type of online sample to use.

The multivariate regression supports these conclusions, and provides a rigorous verification of the above results. While we analyzed the same questions, we employed a different threshold for significance with this model. Specifically, the number of questions exhibiting recruitment effects should decrease because only a difference in the mean rating was considered significant, not mean, top three, and bottom three like with the crosstabs. The threshold change was implemented to accurately reflect the measurements used for the respective analyses.

Table 5 gives coefficients and standard errors for the multivariate regression with each dependent variable in its own column. Table 6 shows that the overall test for a recruitment method effect is significant, making it reasonable to look for recruitment effects at the question level. Table 7 gives the AIC, overall F statistic, overall p-value, and the p-value for the recruitment method variable. All questions that do not have a significant overall p-value or a significant p-value for recruitment (Q5A, Q5C, Q5D, Q5E, Q5I, Q5J and Q5K) exhibit no statistically significant net or total recruitment effects. The questions with a significant overall p-value, but not a significant p-value for recruitment (Q5F, Q5G and Q5L) have total recruitment effects due to observable differences; however, they do not have unobservable differences due to recruitment method. The rest of the question (Q5B and Q5H) have net recruitment effects that are due to recruitment method.

The magnitude of net recruitment effects is materially lower when using multivariate regression. Although this difference is explained (either largely or partially) by the change in significance threshold, more research is needed to identify truly robust measures of net recruitment effect.

Regarding our hypotheses, most of the expected demographic differences did, in fact, materialize. The distribution of age, however, was very similar between the two groups. RDD recruited respondents satisfice about half as often as respondents recruited online. Lastly, there is strong evidence confirming hypothesis number 3. In other words, the effect of unobservable differences between the groups does, in fact, lead to systematic differences in the data collected.

## Conclusion

Recruitment method plays a substantial role in determining both the observable and unobservable differences between panelists. Although controlling for observable differences by quota sampling and removing satisficing panelists reduces the magnitude of the resultant differences, it does not erase them. Unfortunately, the experimental evidence above cannot judge which group's preferences more closely match population taste and preferences. Further research in this area is needed. However, it is not implausible to say that results obtained by mixing these sources will capture a broader cross-section of the population which, in turn, will lead to more representative data. This more representative data will inform better business and better public policy decisions.

