The Multi-Level, Multi-Source (ML-MS) Approach to Improving Survey Research

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Introduction

To more fully understand human society, surveys need to collect and analyze multi-level and multi-source data (ML-MS data). Methodologically, the use of ML-MS data in general and the augmenting of respondent-supplied information with auxiliary data (AD) from sample frames, other sources, and paradata in particular can notably help to both measure and reduce total survey error. For example, it can be employed to detect and reduce nonresponse bias, to verify interviews, to validate information supplied by respondents, and in other ways. Substantively, ML-MS data can greatly expand theory-driven research such as by allowing multi-level, contextual analysis of neighborhood, community, and other aggregate-level effects and by adding in case-level data that either cannot be supplied by respondents or is not as accurate and reliable as information from AD (e.g. health information from medical records vs. recall reports of medical care). Thus, the ML-MS approach will boost both the methodological vigor and substantive power of survey research. It is a general framework for conducting and improving survey research.

The ML-MS Approach

The central goal of the ML-MS approach is to collect and retain as much information as practical about the target sample at both the case-level and at multiple aggregate levels starting during the initial sampling stage. The following description of ML-MS will mainly use the example of national US samples of households based on addresses and as such is most directly appropriate for postal and in-person samples using address-based sampling (ABS) or multi-stage, area probability samples, but will also draw on examples from Europe, Korea, and other areas. With appropriate local adaption to the situation in particular countries, ML-MS has global application. In addition, similar approaches can be applied to other survey modes and target populations (e.g. national, RDD, telephone samples; panel studies; list-based samples; local surveys; mix-mode surveys, and national register surveys).

The first step in ML-MS extracts all relevant, public information at both the case-level and aggregate levels from the sampling frame from which the sample cases are drawn. In European samples based on population registers, there is often very useful information on such matters as gender, age, and household composition (Bethlehem, 2002; Stoop, 2005; van Goor, Jansma, and Veenstra, 2005; Voogt and Van Kempen, 2002). Also, list samples (e.g. of employees and HMO enrollees) often have extensive sampling-frame information (Fowler et al., 2002; Kennickell, 2005; Lessler and Kalsbeek, 1992; Moore and Tarnai, 2002; Smith, 1999). But in the US and many other countries (Turrell et al., 2003), general population samples of addresses are typically nearly devoid of household- and respondent-level information. However, US address samples are rich in aggregate-level information. Address/location of course is the one known attribute of all cases, whether respondents or non-respondents. Moreover, ABS frames are usually based on the US Census and/or the annual American Community Survey and as such the appropriate Census data from blocks, tracts, place, etc. are part of the sampling frame and linked to each sample address. That is, the local sample points are selected based on the Census and then addresses within those sample points are obtained from the United States Postal Service Delivery Sequence File (DSF) and/or special field listings – the latter often used for rural areas (O'Muircheartaigh, 2003).) Besides specific addresses, other information from the DSF can and should be added to the Census information for complete sample frame data (Smith and Kim, 2013).

The key is that the information collected from the sample frames to draw the sample should not be discarded or kept separate from the subsequent survey (as is now typically the case), but instead retained and integrated with the later collected survey data.

Among the information from sampling frames that should be recorded and retained are global positioning system (GPS) and/or longitude/latitude (L/L) readings. They are essential both for calculating many case-level spatial variables (e.g. distance of residence to specific facilities such as hospitals or police stations) and for linkage to much aggregate-level data (e.g. hospital beds per capita in the local community or crime levels in the neighborhood). ABSs in the United States have GPS and L/L associated with residences with city-style addresses. For non-city style addresses, GPS readings in the field can and should be collected to add this information when the sample frame is compiled. Of course, public-use files have to censure or eliminate the GPS information for confidentiality reasons (Dugoni, 2012).

The second step augments the sampling-frame data by linking all cases in the sample to other sources. As Groves (2005) has noted, "Collecting auxiliary variables on respondents and nonrespondents to guide attempts to balance response rates across key subgroups is wise." Likewise, the National Research Council (2013) recommends "Research on the availability, quality, and application of administrative records to augment (or replace) survey data collections."

