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Factors Affecting Response Propensity, with an Interest in Units Sampled Multiple Times

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Abstract

As the need for data has grown over the past number of years, the effect and burden of repeatedly sampling the same units for multiple surveys have become an increasing concern. Response burden is generally assumed to contribute to decreasing response rates; however, there are few empirical studies looking into this question. As part of this study, data on response to social surveys conducted at Statistics Canada between 2021 and 2023 was aggregated in order to investigate factors contributing to the observed response patterns, including the effect of having been selected multiple times. It was found that, relative to some other demographic and geographic characteristics, a unit being sampled multiple times is not an influential factor in predicting response propensity.

Key Words: Response burden; Response rates; Non-response.

1. Introduction

For many years, there has been a decreasing trend in response rates to social surveys at Statistics Canada. At the same time, the number of surveys being conducted has increased, and sample sizes have grown over time. It is often assumed that the burden of being repeatedly asked to respond to surveys is a contributor to these decreasing response rates (Yan and Williams, 2022). Statistics Canada has implemented measures to attempt to manage this burden ahead of time, usually through the use of exclusions of units who have been previously sampled for a survey within a certain period of time. However, this can present issues if a survey is targeting certain small sub-populations of interest, for example, households with children in small provinces or other population groups. In this situation, if the sampled units are subsequently excluded from a general population survey due to burden concerns, there is a risk of underrepresentation of these groups and a potential of bias in the general population survey due to the exclusions if the distinguishing characteristics of the excluded units are related to the survey's parameter of interest. This effect is heightened when small sub-populations are repeatedly targeted for surveys. Understanding the degree to which repeated sampling may contribute to decreased response rates is therefore of interest since it can help guide decisions related to how response burden is managed given the associated risk of bias.

The study presented here looks at response rates among units selected for multiple Statistics Canada surveys. Similar work was carried out by Sinibaldi and Karlsson (2017) who looked at individuals selected for at least two surveys and focused on examining the relationship between rest period (that is, the time between the initial and subsequent selection for the same or a different survey) and response rates. Their study was based on data for 10,605 twice-sampled individuals for 5 household surveys over a 12-year period. Comparatively, this current work examines a larger number of social surveys with greater sample sizes; the large amount of data provides a high level of analytical richness, including being able to look at the effect of multiple selection on response and include units selected a greater number of times.

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2. Data Preparation

To proceed with this analysis, three data sources were linked at the dwelling-level: a manually maintained file used by most of Statistics Canada's social surveys to track and manage response burden, paradata from collection management systems, and a file containing additional demographic and geographic characteristics for individual dwellings that is part of Statistics Canada's dwelling frame. This data was linked at the dwelling-level since that is the unit used for the coordination of samples for social surveys at Statistics Canada. The resulting file contained data for 3,257,270 unique survey selections in 2,980,207 dwellings for 23 different social survey programs at Statistics Canada from 2021 to 2023 inclusively. This data was restricted to dwellings in Canada's 10 provinces. Importantly, this file contained a variable that indicates whether a dwelling responded to each selection. Additional meta-variables related to a given selection and previous or subsequent selections were also added to the file. Examples of these meta-variables include rest period, which selection a given record represents (that is, the dwelling's first chronological instance of selection on the file, the second, etc.), and whether the dwelling responded to the previous survey for which they were selected.

In practice, the process of building this file was not as straightforward as hoped for. There were several surveys whose data on the manually updated burden file was incomplete, resulting in the exclusion of a few surveys from the final file. It was also common to encounter issues where the formats of unique identifiers differed slightly between sources, which required a manual and time-consuming investigation and resolution process. Finally, it was possible for certain dwellings to have missing information across different variables. When there was a successful linkage, this was resolved by attempting to use information from the other source to fill in the gaps. These challenges highlight the advantages to setting up interoperable systems, as doing so can facilitate the type of analysis carried out here.

3. Analysis

3.1 Sampling Levels and Distribution

As a foundation for analysis, it is useful to get a sense of what the burden situation looks like across Canada. Table 3.1-1 shows the distribution of individual survey selections compared to dwelling counts for each province in Canada, followed by the ratio of these counts (in effect, an average sampling fraction). This gives a sense of how much burden is imposed on dwellings in each province and the degree to which this varies by province compared to the global Canadian ratio of 0.2. The three territories in northern Canada, which account for approximately 0.3% of the dwellings in Canada, were excluded from this analysis since linking dwelling-level sample information in these areas is particularly challenging and because these areas face unique challenges related to response burden.