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*Table 1:*

**Weights Used to Create Equilalent Demographic Compositions**

| Weighted | Observed | Adjusted | Variable Levels | | | | | |
|---|---|---|---|---|---|---|---|---|
| Percent | Frequency | Frequency | Weight | Income | Education | Ethnicity | Sample | Gender |
| 0.0292 | 18 | 30.86 | 1.71469 | All | HS | White | RDD | Male |
| 0.004 | 4 | 4.23 | 1.057 | <25K | Some Coll | White | RDD | Male |
| 0.0217 | 25 | 22.94 | 0.91748 | 25-75K | Some Coll | White | RDD | Male |
| 0.0138 | 20 | 14.59 | 0.72933 | 75K+ | Some Coll | White | RDD | Male |
| 0.019 | 31 | 20.08 | 0.64784 | All | Asso/Tech | White | RDD | Male |
| 0.0037 | 6 | 3.91 | 0.65182 | <25K | College | White | RDD | Male |
| 0.0202 | 31 | 21.35 | 0.68875 | 25-75K | College | White | RDD | Male |
| 0.0128 | 48 | 13.53 | 0.28187 | 75K+ | College | White | RDD | Male |
| 0.0219 | 49 | 23.15 | 0.47241 | All | Graduate | vWhite | RDD | Male |
| 0.0253 | 20 | 26.74 | 1.33711 | All | All | Black | RDD | All |
| 0.0926 | 52 | 97.88 | 1.88227 | All | HS | White | RDD | Female |
| 0.0125 | 10 | 13.21 | 1.32125 | <25K | Some Coll | White | RDD | Female |
| 0.0687 | 66 | 72.62 | 1.10024 | 25-75K | Some Coll | White | RDD | Female |
| 0.0438 | 37 | 46.3 | 1.25126 | 75K+ | Some Coll | White | RDD | Female |
| 0.0391 | 30 | 41.33 | 1.37762 | <75K | Asso/Tech | White | RDD | Female |
| 0.0211 | 24 | 22.3 | 0.92928 | 75K+ | Asso/Tech | White | RDD | Female |
| 0.0753 | 69 | 79.59 | 1.15351 | <75K | College | White | RDD | Female |
| 0.0405 | 62 | 42.81 | 0.69046 | 75K+ | College | White | RDD | Female |
| 0.0451 | 32 | 47.67 | 1.48971 | <75K | Graduate | White | RDD | Female |
| 0.0243 | 52 | 25.69 | 0.49394 | 75K+ | Graduate | White | RDD | Female |
| 0.011 | 10 | 11.63 | 1.1627 | <75K | HS | White | ON | Male |
| 0.0059 | 4 | 6.24 | 1.55908 | 75K+ | HS | White | ON | Male |
| 0.0023 | 5 | 2.43 | 0.48622 | <25K | Some Coll | White | ON | Male |
| 0.0204 | 17 | 21.56 | 1.2684 | 25K+ | Some Coll | White | ON | Male |
| 0.0011 | 1 | 1.16 | 1.1627 | <25K | Asso/Tech | White | ON | Male |
| 0.006 | 5 | 6.34 | 1.2684 | 25-75K | Asso/Tech | White | ON | Male |
| 0.0038 | 4 | 4.02 | 1.00415 | 75K+ | Asso/Tech | White | ON | Male |
| 0.0136 | 13 | 14.38 | 1.10578 | <75K | College | White | ON | Male |
| 0.0074 | 13 | 7.82 | 0.60168 | 75K+ | College | White | ON | Male |
| 0.0526 | 29 | 55.6 | 1.91718 | All | Graduate | White | ON | All |
| 0.0007 | 2 | 0.74 | 0.36995 | All | HS | Black | ON | Male |
| 0.001 | 1 | 1.06 | 1.057 | All | Some Coll | Black | ON | Male |
| 0.0005 | 1 | 0.53 | 0.5285 | All | Asso/Tech | Black | ON | Male |
| 0.0014 | 1 | 1.48 | 1.4798 | All | Coll/Grad | Black | ON | Male |
| 0.0534 | 68 | 56.44 | 0.83006 | All | HS | White | ON | Female |

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| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0.0072 | 13 | 7.61 | 0.58542 | <25K | Some Coll | White | ON | Female |
| 0.0395 | 52 | 41.75 | 0.80291 | 25-75K | Some Coll | White | ON | Female |
| 0.0252 | 23 | 26.64 | 1.1581 | 75K+ | Some Coll | White | ON | Female |
| 0.0035 | 4 | 3.7 | 0.92488 | <25K | Asso/Tech | White | ON | Female |
| 0.0191 | 22 | 20.19 | 0.91767 | 25-75K | Asso/Tech | White | ON | Female |
| 0.0121 | 8 | 12.79 | 1.59871 | 75K+ | Asso/Tech | White | ON | Female |
| 0.0666 | 58 | 70.4 | 1.21373 | All | College | White | ON | Female |
| 0.0022 | 3 | 2.33 | 0.77513 | All | HS | Black | ON | Female |
| 0.003 | 9 | 3.17 | 0.35233 | All | Some Coll | Black | ON | Female |
| 0.0014 | 2 | 1.48 | 0.7399 | All | Asso/Tech | Black | ON | Female |
| 0.0028 | 2 | 2.96 | 1.4798 | All | College | Black | ON | Female |
| 0.0017 | 1 | 1.8 | 1.7969 | All | Graduate | Black | ON | Female |

