Address Based Sampling: Census Block Group Data Used to Define Incentive Structure

Anh Thu Burks[1] & Michael W. Link[2]
[1] The Nielsen Company, 501 Brooker Creek, Oldsmar, FL 34677
[2] The Nielsen Company, 1145 Sanctuary Pkwy, Alpharetta, GA 30004

Abstract
Within Address based sampling (ABS), limited focus has been on the vast array of demographic information available to researchers within this sampling frame. Appending demographic information to an ABS frame is a relatively simple process especially since it's comprised of address information for almost every sample unit. As examples, there are socio-economic variables, owner- renter status, household size, occupational and other Census-type variables that are available through sample vendors and can be used by researchers to tailor the survey recruitment process (i.e., mailings and incentives) in an attempt to gain respondent cooperation. Thus the focus here is to examine Census-type data at the block group level for each test case and how these types of variables were subsequently used to target incentives to specific demographic groups. Lastly, a test was conducted using an ABS sampling frame where participants were mailed a survey with a differential incentive and then provided the option to respond by web or mail. The findings from this test are discussed in terms of its effectiveness as indicators to target and gain cooperation among the hard-reach demographic groups (i.e., 18-34 year olds, blacks and Hispanics). In theory, this should help to compensate for the traditionally lower responses observed with these subgroups, serve to enhance the recruitment strategy and begin to address the issue of achieving better representation among these demographics. Findings here, suggest that indicators like Census-type variables provide a viable alternative to improving participation and to further improve sample representation among subgroups.

Key Words: Address based sampling, sample indicators, Census type variables, and incentives

1.0 Introduction

Address-based sampling (ABS) – the sampling of addresses from a near universal database listing of addresses -- offers a number of advantages over other sample design methodologies (such as landline random digit dialing, landline-cell phone hybrid approaches, or online sample designs) in that the initial sample frame can be augmented more completely with an array of additional information from publicly and commercially available sources (Link et al 2008). While there are some exceptions, most ABS samples contain complete or near complete address information from all sampled units. It is, therefore, a relatively simple process to append information to the initial sample frame via county, Zip Code, street address, or via geo-coding to a particular Census Block Group (CBG) or other geographic "hook". For example, CBG information can be merged to provide area or neighborhood-level characteristics, such as mean income or education levels, predominant language spoken, proportion of various racial or ethnic groups, and the like. Data from commercial databases can also be appended to sampled records, often at the household level such as estimated age of the head of household, phone number associated with the address, and whether a name linked to the address is of Hispanic or Asian origin. These sources do vary in quality and are dependent on (1) the availability of information for each sampled record (for instance, CBG data are available for nearly every sampled unit, whereas commercial records may be less complete) and (2) the accuracy of the information as it pertains to the sampled unit (for example, CBG information can inform a researcher about the general characteristics of a neighborhood, but not necessarily the household itself, whereas commercial information may be available at the household level but may or may not be accurate) (Amaya and English, 2011).

Appending additional variables to the initial ABS frame provides researchers with a number of advantages. First, the information can be used to stratify or target the sample being drawn. Stratification of the initial sample based on geographic or household-level can often help ensure the sample is more representative of a given geography, while use of these variables to target the selection of the sample may also help facilitate a more efficient sample, particularly if the study is focused on a specific geography, type of household or respondent. Second, the information can be used to drive different treatments across the sample, such as tailoring specialized materials to particular groups or geographies (i.e., bilingual materials to areas most likely to require them based on language penetration) or targeting incentives to specific groups or areas (i.e., use of “differential” incentives, whereby larger incentives are provided to sampled units where nonresponse has the highest propensity). Third, the appended data can be used in back-end analyses of the survey data. Such data can be used to augment and extend traditional survey data analyses (e.g., providing additional analytic or population segmentation variables) or to conduct a form of nonresponse bias analyses, particularly when the appended data are available for all sampled units (respondents and non-respondents) and those variables are associated with measures of interest in the survey.

In this study, we leverage appended variables to (1) target different levels of incentives to some of the traditionally hardest-to-reach groups (e.g., younger adults, Blacks, and Hispanics) and (2) examine the potential for bias in the survey results by comparing respondents and non-respondents across an array of key sample frame variables. The study finds that appending publicly and commercially available data to the sample frame can help researchers both target respondent treatments in different ways and provide a means of assessing the potential for bias in the resulting samples when different survey design elements (e.g., incentives and data collection modes) are used.

