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Effects of a Government-Academic Partnership: Has the NSF-Census Bureau Research Network Helped Improve the U.S. Statistical System?

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EFFECTS OF A GOVERNMENT-ACADEMIC PARTNERSHIP: HAS THE NSF-CENSUS BUREAU RESEARCH NETWORK HELPED IMPROVE THE US STATISTICAL SYSTEM?

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The National Science Foundation-Census Bureau Research Network (NCRN) was established in 2011 to create interdisciplinary research nodes on methodological questions of interest and significance to the broader research community and to the Federal Statistical System (FSS), particularly to the Census Bureau. The activities to date have covered

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both fundamental and applied statistical research and have focused at least in part on the training of current and future generations of researchers in skills of relevance to surveys and alternative measurement of economic units, households, and persons. This article focuses on some of the key research findings of the eight nodes, organized into six topics: (1) improving census and survey data-quality and data collection methods; (2) using alternative sources of data; (3) protecting privacy and confidentiality by improving disclosure avoidance; (4) using spatial and spatio-temporal statistical modeling to improve estimates; (5) assessing data cost and data-quality tradeoffs; and (6) combining information from multiple sources. The article concludes with an evaluation of the ability of the FSS to apply the NCRN's research outcomes, suggests some next steps, and discusses the implications of this research-network model for future federal government research initiatives.

KEYWORDS: Administrative records; Data collection; Disclosure avoidance; Statistical modeling; Survey methods; Survey statistics.

1. INTRODUCTION

A key problem that statistics agencies around the world face is the decline in participation in household and business surveys over the past 25 years (Tourangeau and Plewes 2013; Groves 2017; Williams and Brick 2018), which lowers the quality and increases the cost of official statistics. Meanwhile,

This article began as a presentation on May 8, 2015, to the The National Academies of Sciences, Engineering, and Medicine Committee on National Statistics by two of the principal investigators of the National Science Foundation-Census Bureau Research Network (NCRN): John Abowd and the late Stephen Fienberg (Carnegie Mellon University). The authors acknowledge the contributions of the principal and co-principal investigators of the NCRN who are not co-authors of the article (William Block, William Eddy, Alan Karr, Charles Manski, Nicholas Nagle, and Rebecca Nugent), the comments of Patrick Cantwell, Constance Citro, Adam Eck, Brian Harris-Kojetin, Eloise Parker, the editor (Ting Yan), and two anonymous referees. They also thank Handan Xu, who organized the references. We note with sorrow the deaths of Stephen Fienberg and Allan McCutcheon, two of the original NCRN principal investigators. The conclusions reached in this article are not the responsibility of the National Science Foundation (NSF), the Census Bureau, or any of the institutions to which the authors belong. The NCRN was supported by NSF grants to the participating institutions: 1129475 to Northwestern University; 1130706 to Carnegie Mellon University; 1131500 to University of Michigan-Ann Arbor; 1131848 to Cornell University; 1131897 to Duke University and National Institute of Statistical Sciences (NISS); 1132008 to University of Colorado-Boulder; 1132015 to University of Nebraska-Lincoln; 1132031 to University of Missouri; and 1507241 for the Coordinating Office (Cornell, Duke, and NISS). The principal investigators also wish to acknowledge Cheryl Eavey's sterling grant administration on behalf of the NSF, and Daniel Weinberg and Nancy Bates (the latter assisted by Krista Park and Renee Ellis) in their role as Census Bureau liaison for the NCRN program.

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large-scale data and computationally intensive methods, popularly known as “big data,” are laying the foundation for a paradigm shift in the way statistical information is conceptualized, produced, and used. The US Census Bureau and its partner, the US National Science Foundation (NSF), recognized a need for the US Federal Statistical System (FSS) to adapt and evolve. The development and reporting of official statistics by government agencies relies heavily on the foundation provided by academic (and self-generated) basic research. Therefore, in 2011, these partners established the NSF-Census Bureau Research Network (NCRN), a novel program of grants to academic institutions that married basic research activities with the applied needs of governmental statistical agencies.

With funding largely from the Census Bureau, NSF disseminated a call for proposals in September 2010 to create research nodes, each of which was to be staffed by teams of researchers conducting interdisciplinary research and educational activities on methodological questions of interest and significance to the broader research community and to the FSS—particularly the Census Bureau. To encourage fresh and innovative approaches of broad applicability, the solicitation posed a wide range of federal statistical problems without specifying the approaches (see the list in Appendix A of the online supplementary material). After peer review of the proposals, the NSF made grant awards to six “medium” and two “small” nodes: Carnegie Mellon University, University of Colorado–Boulder joint with the University of Tennessee (a small node), Cornell University, Duke University joint with the National Institute of Statistical Science (NISS), University of Michigan in Ann Arbor, University of Missouri, University of Nebraska in Lincoln, and Northwestern University (small). A second solicitation to establish a Coordinating Office for the NCRN led to a separate award to Cornell and Duke/NISS (see www.ncrn.info/index; last accessed October 26, 2018). Initial awards were made in October 2011 for a five-year period. Supplemental awards and no-cost extensions allowed parts of the network to be funded through September 2018. Aggregate funding for the network was approximately $25.7 million.

The network includes several investigators with decades of direct collaboration with the FSS. But it also includes many more scholars, from the agencies and from academia, who only recently have invested in understanding the uses of the statistical products and the methods used to produce them. This focus has produced innovative applications and new methodologies that are immediately applicable to current systems. It also advanced the NCRN goal of engaging new researchers—both experienced and those at the start of their careers—in research relevant to the future of the FSS.

The activities to date have covered both fundamental and applied statistical research and have focused at least in part on the training of current and future generations of researchers in skills of relevance to surveys and alternative measurements of economic units, households, and persons. The results of “basic” research covered by this grant program are described in the more than

400 articles sponsored by the NCRN program and published as preprints or in academic journals (see archives.vrdc.cornell.edu/ncrn.info/documents/bibliographies/; last accessed October 26, 2018 for a complete list as of April 2018). Many of these research products have "applied" implications important to FSS agencies.

The remainder of this article will be in three parts. The next section discusses in brief some of the key research findings of the eight nodes, organized into six topics: (1) improving census and survey data-quality and data collection methods; (2) using alternative sources of data; (3) protecting privacy and confidentiality by improving disclosure avoidance; (4) using spatial and spatio-temporal statistical modeling to improve estimates; (5) assessing data-cost and data-quality tradeoffs; and (6) combining information from multiple sources. Section 3 explores collaborations across nodes and with federal agencies. The article concludes with an evaluation of the ability of the FSS to apply the NCRN's research outcomes, suggests some next steps, and discusses the implications of this research-network model for future federal government-academia collaborations. Appendix B of the online supplementary material discusses education activities, outcomes, and new software developed.

2. SELECTED RESEARCH OF THE NCRN NODES

We focus on the network's contributions in six main areas, acknowledging that there is some overlap among them.

2.1 Improving Census and Survey Data-Quality and Data Collection Methods

Given the importance of the Census Bureau's core mission, it is perhaps not surprising that a good deal of NCRN research focused on improving its data collection methods. It is clear to both academic researchers and Census Bureau professionals that one important path to a less expensive decennial census in 2020 is through the use of more up-to-date technology. The traditional Census Bureau approach is being rethought, especially since there will be widespread use of online census forms. Such broad census design issues have been the focus of the Carnegie Mellon node in its interaction with Census Bureau researchers. NCRN research on the effects of different types of census errors on the resulting allocations of funds and representation, which has taken place at the Northwestern node and is described later, provides guidance on where to focus error-reducing resources. Improving the census was a touchstone of the late Stephen Fienberg's career; his vision for the future of the census is summarized in his 2013 Morris Hansen Lecture (Fienberg 2015).

By studying survey data, paradata, and audio recordings, Nebraska-node researchers have consistently found that the design of the questions plays a greater role in predicting survey data quality indicators (e.g., item nonresponse, response timing) and interviewer and respondent behaviors during a survey (e.g., exact question reading, provision of adequate answers) than characteristics of interviewers or respondents (Olson and Smyth 2015; Timbrook, Smyth, and Olson 2016; Olson, Cochran, and Smyth 2018a; Smyth and Olson 2018). For example, Olson and Smyth (2015) found that 53 percent of the variance in response time in a telephone survey was due to the questions compared with only 3 percent due to interviewers and 7 percent due to respondents; they also found that this "question" variance can be largely explained by question features such as complexity (complex questions take longer) and sensitivity (sensitive questions are quicker). Similarly, Olson, Ganshert, and Smyth (2018b) found that between 23 percent and 76 percent of the variance in respondent answering behaviors can be attributed to the questions compared with almost zero due to interviewers and 6 percent to 19 percent due to respondents themselves. In addition, they found that interviewer behaviors and communication processes are affected by those of respondents (Timbrook, Olson, and Smyth 2018) and that respondent communication and cognitive processes are affected by respondent-interviewer interactions (Belli, Bilgen, and Baghal 2013; Belli and Baghal 2016; Olson, Kirchner, and Smyth 2016; Kirchner and Olson 2017; Kirchner, Olson, and Smyth 2017; Olson, Ganshert, and Smyth 2018b; Charoenruk and Olson 2018; Timbrook, Olson, and Smyth 2018).

Nebraska node analysis of paradata has helped to better understand other aspects of interviewer/respondent interactions, including respondent retrieval patterns and prompts, which are especially relevant for questionnaire design in calendar and time diary interviewing (Olson and Parkhurst 2013; Atkin, Arunachalam, Eck, Soh, and Belli 2014; Baghal, Tarek, Phillips, and Ruther 2014; Belli and Baghal 2016). These findings have direct application in the Survey of Income and Program Participation (SIPP) and the American Time Use Survey (ATUS). Specifically, in a validation study of calendar interviewing, Belli et al. (Belli, Bilgen, and Baghal 2013; Belli, Miller, Baghal, and Soh 2016) found that whereas the use of parallel and sequential retrieval probes and strategies (which associate past contemporaneous and temporally ordered events used by interviewers and respondents respectively) are associated with better data quality, interviewer parallel probes are unexpectedly associated with poorer data quality when each is soon followed by a respondent parallel retrieval strategy. With the ATUS, results from Kirchner, Belli, Córdova-Cazar, and Deal (in press) indicate that the resolution of initially missing reports of activities during a day is associated with respondents' engagement to report changes in who was present and where activities took place.

Such work with paradata is also relevant for designing and building computer-assisted telephone instruments that make recommendations to the interviewer (Arunhachalam, Atkin, Eck, Wettlaufer, Soh, et al. 2015; Atkin, Arunachalam, Eck, Wettlaufer, Soh, et al. 2015). For instance, Nebraska-node researchers used paradata to develop an intelligent agent that monitors interview progress and makes recommendations to the interviewer to help streamline data entry, improve the effectiveness and efficiency of interviewer-software interactions, and predict respondent breakoffs in web surveys (Eck, Soh, McCutcheon, and Belli 2015; Eck and Soh 2017). In particular, Eck et al. (2015) used sequential machine learning with Markov chains to learn conditional probabilities of sequences leading to survey outcomes such as breakoff in paradata, and they used recurrent neural networks to learn the likelihood of breakoff using twenty-three instances of the Gallup Web Panel from 2012 to 2014. Between 56 percent and 75 percent of breakoff cases were identified with high precision (above 80 percent) using the Markov chain model, and 77 percent to 89 percent of breakoff cases were identified with even better precision (above 92 percent) using the recurrent neural network model. One interesting corollary of an increased use of paradata in adaptive surveys is the necessity of organizing the storage, retrieval, and increased complexity in analytic tools needed for use of such data for analysis of large surveys (Olson and Parkhurst 2013), such as the multimodal American Community Survey (ACS). Editing the data for consistency to eliminate obvious errors (e.g., children older than their parents, pregnant males) is important.

