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WHO DO YOU KNOW: IMPROVING AND EXPLORING THE NETWORK SCALE-UP METHOD

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WHO DO YOU KNOW: IMPROVING AND EXPLORING THE NETWORK SCALE-UP METHOD

by

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The purpose of this dissertation was to examine ways to improve and explore the network scale-up method (NSUM). This dissertation improved the NSUM by proposing a new mean of sums (MoS) estimation process, improving recursive back-estimation techniques, exploring how NSUM design changes effected estimates of personal network size, what predicts having larger personal networks, and the cognitive process used by participants taking a NSUM survey. Data was collected from an address-based survey (n=617) of Nebraskans conducted in 2014 and a series of cognitive interviews (n=19) conducted in 2016.

The MoS estimator better predicted the size of a target group than the traditional estimator. Further, recursive back-estimation was shown to retain more scaling variables when used with the MoS than the traditional estimator. However, the MoS estimator did produce larger average estimates of personal network size. The application of recursive back-estimation reduced the average of both the MoS and traditional estimates of personal network size to comparable levels. Differences in the treatment of item nonresponse among NSUM scaling questions had little to no impact on the average estimate of personal network size.

Eighteen different estimates of personal network size were calculated based upon different assumptions and methodological choices for regression models. In all eighteen

models rural Nebraskans had larger networks than their urban counterparts, and those who made less than $25,000 had smaller networks than those who made between $50,000 and $99,999. In some models education, religious attendance, and age were associated with expected network size, but these associations were erratic. This shows that NSUM methodological decisions NSUM can have effects on both estimates of network size and statistical inference.

Finally, cognitive interviews revealed a series of issues around participants' ability to accurately answer NSUM questions including memory search, definition retention, and differences between the known-population technique and the summation method. A series of suggestions for practical implementation and further testing of these issues are discussed. This dissertation demonstrates new ways to adapt the NSUM without having to use the generalized NSUM and explores how participants' process NSUM style questions when developing their answers.

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CHAPTER 1: INTRODUCTION

Establishing the size of a social phenomenon is a fundamental part of any research, policy, or legislative agenda. Considerable effort is thus devoted to developing the means and methods necessary to enumerate or estimate the size of phenomena, particularly those that are hidden or hard-to-count. Knowing the size of an event, occurrence, or subpopulation is often the first step in determining how a problem should be addressed and may lead to the development of research programs or government undertakings to further address the problem or phenomena. Differences in size estimation of social phenomena, and the accuracy of those estimates, have serious implications for the allocation of resources toward programs devoted to studying and addressing phenomena. As such, size discrepancies are often hotly contested by parties that wish to see more or less resources devoted to a given issue (Burt 2007; Williams 2011). The practice of counting and estimating population sizes is thus one that is central to wide array of issues and agendas, both political and academic.

Conceptually the simplest way to obtain the size of a population is to directly count everyone who is a member of that population. Taking a census is, however, both expensive and time consuming (Kish 1965). A common alternative to a census is to take samples of the population and look at the prevalence of certain groups or statuses as indicators of their prevalence in the larger population. Such sampling techniques become more complicated when the population of interest is defined by a characteristic that makes them hard to contact (e.g. homeless) or carries stigma such they actively avoid disclosing their status (e.g. HIV-positive) (Shelley et al. 1995). For these types of groups several methods of direct estimation have been developed, such as respondent driven sampling (Heckathorn 2002) and venue based sampling (Jenness et al. 2011). These methods rely on being able to find members of a population and convince them to disclose their status to an interviewer(Heckathorn 2002a, Jenness et al. 2011). Although these methods are effective, they require more resources and time than mail or telephone surveys.

Indirect methods to estimate social phenomenon size seek to provide accurate results without directly counting the target population. One such technique that has become increasingly prominent is the network scale-up method (NSUM) (H. R. Bernard et al. 2010). The NSUM is a technique that is designed to generate estimates of a target subpopulation's size, specifically those that are small, hard-to-reach, or stigmatized. Unlike direct methods that try to contact members of the target subpopulation, the NSUM uses a random sample of the larger population. Survey respondents are asked how many people they know in the subpopulation. When respondents' counts are paired with an estimate of the respondents' personal network sizes, it becomes possible to statistically scale-up reasonable estimates of a range of hidden populations that are otherwise difficult to enumerate. This approach has been used to assess populations such as heroin users (Kadushin et al. 2006), men who have sex with men (Ezoe et al. 2012), and populations at risk for HIV/AIDS (Khounigh et al. 2014). The NSUM provides researchers, public health practitioners, and policy experts the ability to assess the scale of various social phenomena in a time frame that allows them to respond to recent events, with a minimal budget, and at a geographic or political scale that is most appropriate for the social phenomena.

Dissertation Structure

This dissertation is organized around understanding, improving, and testing the NSUM's performance under different conditions.

Chapter 2 provides an extensive review of the NSUM literature. Beginning with the method's origin in social network analysis, the chapter presents the history and development of the NSUM. Then the mechanics of how the method works and its underlying assumptions about social structure are discussed. The NSUM has been in use for over two decades and several of the assumptions and their related errors have been problematic. Different researchers have developed statistical adjustments for these errors and these approaches are discussed in relation to their data requirements. Overall, chapter 2 provides the baseline knowledge needed to understand the fundamental changes proposed by this dissertation.

Chapter 3 describes the two data collection projects upon which the dissertation is based.

Chapter 4 gives attention to the basic estimation formulas used in the NSUM. The analyses critically examine the traditional estimation formula (Benard et al. 1991; Killworth, Johnsen, et al. 1998), propose an improved formula, and tests its accuracy using benchmark data from the American Community Survey. In addition, chapter 3 explores the effects of using recursive back-estimation, and applying sampling weights to the NSUM process. Chapter 3 adds to the growing NSUM field of research by proposing a fundamental shift to how final estimates are calculated, demonstrates a way to correct for poor data, and formally introduces the use of post-estimation weights in the NSUM.

Chapter 5 of the dissertation examines how the different estimation methods proposed in chapter 4 influence the estimate of personal network size generated by the NSUM. Although the NSUM methods estimates personal network size as a means to a different end, the population distribution of personal network size is itself an important social statistic. By examining variation in network size by method, chapter 5 shows how differing methods may produce different social network sizes. Further, by looking at associations between network size and participant characteristics chapter 5 not only demonstrates which personal attributes are associated with changes in estimated network size, but whether these associations are stable across different estimation methods. In doing so, chapter 5 adds to the literature on social network size at large, and as the data is representative of Nebraskans, gives unique insight into how network size varies across a state.

Chapter 6 of the dissertation investigates how participants operationalize "knowing" someone and how they obtain their estimates when answering NSUM-type questions. Using cognitive interviewing a particular focus is paid to how respondents arrive at their final counts, how they decide that a final answer is final, how different NSUM methods are perceived by participants, and how a participant gauges the amount of information they have about the people they know. Offering additional insight into these issues may greatly influence both post-survey adjustments and future NSUM designs.

In the final chapter the major findings of this dissertation are discussed in relation to the growing NSUM field. Other research groups using the NSUM are continually evolving their methods and proposing new implementation practices. Drawing from analyses presented in this dissertation and the lessons learned while collecting the data, a set of future suggestions are developed.

CHAPTER 2: THE NETWORK SCALE-UP METHOD

A Brief History of Social Network Research

The development of the network scale-up method (NSUM) is part of the larger growth in social network research which came to prominence in the latter half of the 20th century (Freeman 2004; Prell 2012; Scott 2000). Modern social network analysis is defined as a research paradigm that is "motived by a structural intuition based on ties linking social actors, grounded in systematic empirical data, makes heavy use of graphic imagery, and relies on computational or mathematical models (Freeman 2004)." Although there are incidents of researchers employing all four of these research elements dating back to the early 1930s, there was not a concentrated disciplinary awakening of social network analysis until the 1970s, which focused around Harvard University and the work of Harrison C. White (Freeman 2004).

Conceptual forms of social network analysis can be found in the early roots of sociology. In Freeman's (2004) history of network analysis, some of the earliest written work on social interconnections is traced back to the writings of Durkheim about how individuals were organized in society (Durkheim 1964). Other notable early researchers such as Georg Simmel, Gustave Le Bon, and Marcel Mauss also published work that dealt with how individuals interact with the social structure around them (Le Bon 2009; Mauss 1967; Simmel 1950). The idea of social network analysis thus arose early in the history of sociological theory and was reawakened by methodological advancements at the end of the 20th century.

Modern social network analysis, as defined by Freeman, came about through the convergence of several fields, including: social psychology, social anthropology, sociology, and graph theoretic mathematics (Freeman 2004; Prell 2012). The convergence was a gradual process that occurred between the early 1930s and the 1960s. The work of Jacob Moreno and Helen Hall Jennings is often credited as the earliest example of modern social network analysis, which they dubbed Sociometry (Jennings 1937; Moreno 1937). During the same time considerable work was being done at Harvard University by a group of researchers headed by W. Lloyd Warner (Warner 1936). For a decade these two groups developed and researched many early network studies, largely independently of each other. However, both groups gradually dissipated and social network research was scattered to small pockets of researchers located across the globe at Lund University, Manchester University, the University of Chicago, Columbia University, Iowa State University, and Michigan State University (Freeman 2004). During this time many of the smaller groups were isolated and the forward progress of social network analysis was limited. This changed in the 1970s as an intense focus on network research developed at Harvard and a rapid coalescence of the scattered research groups occurred as they formed into larger organizations and associations such as the International Network for Social Network Analysis. This renaissance of social network research led to an influx of innovative data collection methods, analytic strategies, and the development of network theory which comprise the current state of network analysis (Freeman 2004).

The Small World, Network Size, and the NSUM

Despite its origins in sociology, many of the more remarkable advancements in network analysis emerged from cross-disciplinary partnerships. For example, mathematician Ithiel del Sola Pool and social scientist Manfred Kochen collaborated to investigate the small world problem (Pool and Kochen 1979). For over 20 years they worked to develop a theory of how the social networks of individuals interact. Their primary focus was to answer questions about the probability of two random people knowing each other, or the length of a chain of personal connections that may exist between two random people. These questions address the common phenomenon which occurs when two seemingly unrelated people realize they both know a person in common, often leading to one or both saying the phrase, “it’s a small world” and thereby naming the question Pool and Kochen tried to solve. In attempting to answer these questions the research of Pool and Kochen has proved remarkably salient to both social network analysis and sociology. They formalized both theoretical motivations and empirical techniques to measure the size of social networks, how they are bounded by social and geographic location, and what sort of structural limitations may define how individuals develop and access their networks. In doing so they set the ground for many sociological inquiries into social stratification of resources and access to power.

Social networks in a general form can be thought of as resources. For the job hunter every relationship, or tie, to another person represents an additional chance to learn about new jobs and employment opportunities (Lin and Dumin 1986). Granovetter’s theory of weak ties (Granovetter 1973) suggests that not all ties represent equal resources and that a tie which brings unique, or less redundant information, may offer more new resources. For Granovetter, it was more likely that ties which crossed out of our normal and everyday connections could be more useful for the hypothetical job searcher. That is, the close friends of the job searcher may all be familiar with the same job openings, but a more distant friend or relative may have access to an entirely new set of job possibilities due to their own set of close friends or their different geographic or social location. Understanding how ties are distributed both by geographic location, through social structures, and by individual characteristics can indicate how the ability to find a job, gain political access, or attain and access many types of power are themselves distributed across a population. These sorts of distributions of access to resources speak to the heart of sociological concern with social stratification by addressing how our social networks may vary by social and geographic location, and the extent to which a network can provide a needed resource. Social network analysis offers methodologies to quantify measures of network size, how far the network may reach from a given starting location, and placement of individuals within larger social structures.

Pool and Kochen were interested in answering the small world questions of quantifying probabilities of random people knowing each other, knowing people in common, the shortest distance between two people, and whether those two random people were aware of the paths between them (Pool and Kochen 1979). In order to address these questions they first had to measure the size of an individual's personal network, the distribution of network size in a population, what individual characteristics are associated with differing network sizes, and how network ties are stratified (Pool and Kochen 1979). Their investigation into these problems sparked considerable interest in not just estimating probabilities of contact (Korte and Milgram 1970; Travers and Milgram 1969), but also many developments in techniques to measure network size(Hill and Dunbar 2003; Killworth et al. 1990; Marsden 1990; Pollet, Roberts, and Dunbar 2011), which have in turn led to the ideas behind the NSUM itself.

Measuring network size is itself a surprisingly daunting task, and there have been several methods developed in an attempt to estimate network size, including the free recall task, contact diaries, name lists, and the name generator. The free recall task has a participant attempt to list everyone in their network. Sometimes they are provided with memory aides such as phone books, yearbooks, or email lists of friends. In such tasks it can be a challenge to correctly remember everyone in a network and research has shown that participants are more likely to forget a network contact if the tie between them is weak (Brewer 2000; Brewer and Webster 1999). It is often up the participant to decide when they should stop searching for more contacts to list in their memory when using a recall task. Terminating a memory search appears to be highly related to a participant's internal sense that their continued efforts to remember more network contacts will be met with increasing failure (Davelaar et al. 2013; Dougherty, Harbison, and Davelaar 2014; Unsworth, Brewer, and Spillers 2011).

One way to address memory issues is by asking participants to maintain contact diaries for a set period of time. Each participant lists everyone with whom they interact every day in a diary, either directly after a contact occurs or writing up summaries at the end of the day. Such a method captures everyday interactions, but has the potential to miss rare or infrequent contacts which may not occur during the time when the participant has the diary. Contact diaries also represent a substantial burden upon the participant and impose a significant delay in obtaining data for the researcher. However, the method has been shown to work and produce reasonable estimates of personal network size (Yen, Fu, and Hwang 2016).

Another method is to provide a participant with a list of names and ask them to indicate which of those names are in their network. Phone books have been used locally as proxy samples of a local population (Freeman and Thompson 1989; Pool and Kochen 1979). However, choosing pages in a simple random fashion gives undue weight to more common names and in the modern era would miss up to 40% or 60% of the population who no longer have a listed phone number (Centers for Disease Control 2016). Lists make sense within more tightly controlled areas, such as schools, where researchers attempting to complete a full network within the school can present a list of students. However, when attempting to estimate network size in a much larger population such as the United States lists become less practical.

The standard approach to this question has become the name generator (Marin and Hampton 2007). Participants are asked to list the names of the people they know in a series of specific categories, such as ‘people they go to for help.’ By asking for those within a specific category the name generator limits some of the problems of free recall by providing a narrower range from which the participant retrieves their answers while reducing participant burden and field time from the contact diary, phonebook, or list approaches. After a participant finishes listing names they are then asked additional questions about either all, or a random subset, of the names they listed which are used to define to quantify the types of ties present between the participant and the people they listed.

Each of these different approaches to estimating personal network size is defined by the ways they parameterize the scope of a participant’s ability to recall network members: free recall, diary, list, or focused free-recall. However, network researchers also need to establish what it means to be a network member in the first place. There is evidence that personal networks are layered around the participant in a hierarchical fashion (Dunbar et al. 2015; Stiller and Dunbar 2007). The way this dissertation parameterizes what it means to be in a network may restrict our analysis to different layers. A network definition that asks only about people to whom a participant may go to for monetary support would likely produce a much smaller network than one that asks about those to whom a participant would go to for emotional support. For many larger studies, and the NSUM itself, the network boundary is focused on the limit of acquaintanceship or “knowing” someone. Here the study seeks to attain a maximal network size which retains reciprocal ties, meaning that ideally if a participant lists someone and by chance that someone was also given the same survey they would in turn list the participant. This limits the influence of popular nodes in a larger population and draws a line between knowing of someone, and knowing someone and being known in return.

For Pool and Kochen, estimating social network size was a step towards being able to calculate the probabilities of two random people knowing each other. As research progressed, the study of network size and how it varies has become an end goal of itself, as a way to measure opportunity, access to resources, and stratification (Beggs, Haines, and Hurlbert 1996; Blakeslee 2015; Hill and Dunbar 2003; Mowbray and Scott 2015; Stauder 2014). For other researchers, particularly for those interested in hard-to-reach or stigmatized populations, network size remains as a step towards other estimations (H. R. Bernard et al. 2010; Heckathorn 2002). Both respondent driven sampling (RDS) and the NSUM, tools often employed to study hard-to-reach populations, require estimates of network size to produce their final estimates. Although each produce that estimate in remarkably different ways. Given their increased use to measure health-related phenomena, there is a continuing impetus to refine how we estimate social network size, and to understand more fully the ways in which participants think and report about their social networks. Accordingly this project looks specifically at the NSUM and how its estimation of personal network size may be improved, how these improvements affect estimation and inference, and explores the cognitive demands the techniques makes upon participants.

Fundamental Technique of the NSUM

The NSUM is a technique that is designed to generate estimates of a target subpopulation's size, specifically those that are small, hard-to-reach, or stigmatized. Unlike methods that try to contact members of the target subpopulation directly, the NSUM uses a random sample of the larger population. These participants are asked how many people they know in the subpopulation, and their responses are statistically scaled-up to generate an estimated size for the subpopulation. The fundamental assumption made by this method is that on average an individual's personal network (i.e. the people they "know") will be representative of the general population (Benard et al. 1991; Johnsen et al. 1995a). That is, the proportion of people in an average individual's personal network who are members of a given subpopulation is indicative of the relative size of that subpopulation to the general population as a whole. This assumption is not without flaws, as illustrated in the discussion of error in the next section.

The fundamental technique is expressed formally in Equation 2.1, where m is the number of people known by the respondent in a given subpopulation, c is the size of the respondent's personal network, e is the size of the subgroup in the larger population, and t is the size of the larger population.

$$\frac{m}{c} = \frac{e}{t} \tag{2.1}$$

Estimating a respondent's personal network size (c) is the first challenge of the NSUM. A common approach for calculating this value is the *known population method* (McCarty et al. 2001). A respondent is asked a series of questions about how many people they know in a series of subpopulations whose size is already known to the researcher. Knowing someone is typically defined as someone whom the respondent knows by name and with whom the respondent has had some form of communication in the past two years. Common subpopulations to ask about are those with certain first names (e.g. Walter, Emily) or jobs (e.g. firefighters, airline pilots). These known populations, or "scaling" variables, can then be used to derive the personal network size of c. Equation 2.2 describes the formal process of establishing this value, where i indicates a respondent, j a scaling variable, m the reported number of people known in scaling variable j, and e is the total size of scaling variable j. In essence, the reported value of each scaling variable is summed and divided by the summed total population for the same scaling variables and then multiplied by the total population size.

$$\hat{c}_i = \frac{\sum_j m_{ij}}{\sum_j e_j} t \tag{2.2}$$

Estimating personal network size is an intermediate step of the NSUM. The next step is to determine the size of the *unknown* subpopulation e. As before, the researcher asks the respondents how many people they know who are in the target unknown subpopulation. This count, m_{ij} , is inserted into Equation 2.3 to develop an estimate of the target unknown subpopulation. The sum of the number of people known by all respondents $(0,1, \ldots i)$ in a given target subpopulation m_{ij}, is divided by the sum of all respondent's personal network size $\hat{c}$ and multiplied by the total population size t.

$$\hat{e}_j = \frac{\sum_i m_{ij}}{\sum_i \hat{c}_i} t \qquad (2.3)$$

The standard error of Equation 1.3 can be expressed as:

$$s.e.(\hat{e}) = \sqrt{\frac{\hat{e}_j}{\sum_i \hat{c}_i} t} \qquad (2.4)$$

Equation 2.3, along with its associated standard error (eq. 2.4) are thus the final product of the NSUM technique, an estimate of how many people in a given subpopulation exist in a larger population. The method is flexible in that it can be adapted to differing geographic or political boundaries so long as it is possible to obtain the total size of the population to which the researcher wishes to generalize, and there are usable known scaling variables for that population. NSUM studies may be used within the context of cities (Shati et al. 2014), regions (Guo et al. 2013), countries (Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998), or any other geographic or political unit so long as this information is available, the respondents recognize the boundaries, and they can place the people they know within or outside of those boundaries.

The Core Estimator

The heart of the NSUM is equation 2 which is used to derive the estimates of personal network size across the sample. This estimator has remained relatively unmodified since its formalization early in the NSUM literature (Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998). In this state the estimator is designed to minimize the influence of a given scaling variable by summing across the numerator and denominator before dividing the sums. Although this approach may protect from outliers, it moves away from the base assumption of NSUM that the proportion of a single group within a personal network is indicative of the proportion of that group within a larger population. This assumption is problematized by an equation which does not consider individual proportions, and instead creates an aggregate proportion. Because prior work has not addressed this mismatch between the assumptions of the method and estimation formulas, how it affects eventual outcomes is unknown. Adjusting the equation to handle the individual proportions may provide more accurate results as it more readily conforms to the assumptions of the NSUM.

Discovery of Error

The discovery of error in the NSUM framework was a gradual process over the course of many studies and the better part of a decade. Early uses of the NSUM were largely focused on whether the technique could produce reasonable outcomes and were less focused on defining specific errors in the process. The first studies were conducted to estimate the number of people who died in the 1985 Mexico City Earthquake (Benard et al. 1991), and the number of suicides, homicides, and AIDS/HIV+ cases in the U.S. (Johnsen et al. 1995a). The estimates of earthquake deaths and homicides were found to be reasonable and thus assumed to be relatively error free. However, Johnsen and colleagues (1995) discovered that their NSUM technique over-counted the number of suicides and AIDS/HIV+ victims by a factor of 1.6 and 3.7 respectively. The authors speculated that these two statuses (suicide and AIDS/HIV+) may not be disclosed within a person’s social network due to stigma, and would therefore result in cases where respondents to a NSUM study would not know the true status of some of the other people in their social network (i.e., alters). Support for this speculation was found through in-depth interviews with HIV+ patients (Shelley et al. 1995, 2006), which demonstrated that respondents with AIDS/HIV+ had smaller personal networks and often restricted information about their health status to key individuals in their personal network.

These early NSUM studies led to a more formal consideration of how the assumptions of the NSUM method may be violated by error. Four general types of error were identified as specific concerns to the NSUM method: transmission errors, barrier effects, recall error, and cognitive errors.

Transmission errors, or the transmission effect, arise when a respondent has imperfect knowledge about the statuses (e.g. health, drug behavior) of their alters leading to under- or over-counts (Killworth et al. 2006). Through the work of these early studies it became apparent that the NSUM carried the assumption that respondents have perfect knowledge of all their alters. In reality knowledge about alters is flawed, but it seems to follow a systematic pattern such that as a given status becomes increasingly stigmatized, then the less likely it will become that information of that status will penetrate the entire social network (Shelley et al. 1995, 2006). Stigma is not the only factor in limiting information flow across a network. Societal notions of privacy and subjects that are taboo to discuss beyond certain types of ties (e.g. close friends, parents) also prevent the diffusion of information (Shelley et al. 2006). Additionally, there is considerable evidence that some types of information (e.g. HIV status) will have different transmission rates depending upon the relationship between a given alter and ego. The awareness of systematic transmission errors among NSUM researchers prompted the development of several adjustments, which are discussed below.

Barrier effects occur when a respondent provides a response that is not characteristic of the subpopulation due to the uneven distribution of that subpopulation across the whole (McCormick, Salganik, and Zheng 2010). A respondent may report not knowing anyone who has been bitten by a shark in the past year, but shark bite victims are most likely not evenly distributed across the U.S. If our respondent lives in Nebraska, they likely know fewer shark bite victims than someone who lives in Hawaii. This becomes more problematic when we consider that those who have a stigmatized or hidden status, such as AIDS/HIV+, are often more likely to know someone who has that same status compared to those who do not (Kadushin et al. 2006). This principle of homophily, that people tend to associate with those like themselves, creates problems not just for estimating a target subpopulation size, but also the scaling variables used to generate estimates of personal network size (Salganik et al. 2011). First names as scaling variables are particularly vulnerable to this as the popularity of certain names shifts over time, class and race, and thus some names are disproportionately clustered in different age cohorts. Using names that were only popular in the 1950s would results with a very different estimate of *c* than if names were only used from the 1990s. This distribution problem, acknowledged early in the history of the NSUM technique, is discussed in almost all modern articles as a limitation, but is only addressed systematically a few times in the literature (Feehan and Salganik 2016; Maltiel et al. 2015; McCormick et al. 2010; Salganik et al. 2011).

The third major source of error in the NSUM is commonly referred to as *recall error*. These effects broadly include the ability of a respondent to accurately recall and report the number of people they actually know in a given category This problem that is not unique to NSUM studies and has received attention in the general survey literature (Sudman, Bradburn, and Schwarz 1996; Tourangeau, Rips, and Rasinski 2000). Whereas general survey researchers are often concerned with a participant's ability to accurately recall a single event, NSUM researchers are asking participants to enumerate 30 or more different and unrelated populations in a small time frame. The most comprehensive examination of this error source to date in NSUM surveys found that respondents are prone to over-reporting the number of people they know in small populations and underreporting the number of those they know in large populations (McCarty et al. 2001), similar to general survey research results that found differences between rare and common events (Tourangeau et al. 2000).

Time was shown to be an additional factor for recall error in NSUM surveys. For example, focus groups revealed that participants had a hard time estimating the number of people they knew in large populations when they were given little time to answer (McCarty et al. 2001). Participants in focus groups often confessed to using estimation and heaping techniques (i.e. providing answers that were divisible by 5 or 10) to generate their answers and save time instead of going through the process of actually counting their answers (McCarty et al. 2001). However, these heaping strategies were found to have little effect on final estimates (McCarty et al. 2001).

Cognitive error, is rarely discussed in any great detail within the NSUM literature, although it has been broadly discussed in survey research and is frequently addressed when developing new survey questions (Tourangeau et al. 2000; Willis 2005). Cognitive error has the potential to be particularly harmful to NSUM studies given their reliance on a participant understanding of what is meant by "knowing" someone and shared definitions of what various phenomena are. Typically "knowing" is defined in the survey as a mutual recognition between the respondent and the alter by sight or name, and that there has been some sort of contact in the past two years (Killworth, Johnsen, et al. 1998). This definition is often modified to include different time ranges (Shelley et al. 1995), or to include alters within a certain age range or geographical location (Guo et al. 2013; Jing et al. 2014; Shati et al. 2014; Shokoohi, Baneshi, and Haghdoost 2012).

It remains unclear how differential understanding of "knowing" may influence estimates of personal network size or subpopulation size estimates. Salganik and Feehan (2016) suggest that changing the written definition of "know" in a survey can change the final survey estimates; however, it is unknown how variation in in a respondent's internal interpretation of "know" affects NSUM outcomes. Cognitive error may also occur when respondents define the target population differently internally (e.g. homeless as on the street, or living in a hotel, or being unstably housed). Briefly described in the literature (Killworth, Johnsen, et al. 1998; McCarty et al. 2001) as a potential problem, cognitive errors are largely unaddressed, and their effects unexplored in the context of NSUM studies.

Checking Accuracy

Much of the work on error in the NSUM has used data benchmarks to gauge the accuracy of the method by comparing results to other sources of data, such as official homicide numbers (Killworth, Johnsen, et al. 1998), or by comparing results to estimates generated by other estimation methods (Guo et al. 2013; McCarty et al. 2001). These types of comparisons are often not available for hidden and hard-to-reach populations, which can leave researchers unable to assess the accuracy of their estimates. The NSUM method includes within it a way to perform a type of accuracy check when these benchmarks are not available, a process known as back-estimation. Back-estimation involves using Equation 1.3 to predict a scaling variable and then comparing the prediction to the known number. For example, if we know that there are 1,200 professional firefighters in Nebraska but our estimate is 18,000, then we can identify that our respondents seem to know considerably more firefighters than would seem likely.

Researchers have used this ratio of the estimated number to the known number (18,000/1,200) to gauge the quality of their scaling variables and how well they are performing in their sample, as well as an indicator of overall accuracy of their estimates (Ezoe et al. 2012; Guo et al. 2013; Killworth, Johnsen, et al. 1998; Rastegari et al. 2013; Shati et al. 2014; Snidero et al. 2007; Sulaberidze et al. 2016). It has been common practice to discard scaling variables that are deemed inaccurate beyond a certain threshold, often more than twice the known. There are differences, however, in the manner by which those scaling variables are discarded. Some researchers have removed all of the egregious scaling variables at once (Ezoe et al. 2012; Guo et al. 2013), while others have removed them in an iterative fashion (Shati et al. 2014; Sulaberidze et al. 2016). The NSUM estimates are dependent upon how the scaling variables work together to produce estimates of personal network size. However, little is known how these different approaches to applying back-estimation affect the estimates of personal network size and final subpopulation estimates.

Adjusting for Error in NSUM

NSUM offers significant potential to estimate subpopulation size, but issues associated with errors have not been fully addressed. Of the four error types listed previously, transmission error has received the most attention by researchers attempting to develop statistical adjustments. One of the earliest suggestions was to avoid scaling variables and target subpopulations that are judged to have high transmission error (Killworth, Johnsen, et al. 1998). Although this is a practical suggestion for choosing scaling variables, it is problematic given that the method was largely implemented to estimate the size of stigmatized populations whose statuses would qualify them as having potentially high rates for transmission error.

To address *transmission error*, Killworth and colleagues (2006) suggested that researchers develop a way to categorize the difficulty of transmission for a given status or attribute. This approach has been widely adopted through several techniques that seek to gauge the likelihood that information is transmitted across a network. Some of these approaches involved seeking out those in the target population and asking them about how many of their own alters know their status (Ezoe et al. 2012; Killworth et al. 2006; Maghsoudi et al. 2014; Salganik et al. 2011). Another approach involves asking professionals to gauge the likelihood that such information would be transmitted, typically on a scale of 0 to 1 (Guo et al. 2013; Rastegari et al. 2014; Snidero et al. 2007). In both cases the information is used to form a weight based upon the likelihood of information flowing across the network and then adjusting the number of reported people in that subpopulation accordingly.

