Applying the Multi-level, Multi-Source (MLMS) Approach to the 2016 General Social Survey

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Introduction

To more fully understand human society, surveys need to collect and analyze multi-level and multi-source data (MLMS data). Methodologically, the use of MLMS 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. It can be employed to detect and reduce nonresponse bias, to verify interviews, to validate information supplied by respondents, and in other ways. Substantively, MLMS 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 MLMS approach boosts both the methodological vigor and substantive power of survey research. It is a general framework for conducting and improving survey research (Smith and Kim, 2014).

The MLMS Approach

The central goal of the MLMS 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 first step in MLMS 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 oben, 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, address-based sampling (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, block groups, 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 (Kreuter, 2013; Smith and Kim, 2013; 2014).

The key is that the information collected from 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, 2014; 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).

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; 2014). Thus, one is generally now dealing with computerized databases that can be crosslinked. 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. 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]

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 2000; 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,

[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.

[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-

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.

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 prior 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, 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; 2014). 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 not-for-profits maintained by the Internal Revenue Service and provided to users by the National Center for Charitable Statistics (Smith and Kim, 2013; 2014).

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]

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).

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

The third step in MLMS 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 can continue throughout the data-collection phase and/or afterwards.

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; West, Kreuter, and Trappmann, 2014). 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, and interviewer experience). 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 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, 2003; Couper, Hansen, and Sadosky, 1997) which would also largely be restricted to respondents.

Second of all, there are additional paradata, especially observational information, that are 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, NORC's General Social Survey (GSS) (https://gss.norc.org) collects information on such matters dwelling type, the presence of children, and estimated income.

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 (Sensorcon, 2013). 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).

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

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.” Similarly, 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 MLMS 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, MLMS data can be used both 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).

If one collects MLMS 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. MLMS approach 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, MLMS 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; Loosveldt and Carton, 2002; Smith and Kim, 2013; 2014) 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, MLMS 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 Billiet, 2011; Sarndal and Lundstrom, 2005).

Not only is the MLMS 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, 2007; 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 MLMS has the distinct advantage of covering all cases, nonrespondents as well as respondents.

Second, error also occurs from item nonresponse or missing data on 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; 2014). 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.

Finally, invalid interviews are another source of error. Interviews are validated using various methods (Smith, 2011a; Smith, 2019) 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 MLMS 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 MLMS 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; 2014). 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, contextual effects that have been examined from the GSS (Smith, Davern, Freese, and Morgan, 2019) 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).

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 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.

In sum, the MLMS approach augments interview data with added data from the sample frame, AD, and paradata. It includes multi-level measures from the case level plus aggregate levels such as neighborhood and community. MLMS is equally useful for various methodological applications such as investigating nonresponse bias and for substantive theory-drive, contextual analysis.

MLMS Cautions

Along with the gains from added depth and power of MLMS come certain cautions. First, there are concerns about confidentiality. 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.[8]

Second, the error structure of MLMS is more complex than for unsupplemented surveys. As the total survey error (TSE) paradigm indicates, surveys have many error components and collectively they produce a complex error structure (Biemer, 2010; Groves and Lyberg, 2010; Smith, 2011a). Incorporating the MLMS approach necessarily involves expanding the TSE paradigm further. Both the use of non-survey data sources and the process of linking together different data sources at the micro and aggregate levels extends the range of errors that can occur. There will be various errors associated with the collection, documentation, and utilization of data from all auxiliary sources and combining data across sources will lead to the danger of various types of linkage error (missing possible linkages, making linkages when no matches actually existed, and mismatched cases that could have been correctly matched). When surveys utilize external data, one needs to expand the

[8] For an example of a sensitive data agreement see
http://www.gss.norc.org/Documents/other/ObtainingGSSSensitiveDataFiles.pdf.
For an example of a data enclave see http://www.norc.org/Research/Capabilities/Pages/data-enclave.aspx.

concept the TSE into total data error (TDE). So TSE plus auxiliary data error (ADE) and linkage error (LE) = TDE.[9]