1.1 Differential Response, Differential Incentives, and Nonresponse Bias

Differential response, whereby some subgroups of the population respond more (or less) readily to a survey request than other subgroups, is a problem with most surveys and ABS designs are no exception. In particular, sampled addresses for which a telephone number cannot be identified (i.e., “unmatched” cases) are often the most problematic in an ABS design (Link and Lai, 2011).[1] These sets of cases include cell phone-only homes and “hardcore” unlisted landline homes (i.e., whereby a telephone number cannot be located thru directory listing or other commercially available databases) and have a

[1] It is unclear at this point whether the differential response is due primarily to the inherent response propensity of these individuals, the ability to recruit “matched” addresses by more than one mode using mail or telephone appeals, or a combination of these two factors.

higher proportion of adults who are younger, Black, and/or Hispanic. These individuals have been shown in a number of studies to have very different behaviors, attitudes and opinions (Blumberg and Luke 2009). This combined with the lower propensity to participate in surveys increases the potential that survey estimates from such studies may be biased.

Typically, researchers use incentives to achieve one or more of the following goals: (1) improving overall response rates, (2) enhancing the characteristics of an unweighted set of survey respondents, (3) decreasing the likelihood of missing data or other factors that affect data quality, or (4) reducing the total costs of fielding a survey (Brehm, 1994; Church, 1993; Dillman, 2007; Singer et al, 1999). In practice, incentives may be used uniformly across all sampled units/respondents or they may be used differentially across populations, contexts, modes, etc. In the first instance, all households/ respondents receive exactly the same form, level, and timing of incentive. This is often done for either reasons of “fairness” (trying to treat all respondents identically) or for operational efficiency (simpler to execute and track). The downside is that incentives may be used where they are not really needed and/or the amount required obtaining participation from a particular subgroup or context may be insufficient. The use of differential incentives, in contrast, is based on the premise that incentives should be targeted to populations or points in the survey process where burden is highest or the likelihood of response is lowest (i.e., where task or burden may result in differential nonresponse) (Martinez-Ebers, 1997; Fox et al, 1988; Trussel and Lavrakas, 2004). Use of differential incentives is often justified on the basis of effectiveness, efficiency, and “need,” but can be criticized for no longer treating all sampled units identically (which some perceive as not “fair”). In this study, we utilize sample frame indicators derived from both publicly and commercially available sources to develop two alternative ways of identifying sampled units that are likely to have a low propensity to respond to a survey request. These differential incentive structures are also tested across several different modes of data collection (mail with Web follow-up and Web only).

Sample frame indicators are also used here to assess whether one method for targeting differential incentives resulted in a potentially less biased sample than did the other approach. Response rates for most surveys have declined over time, increasing the need for researchers to assess the level of potential bias in their survey estimates. Traditionally this has been a very expensive and time-consuming endeavor. Researchers often conduct nonresponse bias assessments by fielding data collection efforts with initial survey nonrespondents using either alternative modes of data collection and/or increased incentives (Curtin, Presser, and Singer, 2005; Kay, Boggess, Selvavel, and McMahon, 2001; Lengacher, Sullivan, Couper, and Groves, 1995). In contrast, ABS designs can facilitate quicker, less expensive forms of nonresponse assessments, utilizing sample frame indicators. Variables appended to the initial sample frame can be used to compare respondents and nonrespondents across and array of measures. It is critical, however, that this information be (1) available for all (or nearly all) initially sampled units – respondents and non-respondents alike, and (2) that these variables be related to measures of interest within the survey. This approach does have some drawbacks compared to more rigorous methods in that the frame variables that are most easily obtained and appended (e.g., Census data) are often reflective of broader geographies than just the household or person-level (e.g., concerns about “ecological fallacy”). In the case of commercially available data, there are also concerns about data completeness and accuracy (Amaya and English, 2011).

In this study we utilize ABS sample frame indicators to assess the potential bias in the resulting samples after the application of two different incentive strategies utilized across two different modes of data collection. The study focuses on five key questions in the use of frame indicators:

- Which incentive structure – survey mode combination produces the highest rates of response?
- Does the differential incentive structure used lead to differences in the key hard-to-reach respondent demographics (i.e., adults aged 18 – 34, Black, and Hispanics)
- What impact, if any, do the different incentive – mode combinations have on the survey estimates obtained?
- Which approach led to the least potential for bias in the overall survey estimates?

The study highlights how nonresponse bias analyses conducted leveraging an array of publicly and commercially available data can help us understand the potential biases in our data.

2.0 Methodology

This study examines the effectiveness of leveraging ABS sample frame indicators in two critical areas (1) to drive differential treatments to try to improve response among hard-to-reach groups (e.g., younger adults, Blacks, and Hispanics) and (2) to assess the potential bias in the resulting sample and estimates derived from the use of differential incentives.