The Duke-NISS node has been working on methods that improve how FSS agencies handle missing and faulty values. Murray and Reiter (2016) develop a flexible engine for multiple imputation or missing multivariate continuous and categorical variables, which they apply to impute missing items in data from the Survey of Income and Program Participation. Their model blends mixtures of multinomial distributions with mixtures of multivariate normal regression models in one joint model. In this way, the model adapts to the distributional features of the observed data, allowing it to automatically capture nonlinearities and interaction effects across entire multivariate distributions. Using simulations, they show that their model produces multiple-imputation confidence intervals and distribution estimates with better properties (e.g., smaller mean squared errors and closer to nominal coverage rates) than intervals based on general location models or chained equations, which are the default standards in multiple imputation of mixed data.

As another example of improved imputation methods, White, Reiter, and Petrin (2018) adapt regression trees as engines for imputation of missing items in the Census of Manufactures. They demonstrate improvements over existing imputation routines for this central data product, which historically have been based on mean and ratio imputations. Other relevant works include methods for handling nonignorable nonresponse (Sadinle and Reiter 2017, 2018) for imputation of missing items in household data (Hu, Reiter, and Wang 2018) and for imputation-based approaches for deciding whether or not to stop data collection (Paiva and Reiter 2017).

For decades, FSS agencies have based their statistical editing practices on the principles elucidated by Fellegi and Holt (1976). Reiter and his colleagues have developed methods to improve upon these time-honored methods by using Bayesian approaches to allow stochastic editing to create multiply-imputed, plausible datasets, building on ideas in Ghosh-Dastidar and Schafer (2003). The approaches are based on hierarchical models that include (1) flexible multivariate models for the true data values, with support restricted to feasible values, (2) models for errors given the latent true values, and (3) models for the reported values when errors are made. Traditional single-error localization and imputation procedures lead researchers to underestimate uncertainty. By assuming stochastic models for measurement errors, this alternative approach generates many plausible "corrected" datasets, propagating uncertainty about error localization, and fully leverages information in the observed data to inform the edits and imputations. These developments include the use of such methods for both numerical-valued economic data (Kim, Cox, Karr, Reiter, and Wang 2015) and categorical-valued demographic data (Manrique-Vallier and Reiter 2018). Using empirical examples and simulations with data from the Economic Census and the ACS, they further demonstrate that the stochastic edit imputation routines can result in secondary data files with smaller mean squared errors and closer to nominal coverage rates than methods based on Fellegi-Holt systems. The Census Bureau has begun a project to incorporate these methods into its 2017 Economic Census by using integrated edit, imputation, and confidentiality protection based on synthetic data models developed by Kim, Cox, Karr, Reiter, and Wang (2015). The methods will permit publication of North American Product Classification System estimates and their margins of error without prespecifying the table layout, as is currently done for the North American Industrial Classification System tabulations; this project illuminates how more accurate modern methods can substitute for less accurate but convenient historical ones.

The Cornell node collaborated with the Census Bureau's Longitudinal Employer-Household Dynamics Program. This program publishes quarterly statistics using administrative records from state unemployment insurance record systems integrated with censuses, surveys, and administrative records from the Census Bureau's household and business production systems. McKinney, Green, Vilhuber, and Abowd (2017) produced the first total error analysis of the publications from this data.

2.2 Using Alternative Sources of Data

Censuses and surveys are not the only ways to collect information about the population and the economy. Independent sources can potentially provide useful data, such as from administrative records collected by governments for their own purposes (e.g., property assessments to levy real estate taxes or program applications to obtain benefits) and information provided by individuals in the course of their everyday activities (ranging from Twitter and Facebook posts to traffic-monitoring stations).

Making use of such information (particularly administrative records) in a statistical-agency environment typically requires record linkage, though there are cases where such information can be used without linkage (such as the Census Bureau's use of income tax records from the Internal Revenue Service for small businesses to avoid burdensome interviews). Record linkage is a critical component of the efforts to reduce census costs and, potentially, to improve accuracy. Of course, administrative records data have their limitations. As Groves and Harris-Kojetin (2017, p. 3–12) point out: "Administrative data can have many limitations including: (1) lack of quality control, (2) missing items or records (i.e., incompleteness), (3) differences in concepts between the program and what the statistical agency needs, (4) lack of timeliness (e.g., there may be long lags in receiving some or all of the data), and (5) processing costs (e.g., staff time and computer systems may be needed to clean and complete the data)."

Record linkage (or matching) occurs at virtually every stage of operational and experimental census designs. Specifically, when the household address frame is the primary control system, record linkage occurs every time this frame is updated, primarily in the operation known as deduplication. The Census Bureau obtains a semiannual list of every address to which the US Postal Service delivers (or plans to deliver) mail, and after removal of commercial and governmental addresses, this list is used to update the Master Address File, which is used to carry out a population and housing census and as a sampling frame for ongoing household surveys. Also, when the first decennial census contact is not from a traditional mail-in mail-back form, record linkage occurs when the responses are integrated as they are received, especially if they are received without a decennial census identification (ID) code.

Traditionally, the address on the mail-back form links directly to the master address file, linking the geography for the household to the accuracy of the master address file. When the first contact is via an online form (IP address) or cell phone (cellular location services), this information must be linked to the master address file. In the 2020 Census, internet response can take one of two forms called ID and non-ID. In the ID form, the respondent enters the encrypted master address file identifier supplied on the invitation to take the census. In the non-ID form, the respondent supplies a residential address directly. Processing the non-ID cases uses this alternative address information. Record linkage is expected to play a critical role in the non-ID processing. It will also likely play a critical role in the nonresponse follow-up stage via the use of information from multiple administrative record lists to complete the form in the absence of directly collected data (or supplementary to an incomplete report). Additionally, record linkage is one of an intruder's possible methods for attempting to break the confidentiality of released data, and thus, one must assess the risk of confidentiality breaches from published tables and public-use microdata samples.

All of these (and other) record linkage applications can be quantitatively improved using new tools that simultaneously link more than two lists, while deduplicating each of the lists. The solutions provide conceptual generalizations of the familiar Fellegi and Sunter (1969) method for two lists (or deduplication of a single list) that are computationally feasible for application at the scale of the decennial census (Sadinle and Fienberg 2013; Steorts, Hall, and Fienberg 2016; Sadinle 2017). Further, the new methods acknowledge and propagate the uncertainty from the matching process into subsequent analyses. Improved record linkage can also improve the data needed to handle nonresponse to the census and to surveys, often by providing data for a particular address from administrative records, but also by providing data for modeling nonrespondents.

Particularly relevant for the Census Bureau is combining these issues into useful statistical models and methods. Fienberg (2015) presents a discussion of the value of addressing (1) record linkage methods for three or more files, (2) combining duplicate detection and record linkage, (3) propagating duplicate detection and record linkage error into subsequent calculations, and (4) measuring both erroneous enumerations and omissions.

Record linkage is also important for business data. In collaboration with the University of Michigan's Sloan Foundation–funded Census Bureau-enhanced Health and Retirement Study, the Michigan node developed and tested methods for probabilistic linkage of the employers of Health and Retirement Study respondents to the Census Business Register. This work addresses the complexity and benefits of linking household and business data to better understand employment of older Americans. The record linkage research confronts the difficulty of how individuals report their place of employment and how it is represented in administrative data. The approach taken highlights the importance of accounting for errors in matching records and of using probabilistic techniques to reflect these errors in subsequent analyses (Abowd and Schmutte 2016). This research also produced new software for standardizing business names, a necessary step in linking organizational data (Wasi and Flaaen 2015).

The second alternative source of data for statistical agencies is "nondesigned data," also sometimes termed "organic data," "third-party data," "naturally occurring data," or "data in the wild," such as from social media like Twitter or transaction data that are digital traces of people's and businesses' daily activities (bank and credit card transactions, shopping, turning on lights, etc.). The key issue is not yet whether those data can replace data that FSS agencies use to report key social, economic, housing, and demographic indicators, but whether that data can provide useful indicators and checks on traditional time series or produce measures at lower cost, greater frequency, more geographic detail, or in conjunction with survey data to reduce respondent burden. Note, however, that their use in official statistics could easily be jeopardized by changes in methodology by the independent provider or even its discontinuation and the proprietary nature of its collection and dissemination.

2.2.1 Account data. Data on consumers' transactions and balances can provide high-frequency and high-quality measures of spending, income, and assets that are difficult to measure accurately using surveys, which rely on infrequent self-reports from relatively small samples of individuals. In collaboration with a Sloan Foundation–funded database development project, the Michigan node pioneered the use of comprehensive account data from linked checking and credit card accounts to confront the difficulties of using such naturally occurring account data to produce economically meaningful measurements and to study economic behavior and outcomes. Gelman, Kariv, Shapiro, Silverman, and Tadelis (2014) show that account data drawn from a large sample of users of a financial services application can be broadly representative of the US population. They use this newly developed data infrastructure to shed light on the excess sensitivity of spending to predictable income, show how households accommodate short-run drops in liquidity (Gelman, Kariv, Shapiro, Silverman, and Tadelis in press), and show how spending responds to a permanent change in gasoline prices (Gelman, Gorodnichenko, Kariv, Koustas, Shapiro, et al. 2016).

The use of transaction and balance data has great promise to improve spending and income measures published by the FSS. Spending reports are either based on very aggregate store-level data (the Census Bureau Advance Monthly Retail Trade Report) or surveys of consumers (the US Bureau of Labor Statistics Consumer Expenditure Survey). Both these surveys suffer from declining response rates and other data-quality problems. Income reports when benchmarked to Internal Revenue Service tax data (such as the US Bureau of Economic Analysis National Income and Product Accounts and its monthly Personal Income and Outlays) show survey underreporting. Tax data is inherently annual and available to the FSS only with a considerable lag and substantial disclosure limitations. Conversely, transaction data is available daily, with high precision for large samples of individuals, with great detail on location and type of spending, and with almost no lag.

2.2.2 Social media data. Official statisticians understand the framework in which a time series indicator like new unemployment insurance claims can be used to measure change. The population at risk is all statutory employees covered by state unemployment insurance systems. When the indicator goes down, fewer such employees filed new claims for unemployment insurance. But what does an increase in Tweets about "job loss" mean? The Michigan node developed a predictive model to assess this question. Job-loss Tweets do forecast the changes in official new claims for unemployment insurance, particularly upward spikes, allowing one to capture turning points in economic activity that are often missed or captured only with a long lag using traditional approaches (Antenucci, Cafarella, Levenstein, Ré, and Shapiro 2013, 2014). The project developed a real-time predictor of unemployment insurance claims and maintains a website giving weekly updates (see econprediction.eecs.umich.edu; last accessed October 26, 2018).

An ongoing challenge to the use of social media data, in particular for measurement over time, is that while there is an enormous amount of this type of cross-section data, no particular social media platform has existed long enough to capture an entire business cycle, let alone multiple such transitions. Thus, the development of measures from social media data requires the systematic use of prior knowledge about the structure of the economy, such as how job flows change over the business cycle, akin to the use of seasonality adjustments. Without a benchmark reference, how can the predictive model detect a change in the weights it attaches to its inputs? The Michigan node is now addressing this issue with the development of an interactive model that allows those with domain expertise to provide benchmark datasets and economic concepts for measurement to a large archive of unstructured, web-based (social media and imaging) data in order to generate and archive new time series measures.

Researchers are also investigating natural-language processing of social media, transaction, and accounting data to help better understand economic measurement. This research is of interest to the Bureau of Labor Statistics, the Census Bureau, the Bureau of Economic Analysis, and the US Federal Reserve Board.