It is important to note that in several of these cases (Ezoe et al. 2012; Maghsoudi et al. 2014; Salganik et al. 2011; Vardanjani, Baneshi, and Haghdoost 2015) adjusting for transmission error required contacting members of the target population, which shifts the NSUM away from its indirect and more cost effective method, into one more akin to ethnography or respondent driven sampling. Several modifications of the NSUM have been based off this additional point of contact and are typically referred to as the generalized NSUM (Jing et al. 2014; Salganik et al. 2011). These transmission error adjustments weights are tailored to a single subpopulation size estimate, if a study has several target subpopulations than the adjustments need to be calculated for each possible outcome. Finally, although there are a variety of proposed techniques to adjust for transmission error which are of a similar theme, there is yet to be any one method that is viewed as best practice for addressing this type of error.

Although statistical fixes for *barrier effects* are not as numerous as those seen for transmission errors, there are still two major methods discussed to adjust for these problems. McCormick and his colleagues (2010) proposed and tested a solution using a latent nonrandom mixing model to account for the uneven distribution of scaling variable names by age and gender. This adjustment essentially estimates a respondent's personal network differently based upon their age and gender, and characteristics of the potential alter population (i.e. the scaling variables). In a comprehensive test of this proposed method the authors found that their adjustment provides superior estimates than the base NSUM model provides. However, the authors also tested a far simpler adjustment, using what they called "scaled-down" scaling variables (McCormick et al. 2010). This technique requires that the scaling variables match population distributions. Using first names as an example, the chosen names would be distributed across the population such that if 15% of the population is males between 21 and 40, than 15% of the people asked about as scaling variables must also be males between 21 and 40. When comparing the base NSUM model with the latent nonrandom mixing model and the scaled-down model, the researchers found that the scaled-down is equivalent to the latent nonrandom mixing model when the scaling variables represent a scaled-down version of the population (McCormick et al. 2010). This suggests that adjusting for the complexity of the mixing model is unnecessary when the scaling variables are appropriately selected.

When seeking to avoid *recall error* there appear to be two separate routes that current NSUM researchers have explored. The first lies in the careful selection of scaling variables. A growing consensus suggests that scaling variables should be sufficiently rare that respondents can quickly and accurately come up with responses without having to resort to shortcuts or response heaping strategies (Zheng, Salganik, and Gelman 2006). A commonly accepted definition of rarity is that the scaling variable should comprise 0.1%-0.2% of the larger population. For example, if names are used to generate a scaling variable, the names should be chosen so that they ideally only have one spelling and no nicknames (McCormick et al. 2010; Zheng et al. 2006). The second path is to use a post-estimation adjustment which fits a correction curve to the count data. This technique is based on documented trends of respondents to over count small populations and undercount large populations (McCarty et al. 2001). The technique increases the count as the scaling variable becomes larger and decreases it for smaller populations (McCormick et al. 2010; Zheng et al. 2006). Although this method has been implemented in one analysis (McCormick et al. 2010), it remains unclear if the technique is solely responsible for improved estimates.

Cognitive errors in the NSUM remain largely unexplored, although exploring cognitive discrepancies in standard survey work is well established (Tourangeau et al. 2000; Willis 2005). Some work has been done with focus groups to examine how NSUM participants create their counts (McCarty et al. 2001), but this is more indicative of recall error than cognitive error. Several studies have altered the operational definition of "knowing" somebody in order to make it specific to a town (Shati et al. 2014), region (Jing et al. 2014), or within shorter time constraints (Feehan et al. 2016; Shokoohi et al. 2012) than the typical two year window (Killworth, Johnsen, et al. 1998). However, these studies have not examined how changing this operational definition affects participant perceptions, the outcome estimates of personal network size, or target estimates. There is one study (Feehan et al. 2016) that does a split ballot experiment comparing different definitions of "knowing" someone and they found differences in both social network size and the final outcome estimates. Although this experiment is focused on changing definitions of "knowing" someone, it is based around ideas of making it easier to recall people in a personal network (Feehan et al. 2016),and not on the ways participants may differentially understand what it means to "know" someone. Despite recent variation in how "knowing" someone is defined, there is still a dearth of information about how participants understand this crucial element of the method.

Current State of the NSUM

The NSUM has seen a recent growth of interest with almost two dozen published academic papers since the start of 2012. Many of these studies have continued to focus on populations related to HIV/AIDs transmission (Ezoe et al. 2012; Guo et al. 2013; Jing et al. 2014; Kanato 2015; Khounigh et al. 2014; Maghsoudi et al. 2014; Shokoohi et al. 2012). There are several studies that have begun to broaden their populations of interest to study abortions (Rastegari et al. 2014), severe physical and mental disabilities (Mohebbi et al. 2014), prevalence of several types of cancer (Haghdoost et al. 2014), and the frequency of spinal cord injury resulting from an earthquake (Daneshi et al. 2014). These new populations begin to extend the NSUM method into populations that may have less transmission error than HIV/AIDs statuses, but these innovations have so far been largely limited to the work being done by public health officials in non-Western contexts, including Japan (Ezoe et al. 2012), China (Guo et al. 2013), Iran (Rastegari et al. 2013), and Thailand (Kanato 2015).

Recent NSUM studies have also introduced new approaches for adjusting error. These developments have focused almost exclusively on transmission error, creating new ways to estimate the flow of information about a given status across a network. In Japan, Ezoe et al. (2012) estimated a coming-out rate where they attempt to determine the rate at which men who have sex with men tell others about their status. In China, Guo et al. (2013) used a social respect factor in which they asked participants how much they respected members of target populations on average and used those factors to adjust participant responses(Guo et al. 2013)(Guo et al. 2013)(Guo et al., 2013). In Iran, Maghsoudi et al. (2014) employed a visibility factor in which participants were asked how many people they knew in each scaling category were aware of their status.

Despite new experiments in adjusting for transmission error, little work has been done to account for other common error sources in the NSUM. By integrating the NSUM fully with respondent driven sampling, there have been methods developed to account for barrier and transmission effects in the generalized NSUM (Feehan and Salganik 2016) and through Bayesian adjustments (Maltiel et al. 2015). These techniques, however, require direct sampling of the hidden population in order to estimate transmission rates for statistical corrections. In requiring direct contact, the generalized NSUM and

Bayesian approaches sacrifices many of the advantageous qualities of the NSUM. Such as the ability to employ cost-effective sampling frames of the general population. Aside from these extensions of the NSUM there have been few other attempts to develop or further understand error in the NSUM due recall errors or cognitive errors.

Dissertation Focus

One aspect of the NSUM that has remained relatively unquestioned since its development is the estimation process itself. First discussed in the original Mexico City study (Benard et al. 1991) and then formalized in a U.S. study (Killworth, Johnsen, et al. 1998), the equations used to generate personal network size have remained the core of most NSUM studies. These formulas (Eq. 2 and Eq. 3) are designed to minimize the influence that a single scaling variable can have over the final estimate of either personal network size or the target population size. In doing so the formulas move away from the core assumption of the NSUM that the direct proportion of the number known in a population to total size of that population is of primary importance to the method. It is open question as to how modifying these equations may benefit or hinder the NSUM and its ability to produce accurate estimates of population size. A central part of this dissertation is thus to reexamine this formula and how it may be improved.

Another aspect of the NSUM that has frequently been implemented but not necessarily understood is the process of back-estimation. This technique was introduced early in the development of the NSUM (Killworth, Johnsen, et al. 1998). Back-estimation involves predicting the scaling populations using the previously estimated personal network size and comparing scaling estimates to their known values in recent years, the method has been reintroduced to the NSUM literature as a way to check the accuracy of the process, and as a way to determine which scaling variables are performing poorly. NSUM researchers have implemented various cutoffs of error to determine when a scaling variable should be discarded or not. For example, Ezoe et al. (2012) discarded estimates if they varied “significantly” (Ezoe et al. 2012). Guo et al. (2013) used a cutoff point when the estimate was twice or more the known value; whereas Rastegari et al. (2013) used a cutoff point of 1.5 times the known value in Iran. What remains unknown is if this discarding process truly improves the final estimates and what the consequences of using back-estimation are.

One part of the NSUM that may be affected by changes in the core estimator and the use of back-estimation is the estimation of personal network size. For most of the NSUM implementations used today, calculating personal network size is a crucial step in order to estimate the size of hidden and hard to reach populations. Not only is personal network size crucial to the NSUM, but reliable estimates of network size can inform some of the earliest questions in social network analysis (Pool and Kochen 1979). Population level estimates of personal network size, the variance of those estimates, and associations between those estimates and personal attributes can also reveal complex social structures. Understanding how choices in the NSUM estimation process result in differences in estimate network size is therefore any important issue to consider.

Beyond changes to the estimation and adjustment process, there remains a considerable amount of work to be done in regards to cognitive and recall errors in the NSUM. Of particular note is the limited understanding of how NSUM survey participants operationalize what it means to know someone and whether this is stable across the survey. Further, many definitions of knowing someone involve spatial and temporal boundaries. In one study, researchers found that participants had an easier time with a smaller time boundary (Feehan et al. 2016), but more work needs to be done to understand how participants actually work through NSUM questions internally. Strongly related to this is understanding the motivations for when a NSUM participants decides to stop searching their memory for more that they know.

This dissertation seeks to address these limitations by proposing several new changes to the NSUM. The first is a new estimation process for the NSUM which estimates both personal network size and the size of the target population differently from traditional implementations. In addition, recursive back-estimation is proposed and tested using a set of census data as a target population in chapter 4. Chapter 5 explores how estimates of personal network size are affected by changes in NSUM estimators and the use of back-estimation. Further, associations between predicted network size and individual attributes are explored among Nebraskans in order generate statewide predicted personal network size values. Finally, Chapter 6 uses cognitive interviews to examine the response process used by NSUM participants and to identify problems which arise through recall and cognitive errors. These observations are used to develop a set of new practices for NSUM survey implementation.

CHAPTER 3: DATA COLLECTION

The Nebraska Community Survey: 2014

Data for this dissertation comes from two sources. The first is the *2014 Nebraska Community Survey* (NCS) which was implemented in the spring of 2014 and was sent to a random sample of 2,000 households in Nebraska. The sample was obtained from the United States Postal Service delivery sequence file (DSF) through the Bureau of Sociological Research (BOSR) at the University of Nebraska-Lincoln. Seasonal and vacant households were removed from the sample by the provider. The DSF covers approximately 97 percent of U.S. Households and provides a reasonable frame for the Nebraska population (Iannacchione 2011; Link et al. 2008). The Institutional Review Board at the University of Nebraska-Lincoln approved the research protocol and granted the project an exempt status (IRB# 20140314288 EX). Each household in the sample was sent a packet which included a letter introducing the survey, a one dollar incentive, a copy of the survey questionnaire (see Appendix A), and a pre-paid return envelope. The person in the household to take the survey was selected using the next-birthday method, a quasi-probability selection design (Gaziano 2005). Eligible respondents had to be at least 19 years old, the age of majority in Nebraska, and be the next person in the household to have a birthday after April 14, 2014. A week after the initial mailing a reminder postcard was sent to any households that had not responded to the initial mailing. Three weeks later, a second survey packet was sent to non-responding households. If at any time a respondent asked to be removed from the address list, all further mailings were stopped. After the third mailing, data was collected for approximately another six weeks, allowing respondents ample time to complete and return their survey.

The goal of this survey was to gather data about a wide variety of hidden and difficult to measure populations. Several researchers at the University of Nebraska-Lincoln came together and developed a list of outcomes that ranged from domestic migration in the US and Nebraska, public health concerns, drug use, contact with the criminal justice system, and crime victimization. The NSUM technique allows for the easy incorporation of research questions that can be measured in counts of persons known to the respondent. Due to the unusual nature of the NSUM questions survey materials were written to emphasize the unique aspects of the survey. When data collection was ended, 618 of the surveys had been completed and returned, an AAPOR Response Rate 1 of 30.9% (The American Association for Public Opinion Research 2015). This NSUM survey achieved a higher response rate than similarly incentivized mail surveys of Nebraskans in the same field timeframe, an increase attributed to the novelty of the NSUM approach.

The NCS used the known-population method to estimate personal network size for the NSUM hidden population estimates. Eighteen known-populations were chosen, 12 names and 8 professions. The names were chosen based upon the prior work done by McCormick et al. (2010). McCormick and colleagues examined the set of names initially used by McCarty et al. (2001) in their early NSUM studies. They found that a subset of 12 names held favorable properties for NSUM researchers in that they were distributed across age cohorts in popularity, they were sufficiently rare that they made up 0.02% of the US population, and they had limited pools of nicknames (McCormick et al. 2010). The NCS uses this list of names for the current study: Rose, Tina, Emily, Martha, Paula, Rachel, Walter, Bruce, Alan, Ralph, Kyle, and Adam. In order to supplement the list of names, the NCS also included six questions about professions. These professions were inspired from the known-populations used by McCarty et al. (2001) and for which information could be obtained about Nebraska population numbers. The final list of occupations was: police officers, firefighters, US postal officers, correctional officers, licensed gun dealers, and airline pilots.

Survey participants were asked to list the number of people they knew in each of the known-populations who currently lived in Nebraska and the total number they knew in the US. Unfortunately, only the number known in Nebraska was usable, as several participants answered the US count as being mutually exclusive from their Nebraska count. This resulted in answers where a participant would know 5 police officers in Nebraska, and 2 in the US. Unfortunately, there was no way to determine if all participants interpreted these questions this way, or if it was only a subset. As a result, the US questions are not used in this dissertation. For the NCS, knowing someone was defined as "… it means that you know them and they know you by sight or name, that you could contact them, and there has been some contact (either in person, by telephone, mail, or web) in the past 2 years." This definition of knowing someone is consistent with prior NSUM work (Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998; McCarty et al. 2001).

Cognitive Interviews

The second source of data for this dissertation comes from a series of cognitive interviews which were conducted in the late summer and early fall of 2016. Cognitive interviews are a technique used to study how people understand, mentally process, and ultimately respond to questions (Beatty and Willis 2007; Willis 2005). A distinctive feature of many cognitive interviews is the think-aloud process. A think-aloud is when a participant is asked to verbally state what they are thinking as they complete a survey or answer a smaller set of questions (Willis 2005). These types of interviews are able to capture high level mental processes which a participant goes through when answering a question (Conrad, Blair, and Tracy 1999). However, these interviews are not capable of revealing information about processes that are spontaneous or those that a participant is not truly aware of (Conrad et al. 1999; Ericsson and Simon 1993).

In addition to the think-aloud process, many cognitive interview protocols may also include interviewer probes (Willis 2005). These may vary by both when they are constructed (prior or during) and what triggers the probe (the interviewer or subject behavior) (Beatty and Willis 2007; Willis 2005). Probes may also occur during the think-aloud process or after the think-aloud has been completed (Willis 2005). Asking probes during the process has the advantage of the immediacy of the probe (i.e. there is little time delay between a behavior and a probe). However, there is evidence that concurrent or near-concurrent probes can effect both the results and the process of a think-aloud interview (Ericsson and Simon 1993; Russo, Johnson, and Stephens 1989; Willis 2005). Retrospective probing, which occurs after the think-aloud is complete avoids these reactive effects, but may make it more difficult for a participant to accurately recall what their response process was when they first answered that question (Ericsson and Simon 1993; Willis 2005). However, when using a survey instrument that is self-administered (as the survey for this study is) it may be more beneficial to replicate how a participant would complete the survey in the field (Willis 2005). As such, the cognitive interviews designed for this dissertation attempt to minimize the number of concurrent probes in favor of retrospective probes which occur after the survey had been completed by the participant.

Participant Recruitment & Instrument Design

A convenience sample was recruited by posting flyers in several classroom buildings on the UNL campus as well as several coffee shops located in the city of Lincoln, Nebraska. Participants had to be at least 19 years of age and current residents of the city of Lincoln or Lancaster County Nebraska. Interviews took place on the UNL campus. As an incentive, $20 cash was offered to compensate for the participant’s time as the interview was expected to last from 1.5 to 2 hours. The completed interviews ranged from 47 minutes to 2 hours and 15 minutes in length. The average interview was 1 hour and 20 minutes long. The interview protocol was approved by UNL’s IRB and given an exempt status (IRB# 20160716187 EX).

The survey used in these cognitive interviews is an adaptation of the 2014 NCS (Appendix A) which has been modified in three key ways. The first is that in the 2014 NCS there was a large section on attitudes about the media and crime. This section was removed for the cognitive interviews as it was not considered to be relevant to the aims of the study and would add more tasks for the participant to complete without a necessary reason. The second change is that a section of summation NSUM questions were added in order to directly contrast the known-population and summation methods. The third change is that the modified survey no longer asks about how many people a participant knows in the US in addition to those known in Nebraska. These questions were originally intended to be used as an experiment about simultaneously measuring nested networks. However, this experiment failed and retaining these elements for the cognitive interviews was deemed to be unnecessary. The final survey for the cognitive interviews is replicated in Appendix B of this dissertation.

A total of 19 interviews were completed out of a target goal of 20. Twenty interviews was set as the maximum due to funding availability. Recruitment began on August 22, 2016 when flyers were posted at five locations on the UNL campus and four locations in the city of Lincoln, Nebraska. The last interview was conducted on October 11, 2016 and all flyers were pulled on October 14, 2016. Recruitment was ended one interview short of the target goal of 20 due to the lack of new participants being interested in the study. Interested participants contacted the interviewer directly through email in order to setup the interview on the UNL campus.

Interview Protocol & Implementation

All interviews were conducted in 104 Benton Hall. This is a room which is used as either a workroom or a classroom, and can comfortably accommodate up to 18 students. The room is private, located near restrooms, and is located on the first floor of the building which is typically quiet. Every interview used the same room setup. A large table was placed in the middle of the room with four chairs on each side. The interviewer sat on one side of the table (with the windows at their back) and the participant sat on the opposite side. In front of the participant's chair were three sheets of legal paper, a pen, and a liter of bottled water. In front of the interviewer's chair were a legal pad, a pen, two copies of the survey, two copies of the interview consent form, a form to record the start and end time of the interview, and a plastic cup of water. A box of tissues and a digital audio recorder were placed in the middle of the table. While interviews were in progress signs were posted on the two doors of the room which said, “Do Not Disturb – Interview in Progress – Thank You – Patrick Habecker.”

Participants were greeted at the door of the room and welcomed by the interviewer. They were shown to their seat and asked to make themselves comfortable. The interviewer used a pre-scripted interview protocol as a framework to describe the study and what the participant will be doing during the interview (Appendix C). The participant was then given the informed consent form and the interviewer went over each element of the form, what it meant, and highlighted the rights of the participant. After jointly going over the consent form, the participant was encourage to ask questions and to take some time to look over the form on their own. Once they agreed, the participant signed a copy of the consent and gave it to the interviewer, who in turn gave the participant a blank copy for their records.

Once the consent form was signed, the interviewer introduced what cognitive interviews are, why we do them, and what the process is like for the participant. As cognitive interviews are unusual, two example questions were used to give the participant a chance to practice the think-aloud technique. The first question asked, “How many residences have you lived in since you were born.” The second asked, “Think about where you live. How many windows are there?” For the first question participants were asked two follow-up questions: “how did you think about what it means to live somewhere?” and, “how did you define what it means to live somewhere?” For the second question, probes were used to ask if the participant was counting windows in doors or counting sliding glass doors. After the practice questions and their follow-ups were completed, the participant was given a chance to ask any other questions before the interview started.

After the practice questions were finished the audio recorder was turned on and the participant was given a copy of the survey (Appendix B). The interviewer followed along with their own copy of the survey and made notes on their copy of the survey and on their legal pad. Concurrent probes were meant to be limited in this interview protocol (Appendix C). Most of the probes were meant to encourage the participant to fully engage in the think-aloud process and to avoid periods of time where the participant may lapse into silence. A handful of probes were written beforehand to assess how accurate a participant may think a given question is, how they decided to stop counting, or how they came up with a response for a question (Appendix C). However, these probes were not linked to specific questions, and could be used at the discretion of the interviewer during the interview.

Aside from the interviewer encouraging the participant to engage in the think-aloud, there was little planned interaction between the interviewer and the participant while the survey was being completed. During the survey, the interviewer was focused on the process the participant was describing and took notes and wrote questions which would be asked after the survey was complete. These notes were added to a set of pre-written end of survey questions (Appendix C) and were used to facilitate a retrospective discussion after the survey was finished. Here the interviewer encouraged the participant to reflect upon some of the choices they made and the behaviors they used while completing the survey. These retrospective questions ranged from queries about specific questions, to reflections about overall response processes. The pre-written questions provided a common set of questions for all participants while the interviewer's notes allowed for emergent behaviors to be examined.

After the end of survey questions were completed the participant was given a chance to ask questions of the interviewer. Once those were finished the digital recorder was turned off. The participant's completed survey was collected by the interviewer as well as the scratch paper that was used by the participant. The participant was then given a $20 bill and a receipt to complete and sign in order to comply with UNL financial rules. At this point all parts of the cognitive interview were complete and the participant was walked to the exit of the building. Once the participant was gone all materials were collected, the table was cleaned, and the do not disturb signs were removed from the doors. The materials were taken to the interviewer's office were they were locked in a file cabinet. The audio file was downloaded from the recorder, copied twice (once onto a USB backup and once onto the interviewer's computer), and then the recording on the recorder was deleted. At this point the emails between the interviewer and the participant were deleted from the interviewer's inbox and then purged from their deleted folder.

CHAPTER 4: THE MEAN OF SUMS, RECURSIVE BACK-ESTIMATION, AND WEIGHTING

Note: Much of this chapter has been previously published elsewhere under a Creative Commons Attribution License (Habecker, Dombrowski, and Khan 2015).

Introduction

The network scale-up estimation method is based on the assumption that, on average, an individual's personal network will be representative of the general population (Johnsen et al. 1995b; Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998). That is, the proportion of people in an average individual's personal network who are members of a given subpopulation is indicative of the relative size of that subpopulation to the general population as a whole. This can be formally expressed with Eq. 4.1, where m is the number of people known by the respondent in a given subpopulation, c is the size of the respondent's personal network, t is the size of the larger population, and e is the size of a subgroup in the population.

$$\frac{m}{c} = \frac{e}{t} \qquad 4.1$$

The challenge of the NSUM method is estimating the size of an individual's personal network, c. Realizing that local conditions can influence mean network size (consider the difference between predominantly urban and predominantly rural populations) a popular method for calculating this value for a sample is the *known population method* (McCarty et al. 2001). This approach asks respondents to report the number of individuals they know from a population whose size *can* be estimated by other means (e.g. Census figures or other official statistics). These data can then be used to estimate the personal network size of each respondent, allowing researchers to "scale up" their answers for unknown populations to population level estimates. Eq. (3.2) describes how the counts for such "scaling" variables can be used to derive the personal network size of a single respondent, where i indicates a respondent and j a scaling variable. In essence, the reported value of each scaling variable m_{ij} (e.g. "firefighters", or "airline pilots," or "persons named Walter") are summed across a range of such categories, and then divided by the total known population e_j for these same groups.

$$\hat{c}_i = \frac{\Sigma_j m_{ij}}{\Sigma_j e_j} t \qquad 4.2$$

Common populations to ask about include the number of people with a given first name, such as Rose, or the number of people known who hold a certain job, such as postal worker; "knowing someone" is normally defined as someone whom the respondent knows by name and with whom the respondent has had some form of communication in the past two years (H. Russell Bernard et al. 2010).

Once an estimate for the respondent's personal network size is in hand it is possible to calculate the size of a previously *unknown* subpopulation using the ratio of the respondents estimated personal network size to the total population. This is shown in Eq. 4.3 (where data solicited from all respondents $(0,1, \ldots i)$ for a given "target" population j, over the sum of all respondent's respective, estimated personal network size $\hat{c}_j$, is used to estimate the number of people in the target population (such as illegal drug users).

$$\hat{e}_j = \frac{\Sigma_i m_{ij}}{\Sigma_i \hat{c}_i} t \qquad 4.3$$

In the method above, the final value for the scaling variables determined in each survey are not treated individually. Rather, as originally practiced both the discovered variable values across all respondents, m_{ij}, and the total (external) estimates of these "known" populations, e_j, are summed (see Eq. 4.2). The resulting ratio is used to calculate an individual's personal network size. In this process, large estimates in one scaling variable m_i are minimized in their ability to alter the resulting personal network size estimate, given relative uniformity across the other scaling variables. Further, by summing across the known network sizes, e_j, differences in the sizes of these known populations introduce a hidden weighting factor, whereby some variables contribute more to the size of the denominator than others. The latter problem is often dealt with by seeking scaling variables that are roughly equal in estimated size i.e. where $e_a \approx e_b \approx e_c \approx \ldots \approx e_j$, in order to minimize the hidden weighting that unequal sizes entails. Further, in a situation where no means are available to discover outliers and remove them from the estimation process, researchers may prefer a method that implicitly mutes the impact of outliers in our estimation process.

Finding scaling variables of uniform size may be difficult, however, and muting the effect of outliers is not the same as removing them from the estimation process. In both cases, alternatives are available. Toward this end, this chapter discusses an alternative estimator that takes into account the performance of the each scaling variable individually and, allows for the selective removal of those that are performing poorly in comparison with the combination of all others. The new estimator and a comparison of results with the original estimation process are discussed below.

Additionally, this chapter proposes a way to integrate sampling and post-stratification weights into both of the estimation processes. One of the strengths of the NSUM technique is that it can use mainstream sampling techniques to generate representative samples and thereby accurate estimates of target populations. These types of frames also have the major advantage of having known distributions which can be used to create weights to ensure greater representativeness of the sample. Incorporating these types of weights in to the NSUM estimation process is a logical and much needed addition to the technique. This chapter demonstrates how weights can be included into both the original and proposed estimators and compares the differences in the final population estimates.

The Mean of Sums Network Scale-up Estimator

The heart of the network scale-up estimation process is based around the number of people a respondent knows from a known subpopulation. When there is only one known subpopulation the ratio is simply that, the number of people an individual knows (say, for example, “persons named Walter”), divided by the total size of that subpopulation (in this case, the number of persons named Walter in the population). Network scale-up researchers, however, often use more than one scaling variable (and thus more than one known subpopulation) in building an estimate of personal network size. Recent recommendations include the use of at least twenty (H. Russell Bernard et al. 2010). As above, the number of people known across all known subpopulations are summed and taken over the sum of the size of all the subpopulations (as shown in Eq. 4.2).

This method can lead to a hidden masking of the performance of a single variable. This may be desirable when there are limited means to judge the performance of the scaling variables individually, but in general the effects on the resulting estimates are not discussed. An example can help make this process more clear. Consider an individual who provides counts for three scaling variables of known population sizes 1000, 1000, and 1000 respectively, who indicates that she knows 1 person in each of these categories. The result (see Eq. 4.5), using the conventional NSUM estimation procedure is that the respondent's personal network size is 0.1% of the total population.

$$\frac{1+1+1}{1000+1000+1000} = 0.001 \qquad (4.5)$$

However, if the size of one of the scaling variable's actual populations is much smaller (say, 100 instead of 1000), and one is much larger (say 10,000 rather than 1000), then the size of this same respondent's personal network is equal to 0.00027 or 0.027% of the total population (see Eq. 3.6).

$$\frac{1+1+1}{100+1000+10000} = 0.00027 \qquad (4.6)$$

Though the number of individuals known remains the same, the differential contribution of the elements of the denominator means that the larger target population (10,000), virtually eliminates the fact that here a person from a rare population is known (1/100). Indeed, it would make little difference if she had reported knowing 2 persons in the first population (2/100). Where significant differences exist in the size of the scaling populations (i.e. the denominator), the significance of knowing individuals in smaller populations can make little difference in the estimate of personal network size. Given this, it might make more sense to take the average of the individual scaling variable ratios (Eq. 4.7, here after the mean of sums (MoS) estimator).

$$\hat{c}_i = \frac{\Sigma_j \left(\frac{m_{ij}}{e_j}\right)}{j} t \qquad 4.7$$

Here, each scaling variable contributes equally to the final estimate. However, the issue is nearly reversed: the smaller population now dominates the sum, and the result is nearly more than 13 times the size estimated using the conventional method (see Eq. 4.8 compared to Eq. 4.6).

$$\frac{\frac{1}{100} + \frac{1}{1000} + \frac{1}{10000}}{3} = 0.0037 \qquad 4.8$$

Following the logic of equation 4.7, a MoS process can also be derived to estimate $\hat{e}_j$ which is shown in equation 4.9 below.

$$\hat{e}_j = \frac{\Sigma_i \left(\frac{m_{ij}}{\hat{c}_i}\right)}{i} t \qquad 4.9$$

Whether the traditional or MoS is the better method for estimating personal network size remains an open question. However, this chapter shows that the MoS estimator performs far better than the traditional estimator in a recursive trimming process, and produces a better outcome estimate, especially when weights are added.

Methodology

This chapter uses data collected through the 2014 Nebraska Community Survey (NCS) which is described in greater detail in Chapter 3. For this chapter item nonresponse proved to be an interesting challenge for the analysis. Item nonresponse is when otherwise complete surveys have individual questions which are missing. Unfortunately, several respondents appeared to favor only writing answers when they had non-zero responses to enumeration questions, leaving large and seeming random numbers of questions blank, even though they completed the survey, and supplied no “0” answers for any of the questions. Faced with this situation, there were two general choices: a conservative approach where blank answers were considered to be missing and thus handled through standard practice such as listwise deletion or multiple imputation; or assume that the empty cell indicates that the respondent knows zero people for that question and substitute a zero for the missing value code. As this latter option infers respondent behavior that cannot be confirmed, it is considered a weaker assumption and was not implemented for treating the present item nonresponse. Instead, listwise deletion was used and the final sample of “mostly” complete surveys was 550 out of the original 618 complete cases.

