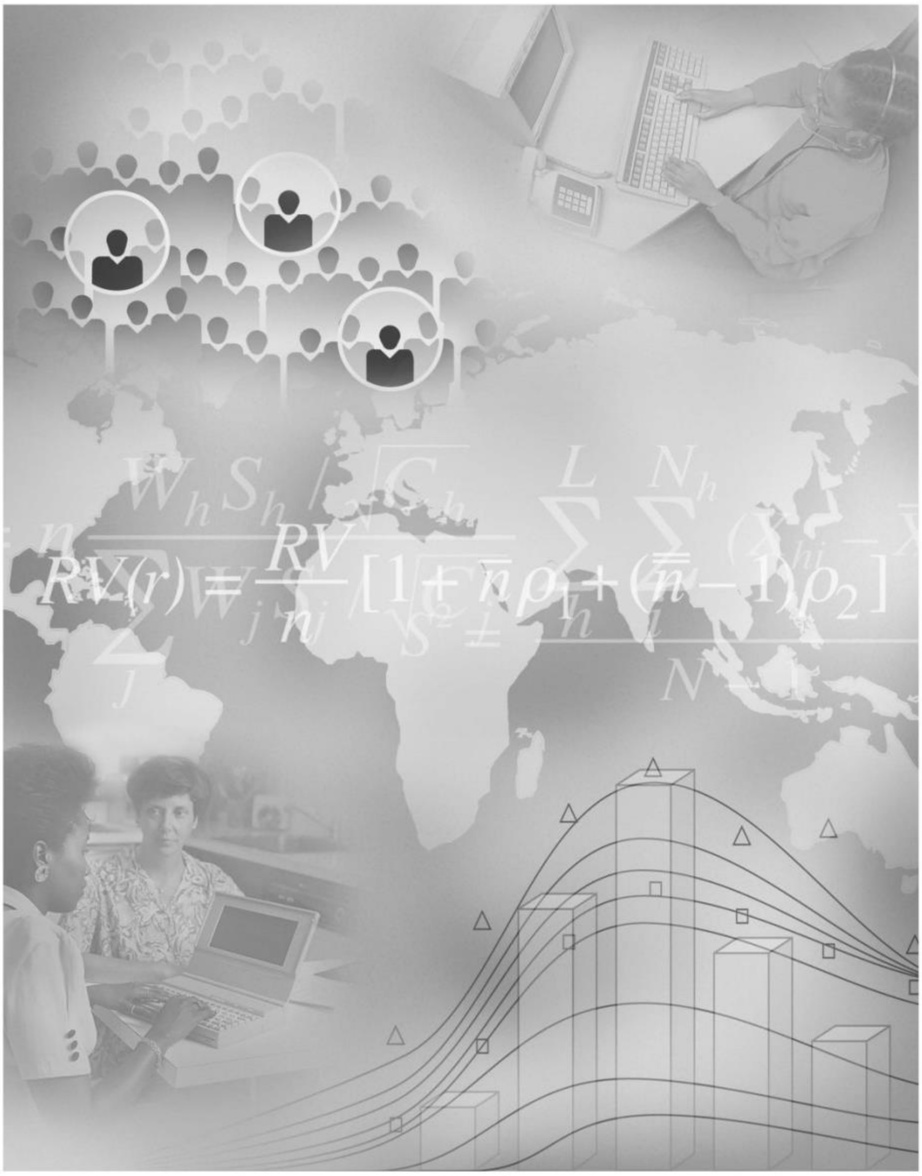
the Survey Statistician

The Newsletter of the International Association of Survey Statisticians

No. 87 **January 2023**



INTERNATIONAL ASSOCIATION OF SURVEY STATISTICIANS

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The Survey Statistician No. 87, January 2023

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Enquiries for membership in the Association or change of address for current members should be found at the section **Promoting good survey theory and practice around the world** on p.11 of this issue or addressed to: isimembership@cbs.nl

Comments on the contents or suggestions for articles in the Survey Statistician should be sent via e-mail to the editors Danutė Krapavickaitė (danute.krapavickaite@gmail.com) or Eric Rancourt (eric.rancourt@statcan.gc.ca).