2.2.3 The impact of nondesigned data on economic statistics and policy analysis. The FSS largely relies on its ongoing data collections for official time series because of the need for consistency over long time periods. This consistency is especially important to policymakers (Yellen 2017). Nonetheless, official statistics are making increased use of nondesigned economic data for price and value measurement (US Federal Economic Statistics Advisory Committee 2015; US Bureau of Economic Analysis Advisory Committee 2017). The Census Bureau, Bureau of Labor Statistics, and Bureau of Economic Analysis are currently making substantial use of commercial data in their programs. The work of the Michigan node has addressed questions of representativeness, timeliness, and coverage that are essential for using this data more systematically in official statistics (Gelman, Kariv, Shapiro, Silverman, and Tadelis 2014).

NCRN work on economic indicators has focused on the question of whether novel economic indicators have incremental information that could be of use to policymakers. Antenucci, Cafarella, Levenstein, Ré, and Shapiro (2014) show that the social media index constructed from tweets has supplemental explanatory power for nowcasting new claims for unemployment insurance beyond the consensus forecast of experts. Hence, even with the short time series of data available from social media, there is evidence that social media data can be used by policymakers or market participants to extract information about the state of economy. That article also shows preliminary evidence of the shift in the relationship between vacancies and unemployment known as the Beveridge curve that is an ingredient to understanding the recovery from the Great Recession.

Nondesigned data can also be used to provide policymakers with information not readily available in official statistics because they are insufficiently granular. Former Federal Reserve Chair Yellen (Yellen 2017) cites two examples of such research that were relevant for Federal Reserve monitoring of the economy: the analysis by Federal Reserve staff of the effects of Hurricane Matthew (Aladangady, Shifrah, Dunn, Feiveson, Lengermann, et al. 2016) and the analysis by Michigan node researchers of the effects of the 2014 gasoline price decline on consumer spending (Gelman et al. 2016).

2.2.4 Other nondesigned data. Another use of auxiliary data comes from combining area-level covariates measured over space and/or time with tabulated survey estimates within a hierarchical model-based framework. For example, Porter, Holan, and Wikle (2015a) model the ACS five-year period estimates of mean per capita income in Missouri counties by using percentage of unemployed individuals in each county as auxiliary information, also obtained from the ACS. Another salient example comes from the Missouri node's use of social media (functional time series) data from Google trends (Porter, Holan, Wikle, and Cressie 2014). The approach extends the traditional Fay-Herriot model to the spatial setting using functional and/or image covariates. A natural use for this methodology could be to incorporate remote sensing data as image covariates to augment information obtained from federal surveys or to assist with in-office address canvassing.

Work by Michigan and Cornell researchers contributes to our understanding of multiply-sourced data. The Michigan node compared survey (SIPP) and administrative (Longitudinal Employer-Household Dynamics [LEHD]) measures of the causes of job loss and studied the implications for estimates of the response of earnings to job loss (Flaaen, Shapiro, and Sorkin in press), developed and studied a measure of firm quality based on the ability of firms in the LEHD to attract and retain workers (Sorkin 2018), and developed explanations of the divergence of survey (Health and Retirement Study) and administrative (social security) measures of earnings (Hudomiet 2015). The Cornell node investigated the coherence of ACS and administrative reports of workplace location (Green, Kutzbach, and Vilhuber 2017).

The Missouri node has proposed improvements to the statistics created from the LEHD database (Bradley, Holan, and Wikle 2015a, 2017) that make use of multivariate spatio-temporal statistical modeling. The Census Bureau and the Missouri and Cornell nodes are collaborating to enhance the precision of the disseminated estimates.

2.3 Protecting Privacy and Confidentiality by Improving Disclosure Avoidance

Privacy is about what information a respondent is willing to share, whereas confidentiality is about the ethical and statutory requirements to keep personal data from unauthorized disclosure to a third party. Three different approaches to confidentiality protection span the ongoing work of the nodes in this area: data swapping (historically the Census Bureau method of choice to date for both the decennial census and the ACS), multiple imputation (involving the preparation of synthetic datasets), and the more recently developed method of differential privacy that emanates from cryptography and computer science and offers the strongest possible privacy guarantees. However, differential privacy has not yet been proven to work for all kinds of data releases that the Census Bureau is accustomed to producing (Abowd and Schmutte 2016). The *Journal of Privacy and Confidentiality* devoted an entire issue (2015–2016, volume 7, issue 2) to differential privacy; see also Murray (2015).

Both the Carnegie Mellon and Cornell nodes have contributed to the "the economics of privacy." Acquisti, Brandimarte, and Loewenstein (2015) and Acquisti, Taylor, and Wagman (2016) highlight how the economic analysis of privacy evolved over time, as advancements in information technology raised increasingly nuanced and complex issues. They highlight three themes: (1) characterizing a single unifying economic theory of privacy is hard, because privacy issues of economic relevance arise in widely diverse contexts; (2) there are theoretical and empirical situations where the protection of privacy can both enhance and detract from individual and societal welfare; and (3) consumers' ability to make informed decisions about their privacy is severely hindered because they are often in a position of imperfect or asymmetric information regarding when their data is collected, for what purposes, and with what consequences.

But a much larger social issue also concerns researchers in the network. What are the appropriate tradeoffs between data confidentiality and data accuracy? As Abowd and Schmutte (2017) show, public statistics will be underprovided by private suppliers, and welfare losses from the under-provision can be substantial (see also Abowd and Schmutte in press). But a key contribution of theirs is that the question cannot be answered from the technology of statistical disclosure limitation or privacy-preserving data mining. It requires understanding how the citizen consumers of an agency's statistics value data accuracy when they must pay with some loss of privacy. All the players in this arena, public and private, understand the risks associated with direct privacy breaches far better than they understand how to measure a society's preferences for public data that can only be produced with some privacy loss. Changes to the current paradigm may require new legislation.

Among the network's new contributions in this area is a focus on quantifying the disclosure risks associated with large-scale record linkage, such as that proposed for the 2020 Census, and on producing accurate statistics that control that risk in a quantifiable way. Much of the NCRN research on disclosure avoidance addresses how to combine statistical disclosure limitation with correct analysis of the published data, including understanding the uncertainty introduced through probabilistic data linkage or model-based data imputation (Kim, Reiter, and Karr 2016).

Several of the network's researchers have worked on extending prior work on the use of synthetic data as a disclosure avoidance technique (Kinney, Reiter, Reznek, Miranda, Jarmin, et al. 2011). The Cornell and Duke-NISS nodes have continued supporting the Census Bureau in learning from and extending the use of synthetic data (Kinney, Reiter, and Miranda 2014; Miranda and Vilhuber 2016; Vilhuber, Abowd, and Reiter 2016). Researchers from the Duke-NISS node are collaborating with the Census Bureau on creating a synthetic-data version of the 2017 Census of Manufactures. The Duke-NISS node has also developed and extended techniques for securely and privately providing users with feedback on the quality of their inferences from the synthetic data (Chen, Machanavajjhala, Reiter, and Barrientos 2016). These include differentially private statistical significance tests, receiver operating characteristic curves (Park, Goo, and Jo 2004), and plots of residuals versus predicted values for linear and logistic regression; an R software package is under development. Synthetic data techniques have caught the attention of the popular press (Callier 2015). Finally, the Missouri and Duke-NISS nodes have collaborated to propose disclosure avoidance methods for spatially correlated data (Quick, Holan, Wikle, and Reiter 2015b; Quick, Holan, and Wikle 2018).

How can the transparency of research using an agency's confidential data be increased, for instance, to ensure reproducibility? Scientific integrity requires curation of the provenance of the data used in such research. In turn, reproducibility of the use of confidential data ultimately improves its quality. But confidentiality concerns have often proven an impediment to achieving these goals. Expansive codebooks or detailed metadata is subject to the same confidentiality constraints as the actual data. For instance, Internal Revenue Service regulations prevent the naming of certain variables (columns) in the data, and yet codebooks need to be complete and accurate. Similarly, standard summary statistics include ranges (maxima and minima) and percentiles, which are subject to disclosure avoidance measures. These constraints are not handled well (or at all) by traditional tools for data documentation and are hard to verify in user-generated documents. Researchers at the Cornell node have proposed enhancing various standards for curating metadata in a way that respects these confidentiality constraints imposed on the curators (Abowd, Vilhuber, and Block 2012; Lagoze, Block, Williams, Abowd, and Vilhuber 2013a; Lagoze, Vilhuber, Williams, Perry, and Block 2014). A software system to implement the enhancement was developed, the Cornell Comprehensive Extensible Data

Documentation and Access Repository, and is used to disseminate various codebooks (SIPP "Synthetic Beta File" and the Census Bureau's Synthetic Longitudinal Business Database). Additional work aims to further expand the standard to embed provenance information, allowing researchers to tie diverse public-use and synthetic data products to common confidential source files (Lagoze, Willliams, and Vilhuber 2013b).

2.4 Using Spatial and Spatio-Temporal Statistical Modeling to Improve Estimates

The ACS design explicitly combines spatial and temporal information to produce annual and five-year estimates for many subpopulations. These estimates are released with associated margins of error (MOEs that define 90-percent confidence intervals). Working with current ACS data, researchers at the Missouri node and the Colorado-Tennessee node have each developed new spatial techniques for aggregating and disaggregating the basic ACS estimates geographically. In particular, the Missouri node introduced methodology that uses a Bayesian spatio-temporal model that can create estimates over customized (user-defined) geographies and/or times, with associated measures of uncertainty (Bradley, Wikle, and Holan 2015b). Public-use software for implementing their approach was presented at the 2017 Joint Statistical Meetings (Raim, Holan, Bradley, and Wikle 2017).

A key challenge in working with ACS estimates is that the ACS reporting uses geography (census block groups and tracts) previously used only for decennial census long-form estimates; yet small geographies have large margins of error (Spielman, Folch, and Nagle 2014; Folch, Arribas-Bel, Koschinsky, and Spielman 2016). Interviews conducted with urban planners (frequent users of small area ACS data) show that while they are often aware of this problem, they ignore it (Jurjevich, Griffin, Spielman, Folch, and Merrick 2018). For example, a survey respondent (planner at a regional planning agency), noting that the margins of error (MOEs) from the ACS were sometimes larger than the estimates themselves, said: "I should not use the data or provide a range from 0–200, but often I don't have the time to look in detail at the MOEs for as many geographies and years of data that we have to provide data for. It gets overlooked much too often, but it's hard to have a good solution when there isn't better data available." The Colorado-Tennessee node also conducted usability studies of ACS data through an experiment that monitored keystrokes, mouse movement, and eye movement. They found that when confronted with uncertain data on a familiar city, subjects tended to substitute their local knowledge of the community for the data when making decisions; but when they did not know the city, uncertainty in the data created variability in outcomes of the assigned task (Griffin, Spielman, Jurjevich, Merrick, Nagle, et al. 2014). Combined, these results indicate that there is both a need and a demand for tools to help end users communicate ACS data uncertainty and to make the estimates more usable for analysis.

That node took two approaches to that task. First, the node developed software that groups demographically similar and spatially adjacent census tracts (or any census geography) into "regions" (Folch and Spielman 2014; Spielman and Folch 2015). As tracts are grouped together, variances of the estimates typically decrease. Since ACS uncertainty varies from attribute to attribute, the user can select the particular attributes relevant for their research question to generate the maximum number of regions, where each region's attributes meet a data-quality threshold. (Data and interactive visualizations are available for four data scenarios on all US metropolitan statistical areas at www.reducinguncertainty.org.) The second approach uses multivariate statistical clustering to group demographically similar census tracts into latent classes. This approach was used to make a broad hierarchical classification of all US census tracts (Spielman and Singleton 2015). This data product is published and distributed by Carto, a mapping startup based in New York (available at carto.com/data-observatory).

In an effort to design "optimal" statistical geographies, the Colorado-Tennessee node has examined the spatial structure of the American population by measuring the sensitivity of census estimates to gerrymandering. That is, it assesses the effect of altering the boundaries of census tracts. The answer, while preliminary, seems to be "quite a lot in some places." For example, over 10 percent of census tracts saw changes of 10 percent or greater in a measure of segregation (entropy) as the result of changing the tract boundary while keeping the total population constant (Fowler, Spielman, Folch, and Nagle 2018).