In order to calculate personal network the 2014 NCS used the known population approach discussed in Chapter 2 and Chapter 3. Each respondent was asked for counts of personal network members of eighteen populations of known size, including twelve categories of people with a given first name and six professions. The set of names are the subset of names identified by McCormick and his colleagues (2010) which are distributed across age cohorts, have limited numbers of possible nicknames, and are sufficiently rare in the larger population (≈0.02%). The six professions were pulled from those used by McCarty and his colleagues (2001) and for which data on Nebraska populations could be obtained. The full list of names and professions can be seen in Appendix A in the 2014 NCS survey and are referred to as scaling variables throughout this chapter. The definition for knowing someone was that there was mutual recognition, that there has been some sort of contact in the past 2 years, that they could contact the person if they wanted to, and that the person currently lives in Nebraska. This definition of knowing someone is consistent with prior NSUM implementations (Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998; McCarty et al. 2001).

In addition to the scaling variables, this chapter focuses on three target subpopulations as well: the number of people who had moved to Nebraska from another state in the U.S. in the last two years; the number of people in Nebraska who would not approve of interracial dating; and the number of people in Nebraska who had used heroin in the last 30 days. Each survey respondent was asked to count the number of people they knew in each of these categories, not including themselves, and these counts were used in Eq. 4.3 to create population estimates of the size of these subgroups in the state-wide population.

Basic Comparison between the Traditional and MoS Estimators

Table 4.1 shows the differences in population estimates of our target populations using the original estimator (Eq. 4.3) and one derived from an estimator that incorporates the MoS method (Eq. 4.9) for three populations in Nebraska. Differences between these two estimators vary depending upon the target population being estimated. The American Community Survey reports that in the year 2013, 45,854 Nebraskans reported living in a different state 1 year ago (U. S. Bureau of the Census 2013). When added to the same report for 2012 of 43,266 people moving into Nebraska (U. S. Bureau of the Census 2012), this provides a two year total of 89,120. The MoS estimate of 75,800 is considerably closer to the two year ACS total than the estimate of 12,184 provided by the traditional NSUM formula. Although the 95% confidence intervals for neither estimate contain the ACS statistic. In addition to an increase in estimated migration into Nebraska, the MoS method also estimates that 22,614 Nebraskans do not approve of interracial dating compared to an estimate of 17,892 Nebraskans from the traditional formula. The estimate for the number of Nebraskans that have used heroin in the last 30 days increases from 368 to 454 when comparing the traditional to the MoS estimation. Not all of the differences in our survey were stark. Overall, of the 46 populations estimated in the larger study, 76% of them changed by less than a factor of 2 using the MoS estimator compared to the original estimator.

A key indicator of how the results change is shown by the differences in calculated personal network size between the two estimation methods. The average estimate network size of Nebraskans is 604 using the traditional method and 1,024 from the MoS. Additionally, the largest estimated network size increases substantially, from 5,944 with the traditional formula to 16,794 when using the MoS. Given the importance that the estimates of personal network size play in the NSUM it is easy to see why the MoS estimates may differ considerably from those using the traditional method.

Using Back Estimates as a Data Quality Check

As the network scale-up method is mainly used to estimate the size of hidden and hard-to-reach populations, it is difficult to gauge the quality of the estimation process. The technique of back estimation offers a way to check the robustness of the estimate of personal network size and, by extension, later estimates of target populations. Briefly, back-estimation works by using the estimated personal network size generated by equation 4.2 along with the number of people known by the participants in the scaling populations to estimate the size of our scaling populations (i.e. names and jobs) using equation 4.3. It is possible to then compare the estimate population size of a name or job to its known population size which is obtained from administrative sources. As Guo and colleagues (2013) have recently shown, this back-estimation process can be used as a self-check for the performance of individual scaling variables. Significant variation between back estimates of target variables and the known values for those populations points to elements in the network size estimation process where respondents deviated most significantly from the expected values, based on the results of all of the other knowns. This process can be used for all versions of the NSUM estimator discussed in this paper, original and MoS, weighted and unweighted. Table 4.2 lists all 18 of the scaling populations used in this study. For each, the known population size is listed in column 1 and the back estimated population size using the original estimator is listed in column 2. A visual comparison of the numbers quickly reveals that some of the estimates are sizably different. For example, the NSUM back estimate for firefighters in Nebraska shows a value of over 18,000, while data from the Bureau of Labor Statistics (which was used in Eq. 4.2 to calculate personal network size) suggests that there are only 1,200. Other back estimates are less drastically divergent, such as the number of people named Adam in Nebraska (which is estimated to be 4,754 while information from the Census suggests that there are 4,839).

Following Guo and colleagues (2013), the performance of the estimators can be compared by using the ratio of the back estimates to the known values for each subpopulation. A larger (or smaller) ratio indicates a greater difference between the back estimate and the known population. Such a measure provides a scale from 0 to infinity, with an ideal value of 1 (where the back estimate, based on all of the scaling variables together, is equal to the known value). In Guo and colleagues study (2013), a correction process was employed that discarded any scaling variable from the estimation process if the ratio of estimated to known exceeded 2 or was below 0.5. Using the over/under of 0.5 and 2, these authors eliminated 11 of their 19 total predictors at once, using the remaining 8 as the basis for their actual estimates of their target population.

Unfortunately, a one-step trimming process misses that the elimination of any single scaling variable will necessarily change the estimate of personal network size, and thus the back estimation of all of the other scaling variables. Under such conditions, viewing the performance of the scaling variables as fixed regardless of their combination seems problematic. In place of this one step elimination process, this dissertation proposes a recursive process of repeatedly removing the worst performing scaling variable, in light of the results of all those remaining at any given stage of the process. Rather than a flat cutoff point, the log base 2 of the ratio of back-estimated to known is used (in essence, the log of Guo et al’s ratio (2013)). This transformation produces a performance metric that is continuous and symmetrical around zero. The absolute value of this number indicates that the greater the value, the greater the distance between the back estimate and the known population of the particular scaling variable regardless of which is larger.

Looking down column 3 of Table 4.2 it is apparent that the greatest difference between back estimates and known populations for the 18 scaling variables is the number of firefighters in Nebraska, with a value of 3.93. Discarding firefighters from the estimation equation is done by returning to Eq. 4.2, which calculates the respondent’s personal network size, and removing the firefighters count and known population from the estimation process. Personal network size is recalculated then the back-estimates are rerun for the scaling variables using Eq. 4.3. The new back-estimates are shown in column 4 of Table 4.2, labeled as IT1 (Iteration 1). By repeating the process of calculating the ratio of estimates to known populations, applying base 2 logarithms, and then comparing the absolute values of the result, the next most extreme variable from the list of knowns can be found. In this case the difference in the NSUM estimate for the number of U.S. Postal Carriers in Nebraska and the known population is the greatest (with a value of 1.77). Removing the Postal Carrier estimator from Eq. 4.2 and recalculating personal network size and new back-estimates sets up the next round of calculating distance.

This process is carried out recursively, until the absolute value of the log distance between estimates and known values is below one for all remaining predictors. The choice of log base 2 absolute value of 1 means that in the ratio of back estimated population to known value, the denominator is no more than twice the size of the numerator, and vice versa—or in other words, that the ratios are the same cutoff used by Guo and colleagues (i.e. 0.5 and 2). The point here is that the recursive process allows for the reconsideration of the performance of every scaling variable in light of all those remaining. Such a process allows for the fact that scaling variables may not be independent, but rather may contain complex interdependencies. According to the initial back estimation at step 0, firefighters, Walter, Martha, and correctional officers performed the most poorly. Yet once the firefighter variable is removed, postal carriers become the most problematic. In the third round airline pilots have the greatest distance between known and estimated values. Finally, at round four, Martha is eliminated. The second and third eliminations (postal carriers and airline pilots) were not among the top 4 worst predictors. Had the one step, block elimination process been used, a different set of variables would have been eliminated. This reordering at each step illustrates how the distance measure changes across iterations and why the bulk removal process could result in removing variables that would not actually need to be eliminated from the calculation. This is particularly important for researchers who have a limited number of predictors and are trying to make difficult decisions about which variables to cut for the best results.

The recursive trimming process also changes the target population estimates at each step. Using the original estimator, seven iterations were completed before the distance metric for all remaining predictors was below a value of one, as shown by Table 4.2. Table 4.3 then shows the differences in the population estimates before the recursive process was begun, and the estimates after completing seven iterations. All three of the estimates increased sizably and by the same factor (1.26). The recursive process will thus have a larger raw effect on population estimates of larger numeric size. Additionally, the estimate of average personal network size decreased from 604.03 to 464.28 by the end of the recursive process, accompanied by a decrease in the variance and maximum size of a respondent's personal network as well.

Incorporating Weights into the Network Scale-up Estimator

One of the strengths of the network scale-up estimator is that it can take advantage of sampling frames with known sampling probabilities to estimate the size of hidden and hard-to-reach populations. These sampling frames also allow for the incorporation of sampling weights into the population estimation process. Weights can adjust for probability of selection, survey nonresponse, and allow for post-stratification adjustments in order to make the sample more representative to the population. Using weights would theoretically result in better target population estimates and the possibility of using NSUM techniques successfully with more complex sampling designs.

Weights can be added to both the original and the MoS estimation formulas with little trouble, modifying Eq. 4.3 and 4.9 respectively. In both cases the number of people known by the respondent in a given subpopulation (m_{ij}) is multiplied by the individual's final weight (w_i). Equation. 4.10 shows the weighted formula for the original estimator and equation 4.11 shows the weighted formula for the MoS estimator. For the current data, a weight which adjusts for the probability of selection within a household and then post-stratifies the sample to match the distribution of sex and age for Nebraska is used. The selection weight is necessary as the sample is address based which randomly selects households in Nebraska which may then have multiple potential survey respondents. Post-stratification by sex and age helps adjust our estimates to match population distributions.

$$\hat{e}_j = \frac{\Sigma_i m_{ij} w_i}{\Sigma_i \hat{c}_i} t \qquad 4.10$$

$$\hat{e}_j = \frac{\Sigma_i \left(\frac{m_{ij} w_i}{\hat{c}_i}\right)}{i} t \qquad 4.11$$

Table 4.4 shows how the three population estimates and the estimated personal network size change when weights are incorporated in both the original and MoS estimators. Sizable changes are seen in all three of the population estimates. According to both estimators, the number of people who moved to Nebraska from another state in the U.S. increases considerably. Compared to the two year ACS total of 89,120, the MoS estimator still performs better (providing a weighted estimate of 114,929 people, compared to the weighted original estimate of 16,232). Although the weighted MoS estimator is now overestimating the population size compared to the ACS numbers, it is still considerably closer than the estimate provided by the weighted original estimate for the same population. The number of Nebraskans who do not approve of interracial dating also increased compared to the unweighted estimates using the original estimator, but decreased according to the MoS. In both cases, the number of people who used heroin in the last 30 days decreased.

Testing All Three Components

In the final stage of this article the previous elements are combined (MoS estimator, recursive back estimation trimming, and the use of population weights) in what is a significant step forward in the NSUM estimation procedure. Table 4.5 shows the final size estimates for our three subpopulations in Nebraska. Moving from left to right Table 4.5 first displays the unweighted and then weighted estimates using the original estimator, and then the unweighted and weighted estimates using the MoS estimator. All four estimates have gone through the recursive trimming process proposed here to remove poor scaling variables.

The estimates for the number of people who have moved to Nebraska from another state in the U.S. vary considerably across all four procedures: 16,039; 21,390; 64,320; and 90,073 respectively. Summing the ACS totals for the same type of migration during 2012 and 2013 gives us a total of 89,120. Each improvement made to the NSUM process provides an estimate which is closer to the ACS figure, but the combination of all three elements discussed in this paper provides a population estimate of 90,073 with 95% confidence intervals that include the ACS estimate of 89,120 (Figure 4.1). Estimates for disapproval of interracial dating (22,734; 23,883; 21,907; 21,250) and heroin use in the last 30 days (535, 404, 385, 281) vary considerably across estimation methods as well. The accuracy of the estimate of state-to-state migration verified by the ACS data suggests that the final estimates for those who disapprove of interracial dating and who have used heroin in the last 30 days are more accurate when using all three of proposed methods as well.

The MoS estimator, used in conjunction with the recursive trimming process, also preserves the largest number of scaling variables (see Figure 4.2). The original NSUM estimator requires the discarding of seven scaling variables before meeting the distance threshold of 1, even given the recursive trimming process. However, the MoS estimator discards only four. Keeping as many scaling variables as possible in the estimation process is highly recommended for robust estimations. This becomes far more important when a researcher is limited in space and resources and can only field a small number of scaling variables.

Personal network size varies considerably between different estimation forms in Table 4.5. Average network size ranges from 397.38 to 584.39 the maximum estimated network size ranges between 1243.25 and 2100.17. Compared to the initial estimates of personal network size shown in Table 3.4 there has been a considerable decrease in both average and maximum network size. Although the recursive process does reduce the estimate of personal network size, the majority of the change between Table 4.4 and Table 4.5 is attributed to removing outliers after the recursive trimming process is completed.

Conclusion

The network scale-up method is an important tool in the study of hidden and hard-to-reach populations. Its ability to generate accurate estimates of these populations using conventional sampling frames and survey techniques allows for data collection efforts that are considerably cheaper and faster than commonly used techniques to study hidden populations. Developing new improvements to the NSUM estimation process is important as the method begins to become more popular in new areas of the world and is applied to new populations.

This chapter proposed three adjustments to the original implementation of the network scale-up method. First, changing the estimation equations to take into account the mean of sums of ratios instead of the ratio of the sums (traditional estimator) preserves a respondent's exposure to each scaling subpopulation and allows these differences to exert equal weight upon the estimates. In doing so, this chapter offers one of the few proposed changes to the core estimation procedure of the NSUM since its original inception (Feehan and Salganik 2016; Maltiel et al. 2015). These changes are simple conceptually, but as shown, can have considerable effect upon population estimates generated by the NSUM estimator (see Table 4.5).

Second, this chapter discuss the benefits of using back estimation in a recursive fashion to improve population estimates. Instead of removing poor predictors in bulk, removing the most egregious predictor and then rerunning the back estimates is suggested. This process recognizes the dependency of the back estimates upon all the predictors that are used in the method. Removing poor estimators singly and in a recursive fashion allows researchers to examine how the removal of each estimator affects the other results. Although back-estimation has been discussed since some of the early work in the NSUM (Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998), this chapter represents one of the first tests of recursive back-estimation in the NSUM literature.

The recursive process provides an important check on scaling variables. A difference in performance across individual variables does not necessarily indicate problems with the estimation technique. Rather, it more likely reveals a measurement error or poor question design. If considering the example of the firefighters in the NCS, there was a wide discrepancy between the “known” value of 1,200 firefighters in Nebraska and the original back estimate of 18,000. This discrepancy likely represents a poorly phrased question. The number of firefighters which were obtained from the Bureau of Labor Statistics (1,200) represents professional and paid firefighters. The NCS did not specify that the firefighters needed to be paid professionals in order to match the criteria used by the BLS (and in retrospect, this may not have made that much of a difference). This is important because Nebraska is predominantly a rural state and thus has a sizeable portion of volunteer firefighters. These volunteers would not be represented in the BLS statistic, but would likely be identified as firefighters by the respondents. Because the question was incorrectly phrased, respondents were free to include anyone whom they considered a firefighter, professional or volunteer, significantly inflating the number of “knowable” firefighters in the population. This provides an unfortunately apt example of why pre-testing surveys and conducting cognitive interviews can eliminate considerable problems after a survey is complete (Dillman, Smyth, and Christian 2014; Willis 2005). The fact that this error can be discovered (and corrected) by the back estimation procedure described here provides something of a safety net for situations where large scale pre-testing is not possible.

Establishing how many predictors to cut, and where an appropriate threshold point for stopping the recursive trimming process may be, is likely to be highly dependent upon the characteristics of the NSUM project. Studies using larger numbers of scaling variables can afford to trim all those that are suspect. However, when there are fewer total predictors, say less than 5-8, over trimming of scaling variables can potentially mask variation across the respondent pool and increase the error of an estimate (see Figure 4.2). Researchers will need to balance the desire to remove inaccurate predictors with the need to maintain sufficient variation in the variables that are used in the estimation of personal network size. In these situations the recursive method becomes more important as analysts seek to eliminate the most egregious predictors while maintaining as many scaling variables as possible.

Third, this chapter introduced the means to incorporate sampling and post-stratification weights into the NSUM estimation process. Building weights into the equations allows researchers to take advantage of the sampling frames and their respective weighting adjustments which are seldom available to those interested in hidden and hard-to-reach populations. As shown above, neglecting to include weights in NSUM estimation ignores an important source of data correction that can greatly improve NSUM population estimates. Much of the recent NSUM literature has focused on exploring and improving transmission and barrier effects (Maltiel et al. 2015; McCormick et al. 2010; Salganik et al. 2011) and either reexamined old data collected by McCarty et al (2001) or has used direct samples of the hidden population (Salganik et al.

2011) . However, one of the strengths of the NSUM is its ability to use representative samples with equal or known probabilities of selection for much larger populations. In demonstrating the use of sampling weights, this chapter brings the NSUM back in line with one of its core strengths, representative sampling.

The final estimate of the number of people who have moved into Nebraska in the last 2 years from another U.S. state and its comparison to ACS benchmark data indicates that the estimation procedure changes introduced here provide a significant improvement over a one-step back-estimation procedure, and over the traditional estimator. This accuracy lends greater confidence to the other target population estimates, which are not as easily checked through verifiable sources. The implications of this new estimation procedure for previously estimated target populations may be a worthwhile question for researchers that have already carried out their own NSUM data collection. Looking ahead, the recursive back estimate trimming process may encourage researchers to rethink how many scaling variables they choose, and widen the potential list of these variables now that questions of equivalent size are less significant. Together this adds greater flexibility to the NSUM method, even as early results indicate that it also improves accuracy.

CHAPTER 5: SOCIAL NETWORK SIZE

In chapter 4 several changes to the traditional NSUM were introduced: the MoS estimator, recursive back-estimation, and survey weighting. Although it was demonstrated how these changes improved the NSUM's ability to estimate a target subpopulation against a benchmark, it is not clear how some of these changes alter the components of the NSUM, or the inference which can be drawn from the final estimates. This chapter takes the changes proposed in chapter 4 and systematically examines how two of them (back-estimation and MoS) alter the NSUM results when used with different missing data assumptions. This is achieved by examining three separate components: estimated social network size, regression associations between estimated network size and individual attributes, and differences in predicted social network size using the prior regression equations. In doing so, this chapter presents a systematic look at how estimation, inference, and prediction may change depending upon implementation choices of a researcher.

Literature Review

The network scale-up method (NSUM) is built around the estimation of social network size in almost all its forms (for an exception see: (Feehan and Salganik 2016)). Whether that estimate is derived through the known population or the summative method does not change the critical role that an individual's network size plays in estimating the final hidden population statistic. Functionally, the estimated network size serves as the denominator in equations 3.3 and 3.9. Error in these equations may push a final estimate to be larger (when the network size is underestimated) or smaller (when the network size is overestimated). Considerable effort is devoted to trying to get as accurate estimate of social network size as possible. In fact, the entire purpose of back-estimation (presented in chapter 3), and the development of better scaling variables for the known population method is to refine the estimate of network size and reduce error. Therefore, understanding how estimates of network size change in response to NSUM methods (i.e. the MoS and back-estimation) and assumptions is important to explore.

Although the NSUM uses estimated network size as a mean to an ends, it an interesting statistic on its own. Population variance of social network size has been of interest since at least Pool and Kochen's work on the Small World problem (1979) and in a broader sense since the early sociological theorists began to think about the relationship between personal interconnection and social structure (Durkheim 1964; Simmel 1950). However, collecting accurate information about network size outside of samples that are geographically contained (e.g. schools, remote communities) is both financially and logistically challenging. As a result, attempts to estimate population networks have often focus on subsets of personal networks. These subsets are often limited in the number of connections they capture, frequently focusing on the top 5 or 10 people a participant is connected to. The NSUM is able to estimate entire acquaintance networks with minimal effort allowing for the estimation of representative samples of network size. As such, the NSUM may provide insight into how social network size varies in larger populations.

Social Network Size

One of the great strengths of the NSUM is its ability to use sampling frames which are representative of the general population. Such samples are only usable in the NSUM framework due to the personal network component. Because the network contains information about the target or hidden population, it is no longer necessary to directly sample those groups. As a result, there has been considerable focus on ways to effectively estimate personal network size. When done accurately, such estimations free the NSUM method from the complex burden of attempting to obtain samples of hidden and hard-to-reach populations. In cases where the estimated network size is not thought to be reliable, or the transmission and barrier effects seem too great to overcome, then the NSUM needs to collect additional data directly from the target group or population (Feehan and Salganik 2016; Maltiel et al. 2015). It is therefore of great interest to understand how changing the NSUM estimation process (e.g. traditional vs. MoS) also affects the estimation of personal network size in order to retain as many of the NSUM advantages as possible.

Not only is accurately estimating personal network size important for a given NSUM study, but it can also reduce costs and increase the flexibility of future NSUM research. Under two broad conditions the estimates of personal network size from a previous NSUM study may be used for future NSUM studies without having to re-estimate network size. The first condition is that there should be no reason for personal network sizes on average to shift in a major fashion since it was last estimated. For this condition to work, it matters less that participants may have different people in their networks, so long as the network size remains similar, and the addition or removal of people from the network is not associated with the target group or subpopulation the NSUM survey is interested in. The second condition is that the prior network estimate is for the same area or frame that the later NSUM project is working with. This means that the personal network estimates for Nebraskans that are presented in this chapter could be used for a future NSUM study in Nebraska, but may not be sufficiently accurate for a study in Iowa or Ohio.

When both conditions are met for using previously estimated network size, some interesting potential applications of the NSUM become available. The best example of this comes from the NSUM research group working out of Kerman, Iran. They spent considerable effort to produce an estimate of urban personal networks that is representative of all the major urban centers in Iran (Rastegari et al. 2013) and one additional estimate that was specific to Tehran (Shati et al. 2014). With these estimates in hand, the researchers were able to develop interview protocols which could be implemented in extremely short interviews on the streets of the cities. This allowed the interview to appear as a brief public conversation about people known by random samples of the population who engage in illegal and highly stigmatized behavior. This provides participants with a strong sense of privacy and a degree of confidentiality that approaches anonymity, as the researcher never knows their name or where they live. Using the NSUM in this way, the Kerman research group has been able to produce estimates for a wide variety of illegal subgroups with minimal costs for interviews (Ali Nikfarjam et al. 2016; A. Nikfarjam et al. 2016; Rastegari et al. 2014; Shokoohi et al. 2012; Zamanian et al. 2016).

A critique of the Kerman approach is that although they established a national urban estimate of network size, they did not examine how their estimate varied by city or region of the country. In the one case where they did, they found that Tehran had a smaller network size (Shati et al. 2014) than their national average (Rastegari et al. 2013). Given that differences in the estimated personal network size can result in shifts in the final estimates of population size (equations 3.3 and 3.9). It is important to determine how geographic and individual attributes may affect the estimates. This becomes critical when attempting to establish estimates of network size for future studies to build upon.

It is not unreasonable to expect that personal social network size may be associated with characteristics of where a person lives or their attributes (e.g. age, rurality, etc.). Sociologists have long speculated the social networks and the social structures they represent may behave or emerge differently in urban and rural settings (Durkheim 1964; Wirth 1938). Durkheim and others thought that social relationships would shift in reaction to the industrialized nature of the cities compared to agrarian rural areas. Indeed, researchers have found that rural networks are denser (Beggs et al. 1996; Freudenburg 1986) and have greater levels of social capital (Beaudoin and Thorson 2004; Hofferth and Iceland 1998; Xu, Li, and Jiao 2016; Yang, Jensen, and Haran 2011). Despite these findings, it is unlikely that the relationship between space and network characteristics remains that simple, if it ever was. In the U.S. there is tendency to paint rural America in a simple, broad, all-encompassing stroke (Lichter and Brown 2011). However, the industrialized aspects of urban areas which first prompted Durkheim have now spread across the rural/urban divide. Industrial farming and herding practices are now the norm, rural areas are becoming sites for food processing factories, and are increasingly first destinations for new waves of immigrants (Lichter and Brown 2011). The extent to which network size itself varies on a rural to urban basis may be changing as a result and prior research which found smaller rural network sizes (Beggs et al. 1996) may no longer be accurate. There is additional research that suggests that there may be considerable variation of network characteristics within rural areas as well (Entwisle et al. 2007).

Beyond spatial differences, there are also established links between network size and other individual attributes. Hill and Dunbar (2003) found that personal network size was smaller among younger and older participants while the largest network sizes were found among those in their 50's and 60's. The decline in network size among older individuals has been found as well (Marsden 1987) Further, the composition of the networks themselves seems to change overtime (Hill and Dunbar 2003; van Tilburg 1998). Larger networks have also been associated with higher levels of income and education (Campbell, Marsden, and Hurlbert 1986; Marsden 1987; McPherson, Smith-Lovin, and Brashears 2006; van Tubergen et al. 2016). White participants in the U.S. have been found to have larger networks than black or Hispanic participants (Marsden 1987; McPherson et al. 2006).

Research Focus

Given the importance of network size to the NSUM estimation process and the general implications of network size in general, this chapter has three primary research foci. The first is how the known-population estimate of personal network size is affected by choices made by the researcher in three regards: traditional vs. MoS estimation, the use of recursive back-estimation or not, and the choices made about handling item nonresponse in the scaling variables. These three choices produce a 2x2x2 experimental design and eight independent estimates of personal network size. The second focus is how the separate estimates of network size from the first focus may differ in their associations with the attributes of participants (i.e. is gender associated with larger or smaller network sizes for all types of estimates) and if missing data treatments influence those associations. The third focus is how the different associations between attributes and estimated network size may then produce different predicted network sizes derived from regression equations.

Methods

Data for this chapter comes solely from the 2014 Nebraska Community Survey (NCS). The NCS used the known population method to estimate personal network size of Nebraskans using 18 scaling variables (12 names and 6 professions). The address-based sampling frame allows the data to be representative of Nebraskans and the questions were asked to restrict answers about the number of people a participant knew to those who were currently living in Nebraska. This means that personal network estimates are representative of Nebraskans (participants) about their current connections in Nebraska (personal networks). Although answers were restricted to those who lived in Nebraska, they were not restricted to those who were 19 years of age or older, thereby not perfectly matching the NSUM frame requirements discussed by Feehan et al (2016).

This chapter presents eight different estimates of personal network size using a 2x2x2 comparison of NSUM techniques (Table 5.1). The first comparison is between the network size generated by the traditional NSUM and the MoS NSUM methods. Considering that the MoS method is still fairly new, it is important to examine the differences between an established method and a new technique. Estimates from the traditional NSUM are labeled “traditional” and those from the MoS NSUM are labeled “MoS.”

The second comparison comes from how missing data in the scaling questions is handled. As a reminder, scaling questions were those which asked a respondent how many people they knew with a given name or professions (e.g. named Walter). These questions and the way they are used (equation 4.2 and 4.7) are highly susceptible to item nonresponse (i.e. when a question is left blank in an otherwise complete questionnaire). As the traditional and MoS estimators use a different process, the estimates they produce should react differently to the presence of item nonresponse among the scaling variables. Item nonresponse is particularly problematic with count questions in a mail survey. In such a situation it is impossible to know whether a blank answer indicates that the respondent knew zero people named "Watler" and did not want to expend the effort to write a zero, or if they just skipped the question. Previous NSUM surveys have had active interviewer involvement either through the phone or in person which makes it easier to tell a true refusal or "skip" from a zero answer. Unfortunately, a zero is meaningfully different from missing when estimating personal network size, as shown by equations 5.1 and 5.2.

$$\hat{c}_i = \frac{1 + 0 + 1}{100 + 100 + 100} t = \frac{2}{300} t \tag{5.1}$$

$$\hat{c}_i = \frac{1 + 1}{100 + 100} t = \frac{2}{200} t \tag{5.2}$$

For previous calculations with the NCS data (Chapter 4) the more conservative assumption was made, that item nonresponse was a result of missing data, and not a zero that the respondent chose not to write. Although this is the more cautious approach, it also resulted in the loss of complete cases to work with. Therefore this chapter also examines what happens to the estimates of personal network size when you assume that such item nonresponse is the result of laziness and should truly be a zero. Estimates which use the first assumption (missing as missing) are labeled with a “1” and those which use the second assumption (missing as zero) are labeled with a “2”.

The third condition is the use of back-estimation. Although back-estimation has been in the NSUM literature for some time, only recently has there been any use of it in a recursive fashion as presented in Chapter 4 of this dissertation. There is thus still some uncertainty about the effects of using recursive back-estimation upon estimates of personal network size. This chapter compares estimates of personal network size when not using recursive back-estimation at all, and using the recursive thresholds proposed in Chapter 4. Estimates which do not use back-estimation are labeled “baseline,” and those which use the recursive bask-estimation are labeled “final.”

These three combined aspects provide eight different distributions of estimated personal network size (estimator, item nonresponse assumption, and back-estimation). However, in order to determine whether an individual’s attributes (e.g age, income) are associated with having different personal network sizes an additional step is required. These attribute variables have their own missing data problems which are addressed through two separate techniques, listwise deletion and multiple imputation. Listwise deletion is a missing data approach where cases (i.e. participants) are not included in the analysis if they do not have complete data for every variable being used in the model. Although a common approach, listwise deletion comes with strong assumptions about the random nature of missing data which are not easily verified. Multiple imputation on the other hand uses statistical models to predict what the missing data is likely to be. By repeating this process multiple times a pooled estimate of what an individual’s missing data might be is generated. This process is more complex than listwise deletion, but has the advantage of retaining more cases. In order to compare how a listwise and a multiple imputation approach affects the outcomes of interest, the 8 separate estimates of personal network size are handled with both missing data approaches, creating 16 analytical models.

