# Changing Survey Modes: Does it Matter How You Get There?

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## 1. Introduction

Multi-mode surveys, among other strategies, have recently been offered as a solution to a decreasing willingness to respond to social and economic surveys (Groves, 2011) and as a companion to Address Based Sampling (ABS) as a method for improving population coverage (Iannacchione, Staab, & Redden, 2003; Link, Battaglia, Frankel, Osborn, & Mokdad, 2008; Williams, Montaquila, Brick, & Hagedorn, 2010; Brick, Williams, & Montaquila, 2011). Raising response rates in diverse populations improves the statistics generated from most surveys. The improvement in population coverage, however, may come at the cost of measurement error introduced by asking questions using different methods. The administration of a multi-mode survey and the underlying motivation for including it in the survey design may affect both the coverage gains made from conducting the survey by more than one method and the consequences for the measurement of key survey statistics.

Previous research has investigated the impact of multi-mode surveys on this tradeoff between improved coverage and a potential increase in measurement error. There is universal consensus that offering other modes of response either simultaneously or sequentially in reaction to non-response improves response rates, but may or may not impact measurement (Dillman, et al., 2009; Tipping, Hope, Pickering, Erens, Roth , & Mindell, 2010; Voogt & Saris, 2005). Both the combination and sequencing of the modes as well as the nature of the questions impact the value of improved coverage at the cost of measurement error in key statistics. Mode effects remain an important challenge for sensitive questions and questions in which social desirability bias is likely to affect measurement where those surveys are mediated by an interviewer (de Leeuw, 2005).

The administration of multiple modes of data collection can occur at the initial design in order to offer more simultaneous response options. It can also occur dynamically in response to incomplete sampling frame information or as a follow up to those persons who have not responded or refused to respond to the initial mode of interview (de Leeuw, 2005; Groves & Heeringa, 2006). In ABS multi-mode designs, all cases may start in a particular mode but quickly be reassigned because of a lack of contact information. Sample cases may also be shifted to other modes as non-contact or refusals occur. To date, all research on multi-mode designs has focused on the ending mode of data collection. For ABS designs, however, the starting mode assignments and nature of the subsequent re-assignments may substantially and differentially affect the composition of the respondent population who end up in each mode. This will, then, impact the calculation of mode effects given the sequencing of modes and the routes by which respondents arrive there can be quite different. Both response rates and measurement will be affected by this sequencing. The confounding of selection and measurement effects in an assessment of the impact mode may have on key survey statistics may be even larger in these instances (Vannieuwenhuyze, Loosveldt, & Molenberghs, 2010). Different types of potential respondents will follow each mode progression.

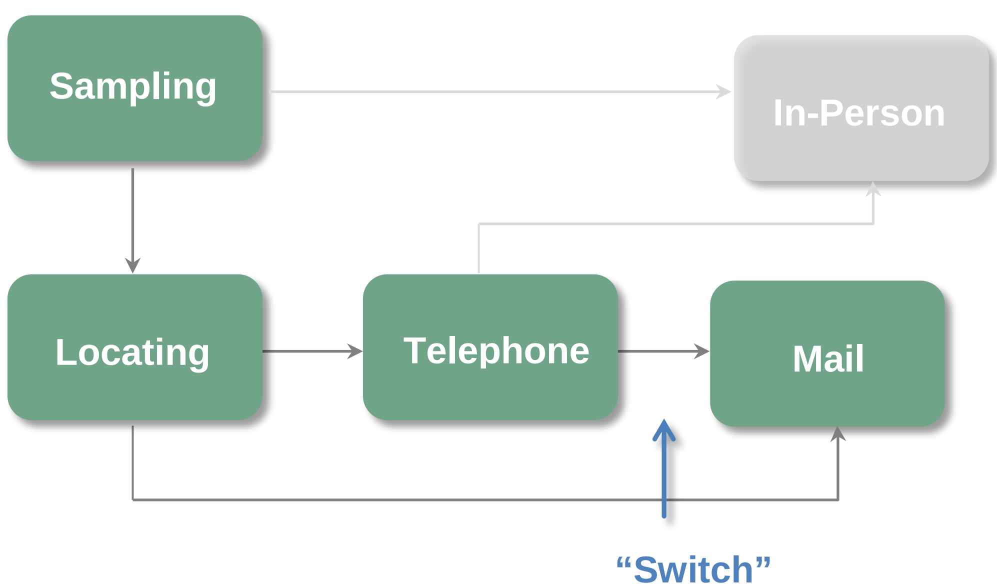
In this paper, we use questionnaire and paradata from Phase 3 of the Racial and Ethnic Approaches to Community Health across the U.S. (REACH U.S.) Risk Factor Survey, a multi-mode ABS study conducted in 28 communities in 2011, to compare the impact of initial mode assignment and mode switching on response rates and measurement error in key survey statistics. We are interested in whether initial assignments to mail or telephone modes based on available contact information has a different impact on survey performance and measurement than the subsequent reassignment from one mode to another. We examine yield and eligibility rates as well as item non-response across modes and conduct multivariate analyses of key items from the questionnaire that are likely to be sensitive to mode, including self-reported height and weight, smoking behavior, and consumption of fruits and vegetables.

