Part I

COVERAGE

Introduction to Part I

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I.1 Coverage bias in online panels

From a survey methodology point of view, coverage bias for online panels is a result of an inequality in Internet access (*undercoverage*) for some segments of the population. The concept of coverage is related to the target population for whom we want to generalize our results. In many cases, it is the general population; in some cases, it is the online population only. In the two of the three chapters in this Part, the online panels discussed have the goal of generalizing their survey findings to the general population, and therefore, are comprised of online and offline households and individuals.

When the primary mode[1] of completing a survey is via an online panel on the Web, it is important to assess which individuals are excluded or have less of a chance to join the panel. Although Internet access is growingly rapidly in many countries, with very few exceptions (e.g., the Netherlands has nearly 100% access), most do not have all of their general population online (International Telecommunication Union, 2013). This gap between those with and without access and the resulting inequalities is called the *digital divide*. Internet access alone is not the only determining factor in online panel membership. How often one goes online, from where (home versus other venues) the Internet is accessed, and a person's skills in using the Internet are other key factors in terms of likelihood of joining an online panel. These inequalities in Internet skills and usage (Brandtzæg, Heim, & Karahasanović, 2011) are part of what is called the *second-level divide* (Hargittai, 2002).

Findings from the literature on the digital divide tell us that when looking just at access, the offline population has specific characteristics generally correlated with low income, low education, and other socio-demographics that are country-specific (Ragnedda & Muschert, 2013). For example, Callegaro (2013) compared the digital divide in the United States using

[1] This is not the case when Internet access is provided to non-Internet households by the panel company, as we explain later.

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data from File (2012) to that of the United Kingdom by looking at Internet access from home. Using a logistic regression model that predicts access from home and controls for demographic variables, File concluded that the non-Internet population in the United States tended to be female, older, non-white, of lower income, and living in the South. In contrast, Callegaro showed how gender and race were not a factor in the United Kingdom when controlling for other demographic characteristics. The non-Internet population tended to be older, of lower social class, and living in Northern Ireland.

As to the second level divide, the literature reveals that a substantial percentage of those with Internet access are low-frequency users, i.e., going online only two or three times a week or less. In addition, Zillien and Marr (2013) found that Internet skills play a substantial role in determining Internet usage and frequency.

When we connect the findings from the digital divide literature to coverage bias in survey methodology, we realize how the digital divide and the second-level divide can help us understand who can and cannot participate in online panel research.

In building an online panel, the issue of coverage error is handled differently depending on the type of panel. Nonprobability online panels do not provide Internet access to non-Internet respondents, nor do they survey them in another mode. In other words, almost by definition and due to the recruiting methods (see Chapter 1), nonprobability online panels do not have non-Internet users and, as we see in Chapter 2, have very few low-frequency Internet users.

In probability-based online panels built to produce surveys with results that are representative of the overall population of a specific country, coverage bias is approached in one of four ways (e.g. DiSogra & Callegaro, 2010):

1. Give everybody who is being recruited (Internet or non-Internet households) the same device and an Internet connection. For example, give each household a tablet with Internet connection.

2. Give a device and an Internet connection to non-Internet households. For example, give them a desktop or laptop computer and pay for their Internet connection.

3. Survey the non-Internet population and/or very infrequent Internet users in another mode, such as by mail or by telephone.

4. Do not recruit the non-Internet population by design and attempt to compensate for their absence using weighting techniques.

Each of these design decisions has non-trivial costs associated with them in terms of recruiting, management, and survey implementation, not to mention the issue of representativity of the general population.

I.2 The chapters in Part I

The chapters in Part I present three different probability-based panels (based in Germany, Finland, and the United States) and how the issue of coverage bias was dealt with in each.

In Chapter 3, Bella Struminskaya, Lars Kaczmirek, Ines Schaurer, and Wolfgang Bandilla present the GESIS Online Panel Pilot, a pilot study conducted in Germany to build a probability-based panel. The panel was built using random digit dialing with a dual-frame sampling design of cell and landline numbers. Because of the pilot nature of the study and also budget considerations, persons who did not use the Internet were excluded in the recruitment. The study's approach to bias is therefore an example of design 4 although the chapter focuses on the Internet population only, and does not attempt to compensate for their lack of non-Internet households. In this chapter, the authors assess the quality of the data coming from the online panel in comparison to external benchmarks. Struminskaya et al. present a great discussion of the difficulties in comparing data from an online panel to external benchmarks. Scholars and researchers attempting to do so face many challenges, namely, locating high quality studies and official statistics benchmarks and dealing with issues of weighting, question-wording, and potential mode effects. In this specific case, the authors had to focus on the comparison between their panel and benchmarks to the Internet population only (given that non-Internet households were not recruited by design). Second, they had to locate benchmark studies where question(s) about Internet access and use were asked in order to restrict the findings to the online population. Then, even the official high-quality surveys needed to be weighted to account for nonresponse and sampling design. Lastly, the authors had to deal with a relatively small sample size (747 cases) available for their data analysis.

