TWO APPROACHES TO THE USE OF ADMINISTRATIVE RECORDS TO REDUCE RESPONDENT BURDEN AND DATA COLLECTION COSTS

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Abstract: Due to issues related to respondent burden and data collection costs, many statistical organizations are considering the integration of administrative records with standard sample survey data. This paper explores two distinct approaches to this administrative-record work. The first approach retains most of the customary structure of sample survey methods, and uses administrative records to strengthen specific features of survey work, e.g., collection of certain items that would be especially costly or burdensome to obtain through standard survey methods. The second approach treats an administrative record system as the core of the collection effort, and uses sample survey methods to provide supplementary data as needed, e.g., to adjust for data quality issues arising from record linkage problems, incomplete administrative records, aggregation effects, or definitional inconsistencies. Evaluation of both approaches will involve a balanced consideration of multiple components of perceived respondent burden, cost, data quality and operational risk.

Key words: Data quality; Filters; Finite-population and superpopulation inference; Multiple stakeholders and multiple utility functions; Operational risk; Originating agency and statistical agency; Substantive inference and operational inference; Systemic risk.

1. INTRODUCTION

This paper explores a wide range of issues related to the design of large-scale statistical programs. We place primary emphasis on the use of data from administrative records and sample surveys, and the integration of data from these sources.

1.1 Design of Statistical Programs to Balance Data Quality, Cost, Burden and Risk

The design of large-scale statistical programs requires one to balance four general factors: data quality, cost, burden and risk. Each of these four factors generally involves multiple dimensions. Some of these dimensions (e.g., complete-data rates defined at various levels of aggregation; or the total budgeted program expenditure in a specified time period) may be relatively well defined and measurable. Other dimensions (e.g., the burden experienced by a given survey respondents, or the risk of losing a given administrative-record source) are more difficult to measure, and in some cases may only be subject to qualitative characterization.

As an illustrative example, consider the U.S. Consumer Expenditure Survey (CE). Its primary goal is to obtain data on a wide range of consumer expenditures at a relatively fine level of aggregation. The CE also collects data on a range of demographic, geographic and socioeconomic factors. At present, the CE collects data through a household sample survey based on a complex sample design. Data collection modes include personal visit and telephone collection for an interview component, as well as diary collection for certain small and frequently purchased items. For general information on the CE design and data collection, see Bureau of Labor Statistics (2011, Chapter 16).

Consumer units selected for participation in the interview component of the CE are asked to participate in a total of five interviews, including an initial bounding interview and four follow-up interviews. In each of the final four interviews, a selected CE interview unit is asked to provide detailed information on its expenditures in the preceding three months. At present, the final four interviews have a mean length of over sixty minutes, and may involve a substantial level of cognitive complexity. In the past three decades, the BLS has focused considerable attention on the measurement and reduction of cost and burden related to the CE, and currently is exploring a wide range of redesign options.

Some CE stakeholders have suggested the possible use of administrative-record sources to improve the balance of data quality, cost, burden and risk in the Consumer Expenditure Survey. For example, one could seek to obtain item-level sales data from selected retailers, aggregated across customers. In some forms, these data could be useful for imputation of missing items or disaggregation of purchase reports provided in survey responses at coarser levels of aggregation. Also, some stakeholders have suggested the collection of data linked with retailer "loyalty cards," subject to strict compliance with informed consent of the applicable sample consumer unit and corresponding confidentiality protections.

To explore these suggestions in greater detail, note that for the Consumer Expenditure Survey, the universe of inferential finite population of all consumer expenditures carried out by the noninstitutionalized civilian population of the U.S. in a specified time period. This population may be classified by several factors, including the hierarchical Universal Classification Code for products and services; time period; geography; the outlet through which the purchase took place; any financial or transportation intermediaries involved in the purchase; and characteristics of the purchaser (including demographic factors and their status as consumers). Some of these classification factors align with the characteristics of a consumer unit, and thus lead naturally to data collection through standard household sample survey approaches, as with the current CE. Some other classification factors, however, align with the characteristics of retail outlets, and lead to consideration of data collection from retail outlets via either sample survey methods or administrative record work. .

