Response Rates & Non-Response Bias in ECA Survey Work

Bureau of Educational and Cultural Affairs
Evaluation Division

INTRODUCTION

Nonresponse bias is defined as a correlation between one or more survey variables and propensity to respond (Wolf 2016). It is based on the recognition of important differences between those who respond to a survey and those who do not, such that the results from those who respond present a distorted picture of what one is trying to measure.

For any research that relies on a voluntary response to the research inquiry, nonresponse bias can become a consuming issue, reducing confidence in results (see discussion in Peytchev 2002). If only half of those who receive a survey respond to it, the researcher may be forever wondering what was captured and whether those views and experiences represent a valid slice of the population.

Nonresponse bias is a consideration in all survey distribution methods, whether census-based (i.e. sent to the entire population in question) or a random sample. A sample approach, for example, might involve sending the survey to a careful and representative random sample of 20 percent of a given population. But if only one-quarter of that 20 percent respond, it may obliterate the representativeness, because the response may contain a disproportionate number of individuals with certain characteristics—e.g. those who take a favorable view of the program under evaluation.

Relevance to Evaluation Work in ECA

Evaluation at ECA relies heavily on survey research, distributed on a voluntary basis, with responses generally unincentivized. We rely on the goodwill of alumni, colleagues, and others to return these inquiries, which in turn supplies data that become the foundation of ECA evaluation efforts.

Like all similar survey research, the response rates achieved are variable, most falling within the wide range of 25-75 percent. These results depend quite obviously on multiple factors, such as the proximity in time of the survey's population engagement with ECA. A current survey of alumnae of one ECA program, for example, focused primarily on the last six years and achieved a 62 percent response rate; while another recent survey of a longer-term ECA program, stretching back 12 years, achieved only an 18 percent response rate. The nature and intensity of the population's engagement is another factor. Program alumni, for example, tend to respond more readily than host family populations, who were not beneficiaries of the program per se and were engaged for a much shorter term.

The fact that ECA engages with populations of diverse backgrounds and country contexts may heighten the salience of nonresponse and potential nonresponse bias. The variability of this bias is well-documented in the literature (e.g. Lyness & Brumit Kropf 2007), with some non-U.S. contexts and demographic variables clearly associated with lower response rates.

Key Principles of Nonresponse Bias

Non-response is not in itself the problem, but can be the basis for a problem.

Nonresponse does not always mean nonresponse bias. Low response rates indicate that the potential for nonresponse bias is increased, but cannot predict the presence of bias in survey estimates (Peytchev 2002). This is because any given fraction of a target population can in fact be well-balanced in terms of representing the total population—though researchers cannot rely on this assumption.

Many studies have been conducted to determine the prevalence of nonresponse bias within survey data. For example, Meiklejohn et al. (2012) examined the non-response bias in a random alcohol use survey with a response rate of 49.5 percent. Their study relied on self-reported alcohol consumption, acknowledging that responses could be impacted by recall errors and intentional falsification common in surveys targeting socially unacceptable behavior. They concluded that selective non-response can bias survey results even when response rates are not particularly low.

There is no minimum response rate to aim for in all surveys.

There is no response threshold beyond which nonresponse bias can be dismissed. It is a problem for which there is no simple, cross-cutting answer, due to the variable and unpredictable nature of the bias (see discussion in Groves 2006). A study can achieve 80 percent response and still have a significant problem, if the non-responding 20 percent have high levels of key characteristics linked to the study's outcomes. Conversely, a study can achieve 15 percent response with no significant bias, if that 15 percent is a true cross-section of the total population—a scenario quite conceivable under some circumstances.

Some researchers have endeavored to set benchmarks through meta-analysis, though the results are more reflective of standards of peer-reviewed research practice than a proven remedy against bias. Baruch & Holtom's (2008) meta-analysis identified 52.7 percent as the mean response rate among published, peer-reviewed survey research targeting individuals, with a standard deviation of 21.2. They recommended that, for surveys with a response rate outside of one standard deviation of the average, researchers explain the variance.