At the case-level that means linking the sample addresses to sources such as telephone directories, consumer records, property records, voter-registration lists, and other publically-available sources (Berge et al., 2005; Brick et al., 2000; Cantor and Cunningham, 2002; Cox, 2006; Davern, 2006; Johnston et al., 2000; Korbmacher and Schroeder, 2013; Marcus at al., 2006; Sarndal and Lundstrom, 2005; Smith and Kim, 2013; Williams et al., 2006). There are two main types of other sources that can be accessed. The first are household-/individual-based files which can be accessed via a given address, name, and/or similar household/individual identifiers and which contain general and often diverse information about the specific sample unit.[1] These are compiled by private business and accessible for a fee. Examples in the United States of specific useful databases/providers are Accurint, Century List Services, Donnelley/infoUSA, Emerges.Com, Equifax, Experian, Info Quest, Peoplefinders, TARGUSinfo, Telematch, Transunion, the Ultimates, and the US Data Corporation.

Administrative records are the second type of other sources. These records are generally collected for a specific public or commercial purpose such as recipients of a particular government benefit, contributors to federal election campaigns, members of a specific volunteer association, or subscribers of a particular magazine. Depending on the source, these may be freely and publically available, generally available, but only for a fee, or only accessible by special arrangement from their owner. While administrative records may contain some general data (e.g. a person's demographics) beyond their specific programmatic information, they usually do not contain general information on other matters about the listees. Survey data and administrative data can be linked together by address, name, and/or other identifiers. Usually administrative data are appended to survey data (but the data exchanges could go in the opposite direction). Such data linkages have been done for decades and are fairly common and often very valuable (Blumberg and Cynamon, 1999; Calderwood and Lessof, 2009; Hewat, 2011; Huynh, Rupp, and Sears, 2000; Moore and Marquis, 1987; Pedace and Bates, 2000; Rhodes and Fung, 2004). In addition, administrative records can sometimes be linked to one another as has been the case in the Netherlands (Everaers and Van Der Laan, 2003).

The increased computerization of more and more household/individual-based and administrative data in recent years has expanded what is available and eased the linkage of surveys and these other data sources (Smith and Kim, 2013). Thus, one is generally now dealing with computerized databases that can be cross linked. In addition, in the US address standardization (i.e. converting irregular, rural addresses to city-style addresses to aid first responders) has facilitated address-based linkages. In addition, a number of special procedures have also been developed to use databases in ways not commonly expected and thereby extract much more information than available from more limited and superficial applications Cantor and Cunningham, 2002; Smith, 2006; Smith and Kim, 2013; Traub, Pilhuj, and Mallet, 2005; Williams et al., 2006).[2]

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[1] In the main example under focus here, only the address is initially known from the sample frame. Other identifiers are only added later. Other types of samples might start with other identifiers such as names or telephone numbers.

[2] Survey researchers already have considerable experience in using databases, but further consultation carried out with other experts such as data librarians, geographical-information-systems specialists, cyber-information technicians and data miners, and records searchers such as skip tracers and investigators would be useful.

Of course correct linkage is not always possible. It depends on the details and accuracy of the data in both the survey and the AD and on whether one wants to be conservative and accept only 100% certain matches or accept links based on less than certainty.[3]

The information obtained should first of all record whether a match was or was not made (e.g. listed in telephone directory or not; having a registered voter at the address or not). Then, if matched, whatever particular information is available (e.g. names, telephone numbers, voter registration status) should be acquired and retained. This means that information is recorded for all cases. Not finding a case in a database is often as valuable as linking to a database. For example, not being in the voting registration databases indicates that no registered voter lives at a particular address. Similarly, not having a listed phone number in telephone directories is a known correlate of nonresponse. (Brick et al. 2003; Brick, Montaquila, and Scheuren 2002; Harvey et al. 2003; Kennedy, Keeter, and Dimock 2008; Minato and Luo 2004; O'Hare, Ziniel, and Groves 2005).