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In this Issue

Letter from the Editors

Dear readers,

We are happy to present the January 2023 issue of The Survey Statistician.

First, we would like to wish you all a Happy New Year 2023. In particular, we wish to all readers peace everywhere in the World for this is a necessary condition for the development of statistics.

This issue starts with the *Letter from the President* by Monica Pratesi, where she highlights a number of successful achievements of the IASS through some still difficult times and as countries are getting back to some normalcy. It is followed by the *Report from the Scientific Secretary*, Giovanna Ranalli where among other things, she underscores solid participation to the Webinar series and increases in the number of our followers on social media.

In the News and Announcement section, congratulations are expressed to Monica Pratesi on the occasion of her 60th birthday and to Carl-Erik Särndal who celebrated his 85th birthday and the 30th anniversary of the Model-Assisted Survey Sampling book. Congratulations are also expressed to Roderick Little and Raymond Chambers who are respectively the 2022 and 2023 recipients of the Waksberg award. This section also remembers Tim Holt who recently passed away. Finally, there is a call for papers for a special issue of the Journal of Official Statistics on integrating data from multiple sources for production of official statistics.

In the Ask-the-Experts section, Barry Schouten from Statistics Netherlands and Utrecht University; Jan van den Brakel from Statistics Netherlands and Maastricht University; Deirdre Giesen, Annemieke Luiten and Vivian Meertens from Statistics Netherlands discuss the current status and future of mixed-mode official surveys. They argue that in the context of declining response rates and in general, surveys will have to adapt and the mode is a powerful feature to enable this.

In the New and Emerging section, Annamaria from University of Bergamo, Camilla Salvatore from University of Milano-Bococca and Silvia Biffignandi from Consultancy in Economic Statistics Studies (CESS) describe how social media can be used to enhance survey data. They propose a modular framework to produce smart statistics and indicators.

In the Book and Software Review section, Maria Michela Dickson from the Department of Economics and management, University of Trento presents the book: Multiple imputation of missing data in practice – Basic theory and analysis strategies. It is then accompanied by a practical paper by Yulei He and Guangyu Zhang Division of Research and Methodology National Center for Health Statistics, U.S. Centers for Desease Control and Prevention on how to use SAS® to conduct multiple imputation.

Then follows the country reports, the list of upcoming conferences and recently published articles in various journals. We would like to express our many thanks to the section editors for their attentive and timely work. This work resulted in 15 interesting country reports to the current issue of TSS. Thank you also to Peter Wright for editing these 15 country reports.

The health of *The Survey Statistician* depends on participation by many members. If you have any information about conferences, events or just ideas you would like to share with other statisticians – please do go ahead and contact any member of the editorial board of the newsletter.

The Survey Statistician is available for downloading from the IASS website at http://isi-iass.org/home/services/the-survey-statistician/.

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Letter from the President

Dear Friends of the IASS,

The year 2022 still saw us going through difficult times and we all tried to identify solutions in different unique ways to keep us healthy and safe from the ongoing pandemic. Thankfully things have been under control in most of the countries and all of us are gradually limping back towards normalcy.

I am happy that amongst all these hardships, wars and difficult times in many countries we have still been able to keep our mission of Promoting good survey theory and practice around the world.

We were successful in conducting IASS webinar programs ourselves and in collaborations with other organizations throughout the year. You will be pleased to know that a series of webinars on survey methods, inference from surveys and other data sources have already been put in place and are available on the IASS website. These webinars are open access and can be used by our members all over the globe for learning purposes. This has been facilitated by our active IASS Executive Committee members along with the colleagues of ISI PO. The lectures are all available on the IASS website for you to revisit and share.

IASS has organized and promoted competitions to award scientific prizes to its members: the new Hukum Chandra prize to Prof. Torabi who provided a special invited webinar on October 26th. See: http://isi-iass.org/home/events/iasswebinar-22-2022-hukum-chandra-prize-winner/, to contribute in research areas of Hukum's work. The 2023 recipient of the Waksberg Award is Prof. Ray Chambers, who will give the Waksberg Invited Address at a special IASS Invited Papers Session at the World Statistics Congress and publish a paper in Survey Methodology. The traditional Cochran-Hansen Prize will be awarded in 2023 for the best paper on survey research methods submitted by a young statistician from a developing or transition country. See http://isi-iass.org/home/cochran-hansen-prize/.