The results for this comparison are based on data collected from a survey, entitled *My Community & Lifestyle Survey*, which was fielded in December, 2011. The survey assessed a wide variety of lifestyle attitudes and opinions including views on local job creation, the economy, television viewing behaviors, technology ownership, and demographic questions. A representative national address based sample (ABS) of 5,000 adults aged 18 years and older were sampled and allocated through random selection and to one of five test groups. The four groups which are the primary focus of the research presented here, followed a simple 2 x 2 design (see Figure 1) based on different ways of identifying respondents to receive differential incentives and by mode of data collection – Mail survey with Web survey follow-up versus Web survey only.[2] All four groups were recruited using mail-based invitations (no telephone contact was made). Those in the Mail with Web Follow-up condition (test groups 1 and 2) received a packet with a survey booklet and return envelope. Seven-days later they were then mailed a letter with a URL (Web survey address), and unique username and password if they chose to complete the survey via the Web (they were also encouraged in the letter to return the hardcopy via mail if they preferred). Those in the Web-only condition received an initial letter with the URL, username and password and a similar appeal 6 days later (no mail survey option was offered). Responses were collected up to 30 days after the initial recruitment mailing. All test groups were recruited via a mail invitation that asked for the head of household to complete the survey. If that person was unavailable or unwilling, then an adult aged 18 or older was requested to respond.

[2] The fifth test group received only a mail survey, with no Web survey component. This group also received no cash incentive. Initially this was to serve as a reference or control group. For the analyses presented here, however, we have opted to compare the remaining four test groups to population estimates from the U.S. Census. This makes for a cleaner and more straightforward comparison of the four test groups.

Respondents in all four test groups received either $2 or $5 in cash as an incentive for completing the survey. Two alternative incentive structures were developed and compared for targeting the higher $5 incentive. In defining the two alternative incentive structures, a series of publicly available (via U.S. Census) and commercially available (via Marketing Systems Group, the sample vendor for this study) data were appended to the initially sampled addresses (see Table 1 for listing of variables). One set of respondents (Test groups 1 & 3) utilized a differential sample strategy traditionally used by The Nielsen Company in targeting incentives for its Television Audience Measurement Diary Service (Nielsen, 2008). This approach provided a higher, pre-paid incentive ($5 cash) to any addresses that (1) has a model-based age indicator provided by MSG indicating that the head of household was likely to be between the ages of 18 to 34 years old, or (2) was located in a Census block group with a 70% or higher percentage of Black households, or (3) had a Hispanic surname associated with the address. This approach is referred to here as the "Three-Factor Design".

The second incentive strategy utilized a broader array of sample indicators, including those in the Three-Factor Design (albeit with some constraints added) as well as variables thought to be of use in targeting young adults (aged 18 to 34 years), Blacks and Hispanics. The Three-Factor Design variables were utilized, but the resulting pool of sampled addresses constrained as follows:

- Presence of Age Indicator (18 – 34 years) only in Census block groups with mean income less than $50,000 per year;
- Address in Census block group with 60% or greater Black penetration and where mean block group income is less than $50,000 and MSG Age Indicator was not 50 years of age or higher;
- Address with associated Hispanic surname (based on listed names matched to address) and where mean block group income is less than $50,000.

The additional criteria for being included in the increased incentive pool for this incentive design included:

- Block group renter penetration for those aged 18 to 34 years old was 25% or higher and mean block group income was less than $50,000 and MSG Age Indicator was not 50 years of age or higher
- Block group income was less than $25,000 and MSG age indictor was not 50 years or higher
- Block group percent for Hispanic was equal to 25% or higher

This approach is referred to as the "Multi-Factor Design". While efforts were made to try to equalize the proportion of respondent receiving the higher payments across all four test groups, there was a somewhat higher percentage among the Muitl-Factor Design groups that received $5 as compared to the proportion of those in the Three-Factor Group (see Table 4). As shown in Table 2, both incentive structures produced substantial differences in the $2 versus $5 groups with regards to Census block group indicators for percent Black, Hispanic and young adult renters as well as average household income and with respect to the commercial database variables of Hispanic surname and age of head of household. The age variable is an example of a commercially available frame indicator that has been shown to be accurate -- particularly for older respondents (Burks et al, 2010) – but for which there is often a marked amount of missing data. Use of this variable in both incentive structures led to significant variation in the amount of missing data for the $2 and $5 recipients across all four test groups.

3.0 Findings

The analysis focused on four key comparisons across the four test groups: (1) response rates, (2) differences in demographic characteristics of the Head of Household among those who did respond, (3) potential impact of incentive and mode on selected survey results, and (4) comparison across respondent and non-respondent sample units for several key sample frame indicators.