## 2. Background

The REACH U.S. Risk Factor Survey (RFS) is sponsored by the Centers for Disease Control and Prevention in 28 communities across the U.S. as part of an effort to understand and eliminate health disparities among racial and ethnic minority populations. Each of the 28 REACH communities has one or more specific racial or ethnic target groups. An address-based, multi-mode design was chosen for this survey as it offers the potential for gains in coverage and response, especially among the harder-to-reach target groups of this study. However, such a design also increases the potential for measurement error due to mode effects. The current analysis is an effort to evaluate the potential mode effects and their sources. In particular, we are interested in determining whether differences in questionnaire response data across modes are due to the composition of the group responding via that mode (selection effects), or whether those differences are due to the mode in which the survey is conducted (measurement effects). The REACH U.S. RFS was conducted in four rounds. We use data from Phase 3, which was conducted in 2011.

As implemented by NORC, the study is a complex multi-mode (telephone, mail, and in-person) survey with sequential mode switching. There are five possible "paths" through the three modes for any given household, depending on available contact information and the responsiveness of the household. Figure 1 illustrates the survey design and possible mode movement. In contrast to previous analyses of mode effects, this analysis categorizes cases based on the path followed, rather than the final mode alone. That is, we consider separately cases that begin and complete via mail and cases that begin in telephone but complete via mail.

**Figure 1: Mode Movement in REACH U.S. Risk Factor Survey**



The design begins with an ABS frame based on the U.S. Postal Service Delivery Sequence File (DSF) and attempts to match all addresses to telephone numbers. Where the address can be matched by a vendor to a telephone number, the household is contacted first by telephone. Where an address cannot be matched to a telephone number, the household is attempted by mail. Thus, based on full contact information (the USPS address and telephone match), we assign households to an initial contact mode of telephone or mail. Households that cannot be reached by telephone (due to refusals, incorrect telephone numbers, or other reasons) are "switched" from telephone to mail mode. These "switch" cases are of particular interest even though the final mode assignment is mail. They are initially contacted by telephone and, therefore, may be different as a group than the households that are initially contacted by mail and either complete by mail or terminate.

## 3. Data and Methods

This analysis has four parts. First, using questionnaire response data and survey paradata from the Phase 3 REACH U.S. RFS, we compare household characteristics and survey paradata from eligible households across three paths of mode movement: cases started and completed in mail ("mail only"), cases started and completed by telephone ("telephone only"), and cases that switched from telephone to mail ("switch"). For this comparison we use questionnaire data to generate household demographic characteristics (size, race/ethnicity, and income) and survey paradata to compare contacts made and the length of time spent in each mode. Then, we examine bivariate differences in survey response and item non-response across the three mode progressions as a means of identifying differences in data quality and survey efficiency. Because this survey is focused on health behaviors and risk factors, our third step is to model multivariate estimates of three health behavior measures: self-reported obesity, current smoking, and daily fruit and vegetable consumption across these three mode progressions using logistic regression. We add controls sequentially to the logistic models to separate out group composition from measurement effects for the three health outcomes. Finally, we explore the characteristics and behaviors of those households and respondents who make the progression from one survey mode to another to assess the degree of heterogeneity introduced by this survey design choice.