At the aggregate level, this involves adding data from sources other than from the sampling frame.[4] The exact number and characterization of levels can vary, but a typical hierarchy would be respondent, household, neighborhood, community, state/region, and country. What can be added depends on the administrative and data-collection units in each country and access rules to same. In the US Census-based statistics are aggregated and released by block/block group, tract, place, county, metro areas, state, etc. In Europe, fairly large areas are coded and released under the nomenclature of territorial units for statistics (NUTS3) (http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction) and more detailed country-by-country data are available. In Korea the main metropolitan units are dong (neighborhood), gu (district), and si (city).One source of indicators for these levels with 31 measures is at the Korea Social Science Data Archive (http://www.kossda.or.kr/index_kossda.asp). Below the dong there are tong (block groups) and ban (blocks). Often information from all levels is either not applicable or not available.

Aggregate-level data beyond that from the Census that could be appended includes consumer information from such sources as Claritas PRIZM NE and Donnelley Marketing's FIND index, the National Address Server, voting information from national elections, and data on such other matters as vital statistics (Salvo and Lobo, 2003); crime rates (FBI, 2004), residences of sex offenders (in both the United States and Korea - http://www.nsopw.gov/ and http://www.sexoffender.go.kr/), assessed land values (Korea - http://www.realtyprice.or.kr), religion (Jones, 2002), public housing (HUD, 1998), HIV/STD rates (CDC, 2004), and public welfare utilization (Salvo and Lobo, 2003). An example of the extensive information that can be linked from databases to schools and school districts is illustrated by a NORC project (Hoffer, Ghadialy, and Halverson, 2006).[5]

Much aggregate-level information can be linked to addresses using geographic information systems (GIS) (Brown et al., 2012; Davern and Chen, 2010; Entwisle et al., 1997; Entwisle and Stern,

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[3] For a general discussion of record linkage involving surveys see Fair, 1996 and Jenkins et al., 2005. On surveys to administrative records see Obenski, 2006 and Davern, 2006.

[4] When starting with addresses without prior Census information as part of the sampling frame, Census and other geographic-based information can be obtained by linking addresses to the geo units (e.g. Census tract, zip code, place/community, etc.) that they fall in. That is, the Census data are added as part of step two if they are not already available as part of the sampling frame. Address linkages to Census tract and higher geo units are possible for from 95-100% of cases (Geronimus, Bound, and Neidert, 1996; Groves and Couper, 1998; Kim, Smith, Kang, and Sokolowski, 2006).

[5] The most extensive example of linking all sample cases (i.e. both respondents and non-respondents) to databases is the matching of cases from six major government surveys to the 1990 Census (Gfroerer, Lessler, and Parsley, 1997; Groves and Couper, 1998). Unfortunately the Census cannot be generally used for this purpose because of the Bureau of the Census' no access policy to household-level information. Although household-level linkage with the Census is not a viable option, the study demonstrates that 1) a very high level of matching can be achieved between surveys and other records using addresses (96% of non-respondents on the surveys and 97% of respondents were linked to the Census) and 2) the information on the characteristics of non-respondents was very useful in modeling and adjusting for non-response bias. See also the UK Census Nonresponse Link Study (Durrant and Steele (2009).

2005; Smith and Davey, 2008; Smith and Kim, 2013; Walker, 2010; Yuan, 2011). In the US the L/L of sample units with city-style addresses is known and this enables these addresses to be linked to any other data source that has L/L coded. A large and growing amount of information is available in GISs. It is possible to code Euclidean distances between sampled addresses and various target locations (e.g. nearest school, hospital, or Superfund site) and to categorize these into discrete categories (e.g. within a mile, 1-9 miles, 10 or more miles). Alternatively, instead of using Euclidean distance, travel-times via the road network can often be calculated and used as either continuous or categorical variables.

GIS linkable facilities include such things as hospitals, trauma centers, schools/universities, places of worship, government offices, cemeteries, golf courses, cultural centers such as museums and zoos, major retails centers, transportation hubs, airports, prisons, military installations, parks and recreational areas, Superfund sites, public housing units, power plants, and rivers/lakes (Smith and Kim, 2013). Examples of studies doing this include Branas et al. (2005) on trauma centers, Downey (2006) and Holmes (1999) on employers, and Salvo and Lobo (2003) on various governmental measures.