IASS promoted Invited Paper Sessions (IPS) Proposals to the 64th WSC 2023. There were 18 submitted invited papers session proposals sponsored by the IASS to the 64th WSC in Ottawa. An evaluation and selection process is now being undertaken by the Scientific Programme Committee of the 64th WSC chaired by Prof. Mark Podolskij.

Following the steps of the IASS strategy for 2022-23, we ended this year with the IASS's Recruitment drive – a letter from the President and the President-Elect, that has been spread throughout our networks using also our new IASS social media accounts, to increase our membership and reinforce IASS representatives in each country. I am sure that the networks of our scientific community continue to expand with solutions and opportunities through IASS communication plan and social networks. I hope that the coming year will come with a safer world to live in and work with our families and friends, and will allow unrestricted travel to consolidate our friendship and sharing of knowledge during ISI-IASS supported conferences.

I take this opportunity, on behalf of the IASS board, to convey our season's greetings to all of you and wish all a happy, peaceful, safe and healthy 2023.

With my best wishes,

Monica Pratesi

IASS President

Report from the Scientific Secretary

These past six months of activities for IASS began on July 14th with the IASS 2022 General Assembly where the IASS annual report for 2021 and the IASS strategy for 2022-2023 were presented by our President and then unanimously approved. The IASS strategy can be found at the following address http://isi-iass.org/home/wp-content/uploads/IASS-Strategy2022-2023.pdf. IASS EC member Jairo Arrow has presented the financial report, I have reported on the scientific activity of the IASS, and Nikos Tzavidis has described the newly introduced Hukum Chandra Prize. TSS Editor, Danuté Krapavickaité has described the achievements of The Survey Statistician and IASS President Elect, Natalie Shlomo, has updated the members on IASS activities for the WSC2023. The slides presented at the Assembly can be found here: http://isi-iass.org/home/wp-content/uploads/IASS-GeneralAssembly_14072022.pdf

In a world where the buzz word is data integration, I thought that social media could be an interesting topic for the **New and emerging methods** section of this issue of The Survey Statistician. I am very grateful to Professors Annamaria Bianchi (University of Bergamo), Camilla Salvatore (University of Milano-Bicocca) and Silvia Biffignandi (CESS, Consultancy in Economic Statistics Studies) for having accepted my invitation to write a paper on **Using Social Media to Enhance Survey Data**. This contribution provides an overview on the role of social media data in survey research. After examining the characteristics and challenges of using social media data, the Authors discuss recent approaches on how social media have been used to enhance survey research and introduce a general modular framework for producing statistics taking advantage of the two data sources. Please, contact me if you are interested in writing an article for the "New and emerging methods" of future editions of The Survey Statistician.

The organization of the monthly **Webinar series** has continued, and we are particularly thankful to Andrea Diniz da Silva for her engagement. We have now reached Webinar number 24 and we are happy to have made it a monthly appointment that has attracted an audience of up to **five hundred registered participants**. Please, visit the webinar section of our website http://isi-iass.org/home/webinars/ for slides, that of ISI https://www.isi-web.org/events/webinars for upcoming and recorded webinars, and contact Andrea andrea.silva@ibge.gov.br if you have suggestions for topics and/or speakers for the upcoming Webinars. Those held in the last six months of 2022 have covered treatment of nonresponse, adjustment of self-selection in the Lithuanian Census, the development of the sample design for the new US integrated economic survey and two interesting "bridges": one between Design-based Inference and Design of Experiments and the other between Big Data and Sampling Methodology. The October webinar has been a special one, devoted to the presentation of the paper "Small area estimation: a novel approach on estimation of mean squared prediction error of small-area predictors" that granted Prof. Mahmoud Torabi the **first Hukum Chandra Memorial Prize**.