The design of the REACH U.S. survey allows for two or more eligible household members to be selected to complete the main health interview. In this analysis, to prevent the introduction of bias, the analysis of household characteristics across modes is limited to households with at least one eligible and selected female member. We, thus, avoid the bias associated with analyzing more than one person per household. The analysis of key health estimates uses data from one randomly-selected female within those households. Furthermore, although a third mode of data collection (in-person) was employed, only 2 of the 28 communities were included in the in-person data collection efforts, and households in those communities did not receive a mail survey. Therefore, this analysis will consider only the communities in which telephone and mail data collection was employed.

## 4. Analysis

### 4.1 Description of Case Progression

Approximately 21,000 households in the REACH U.S. sample were included in the analysis. All of these households completed the screener interview which rosters all adult household members. Not all of these households went on to complete the main interview. As seen in **Table 1**, mail only cases account for 40% of this sample, while 26% are telephone-only and one-third of households switch from telephone to mail. The switch group is composed of slightly more black and fewer Asian households than either the mail only or telephone group. Household size and the proportion of households with income under $25,000 were similar across groups, although income was slightly lower for mail only than for the other two groups. Overall, the composition of the groups by mode progression is heterogeneous, but households for which a telephone number cannot be matched to an address (mail only) are slightly more likely to be black and lower-income than households with telephone number matches.

Survey paradata summarizing contact made with the household is also included in Table 1. Telephone only cases received nearly twice as many dials and were fielded in telephone for almost twice as long as cases that switched to mail. This difference is due to the fact that the switch group is composed of non-responsive, non-working, and incorrectly matched telephone cases that were moved to mail, rather than continuing to be attempted via telephone. Similarly, the average number of days to return the self-administered questionnaire (SAQ) was slightly lower for the switch group, possibly due to the fact that the switch group, unlike the mail only group are more likely to have a landline telephone and thus to represent a more established, older, more educated population, which may manifest itself in slightly faster returns for survey booklets.

**Table 1: Household Characteristics and Contact Paradata Across 3 Mode Progressions**

| | Mail | Switch | Telephone | Overall |
|---|---|---|---|---|
| Total Cases | 8,510 | 5,551 | 7,006 | 21,067 |
| Percent of Total | 40.4% | 33.3% | 26.4% | -- |
| Average Number of Adult HH Members | 2.09 | 2.17 | 2.12 | 2.11 |
| Black HH* | 39.0% | 46.1% | 39.0% | 39.8% |
| Latino HH* | 30.4% | 32.9% | 31.8% | 31.3% |
| Asian/Pacific Islander HH* | 23.3% | 15.3% | 24.7% | 21.5% |
| American Indian HH* | 10.1% | 7.4% | 6.5% | 9.7% |
| Percent with household income under $25,000** | 46.5% | 50.0% | 49.4% | 47.3% |
| Average Call Count | -- | 9.9 | 19.9 | 15.5 |
| Average Days in Telephone | -- | 37.9 | 60.5 | 50.5 |
| Average Days to Return SAQ | 32.1 | 28.3 | -- | 30.6 |

This analysis includes all households with at least one eligible female.
* Households with at least one Black/Latino/API/American Indian household member
** Self-reported income; highest income reported if more than one member responded

**4.2 Survey Efficiency and Data Quality**

One potential effect of conducting a survey in multiple modes is that response rates and data quality may vary across cases completed by mail and telephone. To address this, we consider whether the response and eligibility rates differed across the three groups, and compare data quality, as measured by item non-response for selected questionnaire items, across the three groups. **Table 2** summarizes these differences.