Other information is identified by addresses, but no GIS data are included. As long as the addresses are in city-style format, they could be readily converted to L/L using ArcGIS or a similar routine and then handled as any other GIS-based data. For example, there are national lists of correctional facilities, political contributions under federal election law, and the not-for-profits maintained by the Internal Revenue Service and provided to users by the National Center for Charitable Statistics (Smith and Kim, 2013).

The linked data should include information from multiple-levels of aggregation. The multi-level analysis will start with household-based data and include neighborhood-level data from GPS, mapping programs like Google Maps, Census track, and zip code-based data sources, community-level data from the Census, election counts, crime rates, and other sources, and higher level aggregations (e.g. metropolitan areas, counties, states/regions, and countries) from various sources.[6]

The third step in ML-MS takes information gained from the initial case-level linkages to secure additional information. For example, securing a name and telephone number from a telephone-directory search can lead to households being found in databases when a mere address was insufficient to allow a clear match. Also, once a respondent was identified, links to that person in addition to household-level matching could be carried out. Thus, the process of augmenting the sampling frame is iterative and continues during the data-collection phase.

The final step is to collect, process, clean, and maintain a large amount of paradata for each case (Couper and Lyberg, 2005; National Research Council, 2013; Olson, 2013; Scheuren, 2000; Smith, 2011b). For example, paradata includes having interviewers systematically record information about a) the sample residence (e.g. dwelling type, condition of dwelling) and the local neighborhood (e.g. vacant buildings, litter), b) contacts or call attempts, c) interactions with household members, d) observations on the composition and demographics of the household, and e) other measures generated during data collection (Bethlehem, 2002; Cantor and Cunningham, 2002; Gfroerer, Lessler, and Parsley, 1997; Groves, 2006; Kennickell, 2005; Lynn et al., 2002; Matsuo et al., 2010; Razafindratsima, Morand, and Legleye, 2011; Safir et al., 2002; Smith, 1983; Stoop, 2004).[7]

There are two main types of paradata (for the use of paradata see Smith, 2011b): process and observational. First of all, there are process data that are routinely collected as part of the normal process of conducting the survey. Examples include records-of-calls, listing reasons for refusals, the offering and acceptance/rejection of incentives, and interviewer characteristics (e.g. demographics, experience, interviewer training). These might be particularly useful since a number of them are clearly closely related to nonresponse and should be valuable in the calculation of propensity scores.

One special form of process paradata is when the interviewer obtains more information on the identity of the sample unit, such as the name of the respondent at the sampled address. This information

[6] For multi-level analysis see Bryk and Raudenbush, 1988; DiPrete and Forristal, 1994; and Raudenbush and Bryk, 2002.

[7] Most of this is obviously not possible for postal surveys.

can then be used to carry out additional database searches which can facilitate data-collection efforts, nonresponse analysis, and other research. A second special form of process paradata consists of extended data collection especially via the use of computer-assisted, recorded interviews (Conrad et al., 2010; Kreuter and Casas-Cordero, 2010; Smith and Sokolowski, 2011). But this is essentially restricted to respondents only. A third special form of process paradata is keystroke data from CATI or CAPI programs (Couper, 2005; Couper, Hansen, and Sadosky, 1997).

Second of all, there are additional paradata, especially observational information, that are mostly collected to assess nonresponse or for some other purposes beyond the goal of survey management that is the purpose of the process paradata. For example, both NORC's General Social Survey (GSS) (http://www.norc.org/GSS+Website) and the European Social Survey (ESS) http://www.europeansocialsurvey.org/) collect information on dwelling type and the ESS also collects information on the observed demographics of the household residents (e.g. their age and gender) and the presence of trash, vandalism, and related neighborhood conditions. Other observational data could be used to cross-validate respondent reports of household and residential attributes.

One new form of observational paradata is the use of mobile sensors technology. These technologies are rapidly expanding and becoming both easier to use and more extensive. They include the monitoring of interior and exterior readings of air pollution, noise levels, temperature, and other environmental conditions (Davidovic, Rancic, and Stoimenov, 2013; Kanjo et al., 2009; Lane et al., 2010). For example, Sensordrone has Android sensor applications for measuring carbon monoxide, humidity, color/light intensity, temperature, oxidizing gas, and air quality. It has been adding new applications almost monthly. Some involve applications that can be operated on smart phones, tablets, or other standard computing devices, while others involve special monitoring devices. They may utilize either so-called opportunistic sensing in which the readings are automatic and operate in the background once engaged or participatory sensing in which readings are triggered by the device operator (Davidovic, Rancic, and Stoimenov, 2013). While their use in surveys is still in its infancy, their utilization will greatly expand in the near future (Sensors, 2013).