***Table 2:***

**Demographic Differences by Recruitment Method**

| | RDD | | Online | | | RDD | | Online | |
|---|---|---|---|---|---|---|---|---|---|
| Gender | Count | % | Count | % | Age | Count | % | Count | % |
| Male | 234 | 34%* | 90 | 24% | 18-24 | 20 | 3% | 19 | 5% |
| Female | 452 | 66% | 281 | 76%* | 25-34 | 146 | 21% | 68 | 18% |
| | | | | | 35-44 | 169 | 25% | 89 | 24% |
| Education | Count | % | Count | % | 45-54 | 157 | 23% | 98 | 26% |
| High School or Less | 73 | 11% | 87 | 23%* | 55+ | 194 | 28%* | 97 | 26% |
| Some College | 166 | 24% | 120 | 32%* | Mean | 46.22 | | 45.54 | |
| Associates or Technical Degree | 87 | 13% | 47 | 13% | Median | 45.5 | | 45.96 | |
| Bachelors Degree | 221 | 32%* | 87 | 23% | | | | | |
| Graduate Degree | 139 | 20%* | 30 | 8% | Income | Count | % | Count | % |
| | | | | | Under $25,000 | 43 | 6% | 51 | 14%* |
| Ethnicity | Count | % | Count | % | $25,000 - $49,999 | 160 | 23% | 113 | 30%* |
| Caucasian | 623 | 91% | 328 | 88% | $50,000 - $74,999 | 169 | 25% | 91 | 25% |
| African American | 20 | 3% | 22 | 6%* | $75,000 - $99,999 | 137 | 20%* | 48 | 13% |
| Asian | 16 | 2% | 9 | 2% | $100,000 - $199,999 | 118 | 17%* | 37 | 10% |
| Other | 14 | 2% | 3 | 1% | $200,000 - $499,999 | 18 | 3% | 4 | 1% |
| Hispanic | 21 | 3% | 14 | 4% | $500,000 + | 7 | 1% | 0 | 0% |
| *Significant at the 5% level | | | | | Refused / Don't Know | 38 | 5% | 27 | 7% |

*(continued)*

*Table 3:*

**Satisficing Measures by Recruitment Method**

| | RDD | | Online | |
|---|---|---|---|---|
| Satisficing Measure | Counts | Percent | Counts | Percent |
| Inconsistent Year of Birth | 17 | 2.40% | 18 | 4.41% |
| Nonexistant Products in Q1 | 86 | 12.13% | 33 | 8.09% |
| Refused to answer Income | 36 | 5.08% | 28 | 6.86% |
| Visited Non-existent websites in Q2 | 20 | 2.82% | 16 | 3.92% |
| Failed to follow Instructions in Q2 | 56 | 7.90% | 71 | 17.40% |
| Straightlined in Q2 | 6 | 0.85% | 9 | 2.21% |
| Failed to follow Instructions in Q5 | 46 | 6.49% | 57 | 13.97% |
| Straightlined in Q5 | 33 | 4.65% | 50 | 12.25% |
| Nonsense in Q6 verbatim | 4 | 0.56% | 6 | 1.47% |
| Inconsistent Q7 | 5 | 0.71% | 6 | 1.47% |
| Speeders | 10 | 1.41% | 23 | 5.64% |
| Median of Monthly Surveys | 4 | | 10 | |
| Median Number of Panels | 1 | | 5 | |
| Mean of Monthly Surveys | 6.85 | | 22.79 | |
| Mean Number of Panels | 2.15 | | 5.92 | |

*Table 4:*

**Time Spent by Recruitment Method**

| Time | RDD | Online |
|---|---|---|
| < 5 minutes | 20% | 33%* |
| 5 - 10 minutes | 69%* | 55% |
| 10 + minutes | 11% | 12% |
| Mean | 7.03 | 6.35 |
| Standard Deviation | 2.68 | 3.13 |