The only proven way to reduce non-response bias is to raise the response rate.

If 100 percent of the respondent pool responds, there are no nonrespondents to potentially bias results. By extension, the best and, indeed, only way to mediate nonresponse bias to is take steps to ensure the highest response rate possible (see Hager et al. 2003). Though a variety of methods have been tried (e.g. Heffetz & Reeves 2019), the research concurs that there is no fix for nonresponse bias beyond maximizing response rates.

OPPORTUNITIES TO INCREASE RESPONSE RATES

Pragmatic strategies for increasing response rates will differ based on the survey environment, including variables such as population demographics, time restrictions, and capacity. Common approaches for increasing response rates include altering the survey invitation, opting for an alternative administration method, and offering incentives.

Survey Invitation

Often the first point of contact, the survey invitation, provides an opportunity to increase response rates at low cost and with minimal effort. Research has shown that subtle adjustments in the invitation design can produce significant improvements in response.

Elements

Effort estimates, URL placement, and nudges in the survey invitation have all been shown to elevate response rates. Including accurate time estimates for survey completion can minimize perceived effort, reduce respondent fatigue, and increase retention rates (Trouteaud 2004). Effort estimates should be a range and reflect the average time rather than the maximum completion time. URL links should be placed at the bottom of the invitation (Kaplowitz et al. 2012). Nudges come in the form of the presence of authority, a plea for help, and a sense of community. Recipients are more likely to respond to surveys that are sent from a person in a position of authority (Groves et al. 1992). Including a plea for help and framing survey participation as an opportunity for civic engagement have also been successful in increasing response rates (Trouteaud 2004; Groves et al. 2000).

Invitation Mode

Cost per valid response and response rate are the primary variables that guide decisions on invitation mode. While invitations for web surveys are frequently sent via email, emailed invitations can be missed or deemed fraudulent by recipients. Inviting potential participants to respond via an alternative method can prime them to receive the survey.

Opting for an alternative invitation mode, such as a postcard, can increase response rates at a low cost. Kaplowitz et al.'s (2004) U.S.-based study found that the cost per response of sending a postcard invitation prior to sending out the web survey was less than that of email alone.

Alternative invitation modes present an opportunity to increase response rates but may face logistic difficulties. For invitations sent via mail, the ECA Evaluation Division would need addresses for all potential survey respondents as well as viable mail-delivery systems, which do not exist in many contexts outside of the U.S. where most ECA survey respondents live.

Administration Mode

Four common administration modes for surveying have emerged over the last century: in-person, telephone, mail, and web. Surveys can be self-administered (e.g. mail and web), interviewer-administered (e.g. in-person or telephone), or administered via mixed-mode.

Interviewer-Administered

In-person surveys yield the highest response rates compared to other common administration modes (Baruch & Holtom 2008). However, participants may respond with satisficing answers to avoid discussing sensitive topics or to move through the survey faster, as Holbrook et al. (2014) concluded.

Surveys administered via telephone have the second-highest response rate but have several disadvantages (Garcia et al. 2014). Similar to in-person surveys, participants may use satisficing techniques that limit the reliability of the data. The uptick in scam calls and the expanding telemarketing industry make it difficult to reach participants, forcing interviewers to devote time to potential participants with minimal return (Tourangeau 2004).

Generally speaking, surveys administered by interviewers offer minimal privacy and have more expensive inputs than self-administered modes (Couper 2011; Greenlaw & Brown-Welty 2009). With limited privacy, participants may be wary of communicating accurate information. In addition to the cost of interviewers themselves, interviews have to be scheduled, which presents logistic issues for targeted populations that are in different time zones or are not in close proximity to one another.

Self-Administered

Surveys completed without interviewer interference, also called self-administered surveys, can reduce costs and effort of administration, allowing participants to complete surveys on their own schedule

(Couper 2011). While self-administered surveys offer a high level of privacy, they are also susceptible to incomplete, incorrect, or inattentive responses.