Using MLMS on the 2016 GSS

This section presents some substantial illustrations of the MLMS approach. As indicated in the general description, MLMS starts by retaining information that is part of the sample frame used for the survey. The GSS is a multi-stage, area probability sample of households in the United States with its sample points based on the US decennial Census (DC) and the American Community Survey (ACS) (Smith et al., 2019). Within the selected sample points, addresses are selected from the US Postal Service's DSF augmented by NORC's own listing of addresses in sampling points for which the postal listings were not sufficient. These were mostly rural areas where home delivery is limited and therefore home addresses are not available. In addition, during the actual fieldwork, a missed dwelling unit procedure is employed to locate addresses not covered by either the postal system or NORC own listings. These include both overlooked addresses and new dwellings not yet included in the postal or NORC listings. NORC used the DSF provided by their contractor Valassis. The augmented DSF provides household–level information. The DC and ACS data from the sample frame provide aggregate-level information. Since this Census-based sample frame data set was considerably augmented by additional data from the Census, the combined Census-based data are discussed below.

Supplementing the sample frame data, the addresses and sample points were linked to 12 auxiliary data (AD) sources (Table 1). The Postal Delivery Sequence Data were available at the household level. There were three commercial databases, all with household-level information and one of these also included some aggregate-level information. (Due to contractual restrictions, the three commercial databases cannot be identified.) The commercial databases were mostly collections of various publicly available information, such as voting records and donations, but they also added some estimates based on their models (e.g. consumption patterns and life styles). The 8 remaining databases only have information at the aggregate level starting in some cases with Census block groups and expanding in some cases to counties or metropolitan areas. Aggregate-level information also included measures such as demographic information and poverty rates in the ACS data, as well as distance between households and various other locations (e.g. sites, facilities) in the EPA/FEMA and Street Pro databases. Table 2 lists examples of the type of information from the 12 databases covering the sample frame and AD sources.

Two uses of the auxiliary data will be presented. In the first set of illustrations, information from these 12 databases were used for methodological purposes, mainly to examine the correlates of unit nonresponse. In 2016, there were 2,862 respondents who completed the GSS and 1,455 eligible cases who were nonrespondents. All of these 4,317 cases were used in the analysis if auxiliary information was available, and the percentages of completed cases between characteristics of areas were compared. A total of 956 variables were used to generate 665 tables comparing response rates. Of these 45.7% were statistically significant. First, the most consistent finding was that residents of upper socio-economic status (SES) areas had lower response rates than those from lower SES areas. As Table 3 shows, when areas are divided into quartiles running from lowest in SES to highest, response rates fell by 11.5 to 14.6 percentage points. This is true whether the SES criteria is home value, rental value, living above the poverty line, household income, or receiving food stamps. (And for other SES measures not shown here.) Similarly, examining the GSS samples using a 19-category Mosaic market segmentation typology (Experian, 2018) shows the lowest response rate for their top two categories, Power Elite 57.3% and Flourishing Families 51.8%, and among the highest response rates for their two bottom groups, Aspirational Fusion 72.2% and Economic Challenges 76.2%.

Second, response rates tended to be higher in areas with more crime. 12 of the 20 measures of the estimated crime rates at the block-group level had statistically significant associations between more crime and higher response rates. In 11 of those statistically significant relationships, the response rates were highest in the areas with the most crime. But the difference in response rates from high crime areas to low crime areas was more modest than for SES, typically around – 6.0 points.

Finally, a wide and varied set of other variables show associations between area characteristics and response rates. Table 4 has examples. The response rate was lower in the area where the divorce rate was lower,

[9] For an adaption of TSE to include adding big data, see Hsieh and Murphy (2015).

the proportion of female-led households with no husbands was lower, and the percentage of native-born citizens was lower. On the other hand, it was higher in the areas where the proportion of naturalized citizens was lower and the number of deaths by AIDS was higher. The response rate was also 8.6 percentage points higher in no-flood zones than flood zones.