1.2. Two Approaches to Integration of Survey and Administrative Record Data

With this example in mind, one may consider two approaches to the integration of survey and administrative record data; we will call these the "survey core approach" and the "administrative record core approach," respectively. In the survey core approach, one begins with a relatively standard sample survey design, with administrative records possibly used in the development of frames, selection probabilities and weights. Primary data collection uses standard sample survey methodology, but also obtains some important data through administrative records. For example, if some items are exceptionally difficult or expensive to collect through interview methods, the data collector would request permission from the respondent to obtain those items through relevant administrative sources. One current case of such collection arises in the U.S. National Immunization Survey (NIS), in which sample parents are asked to grant permission for the data collection organization to contact health-care providers to obtain detailed information regarding the dates of specific immunizations for the parents' children. In addition, under the "survey core" approach, the data collection organization could carry out quality-control checks for its survey collection work, based on access to administrative-record data obtained on a subsample or aggregate basis

Under the "administrative record core" approach, data collection centers on access to administrative record data obtained at a relatively fine level of aggregation. Per a suggestion from Lessler (2006), one then collects sample survey data as needed to meet inferential goals that are not met with the administrative record data along. For example, one would carry out a supplementary sample survey to compensate for incomplete population unit coverage; to collect variables not captured in the administrative records; or to adjust for data quality issues (e.g., time-lag effects or aggregation effects) in the administrative records.

Design features may depend heavily on whether one chooses to use a "survey core" or "administrative record core" approach. The remainder of the paper explores some of these features in additional detail. Section 2 develops a mathematical framework for evaluation of error sources and properties of inferential methods. Section 3 reviews several broad classes of methodological issues that arise under both the "survey core" and "administrative record core" approaches. Section 3 also highlights the role of empirical evaluation results in practical design decisions. Section 4 outlines some managerial design issues that are important complements to the methodological design issues covered in Section 3. Section 6 provides some closing remarks.

2. A FRAMEWORK FOR EVALUATION OF ERROR SOURCES AND PROPERTIES OF INFERENTIAL METHODS

2.1 Substantive Inference for Finite Populations and Superpopulations

Large-scale statistical programs generally develop to provide information regarding specified finite populations or related superpopulations. Define a set of finite populations U_t associated with reference periods $t = 1,2,\ldots,T$, respectively. Population U_t contains N_t distinct units, and unit i has an associated k-dimensional vector

$$(X_{it}, Y_{it}), \quad i = 1,..., N_t$$

where Y_{it} is a k_Y-dimensional vector of primary substantive interest, X_{it} is a k_X -dimensional vector of auxiliary variables possibly associated with the Y_{it}, and $k = k_X k_Y$.

In some cases, stakeholder interest centers on finite populations, e.g., inference for functions of finite-population totals or quantiles that could be computed directly from $\{Y_{it}, i \in U_t\}$. In keeping with standard approaches (e.g., Binder, 1983; and Rao et al, 1990), the class of nonlinear functions of finite-population totals will include most finite-population quantities of substantive interest, e.g., means, ratios, quantiles and (logistic) regression coefficients. We will denote these parameters as

$$\theta_{Ut} = h_U(Y_{it}, i \in U_t) \qquad (2.1)$$

Finite-population inference may also include differences between parameters associated with distinct populations defined for different time points, U_s and U_t, $s \neq t$. We will denote these parameters θ_{Ust}.

In other cases, substantive interest centers on characteristics of the *processes* that generated the finite populations U_t. In a formal sense, one assumes that $[(X_{1t}, Y_{1t}), \ldots, (X_{N_t t}, Y_{N_t t})]$ is a $(k \times N_t)$-dimensional realization of a random vector generated by a "superpopulation model" ξ_t with parameters α_t. Substantive interest in superpopulation parameters α_t may include totals, means, ratios, quantiles, or model coefficients related to Y; or other parameters related to the auxiliary variables X and the relationships between X and Y. Similarly, there may be substantive interest in superpopulation models for between time periods s and t, with associated parameters α_{st}. We will denote the superpopulation parameters of primary substantive interest as

$$\theta_{\xi t} = h_\xi(\alpha_t) \qquad \text{and} \qquad \theta_{\xi st} = h_{\xi 2}(\alpha_{st}) \qquad (2.2)$$

for, respectively, a single period t and a pair of periods s and t, where $h_\xi(\cdot)$ and $\theta_{\xi st} = h_{\xi 2}(\cdot)$ are well-defined functions of known form.

