## ENHANCING DATA SHARING VIA "SAFE DESIGNS"

Generating Knowledge
To Inform Scientific Practice

#### Kristine Witkowski

Inter-university Consortium for Political & Social Research, University of Michigan

#### DATA SHARING CONTEXT

- ➤ U.S. policy requires submission of data sharing plan, when applying for research funding
- Current effort to revamp process for protecting human subjects (ANPRM 7/22/2011)
- Multifaceted approach when formulating data for safe and optimal use (Lane 2007)
- Need to think about data sharing early and often, using specialized knowledge

#### **GUIDING PRINCIPLE**

Producers must be able to effectively draw upon disclosure research to accurately determine the work required to optimally meet data sharing goals

#### AIM

- Enhance the value and safe use of social science data particularly for contextualized microdata
- Simulate scientific practice to generate knowledge for broad and responsive use

#### RESEARCH PROJECT

- > 5-year project supported by National Institute for Child Health & Development
- Dan Brown Michael Elliott Trivellore Raghunathan Kristine Witkowski Kevin Leicht

University of Michigan

University of Iowa

#### ADVISORY BOARD

- ► John Abowd, Cornell University
- Marc Armstrong, University of Iowa
- > Jerry Reiter, Duke University
- Natalie Shlomo, University of Southhampton
- Christopher Skinner, London School of Economics & Political Sci.
- Laura Zayatz, U.S. Census Bureau

#### DISCLOSURE SIMULATIONS

- Simulate disclosure work for representative series of artificial microdata files
- Estimate disclosure outcomes, as measured for a comprehensive set of risk, utility, and cost elements
- As determined by alternative specifications of sampling and database design parameters
- Controlling for iterative sets of survey-sites (or a specific set targeted for collection)

#### DISCLOSURE SIMULATIONS

- Restricted microdata from the American Community Survey provides geographically-specific information used throughout project
- Artificial files offer methodological flexibility as well as data confidentiality
- Project conducts experiments to assess the accuracy of estimates derived from artificial data

# MODELS FOR ARTIFICIAL DATA & POPULATION REIDENTIFICATION PROBABILITIES

- Estimate composition of likely-participants as well as general study population
- Multiple imputation
- > Joint probability distributions for 1-km² pixels
  - Identifying personal attributes and non-identifying health outcomes
  - LandScan, decennial census, ACS microdata, BRFSS
  - Areal weighting methods to estimate pixel data from more aggregate data (i.e., blockgroups)
  - Controlling for non-response (weighted vs. unweighted)

#### METADATA

$$\mu^{m}_{a}$$
;  $\sigma^{m}_{a}$ ;  $\delta^{m} = f[s, r, d]$ 

For any given disclosure outcome (m) resulting from sample (s), release (r), and SDL (d) design elements as estimated from replicating artificial files (a, f)

#### Where:

 $\mu_a^m = Estimated outcome (mean)$ 

 $\sigma^{m}_{a}$  = Variance of estimated outcome (reliability, precision)

 $\delta^{\rm m}$  = Difference from observed outcome (validity, accuracy)

$$o_{ra,f}^{m} = m(o_{ra,f}^{m}) + m(o_{ra,f}^{m}) + e(o_{ra,f}^{m})$$

#### Where:

f = File as compiled from specific sample iteration ra = Experiment using either real (r) or artificial (a) data m = Different measures of disclosure outcomes  $o_{ra,f}^m = Disclosure$  outcome for file  $m(o_{--,-}^m) = Grand$  mean outcome across all files  $m(o_{ra,-}^m) = Mean$  outcome for real or artificial files  $e(o_{ra,f}^m) = Variation$  among real or artificial files

#### Accuracy of estimated outcome

$$\delta_{\mu}^{m} = [m(o_{a,-}^{m}) - m(o_{r,-}^{m})] / m(o_{r,-}^{m})$$

$$\delta_{\sigma}^{m} = [s(o_{a,-}^{m}) - s(o_{r,-}^{m})] / s(o_{r,-}^{m})$$

$$\Phi^{m} = s(o_{r,-}^{m}) / s(o_{a,-}^{m})$$

$$\theta^{m} = m(o_{r,-}^{m}) - [\phi^{m} * m(o_{a,-}^{m})]$$

#### Estimated outcome (adjusted)

$$\mu_{a}^{m} = E(\theta_{a}^{m}) + [E(\phi_{a}^{m}) * m(o_{a,-}^{m})]$$

#### Variance of estimated outcome (adjusted)

$$\sigma_a^m = E(\varphi^m) * s(o_{a,-}^m)$$

#### METADATA

$$\mu^{m}_{a}$$
;  $\sigma^{m}_{a}$ ;  $\delta^{m} = f[s, r, d]$ 

For any given disclosure outcome (m) resulting from sample (s), release (r), and SDL (d) design elements as estimated from replicating artificial files (a, f)

#### Where:

 $\mu_a^m = Estimated outcome (mean)$ 

 $\sigma^{m}_{a}$  = Variance of estimated outcome (reliability, precision)

 $\delta^{\rm m}$  = Difference from observed outcome (validity, accuracy)

#### SAMPLE ELEMENTS (s)

- Study population of adults (age 18 +)
- Limited study region: Indiana, Illinois, Michigan, Ohio, Wisconsin
- Household survey based on two-stage sample of tracts and housing units clustered within
- Total sample size
- ➤ Detailed sampling design locations, target populations, and sampling rates

#### RELEASE ELEMENTS (r)

#### Person-Level

- Identifying characteristics of respondent (e.g., age, sex, race/ethnicity, obesity-status, household composition, spousal attributes)
- Non-identifying health outcomes: Self-reported health, chronic condition (e.g., diabetic)
- Sets of 6 or 10 attributes, held constant

#### RELEASE ELEMENTS (r)

- Geography-Level
  - Direct identifiers of region, state, & population density (e.g., MSA-status)
  - Indirect identifiers or contextual variables
    - Administrative and georeferenced spatial-units:
       Counties, tracts, blockgroups, & 1-km² pixels
    - Public-use data: Census, EPA, NASA, others
    - Sets of variables of broad interest (wishlists)
    - Samples representative of all possible sets.