For this chapter, chained multiple imputation is used in Stata 12 with the .mi estimate command suite. Fifty imputations were calculated with a seed value of 3,1337 and burn-in of 10 imputations (i.e. the first 10 imputations are discarded). Stata allows for the specification of model types to predict missing data in separate variables based on their data structure. As such, logistic regression is used to predict missing values for dichotomous variables, multinomial logistic regression for categorical variables, and predictive mean matching for linear variables which are interval in nature (i.e. age). The predictive mean matching produces estimates which do not exceed the bounds of the data, and maintains the internal distance between possible values. As age in this data is measured in year increments, this means that predicted values cannot appear as partial years (e.g. 32.5 years old) and will not drop below the boundaries of the data (i.e. less than 19 years old).

Eight independent variables are used in this analysis. *Female* is measured as a binary where male participants are coded (0) and female as (1). *Age* is measured as an interval variable in one year increments. *Education* measures the highest level of education completed by the participant and has four categories: high school or less, some college, four year degree, and a graduate or professional degree. *Political Affiliation* is self-reported and has three categories: liberal, middle-of-the-road, and conservative.

Race/Ethnicity is measured as white non-Hispanic (1) and all others (0). Although this split may seem unusual, it is a fairly accurate representation of Nebraskans. The 2010 Census reported 89% of Nebraska as being white non-Hispanic and all other categories made up smalls groups individually (U. S. Bureau of the Census 2015). *Religious Attendance* is measured dichotomously where those who attend nearly every week or more are coded (1) and those who attend monthly or less are coded (0). *Income* is measured in four categories: $0 - $24,000; $25,000 - $49,999; $50,000 - $99,999; and $100,000 or more. *Urbanicity* is measured in three categories by classifying zip codes by their associated population centers. *Urban* areas are zip codes associated with areas of 50,000 people or more. This includes Omaha, Lincoln, and Grand Island Nebraska. Papillion and La Vista were also counted as urban as they are immediate suburbs of Omaha. *Midrange* areas are those with 10,000 to 49,000 people which included several smaller towns such as Kearney, Scotts Bluff, Beatrice, Lexington, and a few others. *Rural* areas were zipcodes associated with less than 10,000 people which includes the vast majority of the land area in the state of Nebraska.

The analytic strategy for this chapter has three distinct phases. In the first, the eight separate estimates of personal network size are presented. Second, negative binomial regression models are used to test for associations between estimated social network size and attributes of the participant. This step requires 16 independent models to cover all eight network estimates using both listwise and multiple imputation to address missing data among the independent variables. Results from these models are discussed in terms of associations which appear in all models, those that appear occasionally, and then those which are never associated. Finally, these 16 models are used to estimate the predicted size of personal networks in rural, midrange, and urban areas of Nebraska, while keeping other independent variables at their mean value. Predicted sizes were calculated using the margins and mimrgns commands in Stata 12.

Results

Estimated Personal Network Size

Table 5.2 shows the eight different estimates of personal network size produced through the 2x2x2 design described in Table 5.1. The average estimate of personal network size for Nebraskans using the traditional estimator, treating missing as missing, and without recursive back-estimation is 610.94, which after recursive back-estimation is applied drops to 452.91. If instead, missing is treated as a zero, the average network size without recursive back-estimation is 607.2 and with recursive back-estimation increases to 622.39. Using the MoS estimator, treating missing as missing, and without recursive back-estimation results in an average personal network size of 1,039.71 which decreases to 490.49 with recursive back-estimation applied to the same data. When missing is treated as zero while using the MoS without recursive back-estimation the estimate of average network size is 1,034.93 which decreases to 484.17 once recursive back-estimation is applied. The sample size difference for each estimated network size is a function of how item nonresponse is treated (1 versus 2) and the process of discarding erroneous scaling variables through back-estimation (baseline versus final). As the different estimators discard different scaling variables, and in different orders, the resulting item nonresponse patterns shift in kind, leading to different subsets of cases with complete data.

Back-Estimation

The metrics used in recursive back-estimation for each of the eight estimates are shown in Table 5.3. All 18 scaling variables are listed in the first column and then each of the eight estimate types are listed. Rank indicates which scaling variables were the greatest distance from zero (the most inaccurate) using the distance metric (the absolute value, of the log base 2, of the ratio of the estimated scaling variable to its known value). For the baseline models no action was taken and all scaling variables were left in the estimation process. For the final type models, scaling variables were removed one at time by taking the variable with the greatest distance value from 0, recalculating distance, and repeating until all remaining scaling variables had a distance less than one (see Chapter 3 for more details). The "*eliminated #*" indicates the order in which a given scaling variable was removed from the estimation process.

There are several important takeaways from Table 5.3. First, all 8 implementations of the method removed (or would have removed) the same three scaling variables first (Firefighters, Walters, and Marthas) but, they did not do so in the same order. All but one of the implementations removed Ralph fourth. This suggests a possible alternative to using the debatably arbitrary threshold of one. Instead, scaling variables to be removed could be identified through their common state of distance across multiple estimation methods. This option may be useful. Particularly if one is unsure how deep to cut into scaling variables, and if a researcher only has a small set of scaling variables to work with initially.

Second, the starting distance rank of a scaling variable was not always accurate in predicting if it would be cut given a certain number of iterations of the recursive process. In the Traditional 1 Baseline model there were initially seven scaling variables with a distance greater than the set threshold of 1 (in order: firefighters, Walter, Martha, Ralph, airline pilots, U.S. postal officers, Rose). When this same implementation was put through the recursive process (Traditional 1 Final) not only did the order of elimination change, but not all of the same scaling variables were removed (in order: firefighters, Walter, Martha, airline pilots, Ralph, U.S. postal officers, police officers, and corrections officers). In this example Rose was never eliminated, despite having a distance value beyond the threshold at baseline, but police and corrections officers were. This shows the value in the recursive process of back-estimation instead of a bulk cut. Although some of the initial cuts would be the same, the ones further along shift as the process iterates.

Finally, Table 5.3 shows that the traditional and MoS estimators preserve different numbers of scaling variables. The traditional estimator removes eight or seven scaling variables depending upon the assumptions made about item nonresponse. However, the MoS estimator removes only five scaling variables for both item nonresponse assumptions. Again, in situations where the number of scaling variables is low, or where a research wants to preserve a higher number of scaling variables, the MoS appears to best serve. There is one caveat, such that the MoS 2 Final recursive back-estimation process never actually crosses the threshold of 1. As shown in Table 5.3 police officers have a final distance value of 1.004. If they were removed in the recursive process, the remaining distance values were found to increase and never again approach 1 in any meaningful way. Therefore, the recursive process was halted above the threshold. Considering the threshold value of 1 was somewhat arbitrary to begin (see Chapter 4), it should not be surprising to find limits to its usefulness. This lends weight to the observation about using multiple estimation methods to identify scaling variables that are consistently erroneous for all estimation procedures.

Regression Results

The characteristics of the sample, beyond estimated network size, are presented in Table 5.4. In order to compare missing data treatments among the independent variables two separate datasets were created. The first used listwise deletion and the second multiple imputation. Table 5.4 shows the number of cases, mean or percent, and standard error for both datasets. The amount of missing data for each independent variable is also shown in the listwise deletion dataset and difference of the means between the two datasets is shown in the last column. The difference of means between the two datasets exceeds 1% for average educational attainment, income, and urbanicity, but no estimate was different by more than 3%. This suggests that despite the difference in cases, there are minimal differences in the sample composition between datasets. Unlike most listwise datasets, the cases in Table 5.4 are not restricted to the lowest number of complete data. This is because each predictive model in the listwise dataset will have a different sample size based upon both the descriptive statistics from Table 5.4 and the personal network size estimates from Table 5.2.

On average participants in samples were female (51% in listwise/51% in imputed) and were 47 or 49 years old on average (see Table 5.4). The highest degree completed for the sample was on average, high school or less (15%/17%), some college (37%/36%), a four year degree (27%/27%), or a graduate or professional degree (21%/20%). Most participants identified politically as "middle-of-the-road" (42%/42%), or conservative (41%/41%), with a smaller amount identifying as liberal (17%/17%). A large majority of the sample was white and non-Hispanic (89%/89%) and less than half reported attending a religious service nearly every week or more (45%/45%). The percent of participants who reported earning less than $25,000 in the prior year was 11%/17%, for $25,000 - $49,999 (22%/23%), for $50,000 - $99,999 (42%/41%), and for earnings at or above $100,000 (25%/23%). Slighty more than 30% of the participants were classified as rural (32%/33%), midrange (13%/14%), or urban (55%/53%) based upon their zip code.

The results of the negative binomial regression models for the 16 different estimates of personal network size (see Table 5.1) are shown in Tables 5.5 and 5.6. Each model uses the same set of independent variables, but the conditions which produce the dependent measure vary by model, and the approach to missing data among the independent measures varies by table (5.5 uses listwise deletion, 5.6 uses multiple imputation).

There are two significant associations which appear in in the same direction, with similar magnitude, in all 16 models. The first is that those in urban areas have expected personal network sizes that are significantly lower than those in rural areas. In all 16 models this association is highly significant ($p<.001$) and varies in strength. At its weakest, an average person in an urban area is expected to have a social network size that is 41.3% smaller than an average person in a rural area of Nebraska (Table 5.5: Model 2). The strongest association suggests that an average person in an urban area will have an expected social network size that is 69.9% smaller than an average person in a rural area of Nebraska (Table 5.5: Model 5). Several models do show significant differences between midrange and rural areas as well. However, these associations only appeared in

10 of the 16 models. When they did appear, an average person in a midrange area was likely to have a smaller personal network size than an average person in a rural area.

The second association which is constant in all the models in Tables 5.5 and 5.6 is that those who reported having less than $25,000 in income in the prior year were expected to have on average significantly smaller personal networks compared to those who reported $50,000 - $99,999 of income in the prior year. At its weakest, this association suggested a 23.4% percent lower estimated network size when compared to those who make between $50,000 and $99,999 (Table 5.5: Model 2). The strongest association found a 50.2% decrease in the estimated network size for those who made less than $25,000 in the prior compared to the $50,000 - $99,999 income bracket (Table 5.5: Model 5). Other income categories were occasionally significantly associated with network size. Having income at or exceeding $100,000 was associated with smaller network sizes when compared to the $50,000 - $99,999 income bracket twice (Table 5.5: Model 1, Table 5.6: Table 1), but was otherwise not associated. There were also two models where reporting prior income of $25,000 - $49,999 was associated with smaller expected networks than the $50,000 - $99,999 income bracket (Table 5.5: Model 2, Table 5.6: Model 2).

Three other associations appear in some models, but are not consistent across all 16. Achieving a graduate or professional degree was associated with smaller expected network sizes when compared to those who had completed a four year degree in 7 models (Table 5.5: Models 1, 3, 4 & 7, Table 5.6: Models 1, 3, & 4). The effects sizes were fairly consistent, ranging from a decrease in expected network size of 28% (Table 5.5: Model 3) to a decrease of 25.1% (Table 5.6: Model 1) and were in the same direction. No differences in estimated personal network size were found between having completed a high school degree or less, or completing some college when compared to completing a four year degree.

Religious service attendance was associated with personal network size in 4 of the 16 models. In all four cases attending a religious service nearly weekly or more was associated with an approximately 21% larger expected personal network size compared to those who attended a religious service monthly or less (Table 5.5: Model 2, Table 5.6: Models 2,3, & 4). All four associations were significant ($p < .05$), were in the same direction, and had similar effect sizes.

The age of participants, which was measured with an included quadratic term, was significantly associated with estimated personal network size only once (Table 5.6: Model 5). For every one year increase in age the estimated size of an average personal network increased by 3% ($p < 0.05$) while also decreasing by 0.03% ($p < 0.05$) forming a gradually decreasing curve (Table 5.6: Model 5). This association was not, however, found in any other of the 16 models.

In all 16 models, no differences in personal network size were associated with self-identified political identity. There were also no differences between males and females in their expected personal network size. Finally, there was no difference in expected personal network size between white non-Hispanics and the combined minority measure.

Predicted Social Network Size from Regression

Using the 16 models from Tables 5.5 and 5.6, predicted social network sizes were estimated for rural, midrange, and urban participants in the sample while all other coefficients were held at their mean value. The resulting predictions and their attendant 95% confidence intervals are presented formally in Table 5.7. Differences between urban and rural areas are noticeably different, and in many cases the rural estimate is double that of the urban. In the first column of predicted network sizes in Table 5.7 the traditional 1 baseline with listwise deletion predicts an average rural network size of 974.23 and an average urban network size of 396.56. The distinction between a midsize prediction and that of either an urban or rural estimate is more difficult as the confidence intervals occasionally overlap.

There are several interesting patterns among the predicted personal network sizes in Table 5.7. Figure 5.1 uses the values from to Table 5.7 to visually show how the 16 different models and their rural, midrange, and urban estimates differ. Each set of urban/midrange/rural estimates is labeled using a four character identifier. The first character may be an “L” or “M” and indicates if that cluster was from the listwise deletion or multiple imputation data sets. The second character may be a “T” or “M” in order to indicate whether the traditional or MoS NSUM estimator was used. The third character may be a “1” or “2” and indicates which item nonresponse assumption was used (1 = missing as missing, 2 = missing as zero). The final character may be a “B” or “F” which stands for baseline (i.e. no back-estimation) or final (i.e. complete recursive back-estimation) estimates. In Figure 5.1, baseline models are grouped together on the left side of the figure, and final models are grouped on the right side.

Three key results may be seen in Figure 5.1. First, the much higher predictions based on MoS models in the baseline side are essentially pulled back in on the final side. The back-estimation process tempers the more extreme MoS estimates. In fact in almost every case the final predictions were lower than the baseline (the LT2B-LT2F and MT2B-MT2F models are an exception). Changes in the MoS predictions are the most extreme, as that method is more susceptible to extreme values (as discussed in Chapter 4).

The second, is that among the baseline models (left side of Figure 5.1) there appears to be little difference in predictions between 1 and 2 item nonresponse variants of the models for both traditional and MoS estimators. However, after back-estimation (right side of Figure 5.1) there is considerably more distance between the 1 and 2 item nonresponse variants. For example, from Table 5.7, initially the difference between the LT1B and LT2B rural predictions was about 15 people (974.23-957.16). After back-estimation the difference between the LT1F and LT2F rural predictions was about 255 people in the network (611.59-866.53).

Finally, the back-estimation procedure not only generally reduced the estimated network size, but also greatly reduces the variance of the eight predictions. Using the adjusted sample variance equation below (Eq. 5.1), the variance for the urban, midrange, and rural predictions can be estimated for both the baseline and final groups of estimates. The variance of the predictions at baseline is considerably greater than the variance of the predictions after back-estimation. This suggests that the back-estimation process produces a more stable prediction over all of the experimental estimation processes used in the chapter.

$$s_n^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X}_n)^2 \qquad (4.1)$$

Discussion

Experimental Effects on Estimated Social Network Size

It appears that the MoS estimator will produce estimates of personal network size that are approximately 1.7 times greater than the traditional estimator under the same assumptions. The use of back-estimation alone greatly reduced three of the four estimates of personal network size and also reduced the distance between the MoS and traditional estimates. Looking at the outcomes presented in Table 5.2, it is clear that although using the MoS may produce higher estimates initially, the use of back-estimation appears to find a common value across estimation procedures. The MoS with back-estimation was also able correctly predict the number of people who had moved into Nebraska in the prior two years compared to Census statistics while the traditional procedure with back-estimation could not (Chapter 4). Additionally, the MoS achieved the back-estimation threshold with fewer iterations, and therefore lost fewer scaling variables. It seems reasonable to suggest that the MoS with recursive back-estimation should be the preferred estimator when considering only raw network estimates.

Surprisingly, varying the item nonresponse assumptions resulted in very little change in personal network size when back-estimation was not used. There were, however, substantial differences in the number of cases which were preserved in the data depending upon item nonresponse assumption. Given the lack of variation in network size estimation, but the noticeable differences in available cases, it seems prudent to suggest adopting the “missing as zero” protocol when treating partial scaling data. Hopefully this entire scenario can be avoided in future surveys due to better questionnaire design which would specifically discourage this type of item nonresponse.

Comparing Network Size Estimates to Other Studies

Beyond internal comparisons of network size it is also possible to contrast the estimates from this chapter with other social network size estimates. Unfortunately, comparing the estimates of personal network size generated for Table 5.2 to other studies has several complications. Many studies of network size are focusing on small network circles (e.g. “top five friends”, or “closest people”). In studies such as these network size is often reported to be in single digits and rarely exceeds 100 (Hill and Dunbar 2003; Marsden 1987; McPherson et al. 2006). Such network estimates are clearly well below the range of the estimates produced here. Comparing NSUM results to other NSUM results may make more sense. One of the first NSUM studies in Florida found average network sizes of 105 and 113 (Killworth, Johnsen, et al. 1998) and in another study of 286 (Killworth, McCarty, H. Russell Bernard, Shelley, et al. 1998). In a third study, which used a national telephone sample, estimates of average personal network size were found to be 290.8 and 290.7 for two different estimation methods (McCarty et al. 2001). Other NSUM studies conducted outside of the United States have found average network sizes of 947.3 for medical specialists in Italy (Snidero et al. 2007), 363.5 for Japanese adults (Ezoe et al. 2012), and 308 for urban Iranian adults (Rastegari et al. 2013). The average estimates presented in Table 5.2 are universally higher than previous U.S. and non-U.S. estimates (with the exception of the Italian estimate) although several are closer.

The problem with comparing network sizes from various estimation methods, including the NSUM, is that they are approximations of an unknown which are developed to save time and money during a survey. The network diary method on the other hand, is an attempt to obtain exhaustive detail about all network ties over a longer period of time

(Fu 2005, 2007). The NSUM and other network data collections techniques seek to generate estimates based on short interviews. Contact diaries create a log of contact between a participant and everyone else they interact with over a longer period of time. Logging daily interactions over a three month period (or less) produces a picture of network size that is less prone to recall error. However, contact diaries are not perfect. Even with a three month time frame a diary may not catch individuals with whom the participant does not interact with regularly, but would still fall in the two year window required by most NSUM and “acquaintance” studies. To help remedy this, and to allow diaries to be used in shorter time frames, the alter accumulation curve was developed (Yen et al. 2016). Using diaries to gauge the rate of new alter entrance into the log compared to repeated entries, the authors adapted a technique to estimate the possible numbers of unknown alters that may remain unlisted in the diary (*ibid*). Such method takes a highly reliable and comprehensive source of network data (a contact diary) and corrects its estimate for less frequently activated ties establishing a solid benchmark for acquaintance network size. In their recent application of this method, Yen et al. (2016) estimated an average personal network size of 576.27 and a range that included large networks which exceeded 2,000 alters. This estimated average is fairly close to the back-estimated averages provided in Table 4.2 (452.91, 622.39, 490.49, 484.17). The MoS averages are smaller, and the traditional averages fall on both sides, but all estimates are reasonably close.

Back-Estimation Performance

Moving beyond estimated network size, the comparison of how back-estimation performed across the different estimators and assumptions provides several interesting observations. The first is that there is a commonly identified group of worst scaling variables. The same three scaling variables were independently identified in all eight experimental versions. Although the different experimental versions discarded the three scaling variables in different orders, the commonality has potential applications. In future NSUM studies it might be worthwhile to further explore the idea of using multiple NSUM estimation methods to identify a common group of worst scaling variables which are discarded instead of using a threshold value. Such an approach might preserve a larger number of scaling variables and in some instances more cases in the data. This would be valuable for studies which use fewer scaling variables or those with smaller sample sizes.

This examination of back-estimation also shows that the MoS estimator, under all experimental variations, retains a greater number of scaling variables while attaining the same threshold as the traditional estimator. For studies with a limited number of scaling variables the MoS may prove to be the better choice in order to keep more scaling variables. The traditional estimator eliminated almost half of the scaling variables in this dataset (8 or 7 of 18) using a threshold value of one while the MoS removed only 4 or 5.

The final point from Table 5.3 is the value of recursive back-estimation when compared to a bulk cut of scaling variables. Looking between the baseline and final versions of the same estimator you can see how in some cases certain scaling variables are initially identified as being droppable. However, as the recursive process progresses, the performance of these scaling variables improves to such a point that they fall under the cut threshold. Using a bulk cut process wherein the researcher removes all scaling variables which exceed the threshold before the first cut is made would, in this case, result in the removal of variables that should have been left in. Therefore, using a recursive back-estimation process is highly suggested for all practitioners.

Individual and Spatial Differences in Network Size

Examining the associations between individual attributes and social network size across the models in Tables 5.5 and 5.6 shows several interesting patterns. First, the rural/urban difference in the expected network size is undeniable. In all sixteen models rural networks are expected to be significantly and substantially larger than urban networks. In many models participants in midrange areas with 10,000 to 50,000 people also have smaller networks than those in rural areas. Historically sociologists have often thought of rural networks to be small and dense compared to urban networks which where sparse and superficial (Wirth 1938). The liberated community argument (Wellman 1979) found that although urban dwellers may have networks which are less dense than rural counterparts, their networks are not lacking in support. Instead, that support is spread across multiple networks which may be only loosely interconnected. Unfortunately the NSUM is ill-equipped to measure density of a network, and the prior estimates of differences in network size are focused on intimate networks, or the closer subsets of the acquaintance network that the NSUM measures. This makes it exceedingly difficult to compare the rural/urban distinction found in the Nebraska NSUM estimates with prior findings. However, unless the NSUM rural/urban difference is a function of the method itself, or the statewide geographic boundary which is imposed upon listing alters, it seems likely that in the scope of network degree, rural dwellers have substantially larger network sizes in Nebraska.

The second universal finding in these tables it that those with yearly income of less than \$25,000 have smaller networks than those who made between \$50,000 and \$99,999 in the prior year. Given the lack of other findings relating to income, this suggests a lower threshold where those at the lowest levels have the smaller networks and higher levels of income have similar network sizes. Network size is often associated with social capital and the ability to find employment (Lin and Dumin 1986). Further, larger networks have more weak ties (Granovetter 1973, 1983) which often represent ties that bridge smaller network components. It is this bridging action which provides the potential "strength of weak ties" (Granovetter 1973) as a bridge can possess information which is not available to one of its components. Not all weak ties may serve this function, but a reduction in the total number of weak ties reduces the chance of a participant being able to successfully utilize a given tie. The association between lower income participants and smaller networks may be seen as somewhat self-fulfilling, as they may lack enough contacts to learn about opportunities to make more money (Lin and Dumin 1986).

Many of the other associations found in Tables 5.5 and 5.6 are inconsistent across the different experimental versions of social network size and across the different treatment of missing data amongst the individual attributes as well. Given the prior discussion on network estimates and back-estimation, Model 8 in both Table 5.5 and 5.6 is most likely to be the best model to use (as this uses the MoS with recursive back-estimation). In these models only the universal associations are present (i.e. rural/urban, \$25k/\$50k-99.9k). Under these two models participants in urban areas are expected to have personal networks which are on average 49% or 48% lower than their rural counterparts (Model 8 in Table 5.5 and Table 5.6 respectively). Further, participants who made less than $25,000 are expected to have personal networks which are one average 37.2% or 33.3% lower than those who made between $50,000 and $99,999 in the prior year (Model 8 in Table 5.5 and Table 5.6 respectively). There are no other significant associations between personal attributes and the expected size of personal networks. Sex, age, education, political affiliation, race, and religious attendance are non-significant.

There are serious differences in what statistical associations a researcher may find depending upon their decision to use the traditional or MoS estimator. The models which use the traditional estimates as outcomes show considerably more associations between network size and individual attributes. Depending upon the model chosen from Tables 5.5 and 5.6 a researcher might offer evidence of the association between network size and religious attendance, or education. But these associations do not appear in the final MoS models which use back-estimation, or at all in the case of religious attendance. The choice of MoS or traditional estimator does have consequences for inference, and not even back-estimation (which initially brought traditional and MoS estimates closer together) serves to make these models show similar associations. Readers who might have thus far thought that they could use either estimation method are now faced with an important choice for their own applications of the NSUM.

Limitations

The geographic boundary requirement for knowing an alter is a potentially serious limitation to the work in this chapter. This means that if a study participant knew a police officer in Iowa, they would not list them in their answer. Such a restriction makes sense when trying to develop estimates which are state (or any geographic region) specific. However, in this case, there is no reason to think that social networks are bound by nonenforced political boundaries, or even the rivers that often follow state borders (i.e. the eastern edge of Nebraska is the Missouri River). In such cases, there may be an association with living on a border with increased chances of not knowing someone in the scaling or target variables. This may be exacerbated by the location of Omaha (the largest urban area in Nebraska) directly on the Nebraska – Iowa border which could contribute the rural/urban difference found in Tables 5.5 and 5.6.

Conclusion

There are several different estimation procedures an NSUM researcher may decide to use for their data. This chapter closely examined the traditional and mean of sums (MoS) estimators by comparing their estimates of personal network sizes under different conditions (item nonresponse assumptions and back-estimation). When recursive back-estimation is used the two methods produce roughly similar estimates of personal network size. Considering that the MoS is better able to predict sub-population sizes for which we have a benchmark (see Chapter 4), it seems that the MoS with back-estimation is the better option to use.

Although estimates of personal network size are similar in most cases, the choice of estimator was shown to have consequences when attempting to predict individual personal network size using person attribute data. Depending upon which estimator, and which experimental conditions were used, a research may find results that are only significant under certain conditions and estimators. There were two associations which were constant for all models. Personal network sizes are larger among rural Nebraskans compared to urban Nebraskans and networks were smaller for Nebraskans who made less than $25,000 in the prior compared to those who made $50,000 to $99,999 in the prior year. Other associations were found in subsets of models, but none were consistent across all. This means that a researcher's choice of estimator and how they treat the data may have both significant and substantial differences in the outcomes that they find.

Considering the information presented here and in Chapter 4 it seems clear that NSUM researchers should engage in recursive back-estimation whenever possible. This technique reduces the variance in estimated outcomes and decreases some of the differences between the traditional and MoS estimator. The ideal estimator appears to be the MoS, but researchers who are cautious about its inflation of network size should consider using both estimators and comparing them in their own data. Item nonresponse had a much smaller effect than initially theorized. However, work should be done in the future with questionnaire design to completely eliminate this source of error.

CHAPTER 6: THE COGNITIVE NSUM

Where chapters 4 and 5 explored differences in the estimation, post-hoc data corrections, and statistical inference, chapter 6 turns to the survey participant's response process. NSUM researchers typically focused on four sources of error: transmission, barrier, recall, and cognitive. A considerable amount of time and energy trying has been devoted on these types of errors. This has led to clever corrections for transmission errors (Feehan and Salganik 2016), and barrier effects (McCormick et al. 2010). Recall and cognitive errors have been given considerably less attention. In the NSUM framework recall errors deal with the participant's ability to remember how many people they know and cognitive errors address a participant's ability to understand the constraints of the question (e.g. definitions of knowing someone). This chapter uses cognitive interviewing to closely examine the thought process used by NSUM survey participants. In doing so several issues which may affect both recall and cognitive error are brought into focus.

Within the NSUM framework, recall errors are generally classified as inaccuracy in the counts provided by the participant for either the scaling questions used to estimate personal network size (e.g. names or professions) or the counts of how many people they know in a target subgroup (e.g. people with HIV). Systematic error in either the scaling questions or the target subgroup counts can have serious implications for final NSUM estimates. As such, several corrective efforts have previously been explored such as back-estimation (Killworth, McCarty, H. Russel Bernard, Shelley, et al. 1998), recursive back-estimation (Habecker et al. 2015), and allowing counts to be a random error in a Bayesian framework (Maltiel et al. 2015).

Statistical corrections may be effective in a post-hoc adjustment, but it would be beneficial to better understand the source of the errors and work to reduce them before they enter the data. McCarty et al. (2001) conducted a small set of focus groups to explore the differences between the known-population and summation methods to estimate personal network size. In the process they discovered that participants tended to estimate their answers for large populations instead of actually counting the number of people they knew in that population (McCarty et al. 2001). Not only did participants tend to estimate larger groups, they often provided answers that were divisible by 5 causing the data to become heaped on those numbers. Although McCarty et al. (2001) developed a post-hoc correction, they argued that more work needed to be done to assess the accuracy of NSUM estimates.

Cognitive errors occur when the participant either misunderstands the group they are supposed to be thinking of, or alters the definition and boundaries of knowing someone from what the survey provides. An example of the former would be a case where the participant is asked to count the number of commercial pilots they know and they add to their count people they know who have a pilot’s license, but do not fly for a commercial carrier. The latter type of cognitive error would occur when the participant includes people that they have not have contact with in the last two years, or in the case of the NCS, people who live outside of Nebraska. Such inclusions would violate the temporal or spatial boundary that were placed on the definition of knowing someone. These types of cognitive errors may not be immediately apparent in an interview or survey. A participant may have a correct definition of knowing someone at the beginning, only to develop recall habits which lead them to unconsciously adjust their definition as the survey progresses. For example, if a participant is frequently only finding candidates for their answers among their family and college friends, but not their work acquaintances, they may begin to spend less time thinking about their work acquaintances and more time on their family and college friends as they are able to find answers within those groups. This would put an artificial boundary on knowing someone that was not intended by the researcher.

Some work has been completed on the cognitive aspects of what it means to know someone. McCarty et al (2001) asked their focus groups what they thought about the two year temporal boundary they had placed on knowing someone. Participants in those groups were generally happy with the definition, although some expressed concern alters with whom they contact less than every two years would still be important ties to them if they had a need to get in touch (McCarty et al. 2001). In another study the researchers reduced the temporal boundary to one year in an effort to make it easier for participants to remember all of whom they knew (Feehan et al. 2016). Here they found a reduction in error using the shorter temporal boundary, but they acknowledge that this was a trade-off for losing more of the outlying ties in their networks.