Taking a different approach, the Missouri node has developed a statistical framework for regionalization of multiscale spatial processes (Bradley, Holan, and Wikle 2016a). The proposed method directly addresses the important modifiable areal unit problem (MAUP) and the ecological-fallacy problems associated with multiscale spatial data and introduces a criterion for assessing spatial aggregation error. This criterion, called CAGE (criterion for spatial aggregation error), is then minimized to produce an optimal statistical regionalization. The impact of such methodology has significant implications for various FSS stakeholders. For example, various ACS data-users wishing to aggregate tabulations across geographies (using the methods discussed in Bradley, Wikle, and Holan, 2015b) can evaluate to what extent valid inferences can be made; R software packages for CAGE and spatio-temporal change-of-support are currently under development (e.g., see Raim, Holan, Bradley, and Wikle 2017).

Results can be directly referenced to identifiable inputs in the statistical system and reproduced reliably from those inputs. Advances in the curation of the metadata help ensure that the agency's use of these methods can be audited and its published results can be reproduced. Reproducibility is not always possible for data analysis based on commercial data such as Google Trends, but the Michigan node's research using Twitter feeds can be reproduced because they post their underlying data.

The Missouri node has also been actively engaged in developing hierarchical statistical models that leverage different sources of dependence (e.g., multivariate, spatial, and spatio-temporal) to improve the precision of estimates from various data products. Broadly speaking, many of the proposed techniques can be viewed as natural generalizations of the methods currently used for small-area estimation by most statistical agencies. That is, they are generalizations of the Fay and Herriot (1979) model (Sengupta and Cressie 2013a, 2013b; Porter, Holan, Wikle, and Cressie 2014; Bradley, Holan, and Wikle 2015a, 2016a; Bradley, Wikle, and Holan 2015b, 2016b, in press; Porter, Holan, and Wikle 2015a, 2015b; Porter, Wikle, and Holan 2015c; Cressie and Zammit-Mangion 2016); for additional details, see Appendix C of the online supplementary material. The Missouri node has developed the hierarchical-statistical-modeling approach in ways that will give federal statistical agencies a distinct advantage for their data products over commercial value-added resellers of the same data. This advantage stems directly from the agency's access to and use of the complete set of geographic identifiers and original data values in doing the calculations and then applying statistical disclosure limitation to the outputs (Quick, Holan, Wikle, and Reiter 2015b; Quick, Holan, and Wikle 2018). The methodologies developed at the Missouri node typically use the Census Bureau geography definitions, but they provide the flexibility to depart from this restriction. In other words, the proposed methods retain the ability to operate from customized geographies and/or temporal supports through the use of a change-of-support approach (Bradley, Wikle, and Holan 2015b, 2016b); see Appendix C of the online supplementary material. Furthermore, the small area estimates come with a measure of their uncertainty that allows prediction intervals to be constructed.

There are numerous examples of multiple surveys disseminating related demographic variables that are measured over space and/or time. The Missouri node's methodology combines the disseminated estimates from these surveys to produce estimates with higher precision. Additionally, in cases where estimates are disseminated with incomplete spatial and/or temporal coverage, the Missouri node's approach leverages various sources of dependence to produce estimates at every spatial location and at every time point. The approach for combining the multiple surveys is developed as a fully Bayesian model. The proposed methodology is demonstrated by jointly analyzing period estimates from the Census Bureau's ACS and concomitant estimates obtained from the Bureau of Labor Statistics Local Area Unemployment Statistics program (Bradley, Holan, and Wikle 2016a).

More generally, the Missouri node uses spatial, spatio-temporal, and/or multivariate dependence structures to generate point-in-time estimates of subpopulation quantities and to provide an associated measure of uncertainty. (Traditional Fay-Herriot small-area estimates are a special case.) Flexible models have been introduced that allow estimation for both Gaussian and non-Gaussian settings (Sengupta and Cressie 2013a, 2013b; Porter, Holan, Wikle, and Cressie 2014; Bradley, Holan, and Wikle 2015a, 2016a, 2017, 2018; Bradley, Wikle, and Holan 2015b, 2016b, in press; Porter, Holan, and Wikle 2015a, 2015b; Porter, Wikle, and Holan 2015c). Extensions of the method can be used to incorporate other variables from the frame or related frames. For example, Bradley, Holan, and Wikle (2016a) introduce a multivariate mixed-effect spatio-temporal model that combines estimates from the Bureau of Labor Statistics' Local Area Unemployment Statistics with estimates from the ACS to produce estimates that have significantly improved precision over using either survey individually. Cressie and Zammit-Mangion (2016) take a conditional approach to multivariate modeling in the Gaussian setting.

Visualization constitutes another important component in the analysis of spatial and spatio-temporal data. Using the ACS, Lucchesi and Wikle (2017) develop and present methods for simultaneously visualizing areal (spatial) data and its uncertainty using bivariate choropleth maps, map pixelation, glyph rotation, and animations (see Appendix D of the online supplementary material for further discussion and examples). Spatial data can also be used to provide timely information about changing economic conditions. In work by the Michigan node that combines the themes of nondesigned data and geospatial analysis, Wilson and Brown (2015) use satellite imagery to show how the Great Recession affected southern Michigan by measuring changes in visible impervious surface area (VISA). The article shows that VISA (e.g., structures and paved roads and parking lots) declined from before the Great Recession (2001–2005) to after (2006–2011). This novel application of satellite imagery provides a new tool for measuring changes in economic activity.

2.5 Assessing Data Cost and Data-Quality Tradeoffs

Fundamental problems for the US Federal Statistical System (and for government statistical agencies around the world) include how to understand the value of the statistics they produce, how to compare value to cost in order to guide rational setting of statistical priorities, how to increase value for given cost, and how to better communicate the value of their data programs to those who set their budgets. The market does not provide a measure of value because government statistical data is a public good, so to understand their value it is necessary to understand how the statistics are used and what would occur if the statistics were available with different data quality characteristics. The Northwestern node extended and applied statistical decision theory, including cost-benefit analysis, to attack such basic questions.

Spencer, May, Kenyon, and Seeskin (2017) developed a cost-benefit analysis for the 2016 quinquennial census of South Africa to an alternative of no census. They measured benefits arising from more accurate allocations of funds due to improved population numbers. Improved fund allocation was also a consideration for similar analyses in the United Kingdom and New Zealand, which assumed that the fund allocation formulas optimized social welfare when applied to error-free statistics. In contrast, Spencer et al. explicitly allowed for willingness to pay for improved accuracy in allocations.

The 2020 US Census is highly cost-constrained relative to previous censuses, and there is uncertainty about the quality of the census attainable for the allowed cost. Seeskin and Spencer (2015) considered alternative specifications of census quality and modeled the effects on (1) the funding allocation of more than $5 trillion over the decade of the 2020s and (2) the distribution of seats in the US House of Representatives in 2022. They allowed for vectors of errors in census state population sizes to have arbitrary means, standard deviations, and correlations and to be either multivariate normally distributed or multivariate-*t* on four degrees of freedom. For a given cost-quality relationship, their analysis permits estimation of the distortions in distributions of funds and seats that arise for a given cost in order to reveal the tradeoffs. For example, when the average standard deviation of a state's population is 2 percent of its actual population, the expected number of seats going to the wrong state is about 6.5, and the expected amount of misallocated federal funds over the ten-year intercensal period is $40 billion. The expected absolute deviations in apportionments and in allocations both increased approximately linearly with the average relative standard deviation of state population numbers. Seeskin and Spencer (2018) extend the analysis of changes in apportionment caused by census error, using short-term projections of state populations based on the Census Bureau's postcensal population estimates for 2017 and assuming that patterns of error in 2020 state populations are similar to those measured for the 2010 census, except that the magnitudes may be larger. They found that when three House seats are shifted, the losing states are Texas (two seats) and Florida (one seat).

In other work at the Northwestern node, Manski (2015) distinguished transitory statistical uncertainty, permanent statistical uncertainty, and conceptual uncertainty. He illustrated how each arises as the Bureau of Economic Analysis periodically revises Gross Domestic Product estimates, the Census Bureau generates household income statistics from surveys with nonresponse, and the US Bureau of Labor Statistics seasonally adjusts employment statistics. He anchors his discussion of communication of uncertainty in the contribution of Morgenstern (1963), who argued forcefully for agency publication of error estimates for official economic statistics (as is done by the Census Bureau for monthly and quarterly economic indicators releases). In a related technical article, Manski (2016) elaborated on the theme of communicating uncertainty in official statistics, focusing on the permanent statistical uncertainty created by survey nonresponse. In current work, Manski is focusing on the crucial survey design question regarding how much data to collect and how much effort to expend to enhance the quality of the collected data when faced with a fixed budget. Dominitz and Manski (2017) used decision theory with a minimax regret principle for choosing between a high-cost, high-accuracy survey and a low-cost, low-accuracy one, where low-accuracy is considered in two ways: imprecise survey responses and unit nonresponse.

2.6 Combining Information from Multiple Sources

Distinguished from record linkage, which attempts to combine data sources in a way that matches information from multiple sources, better estimates can be made by combining information from multiple sources by modeling. One particular extant example is the Census Bureau’s Small Area Income and Poverty Estimates program (www.census.gov/programs-surveys/saipe.html; last accessed October 26, 2018). The Missouri node has expanded this research field by developing a hierarchical Bayesian approach using geography and/or time to enhance model estimation and prediction (Bradley, Wikle, and Holan 2015b), in effect creating powerful spatio-temporal mixed effects models that include Fay and Herriot (1979) models as a special case. Given the available surveys, the conditional distributions of the latent processes of interest are used for statistical inference. To demonstrate the proposed methodology, researchers from the Missouri node have jointly analyzed period estimates from multiple surveys (Bradley, Holan, and Wikle 2016a). For example, the proposed model combines data from the ACS and the Local Area Unemployment Statistics program to provide improved estimates of unemployment rates.

Other ways to improve socio-economic estimates from the ACS involve models and data internal to the Census Bureau. For example, should modeling using external data sources be used to improve upon the direct survey estimates available from a household survey? And should survey-based (direct) estimates, model-based estimates, and mixed (weighted) estimates all be produced, or would confidentiality suggest limiting the types of data (and variables) that are modeled? The experience of the Census Bureau with its Small Area Income and Poverty and Health Insurance Estimates programs to address this question is relevant, as it attempts to expand the modeling to unemployment rates (noted above) and to the estimation of jurisdictions required to offer multi-lingual ballots under section 203 of the 1965 Voting Rights Act. Modeling can be used to generate new ACS estimates other than those published for fixed geographies and fixed time periods (currently one year and five years); for example, a four-year period estimate for a particular combination of census tracts representing a neighborhood (Bradley, Wikle, and Holan 2015b).

3. THE IMPORTANCE OF COLLABORATION

As the NCRN matured, the opportunities and desirability of direct collaboration across the nodes and with the FSS agencies (particularly the Census

Bureau) became more apparent. We focus first on internodal collaborations, some of which resulted from movement of students between nodes (e.g., from being postdoctoral fellow at one node to then being a faculty member at another node). It is likely that internodal collaborations took place only because these universities were linked through the NCRN, especially through the biennial meetings convened by the NCRN Coordinating Office (mostly at the Census Bureau), since the topics chosen by the nodes did not overlap very much (a conscious decision by the NCRN program sponsors).