3.1 Response Rates

Response rates varied considerably across the four test groups (see Table 1). The two Mail with Web follow-up groups (Groups 1 & 2) posted response rates double those seen with the Web only approach (Groups 3 & 4). Group 1 showed the highest rate of return (30.5%), with Group 2 being slightly lower (28.0%). Interestingly, the web survey follow-up was not a major contributor to the final response rate for either of these test groups. For Group 1 the increased response rate due to web survey follow-up was 1.25% (12 of 296 completes), while for Group 2 it was 0.6% (6 of 272 completes). In terms of incentive impact, while the 3-Factor approach led to a higher response rate when compared to the Multi-Factor approach (30.5% vs 28.0%); the differences were not statistically different.When Web was the only survey mode used, the response rate for the 3-Factor approach (14.4%) was only marginally higher than that of the Multi-Factor approach (14.1%). These differences were not statistically significant. In sum, the mail with web follow-up designs out-performed the web survey approaches; however, there was little difference in terms of response across the two incentive allocation approaches within these two modes.

3.2 Head of Household Demographic Characteristics

Next, we examine the age, race, and Hispanic ethnicity of the Head of Household for those homes that completed the survey (see Table 4).[3] U.S. Population distributions for these characteristics help serve as a "gold standard" for comparison with the test groups. In terms of age, both mail-based groups under-represented the population for those less than 35 years of age, while over-representing those aged 55 years or older. From an incentive perspective, there were no significant differences in the distribution of age between the 3-Factor and the Mulit-Factor incentive approaches. With regards to race, the percentage of Black Heads of Household was over-represented in both Group 1 (19.4%) and Group 2 (16.1%) when compared to the national estimate (12.4%). There were no statistically significant differences in the distribution of Black heads of Household across the two incentive approaches. Finally, with respect to Hispanic ethnicity among Heads of Household, Group 2 came the closest to mirroring the national distribution (12.2% vs 12.1%), while Group 1 (8.8%) was under the national average. Again, however, the differences between the two incentive groups were not statistically significant. Across the two Web survey groups there was some significant variability in terms of age distribution. The 3-Factor incentive group had a higher penetration of Heads of Household aged 18 – 25 years and 35 to 54 years, whereas the Multi-Factor group was higher among those aged 25 to 34 years, and those aged 55 and older. Although Group 4 had no responses from households with a Head of Household aged 18 to 24, the overall

[3] Head of household is the focus here rather than actual respondent-level demographics as The Nielsen Company uses the My Community & Lifestyle Survey primarily to collect household-level information.

age distribution for this group mirrored most closely the age distribution for the U.S. as a whole with regard to the other three age groups. There were no statistically significant differences, however, across these two groups in terms of the proportion of Heads of Household who were Black or who were Hispanic. Compared to the U.S. population distribution, both groups somewhat over-represented Black Heads of Household, while under-representing Hispanic Heads of Household by approximately half. In sum, when looking at the unweighted characteristics of Heads of Household, neither incentive approach performed better than the other in terms of eliminating the gap with respect to differential non-response among younger homes. In terms of race and ethnicity, however, there was a tendency to over-represent Heads of Household who were Black, but under-represent those who were Hispanic.

3.3 Impact of Incentive and Mode on Survey Estimates

On Table 5, we examine the potential impact of incentive structure and survey mode on selected survey estimates. Using a logistic regression approach with controls added for the age, race and Hispanic ethnicity of the head of household, we found no significant impact from the use of either differential incentive structure. In terms of mode, the Web-only mode led to a slightly lower likelihood that a respondent would indicate owning a tablet computer.

3.4 Respondent/Non-Respondent Distribution Across Frame Indicators

In this section we examine differences in responding and non-responding sample units across several of the key sample frame variables used in the study. Ideally to minimize the potential for bias in the survey estimates, there should be minimal differences between respondents and non-respondents on critical measures. While we lack survey responses from the non-responding households, we do have frame information for all sampled units across a number of important variables used to drive the differential incentive structures tested here (the exception being age of head of household where there is a degree of missing data from some households).

Table 6 provides the mean distribution across these two types of cases for each of the sample indicators. Several patterns emerge from these data. First, for none of the five test groups was there a statistically significant difference in the distribution of respondents and non-respondents with respect to Black heads of household. In other words, differential non-response does not appear to be a potentially biasing factor with respect to Black head of household.

Second, the 3-Factor Web (only) approach (Group 4) showed the least number of differences in terms of the 7 frame indicators examined. An indicator of likely age was significantly higher among non-responding units (34.6%) than among responding units (20.9%). While there was variability across respondents and non-respondents for the other 6 frame indicators, none was statistically different. Interestingly, the similarities in the distributions for respondents and non-respondents is not likely a function of the fairly low response rate for this group, as both Group 1 and Group 5 had similar response rates, yet show a great many more statistical differences across frame indicators.

Third, the test group with the highest response rate (Group 1) also showed the greatest potential for bias due to differential non-response. There were statistically significant differences noted between respondents and non-respondents for six of the seven frame indicators examined. For the Mail with Web Follow-up 3-Factor Incentive group (Group 1), non-respondents were more likely to be located in areas that are Hispanic (12.5% vs

8.6%), have young adult renters (35.3% vs 28.5%), have somewhat lower incomes ($67,103 vs $72,257), and where on commercially available data based the percentage of Hispanic surnames is higher (11.4% vs 6.1%), the percentage of missing age data is greater (36.1% vs 22.0%), and where the average age is somewhat younger (52.1% vs 56.6%).