Despite this prior work, a substantial amount of research remains to be done on the introduction of recall and cognitive error in NSUM studies. This chapter looks at several questions specific to these NSUM error sources. In order to place these questions in a meaningful order, a model of the survey response process is used to organize the questions into common groups.

Survey Response Process

The survey response process is a model of the mental steps a participant goes through when answering a question (Schwarz and Sudman 1996; Sudman et al. 1996; Tourangeau et al. 2000). Although describing the process as a series of steps implies a linear process, these steps may occur in overlapping or simultaneous moments, if they occur at all (Tourangeau et al. 2000). Response process models and their various steps serve as diagnostic tool to identify and sort different types of error. The model proposed by Tourangeau et al. (2000) has four components: comprehension, retrieval, judgement, and response. This chapter uses an extension of the Tourangeau et al. (2000) model which adds the step of perception before comprehension (Dillman et al. 2014). The five-step model is then used to present the main research questions of this chapter and to organize the results of the cognitive interviews.

Step 1: Perception

Perception refers to the participant's ability to understand the structure of a survey, such as where to start, which question is next, and where they should look at all (Dillman et al. 2014). In self-administered surveys, an interviewer is not present to provide instructions that are not directly part of the written question itself. With self-administered surveys many additional instructions are therefore presented for groups of questions instead of being repeated for each one. NSUM questions are typically fairly short (i.e. How many people do you know named Walter?). However, the word "know" has to be very specifically defined around spatial, temporal, and closeness boundaries. These definitions are complex and would substantially increase the survey length if they were repeated for each NSUM question. Additionally, the respondent would have to reread the same instructions for every single NSUM question. If the definition of "know" is not seen by the participant, then their responses for NSUM questions may be substantially incorrect. To ensure the “know” definition was seen in the 2014 NCS survey, the definition was written as its own question (Appendix B: Question 4). However, there were several other sets of instructions in the 2014 NCS which were not written as a question, but were instead written above or below certain questions and question groups. This provides an opportunity to test whether participants saw instructions which were written as a question at different rates than those instructions which were not written as questions.

Step 2: Comprehension

The second step of this response process model is comprehension. This focuses upon the participant’s ability to understand what the question is asking and to link it to prior concepts. For the NSUM this has several implications. Given a question that asks the participant how many people they know who are firefighters, a participant needs to manage several comprehension tasks. First, the participant has to understand that the use of the word “know” is meant to recall the specific definition of knowing someone that they were previously provided with. Second, they then have to understand what the researchers mean by firefighters or another group. As chapter 4 previously discussed, in the NCS, participants’ comprehended firefighters as meaning anyone who worked for, or volunteered for a fire company. However, the researchers meant paid firefighters only and did a poor job of conveying that in the written survey. Finally, the participant has to understand that the question is asking them to think of all the firefighters they know (within the boundaries set by that definition) and then convert that list of people into a number which is what the question ultimately wants. The major risk to NSUM researchers in this step is whether a participant is able to link back to the definition of knowing someone, and if their understanding of the target group matches the researcher's understanding of that group. Discrepancies in either of these may lead to inaccuracy in the final answer.

This chapter looks at several comprehension questions. The first is whether the participant is able to correctly operationalize the definition of knowing someone according to the temporal (two year contact window) and geographic (currently in Nebraska) boundaries imposed upon that definition. The second comprehension question is whether the participant understands that knowing someone can be by general recognition or by name, and that both are not necessarily required. Finally, given that NCS and the cognitive interviews which are based on it ask a substantial number of NSUM questions, the third question is whether the participant's comprehension of knowing someone remains stable across the survey or if it changes over time.

Step 3: Retrieval

The third step covers the actual process used by a participant to find their answer. For the NSUM this mostly involves a participant searching their memory or records to see if they know anyone in a given group. NSUM researchers already know that this is a step which under certain conditions may be shorted by estimating an answer instead of actually counting everyone they know (McCarty et al. 2001), a finding which occurs in other count situations as well (Sudman et al. 1996). However, there are several other aspects of this step which may cause problems. The first has to do with the rarity of the target population about which the participant is being asked. With the known-population method, it has often been recommended that the names used make up 0.02% of the population (McCormick et al. 2010). This is in part due to the idea that it is easier to recall memories which are more distinctive (Sudman et al. 1996; Tourangeau et al. 2000). However, this sets up an interesting question of whether the response process changes when the answer differs between a zero, one, more than one, or some higher threshold. Prior research suggests that estimation may begin as soon as the count exceeds one (Blair and Burton 1987) or once single digits have been passed (McCarty et al. 2001). This chapter, therefore examines how a participant's retrieval process changes depending upon the size of the answer they give for both scaling, summation, and target population questions.

The second major area of retrieval questions addressed by this chapter is how a participant decides to stop searching for more answers. Prior research suggests that participants will stop trying to remember more people for a given answer when they have successively encountered several failures to remember anyone new (Hussey et al. 2014). That is the more times they try to remember if they know more than three people named Patrick and fail to come up with a fourth, the more likely they will be to consider their answer of three to be complete. Other research has suggested that search termination is a function of how much time has been spent on the question, the change in the rate at which new answers are produced, the number of successive failures, and the total number of search failures (Dougherty et al. 2014). Here, the researchers found that the total number of failures best fit the decision of a participant to stop searching for more answers (Dougherty et al. 2014). For NSUM questions, a hypothetical best retrieval scenario occurs when the participant is able of complete a full review of everyone they know within the parameters. Given the prior research, however, this seems unrealistic.

Therefore, it is important to understand the extent to which NSUM participants are willing to search at all as NSUM researchers continue to adjust their recommended practices and post-hoc statistical adjustments.

Finally, there are two major NSUM methods used to determine personal network size: the known population method, and the summation method. These two methods are likely to engage different retrieval processes within a participant. The summation method in particular, by asking how many people a participant knowns in a set of mutually exclusive groups (i.e., family, friends that are not family, work acquaintances who are not friends or family, etc.) is likely to engage very different memory recall processes than asking someone how many people they know named Patrick. By asking for lists of members of groups within social contexts the summation questions are more likely to generate contextual memory references which would help the participant remember more people in that group (Tourangeau et al. 2000). The cognitive interviews, therefore use both the known population and the summation method in order to compare how the memory processes differ. Care is taken to ask the known population questions first, in order to avoid the priming effect which mentally listing everyone a participant knows for the summation method may create.

Step 4: Judgement

The fourth step in the response process is judgement. Here the participant decides if the entirety of their answer is relevant to the question, and most importantly for the NSUM, if they should omit certain parts of their answer. The NSUM is often, if not exclusively, interested in the number of people a participant knows in subgroups for which membership carries stigma. That stigma may alter the way a participant answers the question. Specifically, if the participant is uncertain of a person's group membership, they have to decide whether to report that person as a zero or one. For example, if the participant thinks that alter A has HIV, but they are not certain, they must choose to report alter A as either having or not having HIV. This is distinct from transmission error where a participant may be unaware of alter A's HIV status completely.

Unlike transmission error, which is ignorance of an alter's status, the decision to use partial information is likely to be related to several aspects of the interview itself, particularly when the question is about a sensitive topic. Tourangeau et al. (2000) identify several reasons why a participant may adjust their response when dealing with partial information. The participant may be embarrassed to be associated by the interviewer with a group with a certain status (Tourangeau et al. 2000). They may also be concerned that the interviewer would disclose their associations to other people (Tourangeau et al. 2000). For some sensitive topics these ideas may be extended such that participants may not want to attribute a stigmatized status to someone they know if they are uncertain about it. Finally, participants may decide that it is better to be cautious than potentially tell the interviewer about something that they are not sure of. Thus, cognitive interviews may reveal how participants are likely to treat partial data about group membership and whether they err towards a zero or one in their final count.

Step 5: Response

The last step of the response process is the final answer. Here the participant needs to convert whatever information they have retrieved and judged suitable to present to the researcher into the format dictated by the question. For the NSUM this is often the form of counts of the number of people known in a given group. Although problems with this step were identified in one subsection of the NCS (and briefly discussed in Chapter 5), the focus of this chapter is largely on the four prior steps.

Research Focus

The purpose of this chapter is to look for cognitive and recall errors in the NSUM and use the survey response process to classify and examine these errors. These issues which may cause errors are grouped according to their best alignment with the survey response process and are presented here as a list.

Perception

1. Seeing and reading survey instructions

Comprehension

2. Understanding the definition of knowing someone and the temporal and spatial boundaries of that definition
3. Understanding that knowing someone could mean either knowing them by sight or by name, and not necessarily both
4. Stability of a participant's understanding of knowing someone across a survey

Retrieval

5. Differences in how a participant retrieves a zero, one, two or more count
6. Memory search termination
7. Differences in retrieval between the known-population and summation methods

Judgement

8. Treatment of partial information about group status

Methods

Data for this chapter comes from a series of cognitive interviews which were conducted in the late summer and early fall of 2016. Cognitive interviews are a technique used to study how people understand, mentally process, and ultimately respond to questions (Beatty and Willis 2007; Willis 2005). A distinctive feature of many cognitive interviews is the think-aloud process. A think-aloud is when a participant is asked to verbally state what they are thinking as they complete a survey or answer a smaller set of questions (Willis 2005). These types of interviews are able to capture high level mental processes which a participant goes through when answering a question (Conrad et al. 1999). However, these interviews are not capable of revealing information about processes that are spontaneous or those that a participant is not truly aware of (Conrad et al. 1999; Ericsson and Simon 1993).

In addition to the think-aloud process, many cognitive interview protocols may also include interviewer probes (Willis 2005). These may vary by both when they are constructed (prior or during) and what triggers the probe (the interviewer or subject behavior) (Beatty and Willis 2007; Willis 2005). Probes may also occur during the think-aloud process or after the think-aloud has been completed (Willis 2005). Asking probes during the process has the advantage of the immediacy of the probe (i.e. there is little time delay between a behavior and a probe). However, there is evidence that concurrent or near-concurrent probes can effect both the results and the process of a think-aloud interview (Ericsson and Simon 1993; Russo et al. 1989; Willis 2005). Retrospective probing, which occurs after the think-aloud is complete avoids these reactive effects, but may make it more difficult for a participant to accurately recall what their response process was when they first answered that question (Ericsson and Simon 1993; Willis 2005). However, when using a survey instrument that is self-administered (as the survey for this study is) it may be more beneficial to replicate how a participant would complete the survey in the field (Willis 2005). As such, the cognitive interviews designed for this dissertation attempt to minimize the number of concurrent probes in favor of retrospective probes which occur after the survey had been completed by the participant.

Participant Recruitment & Instrument Design

A convenience sample was recruited by posting flyers in several classroom buildings on the UNL campus as well as several coffee shops located in the city of Lincoln, Nebraska. Participants had to be at least 19 years of age and current residents of the city of Lincoln or Lancaster County Nebraska. Interviews took place on the UNL campus. As an incentive, $20 cash was offered to compensate for the participant’s time as the interview was expected to last from 1.5 to 2 hours. The completed interviews ranged from 47 minutes to 2 hours and 15 minutes in length. The average interview was 1 hour and 20 minutes long. The interview protocol was approved by UNL’s IRB and given an exempt status (IRB# 20160716187 EX).

The survey used in these cognitive interviews is an adaptation of the 2014 NCS (Appendix A) which has been modified in three key ways. The first is that in the 2014 NCS there was a large section on attitudes about the media and crime. This section was removed for the cognitive interviews as it was not considered to be relevant to the aims of the study and would add more tasks for the participant to complete without a necessary reason. The second change is that a section of summation NSUM questions were added in order to directly contrast the known-population and summation methods. The third change is that the modified survey no longer asks about how many people a participant knows in the US in addition to those known in Nebraska. These questions were originally intended to be used as an experiment about simultaneously measuring nested networks. However, this experiment failed and retaining these elements for the cognitive interviews was deemed to be unnecessary. The final survey for the cognitive interviews is replicated in Appendix B of this dissertation.

A total of 19 interviews were completed out of a target goal of 20. Twenty interviews was set as the maximum due to funding availability. Recruitment began on August 22, 2016 when flyers were posted at five locations on the UNL campus and four locations in the city of Lincoln, Nebraska. The last interview was conducted on October 11, 2016 and all flyers were pulled on October 14, 2016. Recruitment was ended one interview short of the target goal of 20 due to the lack of new participants being interested in the study. Interested participants contacted the interviewer directly through email in order to setup the interview on the UNL campus.

Interview Protocol & Implementation

All interviews were conducted in 104 Benton Hall. This is a room which is used as either a workroom or a classroom, and can comfortably accommodate up to 18 students. The room is private, located near restrooms, and is located on the first floor of the building which is typically quiet. Every interview used the same room setup. A large table was placed in the middle of the room with four chairs on each side. The interviewer sat on one side of the table (with the windows at their back) and the participant sat on the opposite side. During the interview only the interviewer and the participant were present in the room. In front of the participant's chair were three sheets of legal paper, a pen, and a liter of bottled water. In front of the interviewer's chair were a legal pad, a pen, two copies of the survey, two copies of the interview consent form, a form to record the start and end time of the interview, and a plastic cup of water. A box of tissues and a digital audio recorder were placed in the middle of the table. While interviews were in progress signs were posted on the two doors of the room which said, "Do Not Disturb – Interview in Progress – Thank You – Patrick Habecker."

Participants were greeted at the door of the room and welcomed by the interviewer. They were shown to their seat and asked to make themselves comfortable. The interviewer used a pre-scripted interview protocol as a framework to describe the study and what the participant will be doing during the interview (Appendix C). The participant was then given the informed consent form and the interviewer went over each element of the form, what it meant, and highlighted the rights of the participant. After jointly going over the consent form, the participant was encourage to ask questions and to take some time to look over the form on their own. Once they agreed, the participant signed a copy of the consent and gave it to the interviewer, who in turn gave the participant a blank copy for their records.

Once the consent form was signed, the interviewer introduced what cognitive interviews are, why we do them, and what the process is like for the participant. As cognitive interviews are unusual, two example questions were used to give the participant a chance to practice the think-aloud technique. The first question asked, "How many residences have you lived in since you were born." The second asked, "Think about where you live. How many windows are there?" For the first question participants were asked two follow-up questions: “how did you think about what it means to live somewhere?” and, “how did you define what it means to live somewhere?” For the second question, probes were used to ask if the participant was counting windows in doors or counting sliding glass doors. After the practice questions and their follow-ups were completed, the participant was given a chance to ask any other questions before the interview started.

After the practice questions were finished the audio recorder was turned on and the participant was given a copy of the survey (Appendix B). The interviewer followed along with their own copy of the survey and made notes on their copy of the survey and on their legal pad. Concurrent probes were meant to be limited in this interview protocol (Appendix C). Most of the probes were meant to encourage the participant to fully engage in the think-aloud process and to avoid periods of time where the participant may lapse into silence. A handful of probes were written beforehand to assess how accurate a participant may think a given question is, how they decided to stop counting, or how they came up with a response for a question (Appendix C). However, these probes were not linked to specific questions, and could be used at the discretion of the interviewer during the interview.

Aside from the interviewer encouraging the participant to engage in the think-aloud, there was little planned interaction between the interview and the participant while the survey was being completed. During the survey, the interviewer was focused on the process the participant was describing and took notes and wrote questions which would be asked after the survey was complete. These notes were added to a set of pre-written end of survey questions (Appendix C) and were used to facilitate a retrospective discussion after the survey was finished. Here the interviewer encouraged the participant to reflect upon some of the choices they made and the behaviors they used while completing the survey. These retrospective questions ranged from queries about specific questions, to reflections about overall response processes. The pre-written questions provides a common set of questions for all participants while the interviewer's notes allowed for emergent behaviors to be examined.

After the end of survey questions were completed the participant was given a chance to ask questions of the interviewer. Once those were finished the digital recorder was turned off. The participant's completed survey was collected by the interviewer as well as the scratch paper that was used by the participant. The participant was then given a $20 bill and a receipt to complete and sign in order to comply with UNL financial rules. At this point all parts of the cognitive interview were complete and the participant was walked to the exit of the building. Once the participant was gone all materials were collected, the table was cleaned, and the do not disturb signs were removed from the doors. The materials were taken to the interviewer's office were they were locked in a file cabinet. The audio file was downloaded from the recorder, copied twice (once onto a USB backup and once onto the interviewer's computer), and then the recording on the recorder was deleted. At this point the emails between the interviewer and the participant were deleted from the interviewer's inbox and then purged from their deleted folder.

Analytic Strategy

The results presented in this chapter are largely based on the retrospective discussion which occurred after the participant completed the survey. This discussion was focused around a number of retrospective probes which were written before the interview implementation and several that were developed during the interview itself. Questions which were developed before conducting any interviews can be found in the interview protocol (Appendix C). These questions focused on how the participant answered NSUM questions and what it meant to “know” someone; whether it was easier to answer with a zero, one, or more than one; how accurate participants thought their questions were; how they decided to stop answering questions; what would help participants answer NSUM questions; and their knowledge of moving intentions among their networks. Some of these questions were derived from prior NSUM research and others were developed through problems with the 2014 NCS survey.

Once the interviews began, new questions were written as other issues became apparent to the interviewer. Some of these questions focused aspects of those which were already developed. Such as questions about the temporal and spatial aspects of what it meant to “know” someone and how this changed over the survey. A common question was about how long a participant had lived in Nebraska and whether this made it easier to answer the NSUM questions or not due to behavior observed in the summation and known-population questions. The flexibility of the retrospective discussion allowed for new issues to be discovered and discussed as part of the interview.

Analysis of the retrospective discussion was completed in two phases. First the interviewer compiled their interview notes to develop potential sources of error that were evident in the cognitive interviews and were discussed in the retrospective portion of the interview. These issues were formed into the list of eight potential sources of error that were previously listed in this chapter. Due to the reactive nature of the interview process not all participants were asked about the same issues. Once the list was compiled, the audio recordings of the retrospective portion of the interview were reviewed. Every participant's response to each question was added to a document that catalogued participant responses by issue. If a participant's response involved more than one issue their response was copied into both section of the catalogue. Their response was not transcribed, but written in a summarized form.

A text summary approach is used to describe the participant's responses and behaviors for each of the eight issues identified by this chapter (Willis 2015). Text summaries use the interview and the interviewer's notes to describe themes and problems which revolve around a question or issue, but do not use a formal coding system to examine notes or transcripts. The issues themselves are organized by their association with the Dillman et al. (2014) five step response process model.

Results

Just over half of the interview participants were female (57%) and none of the participants chose to mark an answer other than male or female. Although Nebraska is predominantly non-Hispanic white (86.1% in 2010 (Anon n.d.)) approximately 57% of the interview participants were non-Hispanic white. Sixteen percent of the participants had completed a graduate or professional degree, 21% had completed a four year degree, 57% had completed either some college or a two year degree, and 5% had completed a high school diploma or GED at the time of the interview. The average age of participants was 27, with the youngest being 19 and the oldest 61.

Perception: Seeing and Reading Survey Instructions

There were four sets of survey instructions written in the cognitive interview survey (Appendix B). The first instruction described who in a household should take the survey (I1) and was located on the first page under the name of the survey. The second told the participant about the next section and what they should expect (I2) and was located above question 4. The third instruction defines what it means to know someone for the purpose of this survey (I3) and was embedded as question 4. The fourth instruction told participants to take their time on the next section as it was particularly important (I4) and was located before question 17. Participants were asked to read-aloud all instructions and questions in the survey. If a participant did not read-aloud the instructions it is assumed that they did not see the instructions. Interview recordings were examined for each instruction and counts were tallied if the participant read-aloud each of the individual instructions.

Only 22% of the survey participants read-aloud I1. This instruction was placed directly under the name of the survey and outside of the normal question flow. However, this number may be artificially low as the participants were not retrieving the survey from an envelope, but were instead handed the survey with a verbal instruction to start. Participants read-aloud I2 72% of the time. This instruction was placed in the flow of questions but was not listed as a question. All of the participants (100%) read-aloud I3 which was written and numbered as a question (Appendix B: Question 4) and immediately followed I2. Even participants who did not read-aloud either I1 or I2, read-aloud I3. One participant even re-read the instruction to ensure they understood it before moving to the response option. Finally, 74% of the participants read-aloud I4. This instruction was in the flow of questions, but was not marked as a question. As such, several participants simply moved from the prior question (#16) to the next (#17), skipping over the heading title and instructions that were in-between.

Comprehension: Knowing Someone – Temporal & Spatial Boundaries

All NSUM type questions in the interview included a requirement that the people they knew lived in Nebraska. This repeated instruction kept the spatial boundary of what it meant to "know" someone fresh. When asked about their recall process during the retrospective interview, some participants described the spatial boundary as a hindrance, and others said it helped. Five participants specifically described how the spatial boundary made it easier for them to sort through everyone they knew because the boundary restricted who they had to think about. This seemed common for those who had only lived in Nebraska for a short period of time, as they said they only had to sort through a smaller subset of everyone they knew.

> "I think it made it a lot easier cause I know a lot more people outside of Nebraska than in Nebraska… It is a shorter list to go through."

These participants were essentially filtering out people who did not qualify for the question. However, this process was not always easy. One participant who said they knew a lot of people outside of Nebraska said they would immediately think of people who lived outside of Nebraska when trying to answer questions. But over the duration of the survey, the participant said that they were able to eventually think only about the people they knew in Nebraska, and not those they knew outside. Here the spatial boundary was initially a burden for the participant until they were able to streamline their response process to not include those outside of Nebraska. Overall, spatial issues came up in six of the retrospective interviews and five of the six reported that the spatial boundary made their responses easier and their awareness of that boundary seemed stable across the interview.

The temporal boundary on knowing someone was initially set at two years, but was not repeated outside of the initial instruction. Participants therefore had to keep the temporal boundary in their mind throughout. For one subset of questions about criminal justice exposure, the temporal boundary was adjusted to be only those "known" in the calendar year of 2015. Temporal issues came up four times in the retrospective interviews. Three participants had difficulty remembering when a certain event occurred and mapping it back to the required timeframe. They knew something had happened, but said they had to think about when specifically it occurred. One participant also had a problem where instead of referencing events that occurred in 2015 (for the criminal justice questions) they instead used "last year" as a reference. When asked in the retrospective interview, this participant said they were thinking of "last year" as the school year. This shift could create opportunities for error if their definition of past year no longer matched that of the 2015 calendar year (e.g. an academic calendar instead). This specific type of behavior only occurred once, but demonstrates room for temporal boundary changes.

Comprehension: Knowing Someone – Sight OR Name

The definition of knowing someone required that a person be known by sight or name. However, in practice participants often created lists which were name-based only. During the cognitive interviews several participants began to write extensive lists of everyone they knew in certain groupings (e.g. family, work, school) on scrap paper. Such lists were usually created when the participant was answering the summation questions (Appendix B: Questions 29-43) which ask about how many people a person knows in several large categories (i.e. immediate family, coworkers). Occasionally, when asked about the number of people in professions, or in extended friendship groups (e.g. friends of friends), participants would recall someone whose name they did not remember, but this was fairly rare. Many participants seemed to be caught on the idea that if they didn't know a person's name, they didn't really know them well enough to include in their counts. This would certainly be true for studies of closer networks which focus only on friends and family. The NSUM frequently seeks to assess larger acquaintance networks, and here a name may not always be an indicator of network membership. Some the participants who made more extensive lists were asked in the retrospective portion of the interview if they thought they would have included people whose name they didn't know, but who might frequently be in some of their groups. These participants said that by making a list they would eventually capture all of the people in their target groups, even if they didn't initially know their names. This would be encouraging for NSUM researchers, but the participants revealed that they would likely not have bothered to make such a list if they had completed the survey outside of the cognitive interview.

Comprehension: Stability of Knowing Someone

Participants were told early on in the survey what it means to know someone (question #4), but are expected to keep that definition in mind throughout the survey (until question #80). For several participants, as they progressed through the survey they reported functionally altering this definition when asked about it in the retrospective interview. Many shifted to only thinking about closer friend and family groups instead of their larger networks. These participants often described developing several groups of people (i.e. mental lists of friends, family, coworkers) whom they knew, which they would then search when asked if they knew someone with a given attribute or experience.

For different questions they may go through those groups in different orders, but they would often stop searching if they exhausted their group list. If this list was exhaustive of their entire network, this would not be a problem. However, these groups seemed to be comprised of smaller subsets of their close network and not their larger acquaintance network as participants seemed to talk mostly about close friends and family. It seems likely that these participants were rarely considering people they knew who were not in their close groups.

> "Whenever I reverted back to friends, it's always like this small close-knit group because you have your like giant friends, and then you those small, that small group fit that you hang out with all the time that you think about. So every time they asked questions about being beaten or attacked I would always revert back to that small group."

A small subset of participants (3 of 19) near the beginning of the survey took the time to write down lists of everyone they knew by different social groupings – often prompted by the summation questions (Appendix B: Questions 29-43). These lists took a considerable amount of time to compile, often filling one or two legal sized pieces of paper. Once finished the lists served as a master reference sheet for the participants as they moved through the later questions. Here, as long as the participant was using the correct definition of knowing someone to build the list, they were then immune to definition decay later in the survey. However, when asked during the retrospective interview if they would create such a list if there were to obtain the survey through the mail, they indicated that they would be unlikely to do so.

Retrieval: Recalling a Zero, One, or More than One

Among the participants there was a theme common to many "zero" and some "one" responses where they described knowing the answer without a verbal response process. This was most often accompanied by phrases such as “not ringing a bell,” “nothing jumps out,” or “nothing comes to mind.” These were often the only thing a participant would describe during the cognitive interview before writing a zero. When asked to further describe their response process for these questions during the retrospective interview, participants often talked about a nearly instant response. One they seemed to have almost no control over. They simply knew the answer. For a smaller number of “one” answers a similar response pattern would emerge. Here a participant immediately had an answer and seemed to give little thought beyond the quick reaction. These instances with a “one” were far less than the “zero” occurrences though.

Even among “zero” answers there was no absolute pattern to how a participant would respond. Several participants reported that although their “zero” responses were fast, they were actively searching, particularly in the cases where they thought that they *should* know someone. One participant said that it felt satisfying to complete an answer with something other than a “zero,” so they would try to find at least one person so that they could answer with a “non-zero.” Other participants described their “zero” or “one” process as fast because they had only lived in the area for a limited time and therefore could search through most of contacts with little effort before reaching a response.

Participants tended to be more uniform in their responses that were greater than one. Here participants seemed to be actively searching their memory or their written lists. However, these responses were still somewhat subjected to the idea that a participant felt they *should* know more people than they had already come up with, which would prompt a more extensive search. Despite this, answers of two or more seemed to have at least some part of the response process expressed in the cognitive interview and it was exceedingly rare for a participant to say a phrase like “nothing jumps out to me” until they had already gone through a memory search process.

Retrieval: Search Termination

Participants reported several general strategies for search termination in the retrospective portion of the interview. These strategies were often dependent upon the method a participant used to search their memories. Participants who had created mental groupings (e.g. close friends, family, college people) they would stop trying to come up with more people once they had gone through each of the groups at least once. Sometimes they described going back through the groups a second or third time, but rarely tried to think of those who might be outside of the groups they had already created. Participants who had opted to write down a physical list of all the people they knew would simply go through their list name by name and count how many people qualified for a given question. Once they reached the end of the list they were generally satisfied with their final answer. A few participants also reported just knowing when they had come to the final number and gave little thought into whether they might know anyone else.

Although the search strategies and termination decisions seemed to vary, there was a common idea of a good faith effort which appeared frequently. Participants said that they would stop searching once they felt that they had made a reasonable attempt to continue coming up with answers after they started to come up empty on their continued memory searches. How much effort was qualified as “good faith” seemed to be subjective and is likely related to how much effort a participant is willing to put into a survey. When asked in the retrospective interview how accurate their answers were likely to be, most participants felt that their answers were within one or two persons of the true answer. Unfortunately, the NSUM is built around the measurement of scarce populations and smaller answers, so that error of one or two could be substantial.

Retrieval: Known-Population & Summation Methods

There are currently two major methods used to estimate personal network size for the NSUM: the known-population and the summation method. The retrieval processes used by participants varied considerably between these two methods. The known-population method asks a series of questions about how many people a participant knows who have a certain first name or have a certain profession. Participants were asked in the retrospective interview which questions they found to be particularly hard or easy and which were more accurate. The known-population questions were said to be easier and felt that they were more accurate. These questions also took substantially less time to complete. However, the known-population questions also featured more zero responses and cases where the participant appeared to spend little or no time on their response process.

Summation questions on the other hand required a considerable investment by the participant and were often identified as the most difficult questions in the survey when asked in the retrospective interviews.

> "Questions about knowing people in broader groups that was hard because I had to think back to it and calculate who I knew."

In some cases it took a participant up to 30 minutes to complete the set of 15 summation questions. Here, respondents very rarely had a zero answer and often had to engage in an extensive recall process. These questions were what prompted several participants to make comprehensive written lists of everyone they knew in Nebraska. Because of the extra work, participants also said that they were inclined to take shortcuts and estimate their final responses instead of actually counting everyone they knew.

A surprising difference between the two methods was how they worked for participants who had not been living in Nebraska for a long period of time. Newer arrivals, particularly those with less than a year in the state often had straight zeros or only one or two non-zero responses in the known-population questions. However, in the summation questions they were able to list a larger number of people in work, school, and acquaintance categories. This likely represents a function of network development which occurs when a person moves to a new area. Someone who has recently moved to Nebraska knows many people who are outside of the state, but has not yet had time to develop contacts within the state. Participants who had moved from somewhere else in Nebraska seemed to be less likely to have all zeros in the know-population questions. The known-population method may be more likely to produce lower estimates of social network size for recent migrants to an area than the summation method. This is because the known-population method seeks to build an estimate off knowing rare populations. However, for a new arrival, their odds of knowing these rare populations would not be the same as someone who has lived in the area for their entire life, or for a substantial period of time. As the summation method seeks to capture everyone a person knows and not just scaling indicators it appears to be better able to reflect the network sizes of those who are recent arrivals and are still developing their networks.