The EC of IASS has decided to support three initiatives in 2022 with 500 euros each: the 7th ITAlian COnference on Survey Methodology – ITACOSM2022 – "Survey Methods for Statistical Data Integration and New Data Sources" held in Perugia, Italy, on June 8-10; the Workshop on Survey Statistics Theory and Methodology, held in Tartu, Estonia, on August 23-26; and the one-day Workshop on Survey Data Management Strategies to Improve National Planning and Development, Ogun State Bureau of Statistics, held in Ogun State, Nigeria, on October 4. The new **Call for Conference Support for 2023** is now out. We will consider providing financial support for workshops, conferences and similar events that promote the study and development of the theory and practice of statistical surveys and censuses and associated subjects, and foster interest in these subjects among statisticians, organizations, governments, and the general public in different countries of the world. To apply for support, please send a document project, including a budget sheet, to IASS President Monica Pratesi (monica.pratesi@unipi.it) and in cc to IASS Vice President Natalie Shlomo (natalie.shlomo@manchester.ac.uk) **before June 30th**. The complete info can be found here: http://isi-iass.org/home/wp-content/uploads/Call-for-Conference-Support-2023.pdf

During these past months, our social media activity has increased thanks to Annamaria Bianchi, our social media manager, who has continued to post about webinars, conferences, books, articles, prizes, the newsletter release and its contents, and the recent recruitment drive. The number of followers to the pages are increasing: since July, Twitter followers increased from 269 to 321, LinkedIn followers from 284 to 706 and Facebook followers from 54 to 100. We are very grateful to Annamaria for her efforts and dedication. Then, please, follow the updates on the life of IASS via **social media** and reading our **monthly Newsletter**. Other than webinars, information on conferences, on the recipients of awards and on call for nominations, it now features a **reading of the month** section in which we suggest monographs, special issues or edited books on topics of interest to the members of IASS. Please, feel free to contact me for news and info to be added in the Newsletter by the 15th of each month.

Maria Giovanna Ranalli

maria.ranalli@unipg.it

IASS Scientific Secretary

News and Announcements

Congratulations, Monica Pratesi!

Monica has been working as a Survey Statistician since 1995. Her research fields include small area estimation, composite indicators, inference in elusive population, non-response in telephone and Internet surveys, design effect in fitting statistical models. She has an interest in studying inclusive growth and in measuring poverty and living conditions.

Her scientific production in these areas includes over 100 publications including articles in national and international journals, chapters in monographs, edited books, working papers and notes produced in the context of conferences and seminars.

Monica is a full Professor of Statistics at the Department of Economics and Management of the University of Pisa and she is currently head of the Department for Statistical Production at ISTAT, the Italian National Statistical Office.

She has coordinated national and international research projects and has participated in European cooperation projects in the field of statistics, aimed at countries such as China, Tanzania, Romania and the Republic of Bosnia and Herzegovina. She has had numerous institutional positions held in Italy and abroad, such as President of the Italian Society of Statistics (SIS), Deputy Director of the Department of Statistics and Mathematics Applied to Economics of the University of Pisa, and Director of the Camilo Dagum/Tuscan Universities Research Center on Advanced Statistics for the Equitable and Sustainable Development.

She has exceptional leadership and organizational skills and has organized several workshops and conferences. Monica has been a member of the ISI since 2012, member of the IASS Executive Committee in 2015-2017, IASS President-Elect for 2019-2021 and is currently the IASS President for 2021-2023.

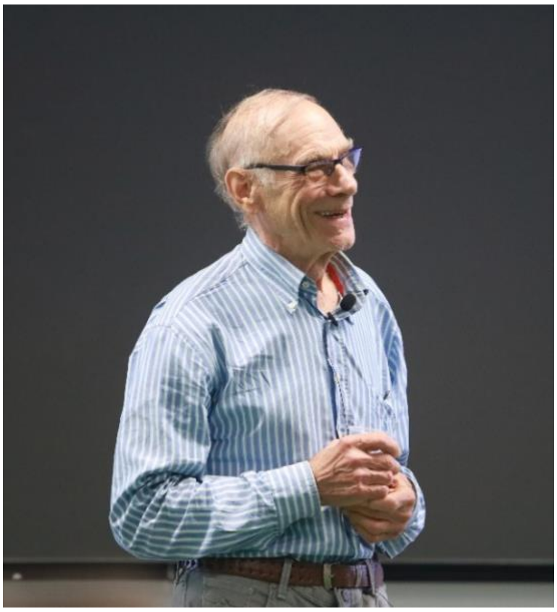
Monica celebrates her 60th birthday.