Examples of internodal collaborations include the following: (1) Duke-NISS and Missouri on generating synthetic geographies; (2) Duke-NISS and Carnegie Mellon on improvements to Fellegi and Sunter (1969) matching models; (3) Duke-NISS and Cornell on continued development of synthetic establishment data; (4) Missouri and most of the other nodes at the 2016 "Workshop on Spatial and Spatio-Temporal Design and Analysis for Official Statistics"; (5) Michigan, Carnegie Mellon, Cornell, and Duke-NISS on evaluating methods for probabilistic linkage; (6) Michigan and Cornell on implementing model-based probabilistic linkage for economic units, enhancing surveys with measures from administrative data, and evaluating quality of survey measures using administrative data; (7) Michigan and Duke-NISS on SIPP training; (8) Nebraska and Carnegie Mellon regarding the development of an automated calendar for survey use; and (9) Missouri and Cornell on spatio-temporal models for the LEHD program.

One of the most active collaborations between Census Bureau and nodal researchers was the Summer Working Group for Employer List Linking (SWELL). The purpose of this group, which included researchers from the Michigan, Carnegie Mellon, and Cornell nodes and Census Bureau staff, was to develop tools for linking person-level survey responses to employer information in administrative records files using probabilistic record linkage. Once the linkage was accomplished, there were four areas of potential payoff: (1) production of a research-ready crosswalk between survey responses and administrative employer records, including quality metrics to help users assess the probability that a particular link is correct; (2) comparison of self-reporting to administrative measures (e.g., location, earnings, firm size, industry, layoffs) enabling the enhancement of data quality by improving edits and imputations; (3) creation of improved or new measures available to users without increasing respondent burden; and (4) investigation of new research questions that could not be answered by either dataset alone (e.g., through creation of new variables and longitudinal outcomes or histories). The group has produced software (in SAS and STATA) for standardizing business names to allow improved linkages between survey reports of business names and administrative data from those employers (for the STATA version, see Wasi and Flaaen 2015). The research also helps to improve the Census Bureau's ability to design employer surveys that sample firms based on the composition of their employees so that there can be better and more representative estimates of the characteristics of the employers of American workers. This successful collaboration was only possible because of the existence of a Federal Statistics Research Data Center (FSRDC) at each location, allowing the sharing of data and research in real time. Despite the seasonality (Summer) implied by its name, SWELL is an ongoing collaboration.

Other examples of direct collaborations of node researchers with Census Bureau staff include the following: (1) development of a model to predict 2020 Census quality, as measured by the accuracy of the state population totals (Northwestern); (2) assessment of respondent comfort with geolocation of their home (Carnegie Mellon); (3) improvements in multiple file matching methods to aid the 2020 Census (Carnegie Mellon); (4) research to better understand residential mobility (Colorado-Tennessee); (5) imputations for missing business and demographic estimates (Duke-NISS); (6) development of methods for creation of synthetic business data (Duke-NISS); (7) creation of a synthetic data version of the 2017 Economic Censuses (Duke-NISS); (8) improvements in confidentiality protection of demographic data (Cornell); (9) participation in the Census Bureau's ACS Data Products Design working group (Colorado-Tennessee); (10) provision of advice on plans for 2020 Census operations, specifically on geographic targeting for the communications campaign, non-response follow-up, and coverage measurement (Colorado-Tennessee); (11) development of an imputation methodology for the Monthly Advance Retail Trade Survey, development of model-based statistical methodology for in-office address canvasing, and implementation of space-time methodology using ACS estimates (Missouri); (12) provision of advice to Census Bureau staff on revising the American Time Use Survey user interface where SIPP Event History Calendar navigation patterns are shown to be associated with data quality, which have potential implications for interviewer training (Nebraska); and (13) working with the Census Bureau's Center for Survey Measurement to assist with detecting measurement error through paradata (Nebraska).

There are still challenges for the transfer of the new technologies and for approaches to practical implementation. The thing most likely to produce technology transfers is direct collaboration between Census Bureau staff and node researchers. Because of the challenges in implementing many of the collaborative innovations, they produce fewer scientific publications but ensure that the research bears direct fruit within the FSS agencies. Many of the NCRN researchers now collaborate in solving ongoing implementation issues because NCRN greatly expanded FSS access to academic collaborators. Appendix E of the online supplementary material lists both active NCRN-FSS collaborations and collaborations that have led to changes in FSS production processes.

The SWELL does demonstrate the value of collaboration between academics and FSS staff when there are common scientific goals, especially where these intersect with operational requirements of the FSS. On the geography front, researchers affiliated with the Colorado-Tennessee node are collaborating with the US Geological Survey (Wood, Jones, Spielman, and Schmidtlein 2015), Oak Ridge National Laboratory, and the US Forest Service to improve their use of small-area data. Researchers from the Missouri node collaborated with the US Centers for Disease Control and Prevention on methodology for disclosure avoidance (Quick, Holan, and Wikle 2015a).

One possible amelioration of this lack of direct collaboration would be through colocation. Several individuals have attempted to take the results of their basic research and assist the Census Bureau in implementing their results by working on-site at the Census Bureau. One common approach has been for these individuals to become temporary federal employees, either through the Intergovernmental Personnel Act, as “Schedule A” employees, or through summer student employment or fellowships (such as dissertation fellowships) or the “Summer at Census” program. Still others have become off-site collaborators, working on such projects as improving the American Time Use Survey time diaries collected by the Census Bureau for the Bureau of Labor Statistics, improving the SIPP Event History Calendar for the Census Bureau, and revising the Census of Manufactures edit and imputation and data-dissemination strategies. Other topics that these “partially resident” researchers are working on include capture-recapture methodology (relevant for the estimation of census error), small-area estimation for the ACS and other surveys, improving editing and imputation for missing data, improving record-linkage practices allowing for uncertainty, implementing better storage paradigms for paradata, determining how to use paradata to identify problems, and improving the LEHD database. Other collaborations include matching the SIPP to the LEHD database (including development of a new-firm quality measure), improving the measurement of pension buyouts, SWELL, and linking import-export data to the Longitudinal Business Database and to non-Census Bureau data on multinationals to allow new types of research (but available only to Census Bureau and FSRDC researchers).

4. LESSONS LEARNED

The NCRN has been recognized with the 2017 Statistical Partnerships among Academe, Industry, and Government (SPAIG) award from the American Statistical Association “for addressing methodological questions of interest to the federal statistical system and training future generations to design, conduct, analyze, and report official statistics.” The network nodes have individually been productive, both in the basic and the applied research domains, with many publications, including many in high-impact journals. Cross-node and government-university collaborations have occurred that probably would not have happened in the absence of a network, encouraged by the semi-annual open NCRN meetings (mainly at the Census Bureau).

Yet, improvements are desirable and possible. We believe that there are five valuable lessons that have been learned about government-academic research partnerships.

First, better coordination between the agency and academic partners leads to more useful research outcomes. One suggestion is that "ways be found to facilitate not only the ability of academic scholars to spend time working within . . . government agencies but also that key agency career researchers be encouraged and detailed to spend significant periods of time at the university-based research nodes where they can actively participate in the development of methodologies and basic science advances being pioneered there" (NSF-designated external reviewers of the NCRN program have suggested that key agency career researchers be encouraged to spend significant time at university-based research nodes where they can actively participate in the development of basic science and statistical methodologies, February 2015). As noted previously, the Census Bureau has already implemented part-time employment relationships, allowing the agency to bring the university-based researchers onto their agency teams directly. Moreover, better dissemination and communication across FSS agencies, perhaps through the Interagency Committee on Statistical Policy (chaired by the US Chief Statistician), would facilitate greater utilization of other relevant research, as well. Should a similar government-academic partnership be pursued in the future, we encourage the government agencies to think about likely collaborations in advance. We note that increased participation of different FSS agencies in the FSRDC network will also support the dissemination of research relevant to the entire FSS.

Second, the cross-fertilization that will result from academics working in close collaboration with government researchers will further enhance technology transfer. It is not enough for academics to invent new and useful methods if it is difficult for the relevant agencies to adopt those new methods. Adoption of several new techniques emanating from the NCRN nodes is well underway at the Census Bureau due in large part to those same researchers assisting the Census Bureau with the adoption.

Third, it is important to think through in advance the issues of academic access to confidential data. While participating in the FSRDC program (then the Census Bureau RDC program) was not a requirement for a grant, all but one of the nodes without an RDC eventually joined that program, and their research benefitted from access to restricted data. The FSRDCs could also provide a convenient way for Census Bureau staff to work in an academic setting for extended periods without losing touch with ongoing agency activities that might require access to confidential data. Furthermore, the FSRDC program can be used to link together collaborators from many locales, whether at the host academic institution or not.

Fourth, the ability of FSS agencies to hire students trained as statisticians, whether through government-academic partnerships or otherwise, needs to be improved. Such students have skills most other potential hires do not have, and hiring them can enhance the integration of research results into FSS practices. The main impediments are threefold: the hiring process is complex, the federal wage structure is often not competitive with the industry or academic labor markets, and many students are foreign nationals and therefore not typically eligible under current rules. One mechanism to consider is a periodic virtual hiring seminar for math- and data-oriented students, perhaps run jointly by FSS agencies under the auspices of the Chief Statistician.

Fifth, big data is ubiquitous in the lives of households and businesses. NCRN research is helping statistical agencies implement the use of nondesigned data in official statistics and helping them be better prepared for ongoing changes that are inevitable as agencies rely less on surveys and more on naturally occurring data.

In closing, we note the (inevitable) challenges of managing a network comprising researchers from many disciplines spread across both academia and government. Breaking the disciplinary silos to engage in true cross-disciplinary research is a challenge under any circumstances, and previous NSF-funded networks have certainly encountered the same challenges. Add to that the difficulty of bridging the gap between theory and practice and the various gaps in expectations between academic researchers and government practitioners, and it is clear that any such project can take a while to produce results. Moreover, the path from preliminary results to applied research is sometimes hard to execute, even if it is a clear goal of the academic researcher. A key insight is to keep the network participants talking with one another and the sponsoring agencies; the NCRN's semi-annual meetings were more frequent than those of many other networks, and hence, they may have led to a faster convergence of ideas and language.

Overcoming the challenges to cross-disciplinary collaboration created a unique research situation. The NSF often recognizes the long-term aspect of creating effective collaborations when creating centers of excellence, but these are not typically initiated in collaboration with a non-grant-making agency like the Census Bureau, and the budgetary intricacies of an NSF-agency collaboration are challenging. Nevertheless, any future attempt at creating a network similar in scale and breadth to the NCRN should consider addressing the budgetary issues for at least a ten-year horizon.

Supplementary Materials

Supplementary materials are available online at academic.oup.com/jssam.

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ONLINE APPENDIX A. EXCERPT FROM THE U.S. NATIONAL SCIENCE FOUNDATION SOLICITATION 10-621 TO ESTABLISH THE NSF-CENSUS BUREAU RESEARCH NETWORK

[The full program solicitation can be found archived at https://web.archive.org/web/20170710231924/https://www.nsf.gov/pubs/2010/nsf10621/nsf10621.htm]

Some questions currently of interest related to data collection, analysis, and dissemination processes include the following (these topics are not exhaustive):

Traditional concepts of family and households, as well as traditional concepts of economic units, are rapidly evolving.

- What methods can improve universe frame coverage of persons with intermittent ties with households, for entrepreneurial activities leading to new economic units in economic unit frames?
- What data auxiliary to households and covered persons might be used to estimate the propensity to be covered, as a targeting tool for alternative ways of assembling universe frames?
- Can theories be developed to guide research decisions for sampling unit definitions (derived from frames) and measurement units (e.g., enterprises vs. establishments, households vs. persons) to improve overall designs?
- How can estimates of immigration (both documented and undocumented) be improved?
- Is the concept of an "establishment" still relevant given changing business models and increasingly heterogeneous economic activity?

Participation rates in sample surveys of households and economic units are declining.