*Significant at the 5% level

*(continued)*

***Table 5:***

Coefficients in the MANOVA Regression Model with Standard Errors

| *Indicator Variables* | *Questions* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q5A | Q5B | Q5C | Q5D | Q5E | Q5F | Q5G | Q5H | Q5I | Q5J | Q5K | Q5L |
| Intercept | 6.08 | 3.827 | 5.545 | 4.301 | 5.694 | 4.318 | 4.154 | 4.689 | 5.258 | 5.040 | 4.734 | 3.785 |
| | (0.4) | (0.37) | (0.37) | (0.36) | (0.32) | (0.34) | (0.42) | (0.51) | (0.24) | (0.25) | (0.35) | (0.33) |
| iinc1 | -0.046 | 0.522 | -0.354 | 0.548 | -0.438 | -0.101 | -0.383 | -0.508 | 0.007 | 0.220 | 0.6 | 0.683 |
| | (0.43) | (0.4) | (0.4) | (0.39) | (0.35) | (0.36) | (0.45) | (0.55) | (0.26) | (0.27) | (0.38) | (0.35) |
| iinc2 | 0.247 | -0.348 | 0.196 | -0.035 | -0.068 | -0.202 | -0.426 | 0.257 | 0.222 | 0.521 | 0.491 | 0.554 |
| | (0.37) | (0.34) | (0.34) | (0.34) | (0.3) | (0.31) | (0.38) | (0.47) | (0.23) | (0.23) | (0.32) | (0.3) |
| iinc3 | 0.415 | -0.420 | 0.046 | -0.169 | 0.066 | -0.540 | -0.67 | -0.039 | 0.123 | 0.305 | 0.335 | 0.497 |
| | (0.37) | (0.34) | (0.34) | (0.34) | (0.3) | (0.31) | (0.38) | (0.47) | (0.23) | (0.23) | (0.32) | (0.3) |
| iinc4 | 0.524 | -0.445 | 0.128 | -0.113 | -0.099 | -0.284 | -0.826 | 0.375 | -0.039 | 0.343 | 0.312 | 0.061 |
| | (0.39) | (0.36) | (0.35) | (0.35) | (0.31) | (0.32) | (0.4) | (0.49) | (0.23) | (0.24) | (0.34) | (0.31) |
| iinc5 | 0.408 | -0.276 | 0.145 | -0.155 | 0.151 | -0.51 | -0.438 | 0.25 | -0.187 | 0.177 | 0.231 | 0.48 |
| | (0.4) | (0.37) | (0.37) | (0.36) | (0.32) | (0.33) | (0.41) | (0.51) | (0.24) | (0.25) | (0.35) | (0.32) |
| iinc6 | 1.24 | -1.399 | -0.125 | -0.407 | 0.195 | -0.626 | -0.764 | 1.587 | 0.082 | 0.442 | -0.229 | -0.616 |
| | (0.65) | (0.6) | (0.6) | (0.59) | (0.52) | (0.55) | (0.68) | (0.83) | (0.4) | (0.41) | (0.57) | (0.53) |
| iinc7 | 2.939 | -1.162 | 3.35 | 0.423 | 2.125 | -1.897 | 0.61 | 3.763 | 1.293 | 2.646 | -2.044 | -1.793 |
| | (1.84) | (1.69) | (1.68) | (1.67) | (1.47) | (1.54) | (1.9) | (2.35) | (1.12) | (1.16) | (1.6) | (1.49) |
| iinc8 | 0.096 | -0.866 | -2.17 | 0.951 | -0.21 | 2.826 | 1.922 | 2.063 | 0.202 | 1.478 | -0.82 | -0.362 |
| | (1.84) | (1.69) | (1.68) | (1.67) | (1.47) | (1.54) | (1.9) | (2.35) | (1.12) | (1.16) | (1.6) | (1.49) |
| iinc9 | -0.091 | -0.837 | 0.342 | -0.73 | 1.196 | -0.724 | -0.879 | -0.073 | 2.089 | 0.793 | -0.785 | 0.501 |
| | (1.51) | (1.39) | (1.38) | (1.37) | (1.21) | (1.27) | (1.57) | (1.93) | (0.92) | (0.95) | (1.32) | (1.23) |
| ieduc1 | -0.275 | 0.257 | -0.105 | -0.348 | 0.109 | 0.345 | 0.956 | -1.17 | -0.174 | -0.322 | -0.068 | -0.238 |
| | (0.32) | (0.29) | (0.29) | (0.29) | (0.25) | (0.26) | (0.33) | (0.4) | (0.19) | (0.2) | (0.28) | (0.26) |
| ieduc2 | -0.442 | 0.223 | 0.002 | -0.108 | -0.105 | 0.247 | 0.306 | -0.471 | -0.079 | -0.116 | 0.035 | -0.042 |
| | (0.27) | (0.25) | (0.25) | (0.24) | (0.22) | (0.23) | (0.28) | (0.34) | (0.16) | (0.17) | (0.24) | (0.22) |
| ieduc3 | -0.25 | -0.291 | 0.017 | -0.092 | 0.123 | 0.061 | 0.758 | -0.433 | 0.045 | -0.124 | -0.175 | -0.036 |
| | (0.31) | (0.29) | (0.28) | (0.28) | (0.25) | (0.26) | (0.32) | (0.4) | (0.19) | (0.2) | (0.27) | (0.25) |
| ieduc4 | 0.014 | -0.228 | 0.056 | -0.15 | 0.342 | -0.287 | -0.038 | 0.525 | 0.047 | -0.03 | -0.244 | -0.176 |
| | (0.26) | (0.24) | (0.23) | (0.23) | (0.2) | (0.21) | (0.27) | (0.33) | (0.16) | (0.16) | (0.22) | (0.21) |
| igen | -0.232 | 0.143 | -0.025 | 0.014 | -0.223 | -0.09 | 0.281 | -0.406 | -0.058 | -0.249 | 0.172 | 0.727 |
| | (0.18) | (0.16) | (0.16) | (0.16) | (0.14) | (0.15) | (0.18) | (0.23) | (0.11) | (0.11) | (0.15) | (0.14) |
| iblack | -0.262 | 0.856 | 0.039 | 0.241 | 0.138 | 0.06 | -0.426 | -0.994 | 0.348 | 0.059 | 0.499 | 0.392 |
| | (0.41) | (0.38) | (0.38) | (0.38) | (0.33) | (0.35) | (0.43) | (0.53) | (0.25) | (0.26) | (0.36) | (0.34) |
| irecruit | 0.318 | -0.348 | 0.118 | -0.177 | -0.155 | 0.001 | -0.056 | 0.488 | 0.018 | -0.004 | -0.294 | 0.165 |
| | (0.18) | (0.16) | (0.16) | (0.16) | (0.14) | (0.15) | (0.19) | (0.23) | (0.11) | (0.11) | (0.16) | (0.15) |