Judgement: Partial Information

Participants were occasionally faced with questions where they recalled people whom they were not sure if they fell into the target group or not. A common question where this appeared asked if they knew anyone who would not approve of interracial dating. Participants would often describe in their think-aloud people whom they thought held this view, but who had never expressed it to them personally. For this specific question the participants were using other cues to infer the presence of this attitude, such as age or political view. In such cases the participants tended to answer affirmatively only about people they were certain of, and who had directly expressed their views in this specific case. In other instances, such as questions about drug usage, the participant might say in their think-aloud that they thought a person used marijuana (for example) but were again not entirely sure. Here, the trend was the same. When uncertain, participants tended to stay away from counting that person. It may be that these behaviors were seen because these questions ask about illegal or stigmatized behavior. Unfortunately, the survey does not ask about people engaged in positive or normative behaviors, aside from professions, so no direct comparison can be made.

Discussion

Cognitive interviews may reveal the inner response process a participant goes through which cannot be inferred from looking at an answer alone. Examining the response process in this way allows a researcher to see why a question or type of question may behave differently when viewed by a participant compared to its design. Using the information discovered through cognitive interviews a series of suggestions can be created to better future NSUM work. This section presents several possible changes to the NSUM implementation process and how these changes address issues found in the cognitive interviews.

Instructions as Questions

It seems clear that when an instruction is important, it should phrased and numbered as a question. Even though a majority of participants in these interviews saw the non-question instructions, all of them saw and read the instruction which was set as a number. This is particularly important when the survey mode is unable to control the order in which a participant sees something (i.e. mail surveys). If questions are particularly sensitive to understanding a set of instructions, forcing a respondent to read the instructions becomes more critical. This suggestion also applies to other self-administered survey modes. Web surveys have the capacity to force a participant's attention to instructions through questionnaire design and rules about progressing to the next page or question. Although there are other ways to enhance the visibility of instructions through visual design, it seems that the simplest would be to turn the instruction into a question, thereby taking advantage of participant behavior which is likely already trained.

Repeating Definitions

For the NSUM surveys, participants often had difficulty retaining the exact boundaries of what it meant to know someone. They shifted timeframes, focused exclusively on names, or began to only search through memories about people that were closer to them. Given this behavior it seems reasonable that the definition of knowing someone should be reiterated at certain intervals throughout the survey. It is unclear from these cognitive interviews how fast a definition began to decay. However, it is possible to reinforce the definition by making it easily available for reference. Within a paper survey this could take the form of the definition always being on top of the page, or repeated every time a new set of pages was opened. Another possibility would be to refresh the definition for every new NSUM section that is introduced in the survey. In the cognitive interview form, question #4 would be repeated after every NSUM section heading. This would refresh the definition six more times and in places where the participant is more likely to make a mental break due to the subheading and visual design which clusters similar questions together. Such repetition could do more harm as a participant grows weary of seeing the same question multiple times. However, there is likely a balanced design which is between too frequent and too few reminders.

Larger Known Populations

The issue of fast zero responses and the seemingly instant response process which many participants used for their zeros could pose a serious problem for NSUM researchers. One way to reduce some of these is to select known populations which are larger. Currently, when possible, the written standard has been to use known populations of approximately 0.02% of the total population (McCormick et al. 2010). However, this size range seems too often produce a zero or a one answer. It may therefore be beneficial to explore using larger populations which would be more likely to produce a 2-5 answer. From the cognitive interviews, spontaneous responses which involved a participant having an answer just occurring to them were restricted to response of zeros or ones. When asked about this behavior in the retrospective portion of the interview, many participants could not define how they had arrived at their answer. However, responses which were two or higher, always involved some sort of response process that was shown in the think-aloud portion of the interview. That is, these answers were not just simply known, but were actively retrieved and considered. However, questions which elicited larger responses, such as the summation questions (e.g. how many people do you know through school?) often resulted in the participant not engaged in a count process in the think-aloud, but instead a tendency towards estimation (mirroring the heaping found by McCarty et al. (2001)). By slightly increasing the size of known-populations, researchers may encourage a full response process. Thereby improving the accuracy of the NSUM method.

Unfortunately, it is not possible to choose the size of a hidden population that the NSUM is being used to measure. Depending on the target group and the spatial and temporal boundaries placed upon the question by a researcher, participants may fall into quick zero memory recall. It may be possible to reduce this by asking participants to go back through their answers and gauge how accurate they think a given answer may be. Such a process would take advantage of the participant having gone completely through the survey. Other NSUM questions may remind them about people or occurrences they had previously forgotten. Asking participants to rate their own accuracy could also be used to as a corrective measure to scale up or down answers.

Encourage Participant Buy-In

It is clear that answering NSUM questions can be demanding for a participant. Even though many participants in the cognitive interview went to great pains to answer questions by writing extensive lists of contacts and reworking their memories in the think-aloud, they also often made it clear that they would not do so in a real-world survey setting.

> “I wanted to provide you, like, since I knew it was part of a research project, I didn’t want to give you just like, broad answers, I wanted to try to and do the best I could, so your data was accurate. But if I just got it in the mail, if it was up to me, I probably wouldn’t have even opened it.”

Unfortunately, most of a researcher's capacity to reduce burden rests on the design of questions and making it easier for a participant respondent. NSUM questions, when done correctly, require a heavy cognitive burden by asking for memory searches about everyone they know. This is likely why participants in the cognitive interviews began to take shortcuts in their recall by regressing to only checking through groups of people they were closer too. This burden could be reduced by suggesting and allowing a participant to check contact lists such as their address books or Facebook. However, this runs the risk of them referring only to those lists and missing other people. Another approach, is to reduce the scope of what it means to know someone. This is what Feehan et al. (2016) implemented by shifting to a one year timeframe for past contact, instead of a two year timeframe. They posed this adjustment as a way to reduce error in answers, but it also works to reduce respondent burden. A third approach would be to use small surveys which focus on only a handful of questions and target populations. Reducing survey length and only asking for a few instances of memory recall would hopefully increase a participant's willingness to expend more energy on coming up with an answer.

Under a social exchange framework (Dillman et al. 2014) researchers may also work to increase the benefits of a survey. The most direct way to do this is by adding a cash incentive, however this is not always feasible. The 2014 NCS tried to express the novelty of the NSUM questions and the importance of the research. Additionally, the materials attempted to express the importance of the participant's answers while also taking advantage of using the logos of the state's largest public university. Combined with a $1 incentive this appeared to slightly boost the response rate to the survey.

Using the logos associated with the university also works to build trust with the participant, assuming they trust/respect the university (Dillman et al. 2014). The more a participant trusts the researchers and the goals of the study, hopefully the more willing they are buy-in and devote more effort to the response process. Trust is important when asking participants to report on hidden and hard-to-reach populations which are often characterized by illegal or stigmatized behaviors. Fortunately the NSUM is advantageous in this regard as it only requires counts, and not any identifiable information about those who may be in a target group. Emphasizing this in the survey materials and questionnaire may decrease hesitation to become involved with the study. However, the NSUM does not remove ideas of guilt of association, which depending upon the population may be strong factor. Ultimately, NSUM researchers should take every advantage they have to increase participant buy-in to the survey. The goal should be not just to encourage a response, but to encourage thoughtful and thorough responses.

Combining Known-Population & Summation Methods

The known-population method of estimating personal network size always runs the risk that a participant may not know anyone in any of the scaling variables (e.g. names and professions). Zeroes across the board result in an estimated social network size of zero, which seems highly unlikely. The risk of straight zeroes, or disproportionate amounts of zeroes seems to decrease the longer a participant has lived in a target area. New residents to an area are unlikely to have extended their social networks to their local capacity and therefore would not have the same probability of knowing someone in the scaling categories as a person who grew up in Nebraska would.

The summation method on the other hand, should only provide an estimated network size of zero when that person truly knows no one. The disadvantage is that this method imposes a substantial response burden and seems prone to estimation instead of enumeration. However, an abbreviated form of the summation method may be a useful catchall to prevent the lower limit of network size from being zero, or relying strictly on just one or two known-population scaling variables. Such a method may ask about four or five mutually exclusive categories (e.g. family, friends, coworkers, other people) to quickly develop a baseline number of people known by a participant. Not only would this catch participants who are new to an area, but it would better serve those who come from backgrounds where the names typically used in NSUM studies are rare or completely absent. An NSUM study which might cover refugee communities would likely do very poorly with the names which were used in the 2014 NCS unless those refugees came from Western Europe. Using both methods imposes a burden, but would likely reduce several potential sources of error.

Length of Residence as a Control/Scalar

If it is not possible to add summation questions to an NSUM survey, it seems wise to add a question about how long a participant has lived in the target area. For studies of Nebraska this would likely include if they were born in Nebraska, how long they have currently been living in Nebraska, or what proportion of their life have they spent in Nebraska. When using other target frames (e.g. Florida, the U.S., Lancaster County) these questions would be adjusted accordingly. If length of residence has no influence on the outcomes it should be uncorrelated with network size and the target group estimates. If there is an association, it may be possible to develop corrections which scale-up reports of a target group from those who have lived in the state for less time. At the very least, these questions should be asked as a check for network development in a given region.

Knowns & Maybes

For several target groups in the cognitive interviews, participants tended to be conservative in their reports of people for whom they were unsure of their status. Although false-positives should be avoided, it would be worthwhile to capture the number of people that a person is uncertain about as well as the number for which they are certain. Considerable effort in the NSUM literature is devoted to correcting for when participants do not fully know the status of their alters (transmission error). Capturing the number of maybes would give researchers as a way to assess uncertainty of information transmission and a framework for developing corrections. Such a framework would not require direct contact with the target group, a requirement of the generalized NSUM (Feehan and Salganik 2016). Two estimates could be produced for each target group, one without the maybes and one with the maybes providing a range of estimates under different assumptions.

Awareness of Question Order

The order in which NSUM questions are asked appears to have the potential to substantially influence questions. Of particular note are the summation method questions. In the cognitive interviews these questions were the most likely to prompt participants to develop written lists and mental groups, if they had not already done so. In some cases this action revealed people who had been missed previously and seemed to encourage a thorough review of who they knew. Given this, it may seem beneficial to place summation questions early in the survey. However, several participants also fell into the habit of only using the list developed by the summation question and not allowing their mental searches to exceed their lists. If the list is perfect, such behavior is fine, but a perfect list seems unlikely and the action of a creating the list could shift responses all the way through the survey. In a survey mode where the interviewer is present it may be possible to minimize these effects. However, in a mail mode, only the survey instrument and its instructions can correct for these kinds of order effects. Here the solution may be to place the summation questions early (if using them) and then frequently remind participants of the “knowing someone” definition. This may prompt their response process to escape the lists created by the summation question and allow for the discovery of other people in their network. Ultimately, awareness of the issue for questionnaire design may have to be sufficient, as the data must be collected in some manner.

Limitations

Cognitive interviews provide an excellent tool to observe otherwise hidden thought processes. However, this style of interviewing can only go so far to reveal response processes which happen simultaneously or so quickly that a participant cannot verbalize them. Cognitive interviews are therefore limited to those response processes which a participant is capable of focusing upon (Tourangeau et al. 2000). These processes may reveal higher cognitive function (Ericsson and Simon 1993; Tourangeau et al. 2000; Willis 2005), but miss those which outside of the participant’s control or recognition. There is also some danger that the participant’s response process may be altered by the cognitive interview itself (Tourangeau et al. 2000; Wilson, LaFleur, and Anderson 1996). By asking a participant to focus upon their response process in a way they do not normally do, it is possible that their process in an interview will not match what would happen in the field and create a lab effect.

In addition to problems directly related to the cognitive interview process, there are also limitations based upon the way participants were recruited. For this study the participants were only recruited from the city of Lincoln and Lancaster county. Although this is a subset of the statewide sampling frame used for the 2014 NCS, it is possible that there may be substantial differences between those recruited for the cognitive interviews and those who received the original survey. Due to the nature of the recruitment process the participants for the cognitive interviews were also more likely to be associated with the University of Nebraska-Lincoln.

Conclusion

Although cognitive interviewing has limitations, the interviews presented here revealed several potential problem areas in the NSUM implementation. The suggested changes to NSUM survey practice work towards a model of minimizing as much error as possible beforehand, without sacrificing many of the unique benefits of the NSUM. Several of the statistical corrections in the literature require either direct sampling of the target population (Feehan and Salganik 2016; Maltiel et al. 2015; Salganik et al. 2011) or reducing the size of the network that a participant has to recall from (Feehan et al. 2016). Having to directly sample the target population may add considerable expense and time to a project. Reducing the size of the recall network decreases the chance that alters on the periphery of the network and who may bridge into different communities may be missed by the NSUM process. Both of these sacrifices might be avoided by developing survey designs which encourage proper response processes.

Through the use of cognitive interviews this chapter provides additional suggestions which through testing and further research may prevent measurement error from initially occurring. These suggestions complement the larger field of NSUM research which has focused on the post-hoc correction of transmission error and barrier effects. These suggestions are not a monolith, but represent several options that may be taken as a whole or piecemeal. Although it is hoped that all of the suggestions will be fruitful, more testing of these and other implementation practices designed to reduce cognitive and recall error in the NSUM should be encouraged. Through scrutiny of the response process NSUM researchers can continue to develop better questions and questionnaires and reduce the need for post-hoc statistical adjustments for future surveys.

CHAPTER 7: CONCLUSION

The network scale-up method (NSUM) provides a flexible, efficient, and timely way to generate estimates of hidden and hard-to-reach groups that are representative of larger populations. This method fills a niche between methods which require direct contact with hidden populations and those which are unable to include hidden populations in their sampling frames at all or in sufficient numbers. Although first proposed in the early 1990s (Russell Bernard et al. 1991) the NSUM only began to receive large amounts of attention with the work of McCarty et al. (2001), Salganik et al. (2007), and McCormick et al. (2010) among others. Since then the pace of NSUM research has increased, with almost two dozen NSUM papers published since 2012.

Several new NSUM procedures have been developed and tested in the recent wave of publications. Many of these innovations have been focused on addressing transmission error. This error occurs when a survey respondent is unaware of their alter's group membership in a target population. Attempts to correct transmission error have roughly fallen into two groups: general weighting based off of estimates on the likelihood of and information being passed (Guo et al. 2013; Snidero et al. 2007), and the incorporation of another data collection phase with the target group to assess how many people they tell about their status (Feehan and Salganik 2016; Maltiel et al. 2015). There has been less attention to barrier effects or recall error, but what has been done remains focused on developing post-hoc statistical adjustments (Maltiel et al. 2015) or adjusting the temporal boundary when defining what it means to know someone (Feehan et al. 2016). Cognitive errors have been seemingly ignored since the work of McCarty et al. (2001).

In addition to the developmental focus on error, there has been some recent innovation in how the core estimation process works. Feehan and Salganik (2016) proposed a generalized NSUM which pairs respondent driven sampling with a traditional NSUM survey. The advantage here is that this method does not have to estimate personal network size and can directly adjust for transmission errors in addition to sampling frame and barrier effects. Another proposed change came from Maltiel et al. (2015) which takes a Bayesian approach to correcting for recall, barrier, and transmission errors. Like the generalized NSUM (Feehan & Salganik 2016), using this method requires direct contact in the form of an RDS or another probabilistic sample of the target population. As a result, these innovations leave room for improvements which can be made to the traditional NSUM which improve its accuracy without requiring direct contact with the target population.

In light of the recent NSUM developments and growing interest in the method as a tool for measuring hard to reach and hidden populations, this dissertation focused on several aspects of the NSUM which can be improved. The mean of sums (MoS) estimator is a new way to handle the core estimation processes which does not require direct contact with the target population. Unlike the traditional estimator, the MoS uses the average of the ratios of known scaling variables to estimate personal network size, and the average of ratio of known target population network members to estimate the population estimate of that target group. The MoS, when used alone, produces larger average estimates of personal network size with greater variance than the traditional estimator. However, when used to estimate the size of a target population, the MoS comes closer to the correct estimate than the traditional NSUM estimator.

Back-estimation has been in the NSUM literature for some time, but has only recently been discussed as a way to remove scaling variables (Guo et al. 2013). This dissertation proposed using back-estimation in a recursive fashion instead of the bulk cuts which had been previously used (Guo et al. 2013). Recursive back-estimation when compared to bulk-cuts was found to frequently preserve more scaling variables, and removed different scaling variables than would have removed in a bulk cut. This is because back-estimation procedures are interdependent such that the removal of even one scaling variable can substantially influence the accuracy of the others. As a bulk cut removes all scaling variables over a set threshold in one step, variables which would have been corrected, or become less inaccurate are lost without recalculation.

When recursive back-estimation is combined with the MoS the average personal network size and variance of the MoS estimator is greatly reduced. However, the MoS estimator kept more scaling variables than the traditional estimator when using the same cut thresholds and recursive process. When comparing final estimates of the target population, the MoS with recursive back-estimation comes closest to correctly predicting the number of people who had moved into the Nebraska in the prior two years. The traditional estimate, even with recursive back-estimation was still substantially off the target value. When sampling weights were applied to both estimates, the MoS with recursive back-estimation generated an estimate that contained the true target value within its confidence intervals, while the traditional was still considerably off target.

Although the MoS estimator with recursive back-estimation has been shown to be more accurate than the traditional estimator under the same conditions, there are still several unknowns regarding the new process. This dissertation systematically examined how using the MoS vs the traditional estimator, conservative item nonresponse assumptions vs. liberal, and the use of recursive back-estimation vs. none, affected three types of statistical outputs: estimated personal network size, associations between network size and individual attributes, and predicted network size. As before, the MoS generally produced larger network sizes compared to the traditional estimator, differences which were reduced through the use of back-estimation. Surprisingly, little difference in estimated network size were found by applying different item nonresponse assumptions, even though they resulted in substantial differences in the number of available cases for analysis.

Sixteen different estimates for personal network size were generated by the prior experiments. These were then used as an outcome to test for associations between network size and individual attributes. Identical models were used for every outcome, the only difference being the conditions that produced that specific estimate of personal network size, and how missing data in the attributes was handled (imputation vs. listwise). Across all the models there were only two constants. Participants in rural areas (less than 10,000 people) had considerably larger estimated personal networks than those in urban areas (more than 50,000 people). Further, participants who earned less than $25,000 always had smaller estimated network sizes than those who earned between $50,000 and $99,999. Although several other associations were occasionally significant, none were constant. This means that the choice of estimator, back-estimation, item nonresponse, and even broader missing data choices may have effects which alter the statistical inference of a model.

These models were then used to develop predicted mean personal network sizes in rural, midrange, and urban areas of Nebraska. Each predictive means were stable in that rural was always larger than midrange, which was always larger than the urban prediction. However, there was often considerable variation between predictions based up MoS and traditional NSUM models. Here the use of back-estimation was shown to substantially reduce the variation of all the predictions, and greatly reduced the differences between the MoS and traditional predictions.

Finally, this dissertation used cognitive interviews to examine the mental response process used by NSUM survey participants. There interviews focused on several outstanding areas in the NSUM literature and produced a number of practical suggestions for future NSUM studies. Participants tended to alter their working definition of what it meant to know someone as they went through the survey, often falling back to only searching through groups of close contacts such as family and good friends. Fortunately, participants did not seem to have trouble with the spatial boundaries placed upon knowing someone. However, their grasp of the temporal boundaries was not as stable as it should be. To remedy this it is recommended researchers test implementations where the definition of knowing someone is repeated during a survey whenever practical, and that the definition should be easy to reference for participants.

There were also interesting recall differences when a participant was trying to remember counts that were a zero, and in fact it often seemed like their response was instantaneous and without thought. This effect was found among some responses of one, but never when a participant was counting two or more people in given group. Participants were also likely to stop searching their memory for more people once they felt that had put forth a “good faith” effort, or enough time had passed since their last recall. The lack of conscious response process for zeroes and some ones is troubling given that the NSUM is often focused sampling from larger acquaintance networks which may not always be searched in such an instantaneous fashion. To remedy this, whenever possible, it is suggested that NSUM researchers test slightly increasing their scaling variable sizes to try and decrease the likelihood of an instant response.

The cognitive interviews also highlighted several other interesting aspects of participant behavior which should be the subject of future testing and research. The first of these is an increased likelihood to skip instructions which are not written as questions. Therefore, important and potentially all survey instructions which a researcher needs a participant to read should be written as numbered questions. Second, questions asking about how much time a participant has lived in the target area should be added to all NSUM studies in order to gauge how much time they have had to develop their networks. Several participants had recently moved and their response processes were substantially different in some areas compared to those who had lived in Nebraska for longer periods of time. Because of these differences, it may also be worthwhile to research combining the summation and known population methods in future studies. The summation method did surprisingly better at capturing network sizes of those who had recently moved as it was not contingent upon the participant knowing someone in a given population (i.e., a certain name). Finally, parts of the NSUM impose substantial respondent burden, and even in the cognitive interview setting participants were oft tempted to take shortcuts. Researchers need to fully explore ways that they can increase participant buy-in and the potential rewards for completing an NSUM survey if they cannot find easier ways for a participant to answer NSUM style questions.

Unfortunately the data this dissertation is built upon is cross-sectional. Further, there is no way to assess how long a person has lived in Nebraska and to what extent their personal networks are still growing from the 2014 NCS data. These restrictions temper the findings of this dissertation as it is not practical to think that a) personal networks are static, and b) that networks of a recent arrival immediately reach their desired size. Further work on the changes in network size over time with a particular focus on how networks grow when an ego is placed into a new social environment are needed.

Despite these limitations this dissertation has demonstrated several ways for the NSUM to be developed and refined into a more precise method. These suggestions will hopefully be incorporated into a wider set of NSUM studies as the method continues to be adopted and as more researchers explore both its assumptions and weakness. The applications of the NSUM are considerably broad, and the potential for the method reaches far beyond the standard hidden populations it has been used for to date. In particular, the ability of the NSUM to provide timely and cost effective estimates of any population should be a boon to researchers hoping to demonstrate just how big a given issue is. Here the NSUM fills a gap for researchers who lack the funding to do a comprehensive in person survey, but have just enough resources to field a basic mail or telephone NSUM survey to bolster their argument about just why they need more funding. I look forward to seeing the NSUM continue to evolve and hopefully incorporate many of the changes proposed in this dissertation.

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Table 4.1: Change in Three Population Estimates and Personal Network Size over the Traditional and MoS Estimator

	Traditional		MoS	
	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI
Moved to Nebraska from within the US in last 2 years	12184	[11673, 12695]	75800	[74821, 76777]
	(260.60)		(499.14)	
Would not approve of interracial dating	17892	[17273, 18510]	22614	[22079, 23148]
	(315.79)		(272.63)	
Heroin use in last 30 days	368	[279, 457]	454	[379, 530]
	(45.28)		(38.64)	
Personal Network Size				
Mean	604.03		1024.28	
Standard Deviation	694.04		1559.17	
Min	0.00		0.00	
Max	5944.31		16794.19	
N	555.00		555.00	

Table 4.2: Recursive Back Estimation Process to Identify and Eliminate Poor Predictors Using the Traditional Estimator Without Weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Names	Known	IT0	ABS[1]	IT1	ABS[1]	IT2	ABS[1]	IT3	ABS[1]	IT4	ABS[1]	IT5	ABS[1]	IT6	ABS[1]	IT7	ABS[1]
Walter	7455	1850	2.01	2351	1.67	2499	1.58	2504	1.57	2303							
Bruce	4914	3929	0.32	4992	0.02	5307	0.11	5317	0.11	4890	0.01	4422	0.15	4500	0.13	4969	0.02
Alan	3812	4704	0.30	5977	0.65	6354	0.74	6365	0.74	5854	0.62	5293	0.47	5387	0.50	5949	0.64
Ralph	5269	2196	1.26	2790	0.92	2966	0.83	2972	0.83	2733	0.95	2471	1.09	2515	1.07	2777	0.92
Kyle	2990	3946	0.40	5014	0.75	5330	0.83	5340	0.84	4911	0.72	4441	0.57	4519	0.60	4990	0.74
Adam	4839	4754	0.03	6040	0.32	6421	0.41	6433	0.41	5916	0.29	5350	0.14	5445	0.17	6012	0.31
Rose	5531	2982	0.89	3788	0.55	4027	0.46	4035	0.45	3711	0.58	3355	0.72	3415	0.70	3771	0.55
Tina	4111	2954	0.48	3753	0.13	3990	0.04	3997	0.04	3676	0.16	3324	0.31	3383	0.28	3736	0.14
Emily	3887	4587	0.24	5828	0.58	6195	0.67	6207	0.68	5708	0.55	5162	0.41	5253	0.43	5801	0.58
Martha	7698	2029	1.92	2578	1.58	2740	1.49	2745	1.49	2525	1.61	2283					
Paula	4055	2553	0.67	3243	0.32	3448	0.23	3454	0.23	3177	0.35	2873	0.50	2923	0.47	3228	0.33
Rachel	4522	3896	0.21	4950	0.13	5262	0.22	5272	0.22	4848	0.10	4384	0.04	4462	0.02	4927	0.12
Jobs																	
Police Officers	4943	9542	0.95	12123	1.29	12888	1.38	12912	1.39	11875	1.26	10737	1.12	10928	1.14		
Firefighters	1200	18248	3.93	23184													
US Postal Carriers	2170	5808	1.42	7379	1.77	7844											
Correctional Officers	2490	764	1.71	970	1.36	1031	1.27	1033	1.27	950	1.39	859	1.53	874			
Licensed Gun Dealers	1159	1466	0.34	1862	0.68	1980	0.77	1984	0.78	1824	0.65	1650	0.51	1679	0.53	1854	0.68
Airline or Commercial Pilots	310	758	1.29	963	1.64	1024	1.72	1026									

[1]: This value is absolute value of the ratio of the estimated to the known (i.e. Column 2/Column 1) which is transformed with a logarithm (base 2). Successive columns (5, 7, 9, 11, 13, 15, 17) use the preceding estimation value.