Fourth, the Mail with Web Follow-up Multi-Factor Incentive group (Group 2) showed similar potential biases as Group 1 across indicators for the young renter, missing age indicators, and average age. The group was more balanced across respondents and non-respondents, however, with respect to the percent Hispanic, availability of Hispanic surnames, and income.

Finally, in contrast, the Multi-Factor Incentive approach showed greater likelihood for differences between respondents and non-respondents compared to the 3-Factor approach when only the Web survey mode was used. For Group 4, four of the seven sample indicators showed significant differences between respondents and non-respondents with respect to percentage Hispanic, younger renters, income, and availability of Hispanic surname. In sum, the analysis of respondents versus non-respondents shows that while the five test groups varied considerably in their potential to introduce bias due to differential non-response, no single mode approach or incentive approach performed consistently. Considering just these results, the Web (only) 3-Factor Incentive design showed the least potential for bias, whereas the Mail with Web Follow-up 3-Factor Incentive design showed the most likelihood for bias due to differential non-response.

3.5 Incentive Cost

From an operational perspective, it is also important to examine the effects of different incentive – mode combinations on cost, at least from a cost-per incentive perspective. In this study, all incentives were pre-paid in the form of cash included in the initial recruitment mailing. Given that the total amount of incentive money spent varied somewhat across the four test groups and the response rates also varied (especially when comparing the Mail with Web Follow-up versus Web-only approaches), we find that the average amount of incentive dollars required by the project to obtain a completed interview also varied across the four test groups: test group1 = $9.00 per completed survey; test group 2 = $10.64; test group 3 = $17.56; and test group 4 = $20.35. Clearly there are also other operational cost differences across the two different mode designs, but in terms of the incentive budget the cost per complete for the Mail with Web Follow-up approach was approximately half that of the Web-only approach.

4.0 Discussion

The problem of differential non-response is one seen with many survey designs, including address-based sampling. Typically, under-representation is largest with respect to younger adults, Blacks, and Hispanics. The data collection design can have a major influence in determining the level of differential response. For instance, when sampled addresses are matched to telephone numbers, thereby facilitating telephone recruitment in conjunction with or in place of mail-based recruitment efforts, the problem of differential response can be exacerbated (see Link and Lai, 2011). Households with multiple channels of recruitment can have a greater chance of participating than those with only one. Here we tried to avoid this situation by limiting the recruitment of homes to mail attempts only. Instead, differential incentives (allocation of which were based on just three sample indicators for some test groups and the other based on multiple sample indicators for other test groups) and different modes of survey return (mail and web) and were used to try to minimize differential response while at the same time achieving as high a rate as possible. In the end, the results were mixed. If we looked simply at response rates, it's clear that the use of mail and either one of the incentive structures worked better at producing response than did use of a Web survey with the same two incentive structures. Yet, while the design included an initial mail survey with a follow-up mailing inviting non-respondents to complete the survey on the Web, in reality the Web survey contributed little in the way of response under this design. Despite the continued growth of the Internet and digital media in the U.S., when it comes to survey response the "old fashion" paper-and-pencil mail approach performed significantly better in terms of response rate than did the invitation to complete a Web survey.

Looking at the resulting characteristics of the Heads of Household for each of these test groups, however, we find that none of them performed particularly well in terms of producing a set of respondents that mirrored the U.S. population in terms of age, Black race, and Hispanic ethnicity. While there was variation across each of these variables for the different designs, in general the trend was for the designs to under-represent younger adult households and Hispanics, while over-representing older and Black households. The incentive structures themselves, however, did not appear to influence the responses obtained for the selected survey questions.

Leveraging the power of an ABS design to have complete sample frame data with respect to Census Block Group indicators and near complete (excepting age) information on some commercially available indicators, we were able to assess the potential for nonresponse bias across the test groups. Comparing the distribution for these sample frame indicators across respondents and non-respondents in each group we found that the web survey approach that leveraged the simpler 3-Factor Incentive design actually showed the lest amount of difference between respondents and non-respondents. The assumption, therefore, is that this design has the least potential for non-response bias – at least in terms of minimized differences between respondents and non-respondents. It did have a response rate half as low as the mail survey design which utilized the same incentive structure. Of note as well is that because the only return mode was Web, the approach does systematically bias the sample towards those with web access – to the degree that those with and without Web access differ significantly on measures of interest. Among the two mail designs which used different incentive structures, the response rates were statistically similar, however the Multi-Factor Incentive approach showed fewer differences between respondents and non-respondents across the sample indicators examined. This could indicate that of the two approaches, the Multi-Factor Incentive design is slightly better (equal in response rate with fewer respondent/non-respondent differences).