Response rates for mail surveys are greater than rates for web surveys but still fall short of response rates offered by interviewer-administered methods (Baruch & Holtom 2008). Mail surveys require more consumable and labor inputs than web surveys; the cost per response may limit its potential as an administration mode per Greenlaw & Brown-Welty's (2009) analysis of response cost and administration mode. Moreover, addresses are needed for all potential respondents.

Web surveys are a relatively new survey method but have grown in popularity because of their cost-efficiency and speed. Gathering data on a large sample is considerably less expensive and faster compared to other modes, but web surveys yield the lowest response rates (Couper 2011; Baruch & Holtom 2008). Tourangeau (2004) recommends giving consideration to computer literacy and Internet access among the population when opting to use a web survey. WhatsApp, a popular messaging service used across the globe, may prove valuable in reaching respondents in other countries. However, no literature has been published on its effectiveness in relation to other administration modes, presumably because many researchers have yet to adopt the service as an administration method.

Mixed-Mode

Mixed-mode administration can reduce nonresponse across heterogeneous populations. Offering a sole method can bias survey results (e.g. some groups within a population may be more likely to respond to a web survey, leading to a higher nonresponse rate among groups who prefer an alternate method—see Introduction in de Leeuw 2018). However, mixed-mode administration operates under the assumption that data collected via different methods are comparable.

For the ECA Evaluation Division's purposes, web surveys offer a low-cost method of reaching large populations. If increasing response rates is a priority, researchers can employ a mixed-mode administration, first sending a web survey to all potential participants and following-up with nonrespondents via mail, for instance. Using two methods within the self-administered category limits the bias of mixed-mode administration and allows the researchers to take advantage of both the low cost per response of web surveys and the higher response rates of mail surveys. While its impact on response rates is still in question, WhatsApp may prove useful for reaching respondents outside of the United States. Qualtrics, ECA's survey platform, has recently integrated WhatsApp into their survey platform (Qualtrics, 2020); this feature will allow the ECA Evaluation Division to build WhatsApp into its existing survey methods.

Incentives

By invoking a sense of reciprocity in potential participants, incentives prompt response through offering material or nonmaterial goods. Incentives can be unconditional and offered to all potential respondents pre-survey independent of response, or they can be conditional and only offered to respondents who complete the survey.

Incentives have varied efficacy. Göritz's (2006) meta-analyses found that monetary incentives like money or gift cards significantly increase response rates compared to nonmonetary incentives (e.g. consumable goods) and nonmaterial goods (e.g. digital goods or social capital). Unconditional incentives yield a larger boost in response rates compared to conditional incentives (Sánchez-Fernández et al. 2010). Though survey researchers have considered the potential bias introduced by incentives, Sánchez-Fernández et al. (2010) concluded that neither incentive type significantly affected response quality.

While monetary incentives will increase survey costs, they have consistently been shown to increase response rates at a higher rate than any other method. With other forms of incentives offering inconclusive results, the cost of providing a nonmonetary incentive to survey participants may be cost-prohibitive. The ECA Evaluation Division should consider the total cost of providing the incentive—including the feasibility of delivering incentives through the survey invitation and administration modes—and weigh the costs against the value of increased response rates.

ASSESSING NONRESPONSE BIAS

Regardless of any strategies to reduce bias, once a survey has been rolled out, how do we determine whether non-response bias is a factor in our data?

Declining response rates and survey fatigue have prompted researchers to explore options for assessing nonresponse bias post-survey through nonresponse bias analysis. For the audience of the survey results, including nonresponse analysis preemptively addresses concerns associated with low response rates. For researchers, performing a nonresponse bias analysis allows them to build credibility with the audience and can help identify variables that may be affecting response rates.

Survey researchers have developed a range of methods to assess non-responses bias, and below we review a selection of those. Nonresponse bias analyses measure different classifications of nonresponse bias and vary in intensity of effort. We propose that, in choosing a nonresponse bias analysis, the ECA Evaluation Division will need to consider the validity of the measurement, its capacity to perform the analysis, and the feasibility of the method.