2.2. Prospective Information Sources: Administrative Records, Sample Surveys, and Integration Thereof

Statistical programs often seek to provide information on finite-population parameters θ_{Ut} and θ_{Ust}, or the superpopulation parameters $\theta_{\xi t}$ and $\theta_{\xi st}$, based on data from administrative records and sample surveys. With very few exceptions, both approaches are imperfect in the sense that they do not allow capture of the full set of substantive variables $\{Y_{it}, i \in U_t\}$ and thus do not allow direct computation of the finite-population parameter θ_{Ut}. Consequently, the methodological literature has developed a large body of work on sources of errors in the administrative-record process and (especially) in development of "total survey error" models for sample surveys. We may summarize som of this literature through the following schematic models.

2.2.1. Administrative Records

Consider a vector of administrative records Z_t, which one would like to use as a source of information on $\{Y_{it}, i \in U_t\}$. Ideally, $Z_t = Y_t = (Y_{1t}, \ldots, Y_{N_t t})$ and questions of estimation and inference for $\theta_{Ut} = h_U(Y_{it}, i \in U_t)$ are statistically trivial, although such work may still involve important challenges in data management and computation.

In many applications, however, our administrative records fall short of this idealized case, and the observed vector of administrative records may be more reasonably represented as the result of multiple steps of "filtering" of the original true values Y. One relatively simple example is:

$$Z_t = M_{ALt} \times M_{AAt} \times M_{AEt} \times M_{AIt} \times M_{AMt} \times M_{ADt} \times (Y_1, \ldots, Y_t)' \qquad (2.3)$$

where

$(Y_1, \ldots, Y_t)'$ is the column vector of true finite-population microdata from periods 1 through t; and the matrices $M_{A\bullet t}$ represent the following effects for period t.

M_{ADt} describes the (inadvertent) inclusion of duplicate records from the true finite-population microdata. (For the case of no duplication, M_{ADt} equals the identify matrix.)

M_{AMt} represents the results of matching of (nominally identical) units across periods 1 through t.

M_{AIt} represents the omission of some data at their the unit, period or item level.

M_{AEt} represents the effect of measurement error on administrative-record microdata. This may include both misclassification for categorical variables and multiplicative measurement error for continuous variables.

M_{AAt} represents the effects of cross-sectional aggregation, e.g., the availability of some administrative data only in summary form.

M_{ALt} reflects the availability of some data only after substantial lags following the reference period t.

We emphasize that the sequence of multiplications in expression (1.3), and other features of the administrative-record filtering process, will vary across specific applications.

In addition, one may view any one of the matrices $M_{A\bullet t}$ as a finite population, with each element of the finite population corresponding to a row of the matrix, itself generated by a superpopulation model arising from the administrative processes of the record-originating agency. In some cases, one would have inherent interest in that finite population, or specific values thereof. For instance, if some rows of a matrix $M_{A\bullet t}$ were constant over t and were associated with a large self-representing unit, then the statistical agency may wish to know the values of the corresponding row, and to adjust its data-collection, edit or imputation procedures to account for those values. In other cases, the statistical agency would have primary interest in the underlying superpopulation models that generated the matrices $M_{A\bullet t}$; this would be analogous to the modeling approaches generally used for nonresponse and measurement-error components of "total survey error" models.

Matrix "filter"-type representations of statistical procedures have been used previous in the literature for sample surveys and administrative record systems. For example, see Duncan (1986) for a matrix-filtering representation of microdata-masking procedures.

2.2.2. Sample Surveys

Now consider the case in which one tries to collect observations Y_{it} for a sample of size n_t selected from U_t. To simplify the exposition, we will assume that the auxiliary variables X_{it} are known for all $i \in U_t$. Thus, in a formal sense we are incorporating into X_{it} all of the imperfections of administrative records reviewed in Section 2.2.1. Explicit decomposition of error terms in the X_{it} would be of interest, but is beyond the scope of the current work.

In parallel with expression (1.3) define the $(n_t \times k_Y)$-dimensional vector of sample observations,

$$\tilde{Y}_t = M_{SEt} \times M_{SIt} \times M_{SSt} \times M_{SFt} \times (Y_1, \ldots, Y_t)' \qquad (2.4)$$

where the matrices $M_{S\bullet t}$ represent the following effects.

M_{SFt} describes the imperfections in the frame used to select the sample. When relevant, it may incorporate some of the effects covered in expression (2.3).

M_{SSt} is the matrix of sample-selection indicators

M_{SIt} is the matrix of incomplete-data indicators for the samle units. This includes indicators for the effects of unit, wave and item nonresponse.

M_{SEt} represents the effects of measurement error for the responding sample units. As noted for M_{AEt}, the matrix M_{SEt} incorporates the effects of both misclassification and continuous-variable measurement error.