Future research in this area could be improved by utilizing more powerful data reduction techniques (such as CHAID techniques) to identify an optimized set of indicators to drive incentive structures. This would be most effective for on-going or repeated surveys where previous survey data could be merged with potential frame indicators to conduct the initial modeling exercise. The approach used in the research here was simply one of choosing variables which appeared to be good potential indicators for identifying the types of hard-to-reach groups being targeted.

The study also has several limits that should be noted. First, only $2 and $5 cash amounts were tested. It may be that for differential incentives to be more effective there needs to be greater differentiation in the incentive amounts used. Second, the incentives were pre-paid only. While pre-paid has been shown to be one of the more effective means of distributing cash incentives, there may be a more optimal combination of pre- and post-paid incentives that could be used (Balakrishnan et al, 1992; Warriner et al., 1996). Third, a relatively simple recruitment design was used – mail invitation only. This was done here explicitly to avoid the potential for exacerbating differential response by adding multiple recruitment modes for some respondents and single modes of contact for others. It may be that differential incentive could be effectively combined with differential recruitment methods, both to improve overall response as well as potentially minimizing the bias introduced by using more than one recruitment method with only a subset of respondents. Finally, a relatively small set of sample indicators was used here, focusing on improving response among a specific subset of respondents. A much wider array of indicators and contexts needs to be explored to identify for which sample indicators, which conditions, and which subgroups such an approach is most effective.

In sum, while there was no clear "winner" across the two incentive structures tested, the study does demonstrate how sample frame indicators can be used to drive different treatments among subgroups of a sample. The study also shows that sample frame indicators can be a powerful tool for relatively low-cost, quick turn-around non-response bias analyses. The approach allows researchers to at least "triage" a situation before determining if more extensive (and expensive) methodologies need to be employed. Testing a variety of potential factors across a range of contexts and subgroups will continue to enhance and optimize our use of address-based sample designs.

References

Amaya, Ashley, and Ned English (2011). "Using Ancillary Information to Facilitate Address-Based Sampling in Rare Populations" Paper presented at the 66th annual meeting of the American Association for Public Opinion Research, Phoenix, AZ.

Balakrishnan, P.V., S.K. Chawla, M.F. Smith, and B.P. Micholski. 1992. "Mail Survey Response Rates Using a Lottery Prize Giveaway Incentive." *Journal of Direct Marketing* 6:54-59.

Blumberg, Stephen, and Julian Luke (2009). "Reevaluating the Need for Concern Regarding Noncoverage Bias in Landline Surveys." *Journal of Public Health* 99(10): 1806 – 10.

Brehm, J. (1994). "Stubbing Our Toes for a Foot in the Door? Prior Contact, Incentives, and Survey Response". International Journal of Public Opinion Research 6: 45-63.

Burks, A. T., Link, M., Yancey, T. & Coser, N. (2010). "Comparing the Availability & Accuracy of Sample Indicators Across Two Samples: Address Based Sampling vs. Telephone," 2010 Proceedings of the American Statistical Association, Survey Research Methods Section, Alexandria, VA: American Statistical Association.

Church, A.H. (1993). Estimating the Effect of Incentives on Mail Survey Response Rates: A Meta-Analysis." Public Opinion Quarterly, 57: 62-79.

Curtin, R., Presser, S., and Singer, E. (2005). "Changes in telephone survey nonresponse over the past quarter century." *Public Opinion Quarterly*, 69: 87-98.

Daily, G., Yancey, L.T., Xiao, R., Sreckov, A, Link, M., & Shuttles, C. (2008). Transitioning to address-based sampling: Results from Nielsen's TV ratings survey pilot. Paper presented at the 63rd Annual Conference of the American Association for