Table 4.3: Change in Three Population Estimates and Personal Network Size over the Recursive Trimming Process through Seven Iterations using the Traditional Estimator

	IT0		IT7	
	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI
Moved to Nebraska from within the US in last 2 years	12184	[11673, 12695]	15407.53	[14761, 16053]
	(260.60)		(329.54)	
Would not approve of interracial dating	17892	[17273, 18510]	22624.97	[21842, 23408]
	(315.79)		(399.33)	
Heroin use in last 30 days	368	[279, 457]	465.19	[353, 577]
	(45.28)		(57.26)	
Personal Network Size				
Mean	604.03		464.28	
Standard Deviation	694.04		444.82	
Min	0.00		0.00	
Max	5944.31		4185.61	
N	555.00		571.00	

Table 4.4: Change in Three Population Estimates and Personal Network Size over the Current and MoS Estimator, with Weights and Without

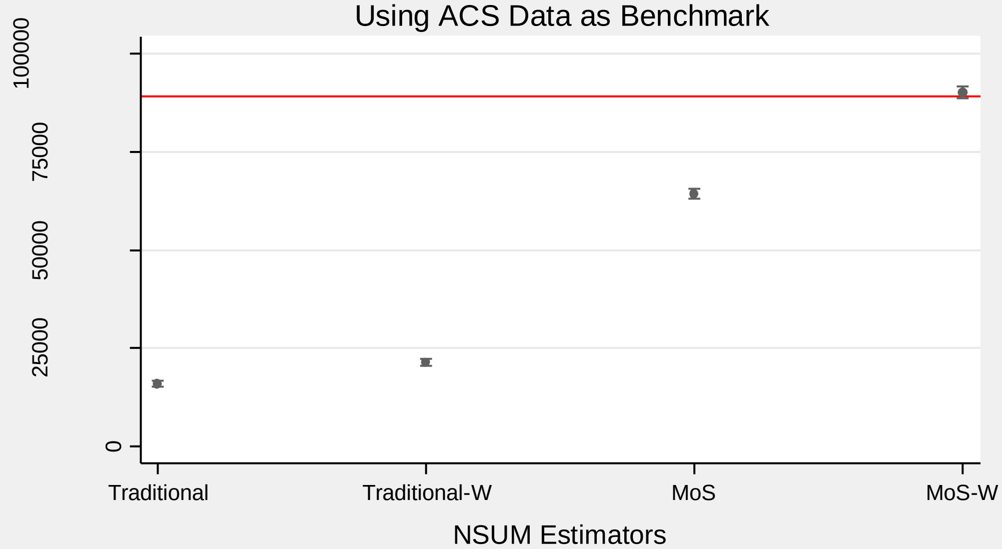
	Traditional				MoS			
	Unweighted		Weighted		Unweighted		Weighted	
	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI
Moved to Nebraska from within the US in last 2 years	12184	[11673, 12695]	16232	[15643, 16822]	75800	[74821, 76777]	114929	[113724, 116133]
	(260.60)		(300.79)		(499.14)		(614.62)	
Would not approve of interracial dating	17892	[17273, 18510]	19234	[18592, 19876]	22614	[22079, 23148]	19655	[19157, 20153]
	(315.79)		(327.42)		(272.63)		(254.17)	
Heroin use in last 30 days	368	[279, 457]	288	[210, 367]	454	[379, 530]	346	[280, 412]
	(45.28)		(40.09)		(38.64)		(33.73)	
Personal Network Size								
Mean	604.03		604.03		1024.28		1024.28	
Standard Deviation	694.04		694.04		1559.17		1559.17	
Min	0.00		0.00		0.00		0.00	
Max	5944.31		5944.31		16794.19		16794.19	
N	555.00		555.00		555.00		555.00	

Table 4.5: Changes in Final Population Estimates and Personal Network Size between Traditional/MoS and Unweighted/Weighted Procedures after Recursive Trimming

	Traditional				MoS			
	Unweighted		Weighted		Unweighted		Weighted	
	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI	Estimate (s.e)	95% CI
Moved to Nebraska from within the US in last 2 years	16039	[15310, 16768]	21390	[20578, 22202]	64320	[63067, 65573]	90073	[88631, 91515]
	(371.99)		(416.58)		(639.30)		(735.76)	
Would not approve of interracial dating	22734	[21867, 23602]	23883	[23025, 24742]	21907	[21175, 22638]	21250	[20550, 21951]
	(442.87)		(440.19)		(373.10)		(357.37)	
Heroin use in last 30 days	535	[402, 668]	404	[433, 516]	385	[288, 481]	281	[200, 361]
	(67.93)		(57.28)		(49.43)		(41.08)	
Personal Network Size								
Mean	397.38		423.37		556.93		584.39	
Standard Deviation	278.23		293.65		453.98		486.36	
Min	0.00		0.00		0.00		0.00	
Max	1243.25		1313.92		1988.66		2100.17	
N	545.00		544.00		528.00		532.00	

Figure 4.1: Comparison of Four NSUM Estimators

Using ACS Data as Benchmark



Note: '-W' indicates the use of postestimation weights

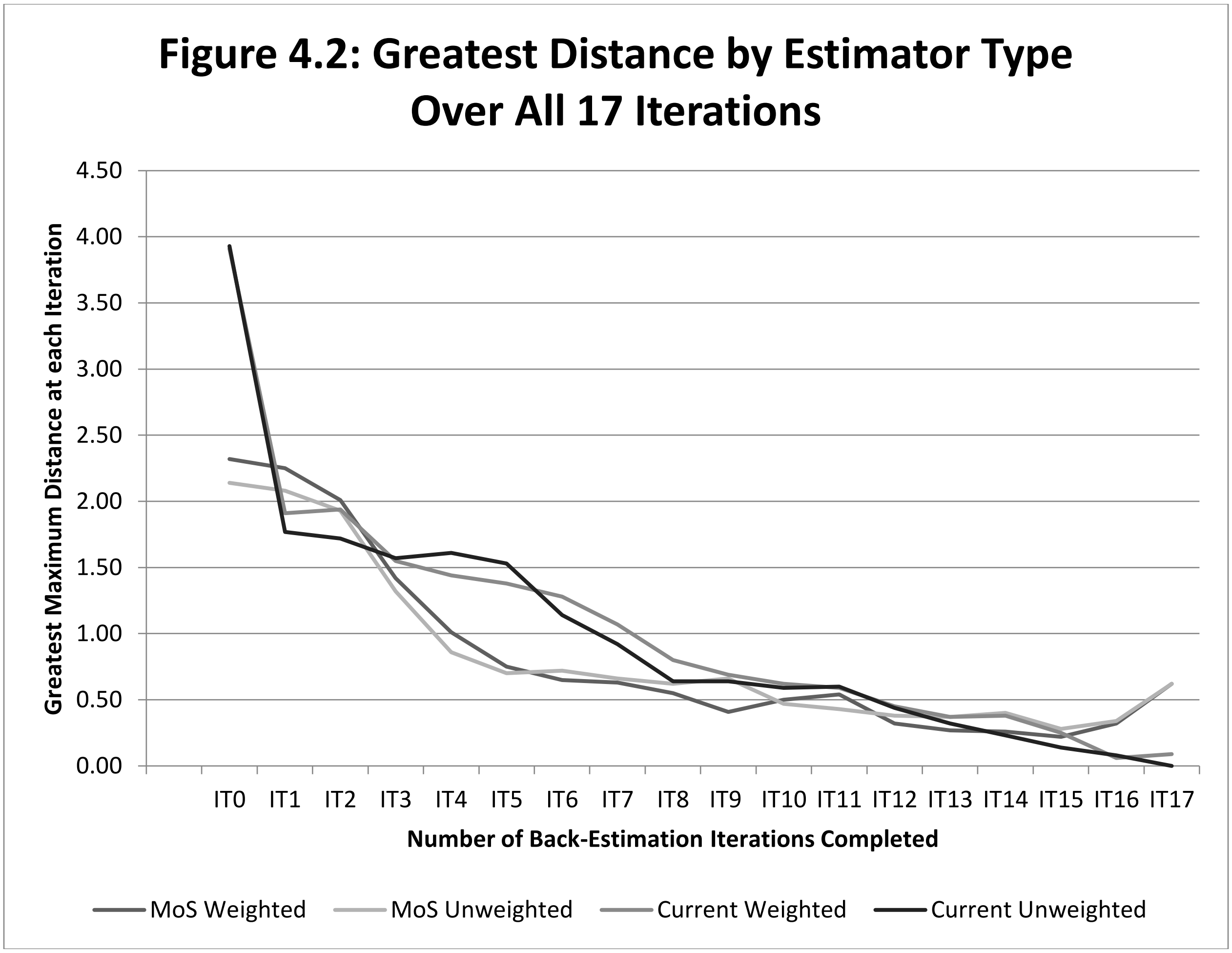


Figure 4.2: Greatest Distance by Estimator Type
Over All 17 Iterations
Greatest Maximum Distance at each Iteration
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
IT0 IT1 IT2 IT3 IT4 IT5 IT6 IT7 IT8 IT9 IT10 IT11 IT12 IT13 IT14 IT15 IT16 IT17
Number of Back-Estimation Iterations Completed
MoS Weighted
MoS Unweighted
Current Weighted
Current Unweighted

Table 5.1: Experimental Design

NSUM Estimator	Item Non-Response Assumption	Before and After Recursive Back-Estimation	Listwise or Imputed Independent Measures	Model Location
Traditional	1 (missing)	Baseline	Listwise	Table 4: Model 1
			Imputed	Table 5: Model 1
		Final	Listwise	Table 4: Model 2
			Imputed	Table 5: Model 2
	2 (zero)	Baseline	Listwise	Table 4: Model 3
			Imputed	Table 5: Model 3
		Final	Listwise	Table 4: Model 4
			Imputed	Table 5: Model 4
MoS	1 (missing)	Baseline	Listwise	Table 4: Model 5
			Imputed	Table 5: Model 5
		Final	Listwise	Table 4: Model 6
			Imputed	Table 5: Model 6
	2 (zero)	Baseline	Listwise	Table 4: Model 7
			Imputed	Table 5: Model 7
		Final	Listwise	Table 4: Model 8
			Imputed	Table 5: Model 8

Table 5.2: Personal Network Size Estimates

Variable	N	Mean	S. E.	Min	Max
Traditional 1 Baseline	555	610.94	34.74	0	5944.31
Traditional 1 Final	574	452.91	18.07	0	3349.89
Traditional 2 Baseline	617	607.20	32.98	0	5944.31
Traditional 2 Final	617	622.39	36.20	0	7031.43
MoS 1 Baseline	555	1039.71	77.52	0	16794.20
MoS 1 Final	561	490.49	33.70	0	6505.38
MoS 2 Baseline	617	1034.93	73.05	0	16794.20
MoS 2 Final	617	484.17	31.92	0	6505.38

Table 5.3: NSUM Scaling Variables across 8 Estimation Techniques Showing Their Back-Estimation Distance and Elimination Order

	Traditional 1		Traditional 1 Final		Traditional 2		Traditional 2 Final		MoS 1 Baseline		MoS 1 Final		MoS 2 Baseline		MoS 2 Final	
Scaling Variable	Rank	Distance	Rank	Distance	Rank	Distance	Rank	Distance	Rank	Distance	Rank	Distance	Rank	Distance	Rank	Distance
Police Officer	8	0.976	*Eliminated (7)*		9	0.820	2	0.846	17	0.053	1	0.890	14	0.157	1	1.004
Firefighter	1	3.910	*Eliminated (1)*		1	3.753	*Eliminated (1)*		3	2.004	*Eliminated (3)*		3	2.124	*Eliminated (3)*	
U.S. Postal Officer	6	1.278	*Eliminated (6)*		7	1.122	*Eliminated (7)*		11	0.418	*Eliminated (5)*		8	0.585	*Eliminated (5)*	
Correctional Officer	9	0.850	*Eliminated (8)*		10	0.693	3	0.72	9	0.572	13	0.015	9	0.505	13	0.059
Gun Dealer (licensed)	13	0.422	2	0.817	14	0.266	7	0.292	6	1.043	10	0.223	6	0.917	12	0.086
Airline Pilot	5	1.336	*Eliminated (4)*		6	1.180	*Eliminated (5)*		12	0.257	8	0.284	16	0.118	8	0.399
Rose	7	1.035	4	0.64	5	1.191	*Eliminated (6)*		5	1.345	5	0.535	5	1.221	7	0.412
Tina	12	0.465	9	0.07	11	0.622	4	0.595	10	0.422	11	0.148	11	0.363	10	0.211
Emily	15	0.331	3	0.726	16	0.175	9	0.202	14	0.206	3	0.780	12	0.299	3	0.868
Martha	3	2.170	*Eliminated (3)*		3	2.326	*Eliminated (3)*		2	2.346	*Eliminated (2)*		2	2.258	*Eliminated (2)*	
Paula	10	0.786	7	0.391	8	0.942	1	0.915	7	0.866	9	0.259	7	0.787	11	0.167
Rachel	17	0.110	8	0.285	15	0.266	8	0.239	13	0.222	7	0.434	15	0.149	6	0.507
Walter	2	2.252	*Eliminated (2)*		2	2.408	*Eliminated (2)*		1	2.472	*Eliminated (1)*		1	2.305	*Eliminated (1)*	
Bruce	14	0.411	10	0.016	12	0.567	5	0.541	8	0.582	12	0.100	10	0.484	9	0.222
Alan	16	0.190	5	0.585	18	0.034	10	0.06	16	0.173	6	0.485	18	0.069	5	0.613
Ralph	4	1.477	*Eliminated (5)*		4	1.633	*Eliminated (4)*		4	1.784	*Eliminated (4)*		4	1.663	*Eliminated (4)*	
Kyle	11	0.545	1	0.94	13	0.388	6	0.415	15	0.197	2	0.854	13	0.266	2	0.922
Adam	18	0.107	6	0.502	17	0.049	11	0.023	18	0.040	4	0.565	17	0.106	4	0.684

Notes: *Rank* indicates which scaling variables were the greatest distance from zero at baseline and after recursive back-estimation

Distance is the absolute value, of the log base 2, of the ratio of the estimated value to the known value for each scaling variable

Eliminated (#) indicates the order in which each scaling variable was removed in the recursive back-estimation process

Table 5.4: Descriptive Statistics of Independent Variables

	Listwise Deletion				Multiple Imputation (m=50)			Difference of
Variable	N	Mean/%	S.E.	% Missing	N	Mean/%	S.E.	Means
Female	614	51%	0.025	0.49%	617	51%	0.023	-0.0030
Age	605	47.44	0.804	1.94%	617	48.57	0.785	-1.1294
Education								
High School or Less	597	15%	0.017	3.24%	617	17%	0.017	-0.0202
Some College	597	37%	0.024	3.24%	617	36%	0.023	0.0026
4 Year Degree	597	27%	0.023	3.24%	617	27%	0.021	0.0074
Graduate/Professional	597	21%	0.020	3.24%	617	20%	0.019	0.0102
Political Affiliation								
Liberal	604	17%	0.019	2.11%	617	17%	0.017	0.0038
Middle-of-the-Road	604	42%	0.025	2.11%	617	42%	0.023	-0.0022
Conservative	604	41%	0.025	2.11%	617	41%	0.023	-0.0016
White Non-Hispanic	610	89%	0.016	1.13%	617	89%	0.016	0.0042
Nearly Weekly Religious Attendance or More	604	45%	0.025	2.11%	617	45%	0.023	-0.0070
Income Categories								
Less than $25k	585	11%	0.014	5.19%	617	13%	0.014	-0.0250
$25k - $49.9k	585	22%	0.021	5.19%	617	23%	0.020	-0.0042
$50k - $99.9k	585	42%	0.025	5.19%	617	41%	0.023	0.0132
$100k or more	585	25%	0.022	5.19%	617	23%	0.021	0.0160
Urbanicity								
Rural (less than 10k)	604	32%	0.023	2.11%	617	33%	0.022	-0.0074
Midrange (10k-49.9k)	604	13%	0.017	2.11%	617	14%	0.016	-0.0121
Urban (50k or more)	604	55%	0.025	2.11%	617	53%	0.023	0.0195

Table 5.5: Negative Binomial Regresion Models Upon 8 Different Estimates of Personal Network Size

	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6			Model 7			Model 8		
	Traditional 1 Base			Traditional 1 Final			Traditional 2 Base			Traditional 2 Final			MoS 1 Base			MoS 1 Final			MoS 2 Base			MoS 2 Final		
Variables	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p
Female	-0.035	0.965		-0.004	0.996		-0.039	0.962		-0.066	0.937		-7E-02	0.935		-9E-02	0.912		-9E-02	0.917		-0.121	0.886	
	-0.09			-0.08			-0.09			-0.09			-0.11			-0.1			-0.11			-0.1		
Age	0.017	1.017		-0.017	0.984		0.012	1.012		0.003	1.003		0.0225	1.023		-5E-03	0.995		2E-02	1.018		-8E-03	0.993	
	-0.01			-0.01			-0.01			-0.01			-0.02	0.980		-0.02			-0.02			-0.01		
Age Squared	0.000	1.000		0.000	1.000		0.000	1.000		0.000	1.000		-0.00021	1.000		4E-06	1.000		-2E-04	1.000		3.56E-05	1.000	
	0			0			0			0			0			0			0			0E+00		
Education																								
High School or Less	-0.105	0.900		0.096	1.101		-0.139	0.870		-0.205	0.815		-0.136	0.873		-0.19	0.827		-0.193	0.824		-0.277	0.758	
	-0.16			-0.13			-0.16			-0.15			-0.2			-0.17			-0.19			-0.16		
Some College	-0.048	0.953		0.119	1.126		-0.060	0.942		-0.126	0.882		-0.0499	0.951		-0.161	0.851		-0.084	0.920		-0.204	0.815	
	-0.13			-0.1			-0.12			-0.14			-0.14			-0.14			-0.14			-0.14		
4 Year Degree	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
Graduate/Professional	-0.319	0.727	*	-0.073	0.929		-0.329	0.720	*	-0.325	0.723	*	-0.303	0.739		-0.199	0.820		-0.312	0.732	*	-0.261	0.770	
	-0.14			-0.12			-0.13			-0.15			-0.16			-0.18			-0.15			-0.17		
Political Affiliation																								
Liberal	-0.0908	0.913		-0.053	0.948		-0.057	0.945		-0.034	0.967		-0.16	0.852		-0.082	0.921		-0.106	0.899		0.002	1.002	
	-0.15			-0.11			-0.15			-0.16			-0.17			-0.18			-0.17			-0.17		
Middle-of-the-Road	-0.096	0.908		-0.081	0.923		-0.082	0.921		-0.18	0.835		-0.0444	0.957		-0.213	0.808		-0.032	0.969		-0.189	0.828	
	-0.1			-0.09			-0.1			-0.1			-0.12			-0.11			-0.12			-0.11		
Conservative	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
White Non-Hispanic	0.0742	1.077		0.162	1.176		0.091	1.096		0.176	1.192		0.101	1.106		0.157	1.170		0.14	1.150		0.206	1.229	
	-0.15			-0.13			-0.16			-0.15			-0.18			-0.16			-0.18			-0.16		
Nearly Weekly Religious Attendance or More	0.128	1.137		0.201	1.223	*	0.165	1.179		0.187	1.206		0.0794	1.083		0.091	1.095		0.104	1.110		0.128	1.137	
	-0.1			-0.08			-0.1			-0.1			-0.12			-0.11			-0.11			-0.11		
Income																								
Less than $25k	-0.52	0.595	***	-0.315	0.730	*	-0.479	0.619	***	-0.349	0.705	**	-0.697	0.498	***	-0.509	0.601	***	-0.638	0.528	***	-0.465	0.628	***
	-0.14			-0.13			-0.13			-0.12			-0.16			-0.13			-0.15			-0.13		
$25k - $49.9k	-0.0439	0.957		-0.21	0.811	*	-0.055	0.947		-0.041	0.960		-0.07	0.932		-0.062	0.940		-0.072	0.931		-0.079	0.924	
	-0.14			-0.1			-0.13			-0.14			-0.15			-0.15			-0.15			-0.15		
$50k - $99.9k	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
$100k or more	-0.242	0.785	*	-0.0939	0.910		-0.223	0.800	*	-0.161	0.851		-0.185	0.831		-0.050	0.952		-0.183	0.833		-0.058	0.944	
	-0.11			-0.1			-0.11			-0.11			-0.14			-0.13			-0.13			-0.13		
Urbanicity																								
Rural (Less than 10k)	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
Midrange (10k - 49.9k)	-0.501	0.606	***	-0.265	0.767	*	-0.502	0.605	***	-0.269	0.764		-0.698	0.498	***	-0.268	0.765		-0.69	0.502	***	-0.256	0.774	
	-0.15			-0.13			-0.14			-0.14			-0.17			-0.17			-0.17			-0.16		
Urban (50k or More)	-0.899	0.407	***	-0.533	0.587	***	-0.913	0.401	***	-0.639	0.528	***	-1.202	0.301	***	-0.69	0.502	***	-1.198	0.302	***	-0.673	0.510	***
	-0.11			-0.09			-0.11			-0.11			-0.13			-0.12			-0.13			-0.12		
Intercept	6.719		***	6.791		***	6.772		***	7.011		***	7.189		***	6.955		***	7.235		***	6.951		***
	-0.42			-0.4			-0.41			-0.46			-0.47			-0.52			-0.46			-0.5		
N	490			501			534			534			490			492			534			534		

Table 5.6: Negative Binomial Regresion Models Upon 8 Different Estimates of Personal Network Size with Multiple Imputation for Independent Variable Missing Values

	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6			Model 7			Model 8		
	Traditional 1 Base			Traditional 1 Final			Traditional 2 Base			Traditional 2 Final			MoS 1 Base			MoS 1 Final			MoS 2 Base			MoS 2 Final		
Variables	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p	b / se	exp(b)	p
Female	-0.041	0.960		-0.028	0.973		-0.062	0.940		-0.084	0.920		-0.075	0.927		-0.090	0.914		-0.107	0.899		-0.133	0.875	
	-0.09			-0.08			-0.09			-0.09			-0.11			-0.1			-0.11			-0.1		
Age	0.022	1.022		-0.011	0.989		0.009	1.009		-0.002	0.998		0.03	1.03	*	0.00			0.02			-0.01		
	-0.01			-0.01			-0.01			-0.01			-0.02			-0.02			-0.02			-0.01		
Age Squared	0.000	1.000		0.00	1.000		0.00	1.000		0.00	1.000		0.00	0.9997	*	0.00			0.00			0.00		
	0			0			0			0			0			0			0			0		
Education																								
High School or Less	-0.080	0.923		0.091	1.095		-0.077	0.926		-0.163	0.850		-0.096	0.908		-0.183	0.833		-0.113	0.893		-0.241	0.786	
	-0.16			-0.12			-0.16			-0.15			-0.19			-0.16			-0.19			-0.16		
Some College	-0.040	0.961		0.122	1.130		-0.074	0.929		-0.138	0.871		-0.040	0.961		-0.150	0.861		-0.104	0.901		-0.201	0.818	
	-0.13			-0.09			-0.12			-0.13			-0.14			-0.14			-0.14			-0.14		
4 Year Degree	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
Graduate/Professional	-0.289	0.749	*	-0.083	0.920		-0.3	0.741	*	-0.318	0.728	*	-0.242	0.785		-0.183	0.833		-0.257	0.773		-0.245	0.783	
	-0.14			-0.11			-0.13			-0.15			-0.16			-0.17			-0.15			-0.17		
Political Affiliation																								
Liberal	-0.085	0.919		-0.026	0.974		0.030	1.030		0.047	1.048		-0.146	0.864		-0.066	0.936		-0.010	0.990		0.058	1.060	
	-0.15			-0.1			-0.15			-0.16			-0.17			-0.17			-0.16			-0.16		
Middle-of-the-Road	-0.077	0.926		-0.073	0.930		-0.034	0.966		-0.131	0.877		-0.020	0.981		-0.176	0.839		0.027	1.027		-0.150	0.861	
	-0.1			-0.09			-0.1			-0.1			-0.12			-0.11			-0.12			-0.11		
Conservative	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
White Non-Hispanic	0.048	1.049		0.156	1.169		0.0894	1.094		0.107	1.113		0.098	1.103		0.084	1.087		0.169	1.184		0.131	1.140	
	-0.14			-0.12			-0.14			-0.14			-0.16			-0.15			-0.16			-0.15		
Nearly Weekly Religious Attendance or More	0.173	1.189		0.212	1.236	**	0.192	1.212	*	0.206	1.229	*	0.131	1.140		0.128	1.137		0.139	1.149		0.146	1.157	
	-0.1			-0.08			-0.1			-0.1			-0.12			-0.11			-0.11			-0.1		
Income																								
Less than $25k	-0.472	0.624	**	-0.267	0.766	*	-0.377	0.686	**	-0.285	0.752	*	-0.624	0.536	***	-0.454	0.635	***	-0.494	0.610	**	-0.405	0.667	**
	-0.15			-0.12			-0.14			-0.12			-0.18			-0.13			-0.18			-0.12		
$25k - $49.9k	-0.024	0.976		-0.192	0.825	*	-0.044	0.957		-0.024	0.976		-0.042	0.959		-0.040	0.961		-0.065	0.937		-0.062	0.940	
	-0.13			-0.1			-0.13			-0.14			-0.15			-0.15			-0.15			-0.14		
$50k - $99.9k	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
$100k or more	-0.226	0.798	*	-0.069	0.934		-0.201	0.818		-0.125	0.882		-0.190	0.827		-0.018	0.982		-0.186	0.830		-0.030	0.970	
	-0.11			-0.09			-0.11			-0.11			-0.13			-0.13			-0.13			-0.13		
Urbanicity																								
Rural (Less than 10k)	*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*			*reference*		
Midrange (10k - 49.9k)	-0.436	0.647	**	-0.236	0.790	*	-0.343	0.710	*	-0.167	0.846		-0.589	0.555	***	-0.212	0.809		-0.468	0.626	**	-0.176	0.839	
	-0.14			-0.11			-0.14			-0.13			-0.17			-0.15			-0.16			-0.14		
Urban (50k or More)	-0.885	0.413	***	-0.542	0.582	***	-0.878	0.416	***	-0.621	0.537	***	-1.177	0.308	***	-0.675	0.509	***	-1.148	0.317	***	-0.653	0.520	***
	-0.11			-0.09			-0.11			-0.11			-0.13			-0.12			-0.13			-0.12		
Intercept	6.56		***	6.661		***	6.725		***	7.083		***	6.912		***	6.915		***	7.082		***	6.936		***
	-0.42			-0.38			-0.42			-0.46			-0.48			-0.51			-0.49			-0.5		
N	555			574			617			617			555			561			617			617		
M	50			50			50			50			50			50			50			50		

Table 5.7: Predicted Average Social Network Size by Estimation Method, Missing Data Treatment, and Rural/Midrange/Urban Zipcode

	Missing Data: Listwise Deletion															
	Traditional 1 Base		Traditional 1 Final		Traditional 2 Base		Traditional 2 Final		MoS 1 Base		MoS 1 Final		MoS 2 Base		MoS 2 Final	
	Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI	
Rural (Less than 10k)	974.23		611.59		957.16		866.53		1853.18		710.17		1815.29		688.43	
	809.11	1139.36	527.87	695.30	800.19	1114.12	718.87	1014.20	1474.33	2232.04	567.58	852.76	1455.82	2174.76	555.19	821.67
Midragne (10k - 49.9k)	590.15		469.08		579.21		662.32		922.41		543.06		910.63		532.86	
	449.64	730.67	371.44	566.72	444.91	713.50	508.68	815.95	662.07	1182.76	386.39	699.74	658.74	1162.52	382.54	683.19
Urban (50k or More)	396.56		358.98		384.18		457.15		557.24		356.15		547.78		351.14	
	346.13	446.98	322.05	395.91	335.67	432.69	399.60	514.71	472.56	641.92	309.80	402.51	466.29	629.27	305.75	396.53
	Missing Data: Multiple Imputation (m=50)															
	Traditional 1 Base		Traditional 1 Final		Traditional 2 Base		Traditional 2 Final		MoS 1 Base		MoS 1 Final		MoS 2 Base		MoS 2 Final	
	Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI		Pr / CI	
Rural (Less than 10k)	939.53		596.46		915.65		831.68		1773.38		677.36		1716.59		654.97	
	799.22	1104.48	525.49	677.01	784.51	1068.71	709.78	974.51	1457.00	2158.45	560.69	818.31	1421.82	2072.47	546.70	784.67
Midragne (10k - 49.9k)	607.26		471.28		649.99		703.83		983.76		548.22		1074.52		549.39	
	485.94	758.86	391.33	567.56	518.80	814.36	564.45	876.08	746.72	1296.05	422.02	712.17	815.57	1415.69	427.72	705.68
Urban (50k or More)	387.68		346.78		380.38		447.07		546.44		344.88		544.37		340.95	
	341.81	439.71	313.27	383.89	335.45	431.32	394.65	506.46	469.75	635.66	303.18	392.31	468.77	632.17	300.07	387.40

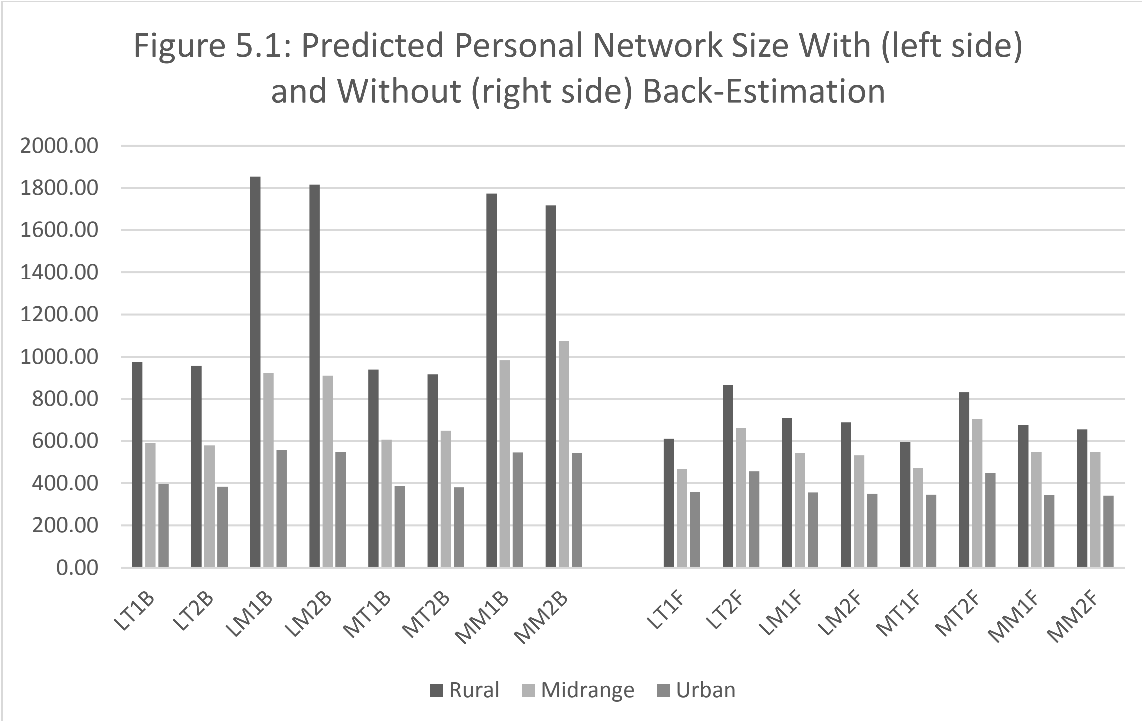
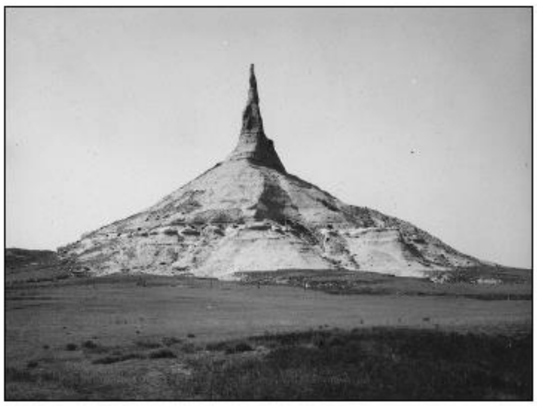


Figure 5.1: Predicted Personal Network Size With (left side) and Without (right side) Back-Estimation
2000.00
1800.00
1600.00
1400.00
1200.00
1000.00
800.00
600.00
400.00
200.00
0.00
LT1B
LT2B
LM1B
LM2B
MT1B
MT2B
MM1B
MM2B
LT1F
LT2F
LM1F
LM2F
MT1F
MT2F
MM1F
MM2F
Rural
Midrange
Urban

APPENDIX A: 2014 NEBRASKA COMMUNITY SURVEY

Nebraska Community Survey

To be completed by the adult (age 19 or older) in your household with the next birthday after April 14, 2014



Please Start Here

1. Overall, how satisfied or dissatisfied are you with living in Nebraska?

- ○ Very satisfied
- ○ Somewhat satisfied
- ○ Neutral
- ○ Somewhat dissatisfied
- ○ Very dissatisfied

2. Do you think the rate of crime in the United States seems to be:

- ○ Increasing
- ○ Staying about the same
- ○ Decreasing

3. Do you think the rate of crime in your area seems to be:

- ○ Increasing
- ○ Staying about the same
- ○ Decreasing

This next section asks about the number of people whom you *know* who are currently working in various types of jobs.