2.2.3 Integration of Data from Administrative Records and Sample Surveys

In keeping with standard approaches, consider a point estimator of θ_{Ut} or $\theta_{\xi t}$ defined by

$$\hat{\theta} = f(X_t, \tilde{Y}_t, Z_t, D_t) \tag{2.5}$$

where X_t, $\tilde{Y}_t$ and Z_t are as defined above, and D_t is a vector that describes design features determined by the statistical program. Also, per Fulton et al. (2009), one may partition $D_t = (D_{At}, D_{St})$ where D_{At} and D_{St} describe the respective designs of the administrative-record and survey procedures. For example, D_{At} may describe methods used to impute missing administrative data or to match these data across periods; and D_{St} may describe the sample design, questionnaire and collection mode for the survey. Fulton et al. then suggest that one choose the design features D_t to reflect a reasonably balance among observable measures of cost, data quality and operational risk. Specifically one may consider schematic models for data quality

$$Q_t = g(D_t, \beta) = \beta_0 + \beta_S D_{St} + \beta_A D_{At} + \beta_{SA} D_{St} D_{At} + e_{Qt} \tag{2.6}$$

and

$$C_t = h(D_t, \gamma) = \gamma_0 + \gamma_S D_{St} + \gamma_A D_{At} + \gamma_{SA} D_{St} D_{At} + e_{Ct} \tag{2.7}$$

In most practical applications, both the quality measure Q_t and the cost measure C_t are multidimensional and subject to important operational constraints. Consequently, it generally will not be feasible to use model (2.6)-(2.7) in a pure design-optimization exercise akin to Neyman allocation.

However, given sufficient empirical information, one could consider estimation of the parameters (β, γ) in model (1.6)-(1.7). The parameter estimates in turn would inform modifications of the design vectors D_t to improve the balance between quality and cost. Consequently, it is useful to distinguish between two types of inference. *Substantive inference*, as considered in Section 2.1, focuses on the finite-population and superpopulation parameters θ_{Ut} and $\theta_{\xi t}$ of substantive interest. *Operational inference* focuses on the parameters (β, γ) of the model (2.6)-(2.7) for operational quality and cost in the statistical program.

3. METHODOLOGICAL ISSUES

Comparison and contrast of the "survey core" and "administrative record core" approaches involve a wide range of methodological issues.

3.1. Evaluation of Properties of Prospective Administrative Record Sources

Under both approaches, practical integration of survey and administrative record data depend heavily on empirical properties of the specific survey and administrative record sources. For example, in the administrative data sources, it may be important to have solid information on the properties of population aggregates (e.g., subpopulation means and totals), as well as relationships among variables (e.g., as characterized by finite-population versions of regression or other generalized linear model relationships). In addition, evaluation of the stability of these properties over time and across subpopulations provides important information for use in development of imputation, allocation and other adjustment procedures.

3.2. Methods for Integration of Sample Survey and Administrative Record Data

For both of the abovementioned approaches, integration of sample survey and administrative record data involve extensions of methodology developed previously for integration of data from multiple survey sources. Two important examples arise in the extension of partitioned-design methods (also known as "multiple matrix sampling" methods) and multiple-frame sampling methods (cf. Lohr and Rao, 2006, and references cited therein). For the latter example, note that the frames in question may involve fundamentally different classification structures. For instance, in the consumer expenditure case described in Section 1, one could consider use of data sources arising from both groups of household units and groups of retail outlets, respectively.

3.3. Distinctions Among Sources of Variability Considered in Evaluation of Bias, Variance and Other Statistical Properties

In evaluation of bias, variance and other properties of integrated-data estimators, it is useful to consider the combined effects of multiple sources of variability, including effects related to superpopulation features, sample designs, incomplete-data patterns, aggregation patterns, reporting errors and imputation procedures. In keeping with work by Davern (2007, 2009) and others, this can lead to extensions of standard "total survey error" (TSE) models. (For general background on total survey error models, see, e.g., Andersen et al., 1979; Groves, 1989; Lessler and Kalsbeek, 1992; and Weisberg, 2005.) For those extensions, it is important to have as much information as possible regarding the underlying processes that have led to the collection and reporting of administrative data. For example, the sample survey literature has carried out extensive empirical studies of factors that influence the decision of a person, household or business to participate in a survey. Considerably less is known about factors in the decision to provide consent for access to administrative records, and such factors would warrant additional study. In addition, it is generally acknowledged that the completeness and quality of administrative record data will often depend on the specific business or administrative uses of those data, and the sensitivity of those uses to missingness or error patterns.