- What theories can inform the linkage between nonresponse rates and nonresponse errors?
- What data might be collected or linked to traditional survey data to improve the postsurvey adjustment for nonresponse to reduce nonresponse errors?
- What mechanisms underlie the finding that offering choices of alternative modes of data collection depress overall participation? What antidotes might be created to reduce that effect?
- How can administrative records on persons, households, and economic units be used in conjunction with traditional sample surveys to reduce the nonresponse error of traditional surveys?

The complexity of economic units is increasing, with multiple establishments, loose alliances, multiple lines of business, virtual spatial attributes, and highly dynamic structures.

- How can administrative records be used to improve the tailoring of measurement techniques to diverse types of economic units?
- How can changes in key attributes of economic units be tracked over time to improve the collection of data from the units?
- In longitudinal measurement, how can deaths, mergers, and acquisitions of economic units be forecasted to permit real-time measurement of those phenomena?
- How can multiple modes of data collection facilitate measurement of complex economic units?
- How can we more accurately classify heterogeneous economic activity within business enterprises, individual locations, or aggregates of locations?

Editing and imputation techniques commonly used in sample surveys currently have few evaluative frameworks that guide decisions on what approaches maximally reduce bias in final *estimates.*

- What logical or statistical approaches might offer guidance to the tradeoff decision of how much editing is optimal for diverse purposes?
- What editing algorithms might be developed to reduce the post-estimation review processes common in statistical estimation?
- What computer-assistance in editing might be developed to reduce the use of subject matter expertise in the review of data from longitudinal and other surveys?
- How can empirical diagnostic tools for evaluating auto-coding algorithms and large scale imputation approaches be improved?

Administrative records, when combined with survey data, may offer radically increased efficiencies in household and business surveys.

- What mathematical and statistical frameworks might be used to improve inference from probabilistically linked datasets?
- How can the social science community effectively monitor public attitudes toward administrative record usage?
- What conceptual frameworks might be developed to measure the error properties of linked survey and administrative record data?
- What imputation techniques can be created to deal with item missing data in linked files with variables common to multiple datasets?

While public use datasets have greatly benefited quantitative research in the social sciences, the data are increasing threatened by risk of inadvertent reidentification of sample members.

- What disclosure avoidance techniques can be developed to preserve pledges of confidentiality and maximize access to data?

- Can disclosure risk measurements be invented to guide practical decisions of data collectors regarding the release of data?
- How can synthetic data be produce that mimic the statistical properties of actual data but protect the identity of respondents?
- What effective analytic software approaches might be used to permit analysis of data without direct access to the data and protect pledges of confidentiality?

Small domain estimation using survey data offers the promise of greatly expanded useful estimates from sample surveys.

- How can model diagnostics be improved on small domain estimators?
- What small domain estimation approaches can exploit the longitudinal nature of surveys?
- What alternative approaches offer improved simultaneous estimation of small domains and higher-level aggregates?
- What practical estimators of total error of small domain estimates might be developed for public dissemination?

Cognitive and social psychological insights into respondent self-reports in social science research have reduced measurement errors.

- What questionnaire development tools are superior for detecting different mechanisms of response error?
- What diagnostic tools in instrument development can be enhanced through computer assistance?
- How do we identify optimal measurement approaches for a single construct using individual modes of data collection?
- What diagnostics can be developed to isolate translation errors as a distinct component of

measurement error in multi-language measurement?

The use of statistical models for large-scale descriptive statistics has advanced in important ways.

- How can diagnostic tools be advanced to measure potential model-specification errors within a total error framework for the estimates?
- What diagnostic tools might be developed using model-based approaches to identify errors in tabular data?
- What models might be useful to estimate sampling error covariances and auto covariances in longitudinal estimates?
- What statistical models might be useful to forecast final estimates based on preliminary measurements of a sample?

New approaches to disseminating census data to users are emerging, and new requirements for confidentiality protection will be required.

- What metadata approaches will be most useful in documenting census data, and how can existing metadata systems be improved?
- How can census data dissemination, including both tabular and microdata, be improved?
- What are the most significant risks in disseminating census data to user communities, and how can those risks be diminished?
- What approaches can be developed that will allow the user community to safely and securely access census and other administrative data that have been merged across multiple agencies or sources?

ONLINE APPENDIX B. OTHER OUTCOMES: STUDENTS, COURSES, AND SOFTWARE

Knowledge dissemination to a broader audience, and fostering of collaborations within the network, were an important component of the overall effort. Beyond the traditional academic research papers, each of the nodes also regularly presented new results in a "virtual" seminar, with researchers and students from all nodes, but also non-affiliated research institutes, actively participating through multi-site videoconferencing. Nodes added "official statistics" components to both undergraduate and graduate courses, often as "special topics." A multi-site course on "Understanding Social and Economic Data," led by researchers from the Cornell node, was taught as a hybrid distance-learning/remote-learning course, with typical attendance involving a dozen sites and over one hundred students and faculty, spread across the United States (course materials and video lectures are available at https://www.vrdc.cornell.edu/info7470/). Several other nodes created new course materials, workshops, and short courses (Michigan, Nebraska, Duke, Missouri) (see online Appendix B).

The University of Michigan offered a seminar for honors economics students, "Naturally-Occurring Data and the Macroeconomy" in 2016, wherein undergraduates did research using "big data" techniques advanced by the Michigan node. This course will be offered in future years. Aaron Flaaen used non-design data to create a new measure of the multi-national status of firms, linked it to the Census Business Register, and made it available to Census Bureau researchers and researchers in the FSRDC network (Flaaen 2015); his analysis using these measures received the World Trade Organization Award for Young Economists. Isaac Sorkin developed and implemented a method for measuring employer quality based on the firm's relative ability to hire and retain employees. This work used eigenvalue techniques that allow analysis of flows across all connected establishments in the United States (Sorkin 2015, 2018).

The Nebraska node created two new courses. The Interviewer-Respondent Interaction course explored different interviewing methods, methods to observe and analyze verbal behaviors during interviews, and methods to analyze these data (Belli 2012). The Survey Informatics course explored the role of technology throughout data collection, data management, and data analysis within survey research, as well as the increasing need for interdisciplinary teams within research to draw from the strengths of different disciplines (e.g., survey research and methodology, computer science and engineering, cognitive psychology, sociology, statistics, etc.); see Eck (2015a, 2015b) and Eck et al. (2015a, 2015b).

The nodes have also developed short courses, workshops, and modules for use in college courses. These include:

- Short course on spatio-temporal statistics taught at the Census Bureau but open to staff at other FSS agencies (Missouri).
- Short course, "Introduction to Privacy" (Carnegie Mellon).[1]
- Short course on record linkage (data matching) (Carnegie Mellon).[2]
- Short course on missing data for the Odum Institute (Duke).
- Short course on synthetic data for the Joint Program on Survey Methodology and the 2017 Joint Statistical Meetings (Duke).
- Topic modules on causes and statistical models for interviewer effects in survey data (Nebraska).
- Workshop on spatial demography and small-area estimation, "Measuring People in Place," at the University of Colorado (Colorado-Tennessee).

[1] http://www.stat.CMU/NCRN/PUBLIC/education.html#Priv
[2] http://www.stat.CMU/NCRN/PUBLIC/education.html#RLF13

- Workshops on using the SIPP and the synthetic SIPP (with matched earnings records from the Social Security Administration), conducted at Michigan, Duke, Census, and Population Association of America annual meetings, taught by Michigan and Census Bureau researchers (Michigan).[3]

A 2-day workshop on Spatio-Temporal Design and Analysis for Official Statistics, organized and hosted by the Missouri node in May 2016. More than 40 researchers invited from both inside and outside the NCRN were involved in a series of break-out discussions. A summary of those discussions was distributed to workshop participants and is archived at the Cornell University library (Holan et al. 2016).

One hope was that node-trained students would choose to work at a FSS agency upon graduation. Of course, successfully trained students also have other options, and it is difficult to assess empirically how many students gave the FSS consideration as an employment opportunity. As of this writing, we are aware of four NCRN-trained graduates at the U.S. Census Bureau, from the Duke and Missouri nodes, though several students have accepted positions at other agencies and companies that interact closely with the FSS. Based on the authors' experience in guiding students through the placement process, and based on interviews with colleagues and former students, a few observations emerge. First, students do consider the agencies comprising the FSS as potential and attractive employers. However, due to the widespread popularity of "data science," the salary structure of the federal government is not competitive enough to attract such individuals. Furthermore, while graduate students are drawn from many countries, and NSF funding is available to international students, those same students

[3] http://ebp-projects.isr.umich.edu/NCRN/training.html

cannot always be hired by federal agencies, due to legal restrictions that require an employee to be a U.S. citizen. Nonetheless, the exposure of such students to federal datasets and the challenges facing the federal statistical agencies likely still has benefits. As these individuals either continue their education or go on to academic jobs, they take with them an appreciation for federal statistical problems and may continue to focus on federal statistics as research topics.

These educational activities have been particularly important in increasing usage of new, innovative Census data products that are related to the NCRN research. For example, synthetic data (the SIPP Synthetic Beta and Synthetic Longitudinal Business Database datasets), have been available for several years, but the novelty of the data has limited its adoption by social scientists. The courses and the workshop organized by the Michigan node and supported by the Cornell node, described in online Appendix B, introduced graduate students and junior scholars interested in studying the causes and consequences of poverty using the synthetic SIPP data, and it culminated in a researcher-initiated panel at the 2016 American Social Science Associations-Labor and Employment Relations Association meeting.

The nodes have also taken on the task of creating software for others to use in both improving and analyzing federal datasets. The Colorado-Tennessee node developed open-source software for producing new statistical areas (out of existing census areas such as census blocks). This software reduces the variance in ACS estimates through intelligent aggregation.

The Cornell node produced software to edit Data Documentation Initiative (DDI)-formatted metadata, called the Comprehensive Extensible Data Documentation and Access Repository. No existing DDI editor could show the additional features that Cornell had incorporated into the existing (DDI-C) standard, thus requiring the creation of the editor to be able to edit and display the additional data. The 2018 version is CED^{2}AR V2.9.0.

The Duke node has developed several R software packages implementing missing data techniques, including the stochastic edit-imputation for continuous data of Kim et al. (2015), the model for mixed categorical and continuous data of Murray and Reiter (2016), the non-ignorable imputation method of Paiva and Reiter (2017), and the model for categorical data with structural zeros of Manrique and Reiter (2014). It also developed software for generating synthetic values of the decennial census short form variables, using the methodology in Hu et al. (2018); the software ensures that structural zeros are respected (e.g., a daughter cannot be older than her biological father), and it captures within-household relationships.

The Michigan node developed software in STATA and SAS, and a related STATA command, to improve the standardization of employer names and thereby improve record-linkage software for businesses (Wasi and Flaaen 2015). It also improved software to impute tax liability to household surveys that are not linked to administrative data in order to compute the Census Bureau's alternative poverty measure.

The Missouri node is working on R software to implement customized geography and/or time periods (e.g., for the ACS). This software will automate the methodology of Bradley et al (2015). It is also collaborating with a private software company, Esri, on R software to quantify aggregation error from combining smaller geographies, allowing more efficient inferences (Bradley et al. 2017).

The Missouri node has developed R code for visualizing the uncertainty in (spatial) areal data. This software appears in the online supplement to Lucchesi and Wikle (2017) and in the VizU R package available on Github (https://github.com/pkuhnert/VizU).

The Nebraska node has developed a program to automate scrubbing of computer-assisted survey audit trails to ensure confidentiality of all text fields, implemented at the Census Bureau.

This program enabled release of thousands of audit trails by replacing costly and time-consuming human intervention with automated processes.

Links to the software listed, and other software products, can be found at https://www.ncrn.info/software.