4. When we ask about how many people you *know* it means that you know them and they know you by sight or name, that you could contact them, and that there has been some contact (either in person, by telephone, mail, or web) in the past 2 years.

- ○ I understand

5. How many people do you *know* who are police officers?

In the U.S. → ☐☐☐

In Nebraska → ☐☐☐

6. How many people do you *know* who are firefighters?

In the U.S. → ☐☐☐

In Nebraska → ☐☐☐

7. How many people do you *know* who are United States postal carriers?

In the U.S. →

In Nebraska →

8. How many people do you *know* who are correctional officers (state or federal prison)?

In the U.S. →

In Nebraska →

9. How many people do you *know* who are licensed gun dealers?

In the U.S. →

In Nebraska →

10. How many people do you *know* who are airline or commercial pilots?

In the U.S. →

In Nebraska →

Migration

11. How many people do you *know* who have moved to Nebraska in the last two years?

From Outside the U.S. →

From Another U.S. State →

12. How many people do you *know* who have moved from Nebraska in the last two years?

To Outside the U.S. →

To Another U.S. State →

13. How many people do you *know* who intend to move from Nebraska in the next two years?

To Outside the U.S. →

To Another U.S. State →

14. How many people do you *know* who have moved from a rural area to an urban area within Nebraska in the last two years?

In Nebraska →

15. How many people do you *know* who have moved from an urban area to a rural area within Nebraska in the last two years?

In Nebraska →

16. How many people do you *know* who would not approve of interracial dating?

In Nebraska →

First Names

Please take your time going through this section, although unusual, it is important.

17. How many people do you *know* named Rose?

In the U.S. →

In Nebraska →

18. How many people do you *know* named Tina?

In the U.S. →

In Nebraska →

19. How many people do you *know* named Emily?

In the U.S. →

In Nebraska →

20. How many people do you *know* named Martha?

In the U.S. →

In Nebraska →

21. How many people do you *know* named Paula?

In the U.S. →

In Nebraska →

22. How many people do you *know* named Rachel?

In the U.S. →

In Nebraska →

23. **How many people do you *know* named Walter?**
In the U.S. →
In Nebraska →

24. **How many people do you *know* named Bruce?**
In the U.S. →
In Nebraska →

25. **How many people do you *know* named Alan?**
In the U.S. →
In Nebraska →

26. **How many people do you *know* named Ralph?**
In the U.S. →
In Nebraska →

27. **How many people do you *know* named Kyle?**
In the U.S. →
In Nebraska →

28. **How many people do you *know* named Adam?**
In the U.S. →
In Nebraska →

Political Membership

29. **How many people do you *know* who are members of a patriot group, but are not members of the Tea Party?** (Groups who believe that unconstitutional actions by the government and some special interest groups threaten individual liberties)
In Nebraska →

30. **How many people do you *know* who are members of the "Tea Party?"**
In Nebraska →

31. **How many people do you *know* who are members of "Occupy Wall Street" or other "Occupy" groups?**
In Nebraska →

Health and Substance Use

32. **How many people do you *know* with Hepatitis C?**
In Nebraska →

33. **How many people do you *know* who are HIV positive?**
In Nebraska →

34. **How many people do you *know* who have used marijuana in the last 30 days?**
In Nebraska →

35. **How many people do you *know* who have used methamphetamines in the last 30 days?**
In Nebraska →

36. **How many people do you *know* who have used heroin in the last 30 days?**
In Nebraska →

37. **How many people do you *know* who sell or provide marijuana to others?**
In Nebraska →

38. **How many people do you *know* who sell or provide heroin, methamphetamines, or other hard drugs to others?**
In Nebraska →

Criminal Justice

39. **How many people do you *know* who had their apartment, home, or garage broken into during 2013?**
In Nebraska →

40. **How many people do you *know* who were beaten up, attacked, or hit during 2013?**
In Nebraska →

41. How many people do you *know* who had something taken from them by force (robbed), such as by a stickup, mugging, or threat during 2013?
    In Nebraska →

42. How many people do you *know* who were the victim of identity theft during 2013?
    In Nebraska →

43. How many people do you *know* who were raped or sexually attacked during 2013?
    In Nebraska →

44. How many people do you *know* who were murdered during 2013?
    In Nebraska →

45. How many people do you *know* who have been questioned by the police during 2013?
    In Nebraska →

46. How many people do you *know* who were arrested during 2013?
    In Nebraska →

47. How many people do you *know* who have been convicted of a crime during 2013?
    In Nebraska →

48. How many people do you *know* who broke into an apartment, home, or garage during 2013?
    In Nebraska →

49. How many people do you *know* who took something by force (a robbery) such as a stickup, mugging, or threat during 2013?
    In Nebraska →

50. How many people do you *know* who beat up, attacked, or hit someone during 2013?
    In Nebraska →

51. How many people do you *know* who believe that some races or ethnic groups are superior to others?
    In Nebraska →

52. How many people do you *know* who are members of a group that believes members of some racial or ethnic groups are superior or better than members of some other races or ethnicities?
    In Nebraska →

53. How many people do you *know* who committed identity theft during 2013?
    In Nebraska →

54. How many people do you *know* who committed insurance fraud during 2013?
    In Nebraska →

55. How many people do you *know* who committed a rape or sexual attack during 2013?
    In Nebraska →

56. How many people do you *know* who committed child abuse during 2013?
    In Nebraska →

57. How many people do you *know* who committed a murder during 2013?
    In Nebraska →

58. How many people do you *know* who have been sent to rehabilitation by the court during 2013?
    In Nebraska →

59. How many people do you *know* who have been placed on probation during 2013?
    In Nebraska →

60. How many people do you *know* who have been placed on parole during 2013?
    In Nebraska →

61. How many people do you *know* whose parents (either father or mother) were in a state or federal prison while they were under the age of 18?

In Nebraska → [ ]

62. How many people do you *know* who have been in a local or county jail during 2013?

In Nebraska → [ ]

63. How many people do you *know* who have ever been in a local or county jail?

In Nebraska → [ ]

64. How many people do you *know* who have been in a state or federal prison during 2013?

In Nebraska → [ ]

65. How many people do you *know* who have ever been in a state or federal prison?

In Nebraska → [ ]

Attitudes about Crime & Media Use

66. How confident are you that:	**Very Confident**	**Mostly Confident**	**Somewhat Confident**	**Not At All Confident**
a. The criminal justice system can reduce crime?	○	○	○	○
b. The criminal justice system can reduce drug use?	○	○	○	○
c. The police can protect you from violent crimes like assault?	○	○	○	○
d. The police can protect you from property crimes like theft?	○	○	○	○

67. How fair is the justice system in its:	**Very Fair**	**Mostly Fair**	**Somewhat Fair**	**Not At All Fair**
a. Treatment of people accused of committing crime.	○	○	○	○
b. Treatment of people victimized by crime.	○	○	○	○
c. Use of the death penalty.	○	○	○	○

68. How often do you personally worry about:	**Almost Always**	**Often**	**Sometimes**	**Rarely**	**Never**
a. Walking alone at night.	○	○	○	○	○
b. Being the victim of identity theft	○	○	○	○	○
c. Your residence being broken into.	○	○	○	○	○
d. Getting robbed.	○	○	○	○	○
e. Being raped or sexually attacked.	○	○	○	○	○
f. Getting murdered.	○	○	○	○	○
g. Someone in my family becoming a victim of a crime.	○	○	○	○	○

69. How reliable is:	**Very Reliable**	**Mostly Reliable**	**Somewhat Reliable**	**Not At All Reliable**
a. The media as a source of information about crime?	○	○	○	○
b. The government as a source of information about crime?	○	○	○	○

70. How angry do you feel when you think about:

	Very Angry	Fairly Angry	Somewhat Angry	Not At All Angry
a. Crime in this country?	○	○	○	○
b. Crime in your community?	○	○	○	○

71. In the past 7 days, on how many days did you:

	Days 0	1	2	3	4	5	6	Days 7
a. Read a print newspaper?	○	○	○	○	○	○	○	○
b. Read or watch news on the internet?	○	○	○	○	○	○	○	○
c. Listen to news on the radio?	○	○	○	○	○	○	○	○
d. Watch local TV news?	○	○	○	○	○	○	○	○
e. Watch national network TV news on ABC, CBS, or NBC?	○	○	○	○	○	○	○	○
f. Watch national cable TV news, like CNN, FOX, or MSNBC?	○	○	○	○	○	○	○	○

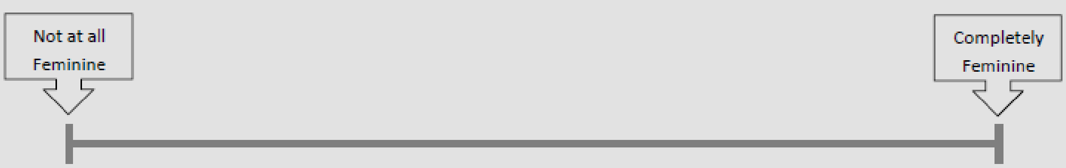
72. In the past 7 days, how often have you seen violent acts:

	Every Day	Most Days	Some Days	Never	Not Applicable
a. In the news?	○	○	○	○	○
b. On a television program, other than news?	○	○	○	○	○
c. In a movie?	○	○	○	○	○
d. On a website?	○	○	○	○	○
e. In a video game, including gaming systems, online games, or a mobile device?	○	○	○	○	○

About Yourself

73. Below is a line with not at all feminine at one end and completely feminine at the other. We are going to ask you to place a couple people on the line. Place the following letters on the line.

Write **A** where you think you land.
Write **B** where you think others view you as.
Write **C** where you think our society's ideal woman would be.
Write **D** where you think our society's ideal man would be.
Write **E** where you think your spouse or partner lands (if applicable).



74. Below is a line with not at all masculine at one and completely masculine at the other. We are going to ask you to place a couple people on the line. Place the following letters on the line.

Write **A** where you think you land.
Write **B** where you think others view you as.
Write **C** where you think our society's ideal woman would be.
Write **D** where you think our society's ideal man would be.
Write **E** where you think your spouse or partner lands (if applicable).

75. Are you:
- ◯ Male
- ◯ Female

76. Do you consider yourself to be Hispanic or Latino/a?
- ◯ Yes
- ◯ No

77. What race or races do you consider yourself to be? *(Check all that apply)*
- ☐ White (Caucasian)
- ☐ Black or African American
- ☐ Asian
- ☐ American Indian or Alaska Native
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Other, Specify: ________

78. What is your current marital or relationship status?
- ◯ Married
- ◯ Married, living apart
- ◯ Not married, but living with a partner (cohabiting)
- ◯ Never married
- ◯ Divorced
- ◯ Widowed
- ◯ Separated

79. What is the highest degree you have attained?
- ◯ No Diploma
- ◯ High School Diploma/GED
- ◯ Some college, but no degree
- ◯ Technical/Associate/Junior College (2 yr, LPN)
- ◯ Bachelor's Degree (4 yr, BA, BS, RN)
- ◯ Graduate Degree (Masters, PhD, Law, Medicine)

80. In general, how would you describe your political views?
- ◯ Very liberal
- ◯ Liberal
- ◯ Middle-of-the-road
- ◯ Conservative
- ◯ Very Conservative

81. Would you say that your overall health and well-being is excellent, good, fair, or poor?
- ◯ Excellent
- ◯ Good
- ◯ Fair
- ◯ Poor

82. Do you typically work full-time, part-time, go to school, keep house, or something else? *(Check all that apply)*
- ☐ Working full-time (35 hours or more)
- ☐ Working part-time
- ☐ Has a job, but not at work (due to illness, vacation, strike)
- ☐ Unemployed, laid off, looking for work
- ☐ Retired
- ☐ In school
- ☐ Keeping house
- ☐ Disabled
- ☐ Other, specify: ________

83. If you could choose between the following approaches, which do you think is the best penalty for murder?
- ◯ Death penalty
- ◯ Life in prison without the possibility of parole
- ◯ Prison with the possibility of parole
- ◯ Unsure/Do not want to answer

84. Have you been the victim of a crime in the past 12 months?
- ◯ Yes
- ◯ No

85. Do you consider yourself to be Christian, Jewish, Muslim, or something else?
- ◯ Christian
- ◯ Jewish
- ◯ Muslim
- ◯ None (no religion)
- ◯ Other, specify: ________

Go to #90

86. Do you consider yourself to be Catholic, Protestant, or Other/Just Christian?
- ◯ Catholic
- ◯ Protestant
- ◯ Other Christian / Just Christian

87. What denomination does your church belong to?

____

88. If you are currently attending a church, what is the name of that church?

____

89. In your view the Bible is:

- ◯ God's word and is meant to be taken literally, word for word
- ◯ God's word, and all it says is true, but not all of it is meant to be taken literally, word for word
- ◯ God's word, and is authoritative for Christian faith and practice, but it is not intended as a book of science or history
- ◯ Written by men inspired by God but does contain some errors, often reflecting the limitations of its authors and their eras
- ◯ A book of myths and fables

90. How often do you attend religious services?

- ◯ Several times a week
- ◯ Once a week
- ◯ Nearly every week
- ◯ About once a month
- ◯ Several times a year
- ◯ About once a year
- ◯ Less than once a year
- ◯ Never

91. Please indicate the category that describes your total family income in the last 12 months.

- ◯ Under $5,000
- ◯ $5,000 to $9,999
- ◯ $10,000 to $14,999
- ◯ $15,000 to $19,999
- ◯ $20,000 to $24,999
- ◯ $25,000 to $29,999
- ◯ $30,000 to $39,999
- ◯ $40,000 to $49,999
- ◯ $50,000 to $59,999
- ◯ $60,000 to $74,999
- ◯ $75,000 to $99,999
- ◯ $100,000 or more

92. Including yourself, how many adults live in your household (age 19 or older)?

93. In what year were you born?

94. What is your current zip code?

Please use the space below to provide any comments or feedback.

Thank You!

This completes our questions. We greatly appreciate the time you have taken to complete this survey. For your convenience, please use the postage-paid return envelope included in your survey packet to return your questionnaire to the Bureau of Sociological Research.

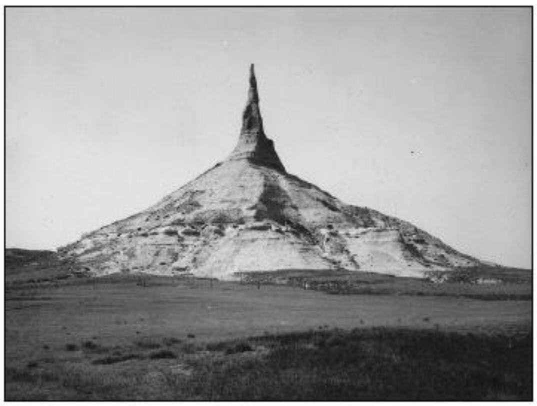
Please direct questions or requests from this survey to:

Bureau of Sociological Research
University of Nebraska-Lincoln
301 Benton Hall, PO Box 886102
Lincoln, NE 68588-6102
Phone: 1-800-480-4549 (toll free)
Email: bosr@unl.edu

APPENDIX B: 2016 COGNITIVE INTERVIEW SURVEY

Nebraska Community Survey

To be completed by the adult (age 19 or older) in your household with the next birthday after June1, 2016



Please Start Here

1. Overall, how satisfied or dissatisfied are you with living in Nebraska?
- ○ Very satisfied
- ○ Somewhat satisfied
- ○ Neutral
- ○ Somewhat dissatisfied
- ○ Very dissatisfied

2. Do you think the rate of crime in the United States seems to be:
- ○ Increasing
- ○ Staying about the same
- ○ Decreasing

3. Do you think the rate of crime in your area seems to be:
- ○ Increasing
- ○ Staying about the same
- ○ Decreasing

This next section asks about the number of people whom you *know* who are currently working in various types of jobs.

4. When we ask about how many people you *know* it means that you know them and they know you by sight or name, that you could contact them, and that there has been some contact (either in person, by telephone, mail, or web) in the past 2 years.
- ○ I understand

5. How many people do you *know* who are police officers in Nebraska?

6. How many people do you *know* who are firefighters in Nebraska?

7. How many people do you *know* who are United States postal carriers in Nebraska?

8. How many people do you *know* who are correctional officers in Nebraska (state or federal prison)?

9. How many people do you *know* who are licensed gun dealers in Nebraska?

10. How many people do you *know* who are airline or commercial pilots in Nebraska?

Migration

11. How many people do you *know* who have moved to Nebraska in the last two years?
    - From Outside the U.S. →
    - From Another U.S. State →

12. How many people do you *know* who have moved from Nebraska in the last two years?
    - To Outside the U.S. →
    - To Another U.S. State →

13. How many people do you *know* who intend to move from Nebraska in the next two years?
    - To Outside the U.S. →
    - To Another U.S. State →

14. How many people do you *know* who have moved from a rural area to an urban area within Nebraska in the last two years?

15. How many people do you *know* who have moved from an urban area to a rural area within Nebraska in the last two years?

16. How many people do you *know* who would not approve of interracial dating in Nebraska?

First Names

Please take your time going through this section, although unusual, it is important.

17. How many people do you *know* named Rose in Nebraska?

18. How many people do you *know* named Tina in Nebraska?

19. How many people do you *know* named Emily in Nebraska?

20. How many people do you *know* named Martha in Nebraska?

21. How many people do you *know* named Paula in Nebraska?

22. How many people do you *know* named Rachel in Nebraska?

23. How many people do you *know* named Walter in Nebraska?

24. How many people do you *know* named Bruce in Nebraska?

25. How many people do you *know* named Alan in Nebraska?

26. How many people do you *know* named Ralph in Nebraska?

27. How many people do you *know* named Kyle in Nebraska?

28. How many people do you *know* named Adam in Nebraska?

Relations

29. How many of your immediate family live in Nebraska?

30. How many of your other birth family live in Nebraska?

31. How many of the family of your spouse, partner, or significant other live in Nebraska?

32. How many of your coworkers live in Nebraska?

33. How many people are there at your work that you don't work with directly who live in Nebraska?

34. How many of your best friends/confidants live in Nebraska?

35. How many people do you know through hobbies or recreations who live in Nebraska?

36. How many people do you know through religious organizations who live in Nebraska?

37. How many people do you know from other organizations who live in Nebraska?

38. How many other people do you know through school who live in Nebraska?

39. How many of your neighbors in do you know in Nebraska?

40. How many people do you know who are just friends and live in Nebraska?

41. How many people do you know who you primarily know through others who live in Nebraska?

42. How many people do you know who provide a service to you in Nebraska?

43. How many other people do you know who live in Nebraska?

Political Membership

44. How many people do you *know* who are members of a patriot group, but are not members of the Tea Party in Nebraska? (Groups who believe that unconstitutional actions by the government and some special interest groups threaten individual liberties)

45. How many people do you *know* who are members of the "Tea Party" in Nebraska?

46. How many people do you *know* who are members of "Occupy Wall Street" or other "Occupy" groups in Nebraska?

Health and Substance Use

47. How many people do you *know* with Hepatitis C in Nebraska?

48. How many people do you *know* who are HIV positive in Nebraska?

49. How many people do you *know* who have used marijuana in the last 30 days in Nebraska?

50. How many people do you *know* who have used methamphetamines in the last 30 days in Nebraska?

51. How many people do you *know* who have used heroin in the last 30 days in Nebraska?

52. How many people do you *know* who sell or provide marijuana to others in Nebraska?

53. How many people do you *know* who sell or provide heroin, methamphetamines, or other hard drugs to others in Nebraska?

Criminal Justice

54. How many people do you *know* who had their apartment, home, or garage broken into during 2015 in Nebraska?

55. How many people do you *know* who were beaten up, attacked, or hit during 2015 in Nebraska?

56. How many people do you *know* who had something taken from them by force (robbed), such as by a stickup, mugging, or threat during 2015 in Nebraska?

57. How many people do you *know* who were the victim of identity theft during 2015 in Nebraska?

58. How many people do you *know* who were raped or sexually attacked during 2015 in Nebraska?

59. How many people do you *know* who were murdered during 2015 in Nebraska?

60. How many people do you *know* who have been questioned by the police during 2015 in Nebraska?

61. How many people do you *know* who were arrested during 2015 in Nebraska?

62. How many people do you *know* who have been convicted of a crime during 2015 in Nebraska?

63. How many people do you *know* who broke into an apartment, home, or garage during 2015 in Nebraska?

64. How many people do you *know* who took something by force (a robbery) such as a stickup, mugging, or threat during 2015 in Nebraska?

65. How many people do you *know* who beat up, attacked, or hit someone during 2015 in Nebraska?

66. How many people do you *know* who believe that some races or ethnic groups are superior to others in Nebraska?

67. How many people do you *know* who are members of a group that believes members of some racial or ethnic groups are superior or better than members of some other races or ethnicities in Nebraska?

68. How many people do you *know* who committed identity theft during 2015 in Nebraska?

69. How many people do you *know* who committed insurance fraud during 2015 in Nebraska?

70. How many people do you *know* who committed a rape or sexual attack during 2015 in Nebraska?

71. How many people do you *know* who committed child abuse during 2015 in Nebraska?

72. How many people do you *know* who committed a murder during 2015 in Nebraska?

73. How many people do you *know* who have been sent to rehabilitation by the court during 2015 in Nebraska?

74. How many people do you *know* who have been placed on probation during 2015 in Nebraska?

75. How many people do you *know* who have been placed on parole during 2015?

76. How many people do you *know* whose parents (either father or mother) were in a state or federal prison while they were under the age of 18 in Nebraska?

77. How many people do you *know* who have been in a local or county jail during 2015 in Nebraska?

78. How many people do you *know* who have ever been in a local or county jail in Nebraska?

79. How many people do you *know* who have been in a state or federal prison during 2015 in Nebraska?

80. How many people do you *know* who have ever been in a state or federal prison in Nebraska?

About You

81. Are you:
   - ◯ Male
   - ◯ Female
   - ◯ ____________________

82. Do you consider yourself to be Hispanic or Latino/a?
   - ◯ Yes
   - ◯ No

83. What race or races do you consider yourself to be? *(Check all that apply)*
   - ☐ White (Caucasian)
   - ☐ Black or African American
   - ☐ Asian
   - ☐ American Indian or Alaska Native
   - ☐ Native Hawaiian or Other Pacific Islander
   - ☐ Other, Specify: ____________

84. What is your current marital or relationship status?
- ◯ Married
- ◯ Married, living apart
- ◯ Not married, but living with a partner (cohabiting)
- ◯ Never married
- ◯ Divorced
- ◯ Widowed
- ◯ Separated

85. What is the highest degree you have attained?
- ◯ No Diploma
- ◯ High School Diploma/GED
- ◯ Some college, but no degree
- ◯ Technical/Associate/Junior College (2 yr, LPN)
- ◯ Bachelor's Degree (4 yr, BA, BS, RN)
- ◯ Graduate Degree (Masters, PhD, Law, Medicine)

86. In general, how would you describe your political views?
- ◯ Very liberal
- ◯ Liberal
- ◯ Middle-of-the-road
- ◯ Conservative
- ◯ Very Conservative

87. Would you say that your overall health and well-being is excellent, good, fair, or poor?
- ◯ Excellent
- ◯ Good
- ◯ Fair
- ◯ Poor

88. Do you typically work full-time, part-time, go to school, keep house, or something else? *(Check all that apply)*
- ☐ Working full-time (35 hours or more)
- ☐ Working part-time
- ☐ Has a job, but not at work (due to illness, vacation, strike)
- ☐ Unemployed, laid off, looking for work
- ☐ Retired
- ☐ In school
- ☐ Keeping house
- ☐ Disabled
- ☐ Other, specify:

89. If you could choose between the following approaches, which do you think is the best penalty for murder?
- ◯ Death penalty
- ◯ Life in prison without the possibility of parole
- ◯ Prison with the possibility of parole
- ◯ Unsure/Do not want to answer

90. Have you been the victim of a crime in the past 12 months?
- ◯ Yes
- ◯ No

91. Do you consider yourself to be Christian, Jewish, Muslim, or something else?
- ◯ Christian
- ◯ Jewish
- ◯ Muslim
- ◯ None (no religion)
- ◯ Other, specify:

→ Go to #96

92. Do you consider yourself to be Catholic, Protestant, or Other/Just Christian?
- ◯ Catholic
- ◯ Protestant
- ◯ Other Christian / Just Christian

93. What denomination does your church belong to?

94. If you are currently attending a church, what is the name of that church?

95. In your view the Bible is:
- ◯ God's word and is meant to be taken literally, word for word
- ◯ God's word, and all it says is true, but not all of it is meant to be taken literally, word for word
- ◯ God's word, and is authoritative for Christian faith and practice, but it is not intended as a book of science or history
- ◯ Written by men inspired by God but does contain some errors, often reflecting the limitations of its authors and their eras
- ◯ A book of myths and fables

96. How often do you attend religious services?

- ◯ Several times a week
- ◯ Once a week
- ◯ Nearly every week
- ◯ About once a month
- ◯ Several times a year
- ◯ About once a year
- ◯ Less than once a year
- ◯ Never

97. Please indicate the category that describes your total family income in the last 12 months.

- ◯ Under $5,000
- ◯ $5,000 to $9,999
- ◯ $10,000 to $14,999
- ◯ $15,000 to $19,999
- ◯ $20,000 to $24,999
- ◯ $25,000 to $29,999
- ◯ $30,000 to $39,999
- ◯ $40,000 to $49,999
- ◯ $50,000 to $59,999
- ◯ $60,000 to $74,999
- ◯ $75,000 to $99,999
- ◯ $100,000 or more

98. Including yourself, how many adults live in your household (age 19 or older)?

99. In what year were you born?

100. What is your current zip code?

Please use the space below to provide any comments or feedback.

Thank You!

This completes our questions. We greatly appreciate the time you have taken to complete this survey. For your convenience, please use the postage-paid return envelope included in your survey packet to return your questionnaire to the Burea of Sociological Research.

Please direct questions or requests from this survey to:
Bureau of Sociological Research
University of Nebraska-Lincoln
301 Benton Hall, PO Box 886102
Lincoln, NE 68588-6102
Phone: 1-800-480-4549 (toll free) --- Email: bosr@unl.edu

APPENDIX C: COGNITIVE INTERVIEW PROTOCOL

Preparation

[Ensure that informed consent, payment, digital recorder, and paper survey are laid out and ready for the interview. Bottled water, tissues, a notepad, and pens are available for the participant to make use of if needed throughout the interview.]

Introduction

[Greet the participant and seat them at the table. Make sure they are comfortable. Describe what is going to happen.]

> First, thank you for your help! Today you will be helping us understand about how people think about other people they know and the ways they access their memories of other people. I am going to ask you complete a paper survey while speaking aloud the questions, the response options, your thought process, and your answers. During the survey I will ask you follow-up questions which may ask you go provide more detail or to think about a question in a different way. I will be recording this session for later reference and taking notes as we go through the survey. I expect the entire interview to take about two hours. Before we start, we are going to go over and sign the informed consent.

Informed Consent and Explanation of Survey Type

[Hand participant two copies of the informed consent form. Go over the key elements of the form with the participant. Ask them if they have any questions. Ask them to sign the top copy and give them the second copy. After completing the informed consent introduce the idea of cognitive interviews.]

> This is a think-aloud cognitive interview, which helps me understand how you are making your decisions in the context of this survey. When we are asked a question, we often go through an internal process before we respond: trying to understand the question, if we have an answer, if that answer is appropriate, and then providing the response. We may do this almost simultaneously or take our time trying to find our preferred answer. The way in which you think about a question will often tell us just as much as your final answer. To learn about how you answer a question we ask you to speak aloud your response process as you go through the survey. You should try to vocalize what you are thinking as you read a question, develop a response, and then finally decide how you want to respond. This type of speaking isn’t something we do regularly, so I want to ask you two warm-up questions to help you get a sense of what I’m asking you to do.
>
> Here is the first question: How many residences have you lived in since you were born?
>
> > Follow-up: How did you think about what it means to live somewhere?
> > Follow-up: How did you define what it means to live somewhere?
>
> Here is the second question: Think about where you live. How many windows are there?
>
> > Probe: Are you counting windows in doors?
> > Probe: Are you counting sliding glass doors?
> > Having gone through two examples do you have any questions before we start?

The Survey

> I’m going to hand you the survey shortly and I would like you to start thinking aloud as soon as you receive the survey. Please don’t hesitate to drink water as needed throughout the interview. Ready?
>
> [Start recorder and hand respondent the survey]

Generic Probes/Responses

What are you thinking about with this question?
Please remember to try and say what you are thinking about.
You are doing great.
This is really great, keep on going.

Specific Question Follow-ups

How accurate do you think that answer was?
How did you decide to stop counting?
How did you come up with your response to this question?

End of Survey Questions

As you moved through the survey did you change how you answered questions?
Were some questions easier than others?
Was it easier to answer with a zero or non-zero number?
Was it easier to answer with a one or a number greater than one?
How accurate do you think your answers were?
- Do any in particular strike you as off or probably wrong?

How did you decide to stop thinking about how many people you knew for some of the questions?
- Did this change for different sections of the survey?

What would help you answer questions like this? [Text, visually, context, memory aides]
If I were to tell you that the average person in Nebraska knows approximately 600 people…
- What would you think?
- Do you think you know 600 people?
- How many do you think are close people?

Would you know if a person you know is planning to move in the next two years?
Would the people you know be aware of your moving intentions?
Is it easier for you to remember people who have moved here compared to those who have moved away?