The resolution rate for the telephone group, defined as the percentage of all addresses that are determined to be households or non-residential, is much higher than the corresponding return rate, defined as the percentage of resolved mail cases, residential or non-residential, reported for the mail and switch modes. This is an artifact of the analytic groups, as cases that do not resolve in telephone are moved to the "switch" group. Although most cases that could not be resolved by telephone were then switched to mail, some may not have switched modes for operational reasons, particularly later in the data collection period. In contrast, the mail "return" rate requires the survey booklets to be returned completed by the household or as undeliverable through the USPS. Because telephone cases are contacted multiple times over the course of the study whereas mail cases receive only one set of survey booklets, the likelihood of reaching a "resolved" but not complete status is by definition higher for telephone than mail cases. This difference, then, is largely an artifact of the mode and rate calculation. Notably, however, the eligibility rates are lowest in the mail sample (56.7%) and highest in the switch group (62.8%). This suggests that had the mode progression not occurred, we would have missed a large fraction of eligible households.

**Table 2: Results and Data Quality**

| | **Mail** | **Switch** | **Telephone** |
|---|---|---|---|
| Return rate (resolution rate) | 34.9% | 36.9% | 69.7% |
| Eligibility rate | 56.7% | 62.8% | 58.4% |
| **Item non-response (selected)** | | **Percent missing*** | |
| General health | 1.19% | 2.00%** | 0.85% |
| Physical health | 2.29% | 3.38%** | 4.78% |
| Mental health | 2.22% | 3.15%** | 3.70% |
| Time since last physical exam | 1.74% | 2.30%** | 1.18% |
| Physical activity | 5.46% | 6.68%** | 0.15% |
| Pneumonia vaccine | 3.03% | 3.68% | 9.93% |
| Influenza vaccine | 0.89% | 1.08% | 0.33% |
| Vegetable consumption | 7.13% | 8.52%** | 2.13% |
| Household income | 17.34% | 17.38% | 10.13% |
| Height/weight | 3.47% | 4.88%** | 7.03% |

Item non-response reported only for questions asked of all respondents.
*Missing responses include "Don't Know" and "Refused" (telephone only).
** Difference between mail and switch rates is statistically significant ($p \leq 0.05$).

Patterns of item non-response are similar between the mail only and switch groups, as respondents in both of these groups ultimately completed a self-administered questionnaire. For several items, respondents who switched modes had slightly higher levels of non-response, notably, for questions about general, physical, and mental health; physical activity; time since last physical exam; vegetable consumption; and height/weight. This may suggest that respondents in the switch group are somewhat less cooperative, which might be expected as some of these households may have been initially unresponsive via telephone. Item non-response in the telephone group did not generally follow the same pattern as either of the other groups.

**4.3 Key Health Indicators**

The next step in this analysis is to model differences in key health indicators across the three modes to begin to identify the types of selection and mode effects present. The REACH U.S. Risk Factor Survey focuses on health behaviors and risk factors. It is, therefore, important to determine whether questionnaire data on these outcomes are affected by the sequential multi-mode design. Three health indicators were chosen for this analysis: obesity prevalence (BMI≥30 calculated from self-reported height and weight), smoking status (current smokers), and fruit and vegetable consumption (respondents reporting consuming three or more servings per day). Several models were generated for each of these indicators, with a stepwise inclusion of control variables for demographic factors. Including these demographic factors (race/ethnicity, education, employment, age, national origin, and native language) separately is an initial step to isolate selection effects from measurement effects.

**Table 3: Predictors of Self-Reported Obesity (BMI≥30)**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| **Telephone** | **0.95**** | **0.95**** | **0.91**** | **0.93**** |
| **"Switch"** | **1.09**** | **1.09**** | **1.08**** | **1.09**** |
| Hispanic | | 0.70** | 0.67 | 0.83** |
| Multi-race | | 0.50** | 0.50** | 0.59** |
| Asian/Pacific Islander | | 0.38** | 0.37** | 0.49** |
| Some college | | | 0.77** | 0.72** |
| High school degree | | | 0.92** | 0.87 |
| Out of the workforce | | | | 1.05 |
| Unemployed | | | | 1.21** |
| Age | | | | 1.02 |
| Born in U.S. | | | | 1.48** |
| Non-English speaker | | | | 0.87 |

Logistic regressions, based on data for one eligible female in each household.
All models include dummy variables for the communities.
** = $p \leq 0.05$ Odds ratios reported.