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ONLINE APPENDIX E: SPATIO-TEMPORAL HIERARCHICAL STATISTICAL MODELS

In this appendix, additional technical details are provided to illustrate one aspect of spatio-temporal modeling and analysis that the Missouri node has undertaken. Data sources in official statistics are often multivariate (contain a large number of variables), are spatially referenced, recorded over discrete time and contain multiple spatio-temporal scales. Adding to this complexity, the datasets are often extremely large (the so-called “big data” problem with millions of observations) and non-Gaussian. Taking advantage of the inherent dependence structure is essential for increasing the precision of desired estimates, especially in under-sampled or unsampled geographies.

The broad approach proposed by the Missouri node for modeling the complex data arising in official statistics settings can be cast in its most general form as a spatio-temporal mixed effects model. The spatio-temporal mixed effects model includes a fixed effects term that accounts for spatial or spatio-temporal covariates, and a random effects term that is typically formulated in terms of the sum of spatial or spatio-temporal basis functions and associated random coefficients. While it is conceptually straightforward, in practice specific modeling choices must be made with the intent of capturing dependence, while delivering computational feasibility. Model development proceeds through the hierarchical-statistical-model paradigm (e.g. Cressie and Wikle 2011; Holan and Wikle 2016), wherein the basic hierarchical model can be written as a “data model” and a “process model.” If the parameters are estimated, the hierarchical model is called an empirical hierarchical model; if instead a “parameter model” (i.e., a prior) is posited, the hierarchical model is called a Bayesian hierarchical model. Borrowing notation from the hierarchical-modeling literature, consider random variables U and V where $[U|V]$ denotes the conditional distribution of U given V, and let Z be an n_Z-dimensional data vector, Y be an n_Y-dimensional latent random vector, θ_D the data parameters, and θ_P the process parameters. Then, a basic hierarchical model can be specified by $[Z|Y, \theta_D]$ and $[Y|\theta_P]$, with the Bayesian hierarchical model also including $[\theta_P]$. From the discussion above, it is these models that are called the data model, the process model, and the parameter model, respectively. Most of the hierarchical-modeling research in the Missouri node has been of the Bayesian type although, in a precursor to NCRN research, Sengupta and Cressie (2013b) developed empirical hierarchical models for high-dimensional spatial count data using a Poisson data model. This work was followed by NCRN-supported research in Sengupta and Cressie (2013a), where the Poisson data model was generalized to an exponential-family data model. In the remainder of this appendix, the Bayesian hierarchical model will be featured.

For illustration, we proceed with a description of the multivariate spatio-temporal mixed effects model (Bradley et al. 2015a). This model was originally used to model public-use Quarterly Workforce Indicators (QWI) data from the Longitudinal Employer-Household Dynamics Program of the U.S. Census Bureau. The Quarterly data are at the county level for both genders and different North American Industry Classification Sectors (NAICS). 6/10/2019 5:10:00 PMFor $\ell = 1, \dots, L$, $t = T_L^{(\ell)}, \dots, T_U^{(\ell)}$, and $A \in D_{P,t}^{(\ell)}$, the data model is defined by

$$Z_t^{(\ell)}(A) = Y_t^{(\ell)}(A) + \epsilon_t^{(\ell)}(A),$$

where $\{Z_t^{(\ell)}: \ell = 1, \dots, L\}$ represents multivariate spatio-temporal data; $Y_t^{(\ell)}$ represents the ℓ-th latent variable of interest at time *t*; *t* indexes discrete time; and $\epsilon_t^{(\ell)}(\cdot)$ is an iid Gaussian process with mean zero and known variance $v_t^{(\ell)}(\cdot)$. The set *A* represents a generic areal unit on the predictive domain, $D_{P,t}^{(\ell)}$, at time *t* for variable ℓ.

The process model is defined by

$$Y_t^{(\ell)}(A) = \mu_t^{(\ell)}(A) + \boldsymbol{S}_t^{(\ell)}(A)'\boldsymbol{\eta}_t + \boldsymbol{\xi}_t^{(\ell)}(A).$$

In this case, we set $\mu_t^{(\ell)}(\cdot) = x_t^{(\ell)}(\cdot)'\beta_{\mathrm{t}}$,where $x_t^{(\ell)}$ is a known p-dimensional vector of covariates with associated unknown parameter vector β_t. In the process model above, $S_t^{(\ell)} \equiv \left(S_{t,1}^{(\ell)}, \dots, S_{t,r}^{(\ell)}\right)'$, for $\ell = 1, \dots, \mathrm{L}$, denote r-dimensional vectors of spatio-temporal basis functions, and $\{\xi_t^{(\ell)}\}$ represents fine-scale variability assumed to be i.i.d. with unknown variance, $\{\sigma_{\xi,t}^2\}$. In Bradley et al (2015a), these basis functions are specified to be the Moran's I (MI) basis functions. A rich class of areal basis functions was later introduced in Bradley et al. (2017b). For each t, it is assumed that the r-dimensional vector η_t follows a vector autoregressive process of order one; that is

$$\eta_t = M_t\eta_{t-1} + u_t,$$

where η_t is Gaussian with mean zero and unknown $r \times r$ covariance matrix K_t, M_t is an $r \times r$ propagator matrix, and u_t is Gaussian with mean zero and $r \times r$ covariance matrix W_t. After vectorizing $Y_t^{(l)}$ for $t = 1, \dots, T$, by stacking, the process model can be rewritten to avoid spatial confounding. In fact, this representation leads to a modeling innovation referred to as the MI propagator matrix, which is defined analogously to the MI basis functions.

Due to issues with confounding, and because of the reduced-rank structure of the MI basis function and MI propagator matrix, various sources of variability may be inadvertently ignored. To address this concern, $\{K_t\}$ and $\{W_t\}$ are specified as positive-definite matrices that imply a spatio-temporal covariance matrix that is "close" to a target precision matrix that includes the various sources of variability. For comprehensive details, see Bradley et al. (2015a) and the references therein.

The methodology outlined above applies to Gaussian data. However, as previously alluded to, many of the applications found in official statistics arise from non-Gaussian data. A typical approach to modeling such data is to specify a generalized linear mixed model using a latent Gaussian process (Diggle et al. 1998; Rue et al. 2009). That is, in the data-model specification, the Gaussian assumption would be replaced with a distribution from the exponential family. In high-dimensional settings, like those encountered in official statistics, estimation in the non-Gaussian setting is especially challenging. Sengupta and Cressie (2013a) give methodology in the spatial univariate empirical hierarchical model context. In the spatio-temporal multivariate Bayesian-hierarchical-model context, Bradley et al. (2017a, 2018) meet the challenge with new distribution theory that produces a latent conjugate multivariate distribution for the natural exponential family and then implements a multivariate spatio-temporal mixed effects model.

For example, in the case of a Poisson data model, a multivariate log-gamma distribution is proposed (Bradley et al. 2018). In particular, let the m-dimensional vector $w = (w_1, \dots, w_m)'$ consist of m mutually independent log gamma random variables such that $w_i \sim LG(\alpha_i, \kappa_i)$ for $i = 1, \dots, m$. Then, define

$$q = c + Vw,$$

where the $m \times m$ matrix $V \in \mathbb{R}^m \times \mathbb{R}^m$ and $c \in \mathbb{R}^m$. Then q is called a multivariate log gamma (MLG) random vector. For the sake of brevity, we do not include the expression of the pdf for the MLG random vector here; instead, for $\alpha \equiv (\alpha_1, \dots, \alpha_m)'$ and $\kappa \equiv (\kappa_1, \dots, \kappa_m)'$, we denote it as MLG$(c, V, \alpha, \kappa)$. Then, in the Gaussian process model, η and β are assumed to follow a MLG distribution and ξ_i $(i = 1, \dots, m)$ is assumed to follow a log-gamma distribution. See Bradley et al. (2017a, 2018) for comprehensive details related to a Poisson data model and the natural exponential family data model cases, respectively.

The models described above are fully parametric. In principle, the classic Fay-Herriot nested error regression model for small area estimation can be thought of as a special case of the mixed effects models described above. In a spatial setting where it is of interest to relax the distributional assumption on the data model, one can take a semiparametric approach. Specifically, the data model can be specified using an empirical likelihood, and the process model can be specified as a latent Gaussian process. Detailed discussion of the semiparametric empirical likelihood approach can be found in Porter et al. (2015a; b).

Federal survey data are usually presented and analyzed over geographic regions. However, often inference is desired on a different spatial and/or temporal support than the support of the survey data. The problem of conducting statistical inference on spatial and/or temporal supports that differ from the support of the data is known as spatio-temporal change of support (ST-COS). The support of the data is typically referred to as the “source support” (e.g., census tracts), whereas the support of interest is designated as the “target support” (e.g., congressional districts). The majority of methodological contributions for spatial COS are based on assuming that the underlying data are Gaussian and consider spatial-only or count data without explicitly accounting for sampling uncertainty; see Bradley et al. (2016) and the references therein. Motivated by the problem of estimating discontinued 3-year period estimates for the ACS, Bradley et al. (2015b) present methodology that performs ST-COS for survey data with Gaussian sampling errors. In contrast, Bradley et al. (2016) propose methodology for count-valued data in which the change-of-support is accomplished by aggregation of a latent spatial point process that accounts for sampling uncertainty. Importantly, when changing spatial support, it is necessary to be concerned with the modifiable areal unit problem or MAUP (and the ecological fallacy). In other words, inferences made at one level of geography should be consistent at other levels of geography. Bradley et al. (2017b) develop methods to determine when COS is appropriate, that is, when aggregation error is problematic. The proposed statistic is called *Criterion for Aggregation Error (CAGE)*.

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ONLINE APPENDIX D: SPATIAL VISUALIZATION

In this appendix we provide additional details related to the methodology provided in Lucchesi and Wikle (2017)6/10/2019 5:10:00 PM; note that it is not intended as an overview of spatial visualization. The simultaneous presentation of spatial data (or predictions) along with their uncertainties is important for conveying the quality of a spatial map. However, there has long been a concern that adding an uncertainty measure to a map will simply clutter the visualization and make the map more difficult to interpret (e.g., MacEachren et al. 2005). Uncertainty visualization for spatial and spatio-temporal data has been gaining increased attention from statisticians and is providing an opportunity to make use of new tools in statistical software (e.g. Genton et al. 2015). The Missouri node considered several tools to visualize the uncertainty of spatial data, including new formulations of (1) bivariate choropleth maps, (2) map pixelation, and (3) rotated glyphs, as described in Lucchesi and Wikle (2017). This appendix only discusses bivariate choropleth maps in detail, though illustrations of the other two techniques are shown.

The Census Bureau produced some of the first known bivariate choropleth maps in the late 1970s (Fienberg 1979; Olson 1981) 6/10/2019 5:10:00 PM. These maps were designed to visualize two variables, such as death rate and population density. However, they were somewhat controversial in that they were widely considered to be difficult to interpret (e.g. Wainer and Francolini 1980). Suggestions to improve these maps included limiting the color bins, selecting more interpretable colors, and adding more description to the map caption.