Public Opinion Research, New Orleans, LA.
Dillman, D. (2007). *Mail and Internet Surveys: The Tailored Design Method* (2nd ed.). Hoboken, NJ: Wiley.
Fox, R., Crask, M., and Kim, J. (1988). "Mail survey response rate: a meta-analysis of selected techniques for inducing response." *Public Opinion Quarterly*, 52: 467-491
Kay, W., Boggess, S., Selvavel, K., and McMahon, M. (2001). "The use of targeted incentives to reluctant respondents on response rate and data quality." *Proceedings of the Annual Meeting of the American Statistical Association.*
Lengacher, J., Sullivan, C., Couper, M., and Groves, R. (1995). "Once reluctant, always reluctant? Effects of differential incentives on later survey participation in a longitudinal study." *Paper presented at the Annual Conference of the American Association for Public Opinion Research*, Fort Lauderdale, Florida.
Link, M., and J. Lai. (2011). "Cell Phone-Only Households and Problems of Differential Nonresponse Using an Address Based Sampling Design." *Public Opinion Quarterly 75, 613-635.*
Link, M.W., Battaglia, M.P., Frankel, M.R., Osborn, L., & Mokdad., A.H. (2008). Comparison of address based sampling (ABS) versus random-digit dialing (RDD) for general population surveys. *Public Opinion Quarterly*.
Martinez-Ebers, Valerie. 1997. "Using Monetary Incentives with Hard-to-Reach Populations in Panel Surveys. *International Journal of Public Opinion Research* 9:77-86.
Nielsen Company. 2008, September. Local Reference Supplement 2008 - 2009: September 2009 (Client Reference Guide). Oldsmar, FL: Author.
Singer, E., J. Van Hoewyk, N. Gebler, T. Ragunathan, and K.A. McGonagle (1999). The effect of Incentives on Response Rates in Interviewer-Mediated Surveys." Journal of Official Statistics 15: 217-230.
Trussell, N., and P. Lavrakas (2004). "The Influence of Incremental Increases in Token Cash Incentives on Mail Survey Response: Is there an Optimal Amount?" Public Opinion Quarterly 68: 349-367.
Warriner, K., J Goyder, H. Gjertsen, P. Hohner, and K. McSpurren (1996). Charities, No; Lotteries, No; Cash, Yes: Main Effects and Interactions in a Canadian Incentives Experiment." Public Opinion Quarterly 60: 542-562.

Table 1. Distribution of Incentives by Test Group

	Test Group			
Incentive Metric	Mail w/ Web Follow-Up, 3-Factor Incentive (1)	Mail w Web Follow-up, Multi-Factor Incentive (2)	Web (Only), 3-Factor Incentive (3)	Web (Only), Multi-Factor Incentive (4)
$2 (%)	77.8	70.2	77.1	72.4
$5 (%)	22.2	29.8	22.9	27.6
Total Incentive Cost	$2,666	$2,894	$2,687	$2,828
(n)	1,000	1,000	1,000	1,000

Table 2 Mean Distribution of Sample Frame Indicators by Test Group and Incentive Amount

Sample Frame Indicators (Mean)	Test Group: Mail w/ Web Follow-Up, 3-Factor Incentive (1)		Mail w Web Follow-up, Multi-Factor Incentive (2)		Web (Only), 3-Factor Incentive (3)		Web (Only), Multi-Factor Incentive (4)	
	$2	$5	$2	$5	$2	$5	$2	$5
Black (%)[1]	7.9	25.4***	7.7	24.1***	6.9	27.5***	8.7	21.6***
Hispanic (%)[1]	8.9	19.6***	5.0	27.4***	8.7	17.8***	5.2	23.8***
Renters under 35yrs (%)[1]	31.1	40.7***	25.0	53.2***	31.4	40.7***	25.5	53.0***
Income ($)[1]	71,034	60,200***	77,489	44,629***	71,477	58,139***	77,145	43,423***
Hispanic Surname (%)[2]	0.0	44.1***	5.0	25.8***	0.0	38.0***	6.1	21.0***
Age Missing (%)[2]	33.9	24.8***	25.5	51.0***	47.7	24.0***	26.4	51.1***
Age (Years)[2,3]	57.5	41.7***	55.3	45.4***	58.2	37.1***	54.2	47.8***
[n]	(778)	(222)	(702)	(298)	(771)	(229)	(724)	(276)***

Note: Significance based on F-test of means comparing $2 vs $5 subgroups within each test group. * = < .05, ** = < .01, *** = < .001

[1] Census Block Group data

[2] Marketing Systems Group commercial data

[3] Excludes households with missing value for age

Table 3. Return and response Rates by Mode/Incentive Condition

Performance Metric	Test Group			
	Mail w/ Web Follow-Up, 3-Factor Incentive (1)	Mail w Web Follow-up, Multi-Factor Incentive (2)	Web (Only), 3-Factor Incentive (3)	Web (Only), Multi-Factor Incentive (4)
(n)	1,000	1,000	1,000	1,000
Completes	296	272	153	139
Response Rate[1]	30.5%	28.0%	15.8%	14.4%

[1] Response Rate = # Completed Interview / ((# Completed Interviews) + (# No Returns * .96) + (# Potential Households with Post Office Returns * .96) + (Refusals))

Table 4. Demographic Characteristics of Head of Household by Mode/Incentive Condition (Unweighted)

Demographic Characteristics Of Head of Household	Test Group					Significance[1]	
	Population Estimate	Mail w/ Web Follow-Up, 3-Factor Incentive (1)	Mail w Web Follow-up, Multi-Factor Incentive (2)	Web (Only), 3-Factor Incentive (3)	Web (Only), Multi-Factor Incentive (4)	Test Group 1 vs 2	Test Group 3 vs 4
Age						.833	.031
< 25 yrs	5.0	1.8	1.6	2.1	0.0		
25 – 34 yrs	15.8	8.9	9.3	12.1	19.7		
35- 54 yrs	38.8	35.0	38.5	46.8	35.4		
55+ yrs	40.5	54.3	50.6	39.0	44.9		
Race/Ethnicity							
Black	12.4	19.4	16.1	12.7	16.0	.332	.429
Hispanic	12.1	8.8	12.2	6.8	6.8	.193	.991
[n]		[296]	[272]	[153]	[139]		

[1]Significance based on Chi Square test.