In the next set of illustrations, the AD was used for substantive purposes. This combines respondent-provided data with the aggregate-level AD to examine contextual, aggregate-level effects. As such, it is restricted to analysis only among the completed cases. Table 5 shows 11 examples of such aggregate-level relationships. The first example shows that respondent reports that they are afraid to walk alone at night in their neighborhood is strongly related to the estimated level of major violent crimes reported to the police in their Census block group. In areas with low levels of personal, violent crimes 22.6% of respondents were afraid to walk alone in their area, when the crime level was medium 33.6% were afraid, and when it was high 44.0% were afraid, an increase in being afraid of 22.4 percentage points. The second example finds that support for more governmental spending for the environment raises from 46.2% if no superfund site in anywhere near their residence (e.g. within 66 miles) to 67.4% when there are superfund both within and 3 miles and further way for an increase of 21.1 points. Finally, the nine remaining examples show the total shift of the contextual effects. For example, support for more military spending rises from areas with few veterans to more veterans in the area by 27.2 points. In brief, these examples indicate that neighbor characteristics often have an appreciable impact on people's attitudes and behaviors.

The final component of added data beyond the survey questionnaire is from paradata. Table 6 shows both observational and process paradata that were available. The five observational paradata measures were records in the household enumeration form "prior to making contact with household." All were significantly related to nonresponse (Table 7). First, the response rate was highest for residents of trailers and low-rise, multi-units structures (70%+). These were lower income dwellings and more accessible units. The lowest was for residents of apartments in buildings over 3 stories which were more likely to have restricted assess (57.3%), other structures (54.5%), and the very few cases with missing data (20.0%). Second, response rates were also higher if the interviewer knew or thought there was as minor in the household (69.8%) vs. not knowing/thinking there was a child present (65.2%). Third, it was higher if the income level was estimated to be below average (75.3%) rather than average (66.1%), or above average (60.5%). Fourth, it was highest for residents in very unsafe neighborhood (84.0%) and lowest for very safe areas (64.4%). Finally, interviewers showed some ability to predict whether an address would eventually yield a successful interview. Those rated as having a high probability had a response rate of 69.1% vs. 59.1% for those given a low likelihood.

It is noteworthy that the paradata income results echoes the SES results from the aggregate-level AD. Similarly, the paradata on neighbor safety is consistent with the AD crime information showing that areas with high crime rates and deemed unsafe by interviewer both have higher response rates.

Summary

The MLMS approach takes what is in the survey box (i.e. the interview with rows of respondents and columns of variables) and augments the box with data from sample frames, auxiliary data sources, and paradata at both case-levels and aggregate levels. By adding to the survey box social-science research is advanced both methodologically and substantively. This is demonstrated by the initial research using the MLMS approach on the 2016 GSS. It identified important predictors of nonresponse bias that were found both in the aggregate-level AD and the case-level paradata and demonstrated that aggregate-level AD were correlates of various attitudes and behaviors.

Table 1

Sources of Information

Database	Household	Aggregate
Postal Delivery Sequence Data	Y	
Commercial Database 1	Y	
Commercial Database 2	Y	
Commercial Database 3	Y	Y
American Community Survey (ACS: County, Place, Tract, Block Group)		Y
Area Health Resource File (AHRF): County		Y
Census Planning Database (PDB: Tract, Block Group)		Y
Community Commons: County		Y
Crime Risk: Block Group		Y
EPA/FEMA: Distance		Y
Superfund: Distance		Y
Street Pro: Distance		Y

Table 2

Examples of Available Information

Database	Examples of Available Information
Postal Delivery Sequence Data	Type of mail delivery, vacancy period
Commercial Database 1	Property value of dwelling unit, number of addressees
Commercial Database 2	Demographic information (e.g. sex, age), voting district codes (precincts, wards, congressional districts)
Commercial Database 3	Voter registration information, contributions to civic groups and parties, voting history
ACS (county, place, tract, block group)	Demographics, employment, housing, income, health, poverty, language
AHRF	Health (e.g. condition, insurance, maintenance)
Census PDB (tract, block group)	Environment, fertility, number of fitness facility, health, poverty
Community Commons	Number of health facilities (e.g. clinics), health behaviors (e.g. alcohol consumption, smokers)
Crime Risk	Number of murder, robbery, property crime
EPA/FEMA	Distances from the nearest pollution sites (e.g. air polluters, brownfields, flood)
Superfund	Distances from the nearest Superfund sites
Street Pro	Distances from the nearest hospitals, libraries, schools