Table 3.1-1
Number of survey selections compared to dwelling counts by province

Province	Survey Selections (2021-2023)		Dwellings (2021)		Ratio of Counts
	Count	Percent	Count	Percent	
Newfoundland and Labrador	152,591	5.1%	269,184	1.7%	0.57
Prince Edward Island	115,238	3.9%	74,934	0.5%	1.54
Nova Scotia	199,882	6.7%	476,007	2.9%	0.42
New Brunswick	199,444	6.7%	366,146	2.3%	0.54
Québec	580,197	19.5%	4,050,164	24.9%	0.14
Ontario	807,208	27.1%	5,929,250	36.5%	0.14
Manitoba	229,054	7.7%	571,528	3.5%	0.40
Saskatchewan	218,249	7.3%	513,725	3.2%	0.42
Alberta	353,518	11.9%	1,772,670	10.9%	0.20
British Columbia	401,889	13.5%	2,211,694	13.6%	0.18
Canada	**3,257,270**	**100%**	**16,235,302**	**100%**	**0.20**

Provinces with a smaller population are over-sampled compared to more populated provinces. This is the case because, despite the fact that Canadian provinces vary substantially in size, survey data is required to be precise enough at the provincial level in order to support policy decisions on portfolios that are managed at the provincial level. Over the three-year period covered by this data, the number of sample selections in the six provinces with a population dwelling count of less than one million is equal to approximately 49% of the number of dwellings. By comparison, in the remaining four provinces with a population dwelling count of over one million, the number of sample selections is equal to approximately 15% of the total dwelling count. This issue is especially pronounced in the least populated province, Prince Edward Island, where the 74,934 dwellings were sampled just over one-and-a-half times on average in three years. Moreover, the distribution of sample selections is unlikely to be uniform among the dwellings within the provinces themselves. Even within the less-populated provinces, some dwellings were never sampled, while others were sampled more than once. Often the dwellings sampled multiple times were part of a population group of interest (for example, households with children), which further exacerbates the burden issues within these groups. It also drives the potential for bias in subsequent surveys selected among the remaining less-sampled dwellings if this difference is not accounted for.

3.2 Response Rates by Instance of Selection

When looking at response rates across surveys at Statistics Canada, it is important to consider the profile of social surveys and the factors that make different surveys unique. Table 3.2-1 highlights four different surveys carried out between 2021 and 2023 that represent this landscape well. The results in subsequent tables are presented for these surveys in particular.

Table 3.2-1
Summary of select social surveys at Statistics Canada conducted between 2021 and 2023

Survey Name	Survey Length	Sample Size	Mandatory	Collection Effort	Response Rate
Labour Force Survey	Panel survey over six iterations	Large	Yes	High	77.4%
National Travel Survey	Short	Very large	No	Low	31.1%
Canadian Community Health Survey	Long	Medium	No	Medium	52.8%
Canadian Social Survey	Medium	Medium	No	Medium	50.4%

Table 3.2-2 focuses on dwellings selected at least twice. Each column compares the response rates of dwellings whose first selection was for a given survey to those whose second selection for that survey. While it is possible for dwellings to be selected twice for the same survey, it is far more common for the dwellings in the table to have been selected for two different surveys due to within-survey sample coordination.

Table 3.2-2
Response rates among dwellings selected at least twice, by instance of selection

Instance of selection	Metric	Survey			
		Labour Force Survey	National Travel Survey	Canadian Community Health Survey	Canadian Social Survey
1	Number of dwellings	9,905	162,039	7,547	10,598
	Response rate	81.9%	27.1%	58.5%	44.6%
2	Number of dwellings	54,999	118,182	31,599	22,031
	Response rate	81.3%	25.8%	54.6%	49.4%

The dwellings selected at least twice do not have the same characteristics as the sample overall; they are more likely to be in less-populated provinces and to be in groups that are sampled more frequently, such as households with children. As a result, in order to investigate whether the instance of selection has an impact, it is important to restrict the analysis to the group of dwellings selected at least twice as done in Table 3.2-2. Indeed, there are generally larger differences between the response rates in Table 3.2-2 and the global response rates provided in Table 3.2-1, than by instance of selection within a survey. This reflects the different composition of the groups on which the response rates are calculated.