Of course some paradata may span these two categories. For example, interviewer estimates of the demographics of the sample unit and/or of the targeted respondent may facilitate both data analysis and the assessment of nonresponse bias.

Interviewers will need special training to completely and reliably record all of the required paradata. Failure to do so increases error and contributes to more interviewer variance (Korbmacher and Schroeder, 2013). In particular, when interviewers are paid primarily by the completed case rather than by the hour, they will have to be explicitly remunerated for collecting paradata for all cases, respondents and nonrespondents alike (Stoop, 2013).

As Cantor and Cunningham (2002) note, surveys "should maintain the date and result of each contact or attempt to contact each subject (and each lead)... The reports should provide cost and hit data for each method to help manage the data collection effort. In the end it helps to determine those methods that were the most and least cost effective for searching for the population of interest and this knowledge can be used for planning future surveys." Similar, the National Research Council (2013) recommends "Research leading to the development of minimal standards for call records and similar data in order to improve the management of data collection, increase response rates, and reduce nonresponse error."

Methodological Uses of the ML-MS Approach

The AD from the sample frame, other sources, and paradata can be utilized for several methodological purposes to reduce total survey error (Biemer, 2010; Groves and Lyberg, 2010; Smith, 2011a). First, nonresponse bias is a major component of total survey error. As the International Workshop on Using Multi-level Data from Sample Frames, Auxiliary Databases, Paradata and Related Sources to Detect and Adjust for Nonresponse Bias in Surveys (Smith, 2011b) has detailed, ML-MS data can be used to identify and correct for error stemming from unit nonresponse. Since information from the sample frame, other sources, and paradata are available for all sample cases (both respondents and nonrespondents), these data can be used to identify and correct for nonresponse bias (Johnson et al., 2006).

For example, the ESS has extensively utilized contextual data to analyse nonresponse; especially observational data of neighborhoods and dwellings (see Stoop et al., 2010). Information on type of dwelling, maintenance, and litter and graffiti in the neighborhood have been used to pinpoint fielding problems and as a proxy for socio-economic status. In the recent past, efforts have been made to further standardize this neighborhood information by providing interviewers with national photos of different types of dwellings and different levels of maintenance (Matsuo et al., 2012). One advantage of these observational data is that they can be collected in every country for both respondents and nonrespondents, although there are some practical problems and restrictions.

A key premise of the ESS when collecting neighbourhood and/or regional contextual information has been that the same information should be available for every country, or for every sample unit. Based on recent efforts to assess and correct for nonresponse bias, this is now being complemented by also looking to collect or use optimal national information to analyse nonresponse. In addition, the ESS is also looking at the possibility of increasing efforts during fieldwork for sample units with a lower propensity to respond with the aim of reducing nonresponse bias. The ML-MS approach could be used in the longer term to help inform such a fieldwork design. Other examples include Australia (Turrell et al., 2003) and the Netherlands (Bethlehem, 2002).

If one collects ML-MS data for all sample cases including both respondents and nonrespondents to study nonresponse bias, one already has the needed contextual data to carry out substantive analysis among the respondents. ML-MS gathers data once and uses it in multiple ways.

The National Research Council (2013) recommends “More research on the use of auxiliary data for weighting adjustments…” In particular, ML-MS can be used both for hypo-deductive and inductive approaches. In the case of the former, one can collect and utilize AD to test specific theories of non-response (e.g. social disorganization, overextension, social isolation, utilitarian individualism, and leveraged salience, see Campanelli, Sturgis, and Purdon, 1997; Kim and Kim, 2011; Groves, Singer, and Corning, 2000; Looseveldt and Carton, 2002; Smith and Kim, 2013) and to develop propensity scores to model nonresponse bias. Alternatively, inductively a wide range of individual and aggregate-level variables could be used and patterns of non-response bias vs. cases being missing at random could be used to detect patterns and formulate new, inductively-generates, empirically-grounded theories of nonresponse.