3.4. Expanded Concepts of Data Quality

Statistical agency definitions of data quality generally incorporate TSE measures into a broader framework involving other criteria related to "fitness for use." For example, Brackstone (1999) considers six dimensions of data quality: accuracy (incorporating all of the abovementioned "total survey error" components), timeliness, relevance, interpretability, accessibility and coherence. In addition, one could expand this definition of quality further to incorporate risks related to data disclosure or violation of confidentiality pledges; see, e.g., Fienberg (2006) and references cited therein.

For these multi-dimensional definitions of data quality, it can be useful to distinguish between *aggregate risk* and *systemic risk*. We define *aggregate risk* as the combined effects of a large number of events, generally characterized as resulting from a large number of approximately independent random variables. For example, under a model that describes incomplete data as the result of a large number of independent quasi-random response decisions, the resulting bias and variance inflation would be characterized as a form of aggregate risk. On the other hand, we define *systemic risk* as the result of one well-defined event. For example, if one decision or system failure led to the missingness of a large number of administrative records, one would describe the resulting bias and variance inflation as a form of systemic risk. In some work with administrative records, systemic risks may be of special interest. Characterization and modeling of systemic risks related to "complex and tightly coupled systems" (Perrow, 1984), or other risk-modeling approaches, would warrant further study.

3.5. Cost Structures

Development, implementation and maintenance of large-scale statistical programs generally involve substantial costs. In some cases, use of administrative records may potentially reduce aggregate costs under either "survey core" or "administrative record core" approaches. However, both approaches generally require substantial initial investments, and the net long-term savings depend heavily on details of the survey and administrative record cost structures.

For the data originators, aggregate costs include the costs associated with the original business or administrative purpose, and the added costs incurred in accommodating the data requests of the statistical agency.   For the statistical agency, costs include contractual costs of obtaining data from the provider; work by statistical agency personnel, including development of expertise in the details of the administrative record data; and modification and maintenance of production systems to integrate the survey and administrative data.

Although there is broad acknowledgement that the abovementioned costs are substantial, there is relatively little empirical information available on the relative magnitudes of specific cost components. In addition, relatively little is known about the extent of homogeneity of cost structures across different types of businesses, types of administrative records, or types of subpopulations. Depending on the specific features of a proposed application, required cost information may involve purely qualitative comparisons, rough order-of-magnitude assessments, or more precise quantification. For cases that require relatively precise cost information, one can consider collecting that information through special studies, e.g., per LaFlamme (2008); or through formal cost-recovery contract accounting.

3.6. Burden for Respondents and Other Stakeholders

In considering the prospective reduction of burden that may follow from use of administrative records, it is useful to consider a broad set of burden factors. For respondents, burden may include the elapsed time required for data collection and related recordkeeping activities. Burden may also include subjective factors like cognitive complexity of survey items, as well as perceived sensitivity related to answering survey questions or providing access to administrative data. Additional burden issues may arise in informed-consent processes.

In addition, it is useful to consider organizational burden encountered by both the statistical agency and the organization providing the administrative record data. These burden components may arise in work with informed consent processes; record linkage activities; data management; and data quality evaluations and adjustments.

4. MANAGERIAL DESIGN ISSUES

As a complement to the *methodological design* issues reviewed in Section 3, it is useful to note that *managerial design* factors can also have an important effect on the balance among data quality, cost, burden and risk for statistical programs. In the current context of work with administrative records, three issues are of primary interest. First, it is important for the statistical organization to consider both standard methodological risk factors (as reviewed in Section 3), and *operational risk*, i.e., risks that arise when a given statistical procedure is not carried out as specified. Second, the contractual relationship between the statistical organization and its administrative-record providers can have an important effect on operational risk. Examples of important contractual factors include objective performance criteria and related incentives for the data provider, e.g., for timely delivery of data, complete-data rates, and notification regarding changes in available data or file structure. Third, both methodological risk and operational risk are affected by factors within the statistical organization, including the general institutional culture, and case-specific skill levels and incentives for personnel and groups.

5. CLOSING REMARKS

In summary, this paper has considered design issues relevant to the integration of survey and administrative record data, with the goal of improving the balance among data quality, cost, burden and risk. The paper highlighted important distinctions between a "survey core approach" and an "administrative record core approach." Either of these approaches may be preferable, depending on inferential goals and empirical results related to the abovementioned four factors, In addition, these four factors can have an important effect on both methodological design and managerial design for the integrated study.

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