Table 5. Impact of Incentive and Mode on Selected Survey Responses (Logistic Regression)

Incentive Structure, Survey Mode, & Head of Household Characteristics	Standardized Odds Ratio (95% C.I)				
	Satisfaction with Efforts to Increase Quality of Jobs Availability	Easy to Save for Retirement	Watch 4+ Hours of Television per Day	Own a Tablet Computer	Cell Phone Only Household[4]
Multi-Factor Incentive[1]	1.35 (.99, 1.84)	1.28 (0.90,1.83)	1.07 (0.79, 1.44)	1.24 (0.85, 1.82)	0.83 (0.59, 1.16)
Web (Only)[2]	0.79 (0.56, 1.10)	1.19 (0.82,1.73)	0.89 (0.64, 1.22)	0.65 (0.43, 0.99)	0.89 (0.62, 1.28)
Age[3]	0.99 (0.98, 1.00)	1.00 (0.98,1.01)	1.03 (1.02, 1.04)	0.97 (0.96, 0.98)	0.94 (0.93, 0.95)
Black[3]	0.87 (0.56, 1.36)	0.62 (0.35, 1.07)	1.85 (1.22, 2.80)	0.46 (0.25, 0.87)	1.12 (0.71, 1.77)
Hispanic[3]	0.73 (0.38, 1.38)	1.06 (0.52, 2.17)	0.61 (0.33, 1.13)	0.79 (0.35, 1.78)	0.83 (0.44, 1.57)
(n)	(756)	(753)	(771)	(756)	(773)

[1] Reference group: 3-Factor Incentive group

[2] Reference Group: Mail with Web Follow-up group

[3] Head of household characteristic

[4] Calculated based on responses to questions regarding landline and cell phone availability within the household.

Table 6 Mean Distribution of Respondents/Nonrespondents by Sample Frame Indicators

Sample Frame Indicators (Mean)	Test Group							
	Mail w/ Web Follow-Up, 3-Factor Incentive (1)		Mail w Web Follow-up, Multi-Factor Incentive (2)		Web (Only), 3-Factor Incentive (3)		Web (Only), Multi-Factor Incentive (4)	
	R	NR	R	NR	R	NR	R	NR
Black (%)[1]	10.2 (19.2)	12.5 (21.0)	10.9 (19.3)	13.1 (21.2)	9.8 (17.6)	11.9 (21.2)	12.1 (22.3)	12.3 (21.1)
Hispanic (%)[1]	8.6 (14.9)	12.5** (19.3)	10.0 (15.4)	12.3 (19.1)	9.1 (14.4)	11.0 (17.7)	7.0 (9.8)	10.9** (16.9)
Renters under 35yrs (%)[1]	28.5 (23.5)	35.3*** (25.2)	29.2 (22.7)	35.0** (26.7)	31.2 (24.1)	33.9 (25.4)	27.4 (22.4)	34.0** (24.7)
Income ($)[1]	72,257 (34,637)	67,103* (33,275)	68,819 (29,833)	67,277 (33,173)	70,318 (31,085)	68,072 (33,985)	80,328 (40,163)	65,821*** (30,943)
Hispanic Surname (%)[2]	6.1 (24.0)	11.4** (31.7)	9.9 (30.0)	11.7 (32.1)	7.2 (25.9)	9.0 (28.6)	5.0 (21.9)	11.0* (31.3)
Age Missing (%)[2]	22.0 (41.5)	36.1*** (48.1)	26.5 (44.2)	35.6** (47.9)	20.9 (40.8)	34.6*** (47.6)	27.3 (44.7)	34.1 (47.4)
Age (Years)[2,3]	56.6 (15.6)	52.1*** (15.8)	57.4 (14.4)	51.3*** (16.3)	52.4 (14.2)	53.1 (16.8)	53.1 (14.7)	52.8 (15.9)
[n]	[296]	[704]	[272]	[728]	[153]	[847]	[139]	[861]

Key: R = Respondents, NR = Nonrespondents

[1] Census Block Group data

[2] Marketing Systems Group commercial data

Note: Significance based on F-Test of means: * = < .05, ** < .01, *** < .001

[3] Excludes households with missing value for age.