Within the group of dwellings selected at least twice, there is little evidence that being selected for a given survey as a second instance (that is, after already being selected for a first survey) has an effect on their likeliness to respond. There was a slight decrease in response rates between dwellings selected for the Labour Force Survey first and those selected for it second. For the National Travel Survey and Canadian Community Health Survey, there were slightly larger (but still small) decreases in response rates for dwellings selected first and those selected twice. However, response rates increase between those selected for the Canadian Social Survey on their first and second selections. Table 3.2-3 extends this to look at dwellings selected at least three times and compares response rates for these same surveys on first, second and third instances of selection.

Table 3.2-3
Response rates among dwellings selected at least three times, by instance of selection

Instance of selection	Metric	Survey			
		Labour Force Survey	National Travel Survey	Canadian Community Health Survey	Canadian Social Survey
1	Number of dwellings	351	13,961	136	617
	Response rate	81.8%	21.9%	61%	33.7%
2	Number of dwellings	2,703	19,949	1,203	2,910
	Response rate	81.6%	21.8%	59.4%	45.5%
3	Number of dwellings	5,858	11,214	1,944	2,523
	Response rate	81.2%	22.8%	51%	43.8%

For dwellings selected at least three times, the story is similar to what is seen in Table 3.2-2 in that there is no consistent trend across these surveys that shows a decrease in response rates on increasing instances of selection. It is therefore natural to consider an alternative approach that accounts for additional factors that may influence the likeliness to respond, beyond the number of times a dwelling is selected.

3.3 Logistic Regression

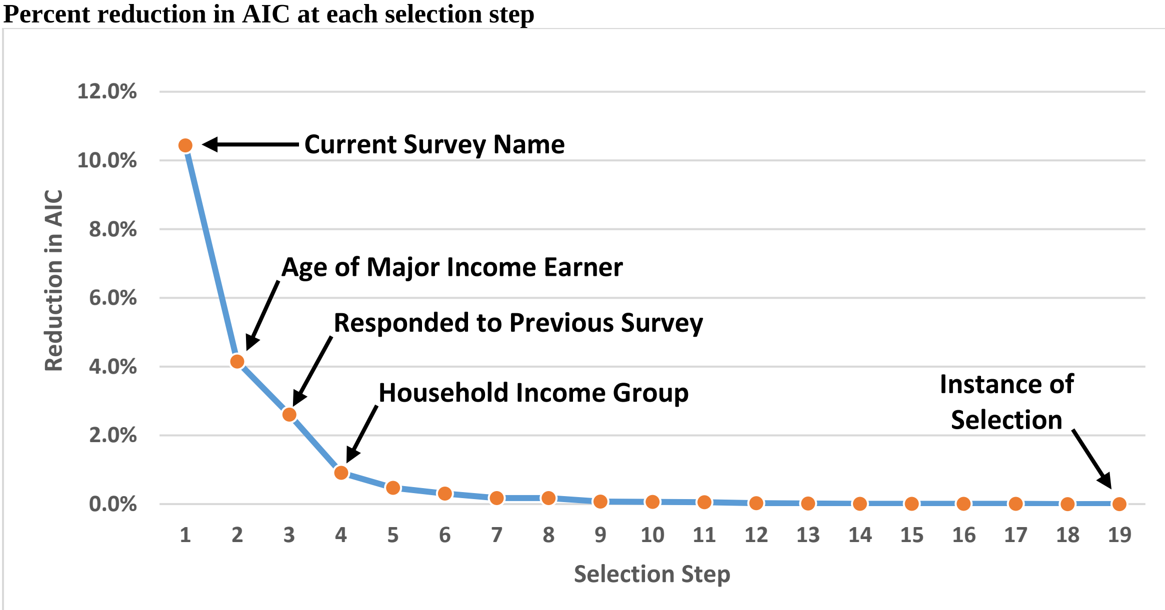
In order to determine which factors influence response propensity and the relative importance of these factors, a logistic regression model was built to predict response among dwellings selected at least twice. Logistic regression was chosen due to the categorical nature of the variables, and because it is commonly used to predict response propensity in social surveys. Multiple sets of auxiliary variables were examined with the goal of finding a single model that best accounted for interaction between variables, as well as the response rate and sample size differences between surveys. There were different collinearity challenges introduced when working with some of these models, though the conclusions drawn were similar across all models compared. To help focus on key conclusions, the model featured in this work is the simplest one. The dataset used as input for this model contained 698,444 records, representing individual survey selections for dwellings selected at least twice. The variables in the model can broadly be categorized into variables related to survey selection and geographic and demographic variables. Table 3.3-1 provides a list of these variables and the p-value associated with the Chi-square statistic for each of these variables as predictors of response.