Using logistic regression, odds ratios were generated for a series of models predicting the outcomes indicated. Because we selected 26 of the REACH U.S. communities, dummy variables for the communities are also included in the model to control for potential unmeasured community-level effects. Tables 3 through 5 indicate that there are significant differences in the predicted health behaviors among the three mode groups. For each model, the mail only mode progression group is used as the reference. **Table 3** indicates that respondents who switch from telephone to mail report higher rates of obesity than those who begin in mail. Respondents who complete by phone are less likely to report being obese than those who complete via mail. This effect is significant across all model specifications, even when controlling for demographic factors such as race, education, and employment status. Self-reported weight usually suffers from under-reporting (especially among women) and it is clear that when an interviewer is present there is additional underreporting (Stommel & Schoenborn, 2009). This analysis suggests that those persons who end up completing the survey by mail, although the household is initially contacted by phone, are more likely to report being obese than those persons who begin in mail and stay there.

**Table 4** presents models for current smoking status. For individuals who begin in telephone and complete interviews there, the results are robust across all model specifications and suggest that respondents completing by telephone are less likely to report being current smokers than those who complete by mail. There are no significant differences between the mail only and the telephone-to-mail "switch" group.

**Table 4: Predictors of Smoking Status (Current Smoker)**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| **Telephone** | **0.78**** | **0.79**** | **0.73**** | **0.80**** |
| **"Switch"** | **0.98** | **0.98** | **0.95** | **0.99** |
| Hispanic | | 0.43** | 0.39** | 0.71** |
| Multi-race | | 0.98** | 0.99** | 1.36** |
| Asian/Pacific Islander | | 0.60 | 0.61 | 1.00 |
| Some college | | | 0.54** | 0.39** |
| High school degree | | | 0.74 | 0.58 |
| Out of the workforce | | | | 1.02** |
| Unemployed | | | | 1.89** |
| Age | | | | 0.99** |
| Born in U.S. | | | | 2.45** |
| Non-English speaker | | | | 0.47 |

Logistic regressions, based on data for one eligible female in each household.
All models include dummy variables for the communities.
** = $p \leq 0.05$ Odds ratios reported.

Finally, **Table 5** shows the likelihood of consuming three or more servings of fruits and vegetables per day. As with the smoking status, there are significant differences between the telephone-only and mail only groups, but not between the switch and mail only groups. Those completing by telephone were significantly more likely to report eating three or more servings of fruits and vegetables per day than those completing by mail. However, this effect does not persist across all models, and when all controls are included, the relationship is no longer statistically significant.

**Table 5: Predictors of Fruit and Vegetable Consumption (3+ servings per day)**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| **Telephone** | **1.12**** | **1.12**** | **1.14**** | **1.08** |
| **“Switch”** | **1.06** | **1.06** | **1.06** | **1.04** |
| Hispanic | | 0.93 | 0.94 | 0.87 |
| Multi-race | | 0.91 | 0.9 | 0.82 |
| Asian/Pacific Islander | | 0.92 | 0.9 | 0.75 |
| Some college | | | 1.13** | 1.38** |
| High school degree | | | 0.85** | 1.05** |
| Out of the workforce | | | | 1.25** |
| Unemployed | | | | 1.08 |
| Age | | | | 1.01** |
| Born in U.S. | | | | 0.74** |
| Non-English speaker | | | | 1.09 |

Logistic regressions, based on data for one eligible female in each household.
All models include dummy variables for the communities.
** = $p \leq 0.05$ Odds ratios reported.

### 4.4 Characteristics of Mode “Switchers”

Households and respondents are reassigned from telephone to mail for reasons that can be divided into four categories: refusal, incorrect address or disconnected number, no contact, and “grid out.” Definitions and frequencies of each of these categories can be found in **Table 6.** The most common reason for switching from telephone to mail is that no contact could be made by telephone, followed by households in which a potential respondent refused at least once and households where the phone number provided by the vendor did not match the address of the respondent or where the telephone was disconnected on more than one call attempt.