Thus, in terms of nonresponse, ML-MS can be used to detect nonresponse bias on specific surveys, to develop weights to compensate for same, and to advance our general, theoretical understanding of the correlates of nonresponse bias and how to minimize its occurrence (Biemer and Peytchev, 2013; Matsuo and Leuven, 2011; Sarndal and Lundstrom, 2005).

Not only is the ML-MS approach extremely valuable in detecting and formulating adjustments for nonresponse bias in general, it is also well suited for use with some of the newer, innovative methods for assessing the representativeness of achieved samples such a R-indicators (Cobben and Schouten, 2004; Schouten and Cobben, 2007; Schouten, Cobben, and Bethlehem, 2009; Schouten, Shlomo, and Skinner, 2011).

While there are other techniques that can and should be used to assess nonresponse bias such as comparing more and less hard-to-survey respondents (Smith, 1983) and using follow-up surveys (Matsuo et al., 2010; Schouten, Cobben, and Bethlehem, 2009; Stoop, Billiet, Kohn, and FitzGerald, 2010), the ML-MS has the distinct advantage of covering all cases, nonrespondents as well as respondents.

Second, error also occurs from item nonresponse or missing data from specific items. AD can be used to fill in some missing information, especially demographics and readily-observable conditions (e.g. type of dwelling and neighborhood characteristics). For example, in the US some household-level demographic data can be secured for up to 97% of households with city-style addresses (Smith and Kim, 2013). If AD is used to insert data into a survey-based analysis file, that data should be tagged to indicate its external source.

Third, misreports are another major source of error in surveys. AD can be used both to validate self-reports from surveys and provide data that in some cases are more accurate than respondent-supplied information. Respondent reports may be in error either due to unintentional errors such as forgetting or misremembering or from intentional distortion such as due to social-desirability effects. Examples of general information that can validated with AD include age, political party registration, and voting. An example of AD that can supply more accurate information than can be obtained from direct reports from respondents is the distance of the respondent's residence to various facilities (e.g. schools, power plants, hospitals, superfund sites) from GPS-based calculations. For focused studies on sub-populations such as of employees of a particular employer or patients of a particular healthcare plan or health maintenance organization, employment and healthcare records would generally be more reliable than self-reports of particular details related to employment or healthcare. In some European countries, using population registers and linked government databases, the amount of high-quality AD is large, although its use is very restricted (Everaers and Van Der Laan, 2003).

Finally, invalid interviews are another source of error. Interviews are validated using various methods (Smith, 2011a) such as via close supervision of field interviewers and/or the recontacting of respondents to verify that an interview had been conducted with the eligible respondent. The ML-MS data can reduce invalid interview error further by allowing the information from the databases to be used along with recontacts to help corroborate that interviews were truly and correctly done. Checks can include comparing GPS readings with household coordinates and validating the names and socio-demographics from surveys against database records.

Substantive Uses of the ML-MS Approach

Human societies are complex, multi-faceted entities and social-science research designs need to measure that complexity. A key requirement is contextualization. Most people live in households which are nested in neighborhoods, communities, and countries. They are not isolated individuals, but interact with and are notably influenced by their families, neighborhoods, communities, nations, etc. Surveys need to collect information on each of these levels from the individual to the nation so the contexts in which people live are understood and that through multi-level analysis the impacts of these different levels can be measured and modeled. Such a geographically-contextualized dataset can be compiled by combining together information from surveys with geographically-linked data from other sources. Surveys should naturally collect information on respondents and their households and should augment the survey data with both observational and process paradata that are generated as part of the activity of conducting the survey. Then the survey-based data should be further enriched with data from other sources (e.g. US Census, economic databases, voting records, environmental readings, etc.) which are linked to the survey data via GIS and other geographically-coded data sources (Smith and Kim, 2013). Such aggregate-level data can notably enhance our understanding of individual-level attitudes and behaviors.