*(continued)*

*Table 6:*

**Multivariate Statistics and Exact F Statistics for MANOVA**

| Statistic | Value | F Value | Num DF | Den DF | Pr > F |
|---|---|---|---|---|---|
| Wilks' Lambda | 0.97681864 | 1.91 | 12 | 967 | 0.0295 |
| Pillai's Trace | 0.02318136 | 1.91 | 12 | 967 | 0.0295 |
| Hotelling-Lawley Trace | 0.02373149 | 1.91 | 12 | 967 | 0.0295 |
| Roy's Greatest Root | 0.02373149 | 1.91 | 12 | 967 | 0.0295 |

*Table 7:*

**Results from the MANOVA Analysis on Google Attitudes**

| | *Questions* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q5A | Q5B | Q5C | Q5D | Q5E | Q5F | Q5G | Q5H | Q5I | Q5J | Q5K | Q5L |
| AIC | 1879 | 1710 | 1700 | 1684 | 1428 | 1525 | 1947 | 2367 | 884 | 958 | 1607 | 1466 |
| Overall F | 1.55 | 2.95 | 0.75 | 0.66 | 1.17 | 1.8 | 2.02 | 4.25 | 1.09 | 1.31 | 1.28 | 2.83 |
| Overall p | 0.076 | <.001 | 0.746 | 0.834 | 0.29 | 0.027 | 0.01 | <.001 | 0.361 | 0.185 | 0.202 | 0.001 |
| Recruit p-value | 0.076 | 0.035 | 0.472 | 0.277 | 0.278 | 0.998 | 0.764 | 0.034 | 0.871 | 0.979 | 0.061 | 0.257 |

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