Table 3

Response Rates by Area Socioeconomic Status (SES)[1]

Area SES Indicators[2]	Low	Lower-Mid	Upper-Mid	High	Diff. between High and Low
	Quartiles of Area SES Indicators[3][4]				
− Home Value (BG)	69.4	70.3	66.4	57.9	-11.5
− Rental Value (Place)	72.5	70.3	67.5	57.9	-14.6
− Persons with Income at or above 200% of Poverty (Tract)	71.3	69.5	64.2	59.8	-11.5
− Household Income $75,000+ (Tract)	72.4	69.6	65.3	59	-13.4
− No Food Stamps (Tract)	72.2	66.6	66.3	59.5	-12.7

Mosaic Segmentation[5]	Percentage[6]
Power Elite (Top)	57.3
Flourishing Families (2nd from the Top)	51.8
Aspirational Fusion (2nd from the Bottom)	72.2
Economic Challenges (Bottom)	76.2

Notes:

(1) N=4,317. This total includes both the 2,862 cases completed in GSS 2016 and the 1,455 non-respondents. The actual total varies slightly by SES indicator because some information is not available to all cases.
(2) Source: American Community Survey 2009-13
(3) Each indicator has different quartile values based on its distribution. Thus, each quartile has a different total although it is roughly a quarter of all cases that have information.
(4) The numbers shown are the percentages of the completed 2018 GSS cases out of totals in each cell.
(5) Mosaic USA classifies US households into 19 groups based on socio-demographics, lifestyles, and culture (Experian, 2018). Only the top two and the bottom two groups are presented here.
(6) The numbers shown are the percentages of the completed 2016 GSS cases in each segment group.

Table 4

Other Factors Associated with Nonresponse[1]

Selected Area Indicators	Quartiles of Selected Area Indicators[5][6] Low	Lower-Mid	Upper-Mid	High	Diff. between High and Low
• Percentage of Divorced (Tract)[2]	60.5	64.0	68.3	70.7	10.2
• Percentage of Female Head of Household, no Husband (Tract)[2]	61.1	65.0	68.2	71.6	10.5
• Percentage of Native Born Citizens (Place)[2]	59.7	66.0	71.8	69.4	9.7
• Percentage of Naturalized Citizens (Place)[2]	71.7	69.5	67.0	59.2	-12.5
• Percentage of AIDS Deaths (County)[3]	68.9	68.1	61.4	58.5	-10.4

	No flood zone	Flood zone	Diff. between High and Low
• In Flood Zone[4]	66.3	57.7	-8.6

Notes:

(1) N=4,317. This total includes both the 2,862 cases completed in GSS 2016 and the 1,455 non-respondents. The actual total varies slightly by area indicator because some information is not available to all cases.
(2) Source: American Community Survey 2009-13
(3) Source: Area Health Resource File 2010-12
(4) Source: Federal Emergency Management Agency (FEMA)'s National Flood Hazard Layer. Accessed in February 2017.
(5) Each indicator has different quartile values based on its distribution. Thus, each quartile has a different total although it is roughly a quarter of all cases that have information.
(6) The numbers shown are the percentages of the completed 2016 GSS cases out of totals in each cell.

Table 5

MLMS-Substantive Analysis Examples (Respondents Only)[1]

Fear of Crime by Personal Crime in BG[3][4]

	Low	Medium	High	Diff. between High and Low	Sig. (χ^2 test)
Afraid[2]	21.6	33.6	44.0	22.4	p<.001

Spending on Environment by Superfund Site[6][7]

	No site recorded	3-66 miles only	Less than 3 miles only	Both	Diff. between Both and No site	Sig. (χ^2 test)
Spend more[5]	46.2	62.6	65.8	67.4	+21.2	p<.001