Aggregate-level information is of great utility for understanding human societies. Research has demonstrated that contextual, aggregate-level geographic effects in general and neighborhood characteristics in particular influence a wide range of attitudes and behaviors independent of the attributes of individuals (van Ham et al., 2011). For example, research has shown that impacts exist on 1) political involvement (Bobo and Gilliam, 1990; Cohen and Dawson, 1993; Gilbert, 1991), 2) residential and social mobility (Lee, Oropesa, and Kanan, 1994; Massey and Eggers, 1990; Massey et al., 1994; Small and Feldman, 2012; South, Baumer, and Lutz, 2003), 3) the sexual and reproductive activities of youths and adults (Billy and Moore 1992; Brewster 1994a; Brooks-Gunn et al., 1993; Browning and Olinger-Wilbon, 2003; Browning, Leventhal, and Brooks-Gunn, 2004; Cohen et al 2000; Crane 1991; South and Baumer, 2001), 4) responses to poverty (Jencks and Mayer 1990; McLeod and Edwards, 1995; Oreopoulos, 2003), 5) racism and tolerance (Gibson, 1995), 6) fear of and involvement in crime (Covington and Taylor, 1991; Peeples and Loeber, 1994; Sampson, Raudenbush, and Earls, 1997), 7) minorities politically (Cohen and Dawson, 1993), economically (Lee et al., 1994; Massey and Eggers, 1990), and in other ways (Brewster, 1994b; Smith, 1994), 8) social capital and better health (Mellor and Milyo, 2004), 9) group membership and economic improvement (Tolbert, Lyson, and Irwin, 1998); 10) inequality and political trust (Rahn and Rudolph, 2005); 11) religion and deviant behavior (Regnerus, 2003), 12) drug use (Boardman et al., 2001; Ford and Beveridge, 2006; Galea, Ahern, and Vlahov, 2003; Snedker, Herting, and Walton, 2006), 13) family development and childrearing (Booth and Crouter, 2001), 14) health outcomes (Cochrane et al., 2009; Jen, Jones, and Johnston, 2009; Kawachi and Berkman, 2003), and 15) depression and mental health (Curry, Latkin, and Davey-Rothwell, 2008; Das-Munshi et al., 2010).

For example, contextual effects that have been examined from the General Social Survey (GSS)(Smith, Marsden, Hout, and Kim, 2013) specifically include the following: 1) racial composition of the local population predicts levels of racial prejudice (Alesina and LaFerrara, 2000; Charles, 2003; Dixon and Rosenbaum, 2004; Taylor, 1998 and 2002) and class voting (Weakliem, 1997), 2) higher collective levels of trust and civic engagement are associated with lower homicide rates (Rosenfeld et al., 1999 and 2001) and lower mortality in general (Kawachi et al., 1997b), 3) areas with greater aggregate happiness have lower mortality (Jencks, 1999), 4) higher levels of anomia are related to higher local crime rates (Rosenfeld and Messner, 1998), 5) community-level differences in attitudes on gender roles do not affect the demand for female labor (Cotter et al., 1998), 6) the prevalence of Fundamentalists reduces support for feminism (Moore, 1999), 7) a higher level of people on welfare reduces support for welfare spending (Luttmer, 1998), 8) living around gun owners increases one's likelihood of acquiring a gun (Glaeser and Glendon, 1998), 9) lower income equality is associated with lower social trust and group membership (Kawachi et al., 1997a), 10) community heterogeneity influences civic engagement (Costa and Kahn, 2002), 11) community norms shape attitudes toward capital punishment (Baumer, Messner, and Rosenfeld 2003), 12) state and regional differences may be declining over time (Weakliem and Biggert, 1999), 13) voting and civic involvement vary by community as well as individual demographics (D'Urso, 2003), 14) greater community acceptance of immigrants relates to more occupational achievement by immigrants (De Jong and Steinmetz 2004), 15) community religious beliefs and behaviors influence gender roles (Moore and Vanneman 2003), 16) aggregate public opinion affects public policies on such as abortion laws, welfare payments, and AIDS-related funding (Brace et al. 2002), 17) immigrant population influence views on immigration and other social viewpoints (Caraway, 2010; Hopkins, 2007; Hopkins, 2009b; Taylor and Schroeder 2010), 18) causes of fear of crime (Rader, Cossman, and Porter 2012), contextual characteristics affect discrimination against gays and lesbians (Baumle and Poston, 2011), 19) community racial diversity influence social trust (Rothwell, 2009), 20) community-level demographics affect public support for redistribution policies (McClendon, 2011), 21) community characteristics are related to the causes/effects of poverty (Hopkins, 2009a; Kim, Lauderdale, and Kang, 2010), and 22) the religious orientation of areas and their level of fear of crime influence the severity and certainty of sentences involving murder (Baumer and Martin, 2013).