Comparison of Sample to Population

Validity: Low
Capacity Requirements: Moderate
Feasibility: Low

Several nonresponse bias assessments involve a comparison between the sample and the population, which is optimal. If the sample data do not differ from the population data, the sample is representative of the population, and nonresponse bias is not present. Types of analyses within this category include the namesake comparison of sample and population method and a priori characteristic comparison. However, both methods rely on a comparison of demographics. If demographic variables are not primary variables, the methods will not necessarily capture or assess nonresponse bias.

Most commonly, the ECA Evaluation Division takes a census approach to survey populations, rather than a sampling approach, which will rule out this method. In cases when a sample is used, the analysis requires existing data covering the entire population, to which the sample can be compared, and in many or most cases for the ECA Evaluation Division, this population data is unlikely to be present.

Comparison of Sample to External Data

Validity: Moderate

Capacity Requirements: High
Feasibility: Low

Using analyses like benchmarking and replication can provide a frame of reference for survey data and assist in identifying nonresponse bias. Benchmarking compares data to published data while replication requires researchers to duplicate the study and compare findings.

As the ECA Evaluation Division examines programs unique to ECA, benchmarking has limited applicability. Moreover, with the ECA Evaluation Division's commonly-employed census approaches, replication would require the population to be sampled twice with the same survey. While results may differ, the findings could not be attributed solely to nonresponse bias.

Within-Sample Comparison

Validity: Moderate
Capacity Requirements: Moderate
Feasibility: Moderate

Comparisons within samples rely wholly on data collected either during the pre-survey administration or during follow-up surveys within the sample. Some of these, such as the "Days to Respond" analysis, are highly practical because they require no data or inputs beyond what has already been collected in the course of the survey. Other forms, such as active and passive nonresponse analysis, call for additional surveys targeting nonrespondents within the sample. Though the validity of the assessment is weaker than other methods, within-sample analyses are generally accepted as valid measurements of nonresponse bias (Dooley & Lindner 2003).

As a best practice, Groves (2006) recommends the use of more than one type of analysis to counteract the weaknesses of each method. In the absence of circumstances that allow for comprehensive analyses that compare the sample and population, incorporating a mixed-mode assessment improves the validity of measurement (Dooley & Lindner 2003). On this basis, we review the two methods below.

"Days to Respond" Regression

The "days to respond" regression analysis is based on the assumption that early respondents differ from late respondents, with late respondents more closely resembling or serving as a proxy for nonrespondents (Dooley & Lindner 2003). The "Days to Respond" variable is coded as continuous and independent, while the primary variables of interest serve as the dependent variables. If the model does not reach statistical significance, this form of analysis posits that respondents and nonrespondents are unlikely to differ.[1]

For the ECA Evaluation Division, this method has an key advantage: it can be performed using existing survey data only—nothing in the way of external data or additional surveys. The regression can be performed via a statistical software package such as Stata. To illustrate how this would be applied in practice, Appendix A outlines a "Days to Respond" regression conducted on data from the Repatriation

[1] Levels of significance vary, though results <0.05 or <0.01 are common thresholds in the social sciences.

survey administered by the ECA Evaluation Division in fall 2020. Excel was used for data cleaning and Stata was used to perform the regression.

Active and Passive Nonresponse Analysis

Active and passive nonresponse analysis operates on the assumption that active nonrespondents and passive nonrespondents consequentially differ (Halbesleben & Whitman 2013). Passive nonrespondents are those who did not intentionally forgo responding. In these cases, nonrespondents may have missed the survey invitation or forgotten to respond. Active nonrespondents, on the other hand, deliberately opt out of responding. Passive nonrespondents are seen as similar to respondents, whereas active nonrespondents differ from both passive nonrespondents and respondents. There is not always a sole reason for active nonresponse, but the causes pose a great risk for nonresponse bias.