To determine whether there are key differences among respondents who were switched from telephone to mail, we then analyze two of the three key health behaviors that had robust mode effect in the previous analyses by the reason for switching modes. The goal is to determine whether the various reasons for switching modes are related to responses to key health indicators. We analyze obesity prevalence and smoking status across the four groups of mode switch cases (refusal, wrong address/disconnect, no contact, and grid out) using logistic regression.

**Table 6: Reason for Switching from Telephone to Mail**

| Reason | Definition | Frequency | Percent |
|---|---|---|---|
| **Refusal** | More than one refusal* | 1,550 | 27.92% |
| **Incorrect Address / Disconnect** | Respondent indicated address does not match or more than one disconnect | 1,529 | 27.54% |
| **No Contact** | No human contact ever made | 1,821 | 32.80% |
| **Grid Out** | Contact made at least once, but not able to be resolved by phone | 651 | 11.73% |
| **TOTAL** | | 5,551 | |

*Refusal group excludes cases with incorrect address or multiple disconnects

As **Table 7** indicates, there are robust differences for obesity and smoking status among respondents who are switched to mail. For both models, the reference group is those cases that "grid out," that is, move to mail because the household could not be resolved after initial contact was made. Those who complete by mail because no contact could be established report lower rates of obesity than those that are lost after initial contact. Persons who respond by mail because their phones are disconnected or do not match the vendor-provided address were much more likely to be a current smoker than those that are lost after initial contact.

**Table 7: Predictors of Key Health Behaviors by Reason for Switching Modes**

| Variable | Self-Reported Obesity | Current Smoker |
|---|---|---|
| **Wrong Address/ Disconnect** | **1.12** | **1.36**** |
| **No Contact** | **0.86**** | **1.02** |
| **Refusal** | **1.04** | **0.95** |
| Hispanic | 0.77** | 0.87 |
| Multi-race | 0.46 | 1.34 |
| Asian Pacific Islander | 0.31** | 1.33 |
| Some college | 0.73** | 0.43** |
| High school degree | 0.95 | 0.55 |
| Out of the workforce | 1.02 | 1.00** |
| Unemployed | 1.00 | 1.93** |
| Age | 1.00 | 1.00 |
| Born in U.S. | 1.40** | 2.71** |
| Non-English speaker | 0.79 | 0.41** |

Logistic regressions, based on data for one eligible female in each household.
All models include dummy variables for the communities.
** = $p \leq 0.05$ Odds ratios reported.

## 5. Conclusions

These analyses demonstrate that complex, sequential multi-mode surveys generate heterogeneous populations in the various modes of data collection. In particular, comparing respondents who are contacted only by mail with those who are initially contacted by telephone indicates that potentially different populations are being reached. Those who are initially contacted by telephone are less likely to respond to certain questionnaire items. They are more likely to report being obese, even when controlling for other factors such as education and employment. Therefore, it is not clear whether the forces that create selection into a mode switch (i.e., refusal or a change in telephone status) are the only factors responsible for reporting differences. We do find robust mode effects for self-reported weight and current smoking status in the expected direction for persons interviewed on the phone when compared to those who completed by mail. Finally, there appear to be differences in key health indicators among cases that were switched from telephone to mail, which may be related to the reason for switching modes.

Further exploration is needed into the characteristics of cases that are moved or switched from telephone to mail, to determine how they differ from the populations that complete by telephone or mail only. The analysis as presented is not able to separate out true mode effects from the selection effects into each mode group completely. Propensity modeling may help determine whether any of the mode effects demonstrated here are indeed “pure” mode effects, or whether they can be attributed to selection bias related to the factors assigning the cases to the initial mode. The complex and dynamic multi-mode designs that are vital to bolstering the efficiency of ABS sampling frames may then suffer from more than a tradeoff between non-response and measurement error.

Integrated and automated methods of collecting data have allowed survey practitioners to alter designs in situ. The triumph of an ABS multi-mode survey design is that it allows for both initial assignment to mode based on complete sample information and a subsequent re-assignment of cases to a mode when the first mode is not successful. The consequences of these responsive design choices, however, may be that we reach populations previously ignored by single mode or multi-mode surveys with a single point of re-assignment. As noted by others who use responsive survey design (Axinn, Link, & Groves, 2011), this can have profound impacts on our understanding of health-related behavior.

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