Similarly, in the ESS contextual data have been collected mainly for substantive purposes. In 2007, an overview of extant contextual databases was drafted (Rydland et al., 2007)[8]. Based on this report, a MacroDataGuide (http://www.nsd.uib.no/macrodataguide) has been prepared, providing information from multiple sources. A major aim of this project was providing high quality, comparable information that can be related to the ESS survey to multiple users. For this reason, only sources were selected that comprised information on almost all ESS countries. This information was usually available on a high aggregate level (see Rydland et al., 2007). A multi-level data repository will shortly become available at the ESS Data Archive (NSD) to enable contextual data to be accessed alongside substantive ESS data, again with most information made available at aggregate level.

As the Panel on New Research on Population and the Environment of the National Academies observed, surveys "should be increasingly coordinated to promote creation of a body of integrated knowledge that links demographic, land use, and environmental variables (Entwisle and Stern, 2005)." The coding of a rich array of aggregate-level data from the sampling frame and a wide range of databases facilitates such contextual analysis and makes it an integral part of survey analysis rather than an occasional approach carried out only when additional multi-level data are added to surveys as a special

[8] http://ess.nsd.uib.no/ess/doc/ESS_context_sources.pdf

extra effort and often after the fact. Making the inclusion of contextual data a standard part of sample frames will make the incorporation of aggregate-level data easier, quicker, and much less expensive. Aggregate-level data appended to all cases in a sample frame make it automatically available to all surveys utilizing that sample frame. This will in turn greatly expand their use in analysis and improve our modeling of societal processes. In brief, the information in the augmented sampling frame that can and should be used to assist data collection, adjust for non-response bias, and otherwise improve data quality and can and should in turn be utilized for substantive, multi-level, contextual analysis. Rather than having multi-level, contextual analysis be an occasional extra added to some surveys, it can and should become a standard and routine component of surveys in general.

Confidentiality Concerns

Since adding more AD increases the likelihood of deductive disclosure and thus potentially undermines confidentiality, special steps need to be taken to ensure confidentiality (Crises, 2004; Dugoni, 2012; Sherman and Fetters, 2007). Files with extensive AD need to either be restricted, sensitive-data files or the AD needs to be partly masked to eliminate the possibility of deductive disclosure. A full disclosure analysis must be carried out on the public-release files. Data files can be thought of as falling along a sensitivity continuum from public-use files that have been designed to ensure that respondent identity cannot be broached via deductive disclosure or other means to in-house files with explicit respondent identifiers. In between these are restricted-access data files which contain more detailed information than the public files, but lack explicit identifiers. These may be made accessible to researchers via sensitive-data access agreements and/or via data enclaves.[9]

Cross-national Applications

ML-MS can clearly be applied across countries. But there cannot be one standardized, rigid approach. Countries vary in available sample frames and the information available from same, in what other data sources exist and are accessible, in how geographic information from censuses and administrative records are organized, and in legal rules on access to various data sources. Only paradata could be readily standardized across surveys in different countries and there are notable impediments to even that achievement. But these impediments to standardization do not mean that ML-MS should not be used in cross-national surveys, only that one must pay close attention to country-specific data resources and regulations and develop the optimal application for each particular nation.[10]

Summary

The ML-MS approach will help improve the next-generation of social-science data. By augmenting data collected from surveys with AD from sample frames, other sources, and paradata social-science research will be advanced both methodologically and substantively.

[9] For an example of a sensitive data agreement see http://publicdata.norc.org:41000/gss/documents//OTHR/ObtainingGSSSensitiveDataFiles.pdf. For an example of a data enclave see http://www.dataenclave.org/index.php/home/welcome.

[10] Kish (1994) makes a similar observation about probably samples using different sample frame, but still representing equivalent target populations across countries.

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