Passive nonrespondents can be reduced by sending out targeted follow-up messages. Noting a dearth of research on the optimal number of reminder messages and interval between messages, Sánchez-Fernández, Muñoz-Leiva, & Montoro-Ríos's 2012 study concluded that no more than three messages, including opening invitation and final notification, should be sent. Finding that the timing of reminders did not impact the retention rate, they recommend using the time constraints of the survey to guide decisions on scheduling reminders. Suggested times range between one to two weeks, but researchers can monitor response rates after a follow-up to inform the timing for future reminders.

For active nonresponse analysis, researchers can survey a sample of the population, assess their intent to respond, and gather information on reasons for nonresponse. If the percent of active nonrespondents from the survey is high, it indicates that nonresponse bias is a concern. Halbesleben & Whitman (2013) suggest that if more than 15% of respondents to the survey are active nonrespondents, nonresponse bias is significant in the data. This approach provides both an assessment of the level of active nonresponse and reasons for nonresponse, which can assist researchers in improving response rates in future survey research.

Within the ECA Evaluation Division, conducting an active and a passive nonresponse analysis could provide data on the level of active nonresponse among respondents. Using Halbesleben & Whitman's (2013) metric, the threat of nonresponse bias is minimal if 15% or less of nonrespondents are active. To mitigate costs and effort associated with this method, the analysis can be carried out once per survey rather than each time the survey is administered. As the ECA Evaluation Division maintains a survey library, the results of the analysis can inform future survey administration and provide a frame of reference for assessing nonresponse bias.

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Appendix A - "Days to Respond" Regression for Repatriation Survey

Responses for questions that measured primary dependent variables were multiple-choice options using Likert scales, which provide ordinal-level variables without an exact distance established between options (Berman 2002). The primary variables and their corresponding survey questions are provided in Table A1. While it is understood that "excellent" ranks higher than "very good," the distances between the options can be varied. Two types of Likert scales, a satisfaction variation and an agreement variation, were used. Table A2 and Table A3 outline the two scales (coded 1, 2, 3, 4, 5) and relevant variables.

Table A1: Primary Dependent Variables and Corresponding Survey Question

Variable	Question
ECA COVID-19 Task Force Performance	The overall performance of the ECA COVID-19 Task Force was ____________.
Department Coronavirus Global Response Coordination Unit (CGRCU) Performance	The overall performance of the Department Coronavirus Global Response Coordination Unit (CGRCU) was ____________.
ECA Response to Repatriating Exchange Participants	Overall, how would you rate ECA's response to repatriating exchange participants?
COVID-19 Repatriations Efforts Impact on ECA Crisis Response	The repatriation efforts related to COVID-19 will help ECA be more prepared for crisis management and response in the future.

Table A2: Satisfaction Likert Scale

Option	Numerical Equivalent	Variables
Excellent	5	ECA COVID-19 Task Force Performance Department Coronavirus Global Response Coordination Unit (CGRCU) Performance ECA Response to Repatriating Exchange Participants
Very Good	4	
Good	3	
Fair	2	
Poor	1	

Table A3: Agreement Likert Scale

Option	Numerical Equivalent	Variables
Strongly Agree	5	COVID-19 Repatriations Efforts Impact on ECA Crisis Response
Agree	4	

Neutral	3	
Disagree	2	
Strongly Disagree	1	

Blank responses and responses of "I don't know" were not coded in the Likert scales as they do not align with the ordinal patterns established by the satisfaction and agreement variations.

As the Likert scales are coded as ordinal-level dependent variables, ordered logistic regression can be conducted through a statistical software package such as Stata or SPSS to determine statistical significance (Berman 2002).