Other Examples

	Low	Middle	High	Diff. between High and Low
Spend more to fight crime by burglary in area[8][9]	54.2	63.2	62.4	+8.2
Allow more immigrants by limited English in area[10][11]	12.7	16.4	23.2	+10.5
Afraid of crime by more walking to work in area[12][13]	27.8	29.3	41.9	+14.1
OK if police hit adult male by personal crime in area[14][15]	78.9	70.0	56.6	-22.3

	Low	Lower-Mid	Upper-Mid	High	Diff. between High and Low
Spend more on military by more veterans in area[16][17]	23.5	33.5	39.8	50.7	+27.2
Spend more for poor by more on pub. asst. in area[18][19]	63.2	68.6	73.8	81.4	+18.2
Satisfied financially by area's recession sensitivity[20][21]	31.2	30.9	32.0	25.0	-6.2
Satisfied financially by income rank in area[22][23]	27.8	26.2	23.7	40.6	+12.8
Being Republican by number of making Democratic contribution in county[24][25]	44.2	32.1	33.0	22.9	-21.3

Notes:

(1) N=2,862. This total includes the completed GSS respondents in 2016 only.

(2) This GSS question asked "Is there any area right around here—that is, within a mile—where you would be afraid to walk alone at night?" The response option was either "Yes" or "No".

(3) The numbers of personal crimes in block groups are from Crime Risk 2010-14. They are divided into three groups (low, medium, high) by level.
(4) The numbers shown are the percentages of those who responded “Yes” in each cell
(5) This GSS question asked if we are spending appropriate amount on “improving and protecting the environment” or on “the environment”. The response categories included “Too little,” “About right,” and “Too much”. The numbers shown are the percentages of those who responded “Too little” in each cell.
(6) The number of Superfund sites within the areas of respondents’ residence are from EPA’s Superfund (accessed in October 2016). They are divided into ranges of distance. The longest distance in the data used here is 66 miles from the housing unit.
(7) The numbers shown are the percentages of those who responded “Too little” on the spending question (see Note 5 above) in each cell.
(8) This GSS question asked if we are spending appropriate amount on “halting the rising crime rate” or on “law enforcement”. The response categories included “Too little,” “About right,” and “Too much”. The numbers shown are the percentages of “Too little” response in each cell.
(9) The numbers of burglaries in block groups are from the Crime Risk 2010-14. The number is divided into three levels (low, middle, high) based on the distribution.
(10) This GSS question asked, “Do you think the number of immigrants to America nowadays should be...”, and respondents were given five options ranging from “Increased a lot” to “Reduced a lot” with “Remain the same as it is” in the middle. The numbers shown here are the percentages of those who responded “Increased a lot” or “Increased a little” in each cell.
(11) The percentages of households with limited English speaking capability in tracts are from the American Community Survey 2009-13. The percentages are divided into three levels (low, middle, high).
(12) This afraid question is from GSS (see Note 2 above).
(13) The percentages of people commuting by walk in tracts are from the American Community Survey 2009-13. The percentages are divided into three levels (low, middle, high).
(14) This GSS question asked, “Are there any situations you can imagine in which you would approve of a policeman striking an adult male citizen?” and respondents could answer “Yes” or “No”. The numbers shown here are the percentages of those who responded “Yes” in each cell.
(15) The percentages of personal crime in block groups are from the Crime Risk 2010-14. The percentages are divided into three levels (low, middle, high).
(16) The GSS question asked if we are spending appropriate amount on “the military, armaments and defense” or “national defense”. The response categories included “Too little,” “About right,” and “Too much”. The numbers shown here are the percentages of those who responded “Too little” in each cell.
(17) The percentages of veterans in tracts are from the American Community Survey 2009-14. The percentages are divided into quartiles.
(18) This GSS question asked if we are spending appropriate amount on “assistance to the poor”. The response categories included “Too little,” “About right,” and “Too much”. The numbers shown here are the percentages of those who responded “Too little” in each cell.
(19) The percentages of households with cash public assistance in tracts are from the American Community Survey 2009-14. The percentages are divided into quartiles.
(20) This GSS question asked respondents if they are “pretty well satisfied with your present financial situation, more or less satisfied, or not satisfied at all”. The numbers shown here are the percentages of those who responded “Satisfied” in each cell.
(21) The recession sensitivity ranking of households within an area is from Commercial Database 3. The ranks are divided into quartiles.
(22) See Note 20 above.
(23) The income ranks of households within areas are from Commercial Database 3. The ranks are divided into quartiles.
(24) GSS respondents self-reported their party identity.
(25) The total number of FEC contributions to Democrats in the county is from Commercial Database 3. The numbers are divided into quartiles.