Data collected in the GESIS Online Panel are compared and contrasted with two high-response-rate gold standard surveys: the German General Social Survey (ALLBUS) and the German dataset of the European Social Survey (ESS). When comparing point estimates, the authors find differences between the GESIS Online Panel and the benchmarks, although of few percentage points for most variables. When comparing regression models coefficients across sources, the direction of the coefficients is almost always the same. The authors conclude that the data collected by the GESIS online panel are fairly comparable with the two benchmarks.

Chapter 4 by Kimmo Grönlund and Kim Strandberg presents a comparison of results from a probability-based panel in Finland with two surveys conducted at the same time: one a telephone survey and the other a face-to-face survey. Finland is a country with a very high Internet penetration, estimated at 89% at a person level at the time of the study (International Telecommunication Union, 2013). The panel was built in conjunction with the parliamentary election of 2011, and thus the analysis and topic of the surveys are political in nature. The panel was recruited using the Finnish population registry, which contains addresses, names, gender, year of birth, and other information. We remind the reader that in the survey world, it is a luxury to have such a sampling frame. Most countries do not have a population-based registry. The panel was recruited via a mail invitation, and no other survey mode was offered for the offline population. This chapter presents another example of design 4. The mail recruitment yielded a cumulative recruitment rate of 5.3% with a total sample size of 692 people who joined the panel at wave 1. The panel lasted for three months of data collection with an overall attrition rate of 25% at the last wave. When comparing the point estimates of the online panel with the two benchmarks, the authors' findings reproduce the results of other research looking at online panels and political surveys (Malhotra & Krosnick, 2007). For example, younger panelists were under-represented. That is definitely a nonresponse issue more than a coverage issue, as young adults tend to be almost entirely online. Online panelists were also more interested in politics, more likely to have voted in the past election, and heavier Internet users in comparison to the two benchmarks. Interestingly, demographic weighting helped in the right direction but did not fully bring the point estimates in line with the benchmarks.

This Finnish experience reminds the reader how, even in an ideal situation with a great sampling frame, actually building a high-response/low-attrition rate panel is definitely challenging and requires many resources and a great deal of panel management.

The German and Finnish studies are two examples of how to compare data collected from a probability-based panel to known benchmarks, attempting to keep everything else constant. On the other hand, in Chapter 5, by Allan McCutcheon, Kumar Rao, and Olena Kaminska a different issue is presented: the effects of varying recruitment methods on attrition rates in the US Gallup Panel. The Gallup Panel's approach to coverage bias is an example of design 3. Members were recruited via RDD, and non-Internet households or low-frequency Internet users were assigned to participate via mail surveys. Of particular interest is the fact that the Gallup Panel attempted to recruit every eligible member of the selected household. This study is a follow-up attrition analysis of an experiment varying recruitment modes (mail versus RDD) advance letters, a prepaid monetary incentive ($2), and a phone follow-up (Rao, Kaminska, & McCutcheon, 2010). An examination of the demographics of recruited members by mode reveals that the mail mode elicited a sample composition more likely to be non-white, lower-educated, and of lower income than their counterpart recruited by telephone.

By looking at a time span of about three years in terms of attrition rates, the authors find that the combination of recruitment by mail and assigning non-Internet/low-frequency-user households to mail surveys produced the highest attrition rate of the entire panel. Overall, the phone-recruited panel members retired at a lower rate than those recruited by mail. The entire picture is, however, not complete because these attrition comparisons do not take into account the initial recruitment mode which, as we just reported, elicited a different sample composition in terms of demographics. However, with the use of survival analysis, the authors are able to control for all these factors. This chapter is therefore a good example of the complexities of studying attrition in an online panel and of how numerous variables can have an effect on the overall attrition rates. When looking at recruitment mode by incentive and controlling for everything else, the authors find that mail-recruited respondents tended to leave the panel at a higher rate than their phone-recruited counterparts. The effect of the incentive was practically non-significant. When looking at the effect of mode of recruitment by assignment (Web versus mail surveys), then the distinction among the four groups is even stronger: mail-recruited/mail-assigned respondents had the highest and sharpest attrition rate. Then attrition is less for phone-recruited/mail-assigned respondents, followed by the mail-recruited/Web-assigned group, and lastly for phone-recruited/Web-assigned group, which had the lowest attrition rate. Even when controlling for demographics, the overall findings show how difficult is to retain non-Internet or low-frequency Internet user households even if they are asked to complete the survey via mail.

Finally, the authors perform a unique analysis of within-household attrition that shows a domino effect, i.e., family members tended to leave the panel together more or less as a unit. This chapter presents a rare investigation of attrition in an online (and offline) panel and makes us (survey methodologists) think about the effect that different strategies for recruiting and surveying panel members have on: (1) the initial composition of the panel in terms of demographics; and (2) the overall attrition rates. We hope more studies like this will follow.

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