Table 3.3-1
P-value associated with the Chi-square statistic for model variables

Variable	P-value	Variable	P-value
Current survey name	<0.0001	Province	<0.0001
Instance of selection	<0.0001	Building type	<0.0001
Year of selection	<0.0001	Community size/metropolitan influence	<0.0001
Quarter of selection	<0.0001	Household size	<0.0001
Season of selection	<0.0001	Household income group	<0.0001
Previous survey name	<0.0001	Household type	<0.0001
Same survey flag	<0.0001	Age group of major income earner	<0.0001
Responded to previous survey flag	<0.0001	Sex of major income earner	<0.0001
Refused previous survey flag	<0.0001	Language of major income earner	<0.0001
Rest period (6-month periods)	<0.0001		

All variables have a p-value of less than 0.0001, which is not surprising given the large number of observations used to build the model. To understand the relative importance of these variables, an approach not based on the p-value was used. The Akaike Information Criterion (AIC) can be used to evaluate model fit for a given dataset. The formula for AIC is *2k-2(log-likelihood)*, where *k* is the number of parameters in the model. The addition of the constant *2k* penalizes complexity, and a common test for significance when comparing two models applied to the same data is to compare the associated AIC values. If the AIC for a model with one additional predictor is more than two units lower than the base model then this model is a better fit for the data and explains more variation, despite the increased variance caused by an increase in complexity. To obtain AIC values associated with the burden data, the same logistic regression model was generated in SAS using a stepwise variable selection algorithm based on the AIC. The AIC provides insight into the relative significance of variables at each step. Figure 3.3-1 shows the percent reduction in AIC between each step of the variable selection algorithm.

Figure 3.3-1
Percent reduction in AIC at each selection step



Most of the reduction in AIC is accounted for by the addition of the first four variables: the current survey the dwelling is selected for, the age group of the major income earner in the selected household, whether the dwelling responded to the previous survey they were selected for, and the household income group of the selected household. These four variables account for 17.2% of the reduction, with all remaining variables further reducing the AIC by only 1.4%. Notably, the instance that a dwelling was selected was entered into the model last, and of the chosen variables, provided the lowest reduction in AIC. This variable does not provide much more information to the model once all other variables are accounted for, and most of the predictive power of the model comes from a relatively small number of variables. This is coherent with the findings in tables 3.3-2 and 3.3-3, which suggests that selection for a previous survey does not have an operationally measurable impact on the response rates to subsequent surveys.

4. Conclusion

Building sample designs that reflect the experiences of diverse populations is a complex process that may require the oversampling of specific subgroups. It involves the balancing of survey objectives together with ethical considerations and practical constraints. In this context, sample coordination rules can lead to subgroups oversampled elsewhere being underrepresented on general population surveys and is therefore one of the factors that must be balanced as part of the sample design process.

This investigation suggests that relaxing coordination rules would not have a large impact on response rates. Whether examining response rates or the output of a logistic regression model, a dwelling being sampled multiple times does not appear to be an influential factor in predicting response, relative to other demographic characteristics and meta-information on survey selection. This suggests that it could be possible to relax exclusion rules for previously selected dwellings, in particular rules related to the number of times a dwelling has been selected and the time between these selections, without further decreasing response rates. This is therefore an avenue that will be explored at Statistics Canada.

Nevertheless, response rates are not the only reason for managing response burden. From a practical perspective, selecting the same dwelling for two surveys that are being collected at the same time is confusing and difficult to manage operationally. Moreover, given the time and effort being requested of survey respondents, it is more equitable to ensure that sample selection is not overly concentrated on a subgroup of the population, be that by design or by random selection, as long as any impact on representativity can be managed. Sample coordination will therefore remain necessary even if it can be relaxed. Since the analysis presented here was carried out under sample coordination rules that limited multiple selections, the consequences of using eased sample coordination rules will be reevaluated with additional data when future surveys have undergone collection using more relaxed rules.

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