Table 6

Paradata on 2016 GSS

Observational Paradata:

Circle the number below which best describes the type of structure in which the respondent lives

Trailer
Detached single-family house
2-family house, 2 units side-by-side
2-family house, 2 units one above the other
Detached 3-4 family house
Row house (3 or more united in an attached row)
Apartment house (5 or more units, 3 stories or less)
Apartment house (5 or more units, 4 stories or more)
Apartment in a partly commercial structure
Other (Specify)____________________________

Base on the features of this housing unit and the surrounding property/neighborhood that you can see, do you believe that there are children under the age of 15 present at this household? Yes/No

Based on what you have learned about this housing unit, what is your estimate of the probability that this household will respond to the survey? High/Low

What do you believe the income status of the housing unit is relative to the rest of the general United States population? Higher than average/Average/Lower than average

Now thinking about safety in this neighborhood, how safe do you think it is? Would you say it is… Very safe, Somewhat safe, Somewhat unsafe, Very unsafe?

Process Paradata:

Required Questions – Prior to contact with Household: Is there a housing unit at the address shown on the assignment label? Yes/No + 3 follow-up questions if No given

Record of Calls: Disposition & Contact Spoken to: Date & Time of Contact: Type of Contact – In person, Phone, Mail; Call Window – SU-Thu 6PM-9PM, F-SA 6PM-9PM, SA-SU 9AM-6PM, MTWTF 9AM-6PM; Contact Results <All fields for each call attempt>

Case Management System: includes sections on Address Detail; Contact Person/Leads/Respondent Details; Address Details; Phone Details; Email Details; Records of Calls; and Appointment Details Excluding PII fields has over 50 variables including information on age, language, gender, race, ethnicity of contactee/designated respondent, verbatim comments on call results, email information, type and number of contacts

Final Disposition codes: Out of Scope (OOS) Final Codes: Not an HU, Vacant HU, No Eng/Span spoke in HU, R not Speak Eng/Spn Final Non-Interview Response (NIR) Codes: Not Accessible HU, R Absent All Field Period, Entire Hu Unavailable, Refusal for HEF, Refusal for Quex, Refusals, Final Permtly Incapcitd, Other

Table 7

% Completed Cases for Observational GSS Paradata

Housing type	% Yes
2-family house, 2 units one above the other	72.9
Trailer	72.3
Row house (3 or more united in an attached row)	71.3
Apartment house (5 or more units, 3 stories or less)	70.3
Detached single-family house	66.0
Detached 3-4 family house	65.5
Apartment in a partly commercial structure	62.5
2-family house, 2 units side-by-side	61.8
Apartment house (5 or more units, 4 stories or more)	57.3
Other (Specify)____________________________	54.5
Missing/Don't know	20.0
Probability Level	.000
% No Answer + Don't Known	0.7
Children under 15	
Yes	69.8
No	65.2
Missing/Don't know	50.0
Probability Level	.004
% No Answer + Don't Know	1.7
Likelihood of Becoming Respondent	
High	69.1
Low	59.1
Missing/Don't Know	47.1
Probability Level	.000
% No Answer + Don't Know	1.4
Income Status Level	
Higher than Average	60.5
Average	66.1
Lower than Average	75.3
Missing/Don't Know	53.8
Probability Level	.000
% No Answer + Don't Know	1.0

Table 7 (continued)

Neighborhood Safety	
Very Safe	64.4
Somewhat Safe	67.2
Somewhat Unsafe	76.0
Vey Unsafe	84.0
Missing/Don’t Know	50.0
Probability Level	.000
% No Answer + Don’t Know	1.0

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