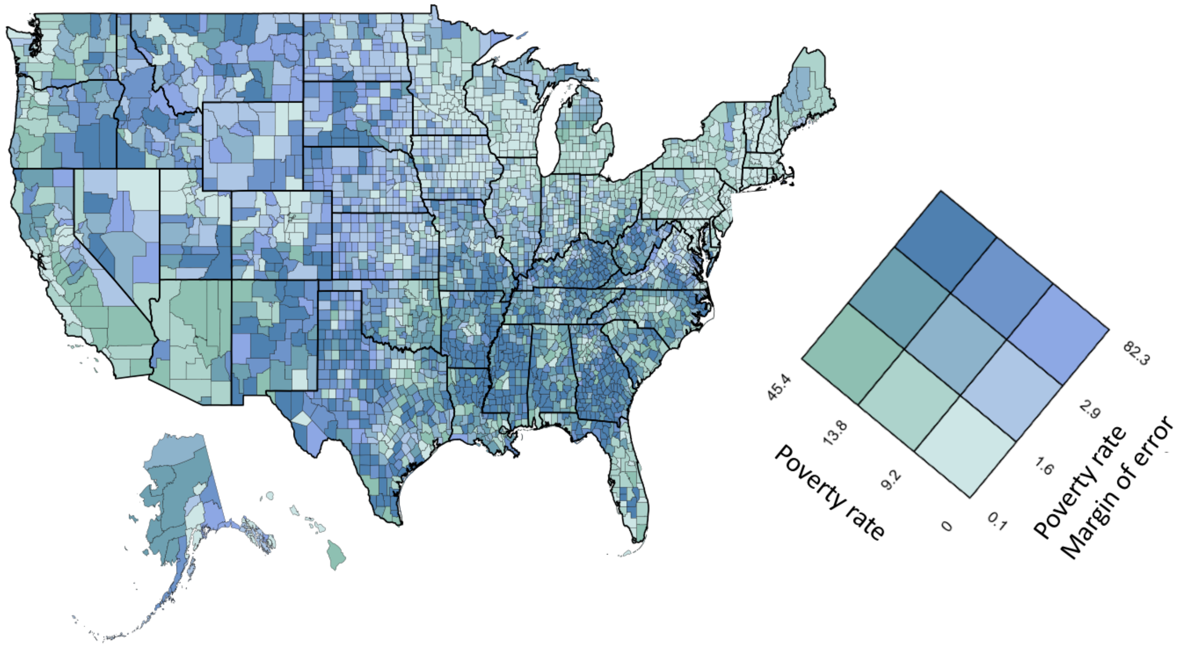
Bivariate choropleth maps have been typically used to visualize two variables; in contrast our interest is in visualizing a variable and its associated uncertainty. There have been previous attempts to perform such a visualization, for example using a diverging color scheme to represent uncertainty and the relative contrast to represent the variable (e.g., Howard and MacEachren 1996). In addition, Retchless and Brewer (2016) used a 4 x 5 grid to represent the variable with color and its uncertainty with the saturation value of those colors. These are not choropleth maps.

The bivariate-choropleth map approach that Lucchesi and Wikle (2017) developed is novel in that it visualizes uncertainty and improves visualization of traditional bivariate choropleth maps. In particular, they use a low-dimensional and interpretable 3 x 3 color scheme that is a natural additive blend of two single-hue red-green-blue color palettes. In addition, the associated key is rotated 45 degrees so that the highest values for both the variable and the uncertainty are at the top of the grid, which is easier to interpret.

This approach is demonstrated here using U.S. county-level poverty rates from the 2011-2015 ACS (see Figure E.1). In this case, each county is assigned one of nine colors depending on the poverty rate and the associated 90% margin of error (MOE). In this case, the counties with the lowest poverty rates and the smallest MOEs are represented by the lightest blue/green color at the bottom of the grid, which is an average of the lightest blue and lightest green color. In contrast, the darkest color is an average of the darkest blue and darkest green color, and it represents counties with the highest poverty rate and the largest MOE. Spatially contiguous clusters and trends in poverty rate and the associated MOEs are apparent in this map.

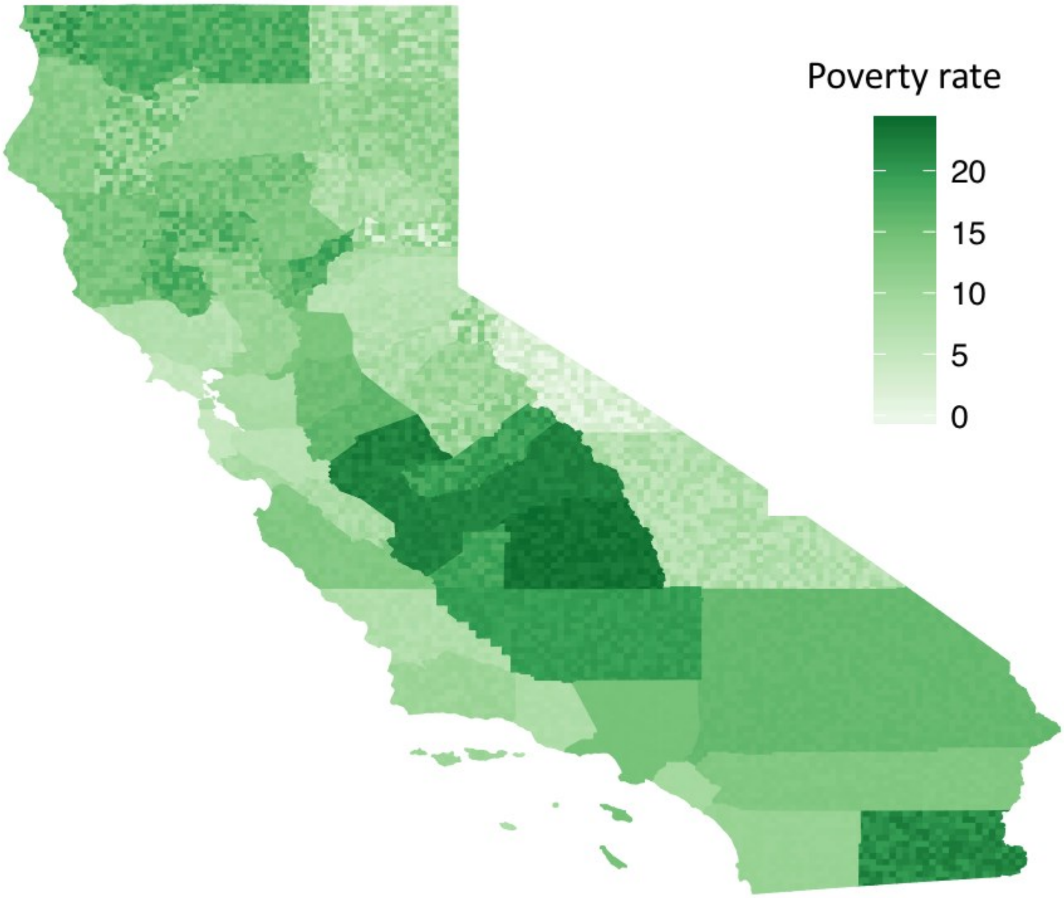
The VizU R package (https://github.com/pkuhnert/VizU) developed by P. Kuhnert and L. Lucchesi allows users to easily investigate different color palettes to aid in the interpretability of a particular map and its uncertainty. The package also allows for other spatial-uncertainty visualization approaches, including map pixelation (see Figure E.2), and glyph rotation (see Figure E.3). Note that the package also allows for the animation of the map pixelation to accentuate the uncertainty.

Figure D.1. U.S. county-level poverty estimates and their uncertainty, 2011-2015, using bivariate chloropleth map approach



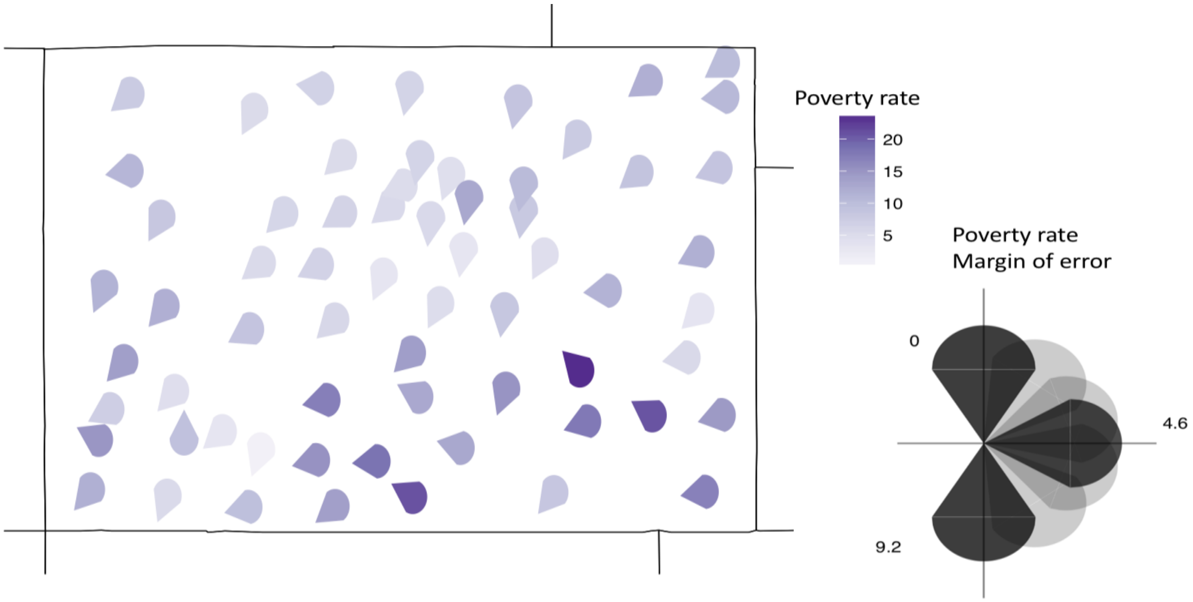
Further details: The bivariate choropleth map shows U.S. county-level 2011-2015 American Community Survey poverty estimates (percentage of families whose income was below the poverty level) and associated uncertainties (90% margin of error, or MOE). The estimates and MOEs are divided into 3 categories by terciles. Each square in the 3 x 3 color key is an average of green, representing poverty rate, and blue, representing MOE.

Figure D.2. State of California county-level poverty estimates and their uncertainty, 2011-2015, using pixelated map approach



Further details: The pixelated map shows county-level 2011-2015 American Community Survey poverty estimates for California and their associated MOEs. Each pixel in a county is assigned a color within the county estimate's MOE. Areas of high uncertainty appear pixelated because the MOE covers a wide range of colors within the palette. Areas of low uncertainty appear smoother because the differences in color between pixels is much smaller.

Figure D.3. State of Colorado county-level poverty estimates and their uncertainty, 2011-2015, using glyph approach



Further details: The glyph map shows county-level 2011-2015 American Community Survey poverty estimates for Colorado and their associated MOEs. The color of each glyph represents the estimated poverty rate among families, and its rotation represents the estimate's MOE.

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ONLINE APPENDIX E. ACTIVE AND IMPLEMENTED NCRN-FSS COLLABORATIONS BASED ON NCRN RESEARCH PUBLICATIONS

Below is a list of the research publications that have had a substantial impact on methods and activities at the U.S. Census Bureau. "Active collaboration" means that there is a current research project at the Census Bureau or another statistical agency based on this work, and one of the NCRN researchers is a current collaborator. "Implemented" means that techniques originally developed or elaborated in the cited research are being or have been engineered into at least one production system. Citations refer to the main article's reference list.

Active Collaborations (as of April 2018)

Belli et al. (2016)

Bradley et al. (2015a, b; 2016a, b; 2017a, c; forthcoming)

Flaaen et al. (2017)

Green et al. (2017)

Kirchner and Olson (2017)

Manrique-Vallier and Reiter (2018)

Olson and Smyth (2015)

Olson et al. (2016)

Olson et al. (forthcoming)

Porter et al. (2014, 2015c)

Quick et al. (2015a)

Seeskin and Spencer (2015, 2018)

Simpson et al. (2018)

Smyth and Olson (forthcoming)

Spielman and Folch (2015)

Sorkin (2016)

Steorts et al. (2016)

Wasi and Flaaen (2015)

White et al. (2018)

Wood et al. (2015)

Implemented Collaborations (as of April 2018)

Abowd et al. (2012)

Abowd and Schmutte (2016, 2017)

Chen et al. (2017)

Kim et al. (2015)

Kinney et al. (2011, 2014)

Lagoze et al. (2013a, b; 2014)

McKinney et al. (2017)

Miranda and Vilhuber (2016)

Murray and Reiter (2016)

Sadinle and Reiter (2017, 2018)

Vilhuber and Schmutte (2017a, b)

Vilhuber et al. (2016)