Conducting an Ordered Logistic Regression

Cleaning Survey Data

1. Open an Excel workbook with survey data.
2. Use the filter tool for the column labeled "Finished" to only show rows for "False." Delete all the rows with "False" responses, leaving only the responses of participants who completed the survey, then clear the filter.
3. Delete all columns outside of End Date and columns that provide data on primary variables. Column A should be labeled "End Date."
4. Rename remaining columns to abbreviations of variables associated with each question (e.g. "COVIDTF" for "ECA COVID-19 Task Force Performance" or "CGRCU" for "Department Coronavirus Global Response Coordination Unit (CGRCU) Performance").
5. Delete Row 1. Your top row should now be the abbreviated variables.
6. Create a new sheet called "Distribution Date" and type in the date of survey distribution in Cell A1.
7. Insert a new column into the sheet to the right of the End Date column.
8. Insert the following formula into the first cell under the header cell in the End Date Column: =DAYS(A2,'Distribution Date'!A1)
9. Click and drag the formula to fill the entire column.
10. Insert a new column to the right of Column B. Copy the data in Column B and paste the data as values only (Paste Special → Values). Label this column "DaysToRespond."
11. Select the "DaysToRespond" column and change the format to Number. Use the Decrease Decimal button to display a whole number.
12. Delete Column B, leaving only the columns labeled "End Date," "DaysToRespond," and the columns displaying data for your primary variables.

13. Use the Find and Replace option to replace the Likert data with their numerical equivalent listed in Table A1 and Table A2.
14. Select all columns with dependent primary data and change the format to Number. Use the Decrease Decimal button to display a whole number.
15. To preserve the original data set, save the Excel workbook with an alternate title such as "Repatriation Survey - Stata."
16. For the column of the variable being tested, use the filter tool to show only "I don't know" and blank responses. Delete all rows showing these values, then clear the filter.
    NOTE: This may delete valid responses from other variables of interest. If the Stata test will involve more than one variable, it is recommended to Save As and then complete Steps 15 and 16 for each variable with the Excel workbook created in Step 14.
17. Save the Excel workbook with a notation on the variable of interest (i.e. Repatriation Survey - Stata - COVIDTF).

Figure A1 provides a visual reference for the final product for the COVIDTF variable.

Figure A1: Cleaned Excel Sheet for COVIDTF Variable

	A	B	C
1	StartDate	DaysToRespond	COVIDTF
2	9/24/20 10:29	0	5
3	9/25/20 12:22	1	3
4	9/25/20 12:25	1	5
5	9/25/20 12:29	1	5
6	9/25/20 12:30	1	5
7	9/25/20 12:30	1	5
8	9/25/20 12:27	1	5
9	9/25/20 12:33	1	2
10	9/25/20 12:43	1	5
11	9/25/20 12:52	1	5
12	9/25/20 13:02	1	5
13	9/25/20 13:06	1	5
14	9/25/20 13:10	1	5
15	9/25/20 13:21	1	3
16	9/25/20 13:23	1	5
17	9/25/20 13:17	1	5

Importing Data into Stata

1. Open Stata.
2. Select File → Import → Excel spreadsheet. Choose the Excel file with the cleaned survey data.
3. Select the option to import the first row as variable names.
4. Conduct an ordered logistic regression by typing the following into the Command window: ologit <dependentvariable> <independentvariable> and hitting the Enter key. For example, with an independent variable of DaysToRespond, for the ologit COVIDTF DaysToRespond

Determining Statistical Significance

Statistical significance provides the probability of an assumption that a relationship exists between an independent and dependent variable when a relationship doesn't exist. Standards for statistical significance vary from a minimum of 5 percent to a more rigorous 1 percent, allowing for a 5 percent or 1 percent chance of incorrectly stating a relationship in the absence of one (Berman 2002). The level of statistical significance is up to the discretion of the researcher.

Figure A2 shows the Stata output for the COVIDTF variable. The p-value under P < chi2 provides the probability of observing the same or a more extreme difference in repeated studies if there is no relationship between the independent and dependent variables (Andrade 2019). For a level of statistical significance equal to 5 percent, if no relationship exists, then there is a 5 percent chance that the outcome is attributable to chance alone. Consequently, a lower p-value is preferred, as it limits the probability that observed results are the result of random chance.

For the COVIDTF variable, the p-value shown in Figure A2 is 0.3397, meaning there is an approximately 34 percent probability that the results are due to chance. This p-value indicates that there is no relationship between responses to the COVIDTF question and the number of days it took for a participant to respond.