## RELEASE ELEMENTS (r)

- Geography-Level
  - Indirect identifiers or contextual variables
    - Domain or measurement: Population and housing characteristics, air quality, tree coverage, proximity to incinerators, miles of road
    - Type or areal size of underlying geography:
       Pixels, blockgroups, tracts, & counties
    - Number of variables to be released
    - Entropy

## SDL ELEMENTS (d)

- Linkage Experiments: Geographic-Level
  - Strangers and acquaintance intruders
  - Link to public sources of contextual variables
    - Complete and accurate data
  - Matches: Geographies (in population) with same attributes as surveyed locations
  - Blocks: Region, state, population density
  - Personal attributes, coupled with geographic attributes, used to refine estimates that particular areas have been drawn into study

## SDL ELEMENTS (d)

- SDL Techniques: Geographic-Level
  - Assume personal identifying variables are not masked
  - Applied after collection: Global recoding and synthetic values of contextual variables
    - Deterministic linkage, probabilistic linkage, k-nearest neighbor, Mahalanobis distance, others
  - Applied before collection: The "Safe Design"

#### SAFE DESIGN

- Formulate innovative SDL technique for addressing reidentifying personal attributes, holding constant geographic attributes
- Study that supplements their sample and responsively collects data to minimize risk of being a sample unique (i.e., k-anonymity)
- Circumvents constraints from established practice of addressing disclosure after data are collected

#### SAFE DESIGN

- ➤ Baseline sample: Sampling design formulated to meet analytical goals (U<sub>b</sub>, C<sub>b</sub>)
- ▶ Preemptive disclosure review: Disclosure risk of baseline sample (R<sub>b</sub>)
- Supplemental sample: Sampling design formulated to meet confidentiality goals ( $R_s \sim o$ ,  $U_s > U_b$ ,  $C_s > C_b$ )

Where: R = Risk, U = Utility, C = Cost

## DISCLOSURE OUTCOMES (m)

#### Risk

- Identity disclosure: Population reidentification probabilities and k-anonymity
  - Persons in study population sharing similar geographic and personal attributes
  - Respondents sharing similar geographic and personal attributes within data release
- Continuous cell sizes; at-risk status with thresholds defined by content sensitivity
- Per record per target subpopulation per design

## DISCLOSURE OUTCOMES (m)

#### Utility

- Information loss: Characterizing release as a whole, including both continuous and categorical measures, scale-invariant
  - 12 measures provided by Domingo-Ferrer, Torra, and Mateo-Sanz
- Suppression bias: Geographies and subpopulations most at-risk
- Statistical inference: Relationships between health outcomes and spatial contexts

## DISCLOSURE OUTCOMES (m)

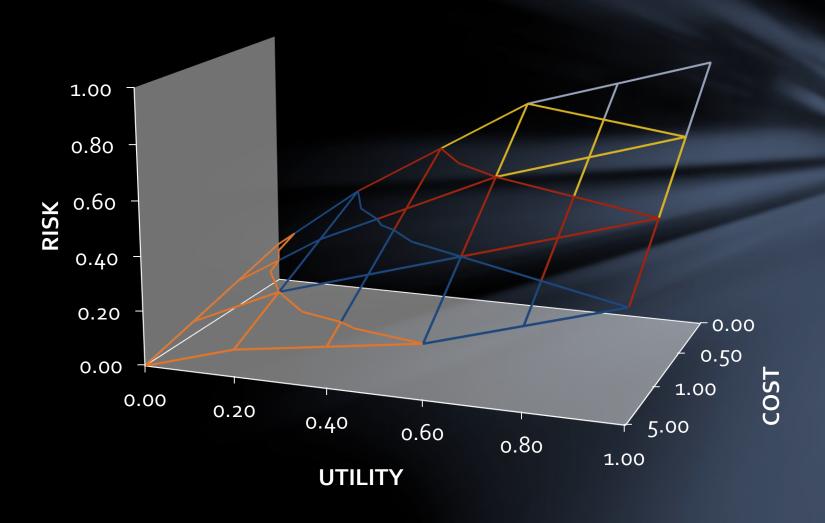
#### Cost

- Average dollar values of survey expense
- Function of number of draws required to meet targeted sample sizes for broadly defined and detailed subpopulations
- Directly informed by scientific practice

#### ADDITIONAL CONSIDERATIONS

- Added value and cost of spatially-dispersed samples that maximize variance in geographic attributes (s)
- Trading-off data on personal attributes for geographic detail (r)
- Protection offered by measurement error and concentration of hard-to-count populations (d)
- The role of administrative data sources (d)

#### **RISK-UTILITY-COST MAP**



#### **IMPLICATIONS**

- Flexible framework for generating empirical data that can broadly inform decision-making
- Supports sharing and consumption of complex and highly specialized knowledge
- Supports policies regarding data sharing and protection of human subjects
- Audiences: Established and new studies of federal statistical agencies and academic institutions; DRBs, IRBs, archives; funders