Dear Monica, we wish you a joyful life, unfading energy, creative and fruitful work and much happiness.

TSS editorial board
IASS Executive Committee

Congratulations, Carl-Erik Särndal!

The Baltic-Nordic-Ukrainian Network on Survey Statistics has organized workshops and conferences every year since 1997. Carl-Erik has participated in most events, including the first workshop and the most recent one in 2022. Several generations of students, teachers and practising statisticians have had the opportunity to meet Carl-Erik, discuss with him and enjoy his lectures on important topics in survey statistics, such as the GREG estimator and calibration of survey weights, the various aspects of adjusting for nonresponse in surveys, and more.



At the 2022 workshop of the BNU network in Tartu, Estonia, we celebrated the 85th birthday of Carl-Erik. In addition, two of his significant works celebrated their 30th anniversary in 2022: the “Big Yellow Book” on model assisted survey sampling, written together with Bengt Swensson and Jan Wretman, and the milestone article on calibration estimators in survey sampling, published together with Jean-Claude Deville. It is impossible to overestimate the importance of these works to the survey statistics community. All middle-aged survey statisticians have studied survey sampling from the “Yellow Book”, statistical offices around the world use calibration in their sample surveys.

Carl-Erik Särndal’s work has received much international recognition among statisticians and professional communities. His awards include the Waksberg Award of 2007, by the American Statistical Association and Statistics Canada, the Morris Hansen lecture of 2010, established by the Washington Statistical Society, the Jerzy Neyman Medal of 2018, by the Polish Statistical Association, Honorary doctor's degree, by the University of Neuchâtel, Swizerland, in 2022.

His work and warm personality are an inspiration to many. His healthy lifestyle encourages everyone. Carl-Erik is famous for holding high jump world records in several age groups. Carl-Erik's bright thinking and open smile enrich the events of the BNU network.

Dear Carl-Erik, we are happy to have you among us and to learn from you and cooperate with you. We wish you happy days, good friends and enjoyment from survey statistics!

Steering Committee of the BNU network
https://wiki.helsinki.fi/display/BNU/Home

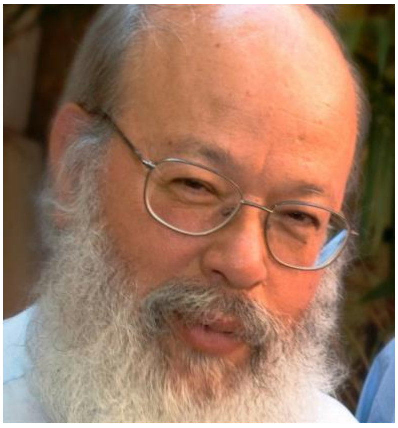
References

C.E. Särndal, B. Swensson, and J. Wretman (1992). *Model Assisted Survey Sampling*, Springer, New York.

J.C. Deville, C.E. Särndal (1992), Calibration estimators in survey sampling. *Journal of the American Statistical Association*, 87, 376-382.

European Masters Athletics. https://www.european-masters-athletics.org/news-overview/1678-highlight-high-jump.html

Congratulations, Roderick Little and Raymond Chambers!



The recipient of the 2022 Waksberg Award, Prof. Roderick Little, has delivered the invited lecture on November 4th at the Statistics Canada Symposium. His article “Bayes, buttressed by design-based ideas, is the best overarching paradigm for sample survey inference” is published in the December, 2022, issue of *Survey Methodology*.

The 2023 recipient of the Waksberg Award, Prof. Raymond Chambers, has been announced. He will give an invited lecture and publish an exclusive article in *Survey Methodology* in 2023.

The journal *Survey Methodology* has established an annual invited paper series in honour of the late Joseph Waksberg to recognize his outstanding contributions to survey statistics and methodology. Each year a prominent survey statistician is chosen to write a paper that reviews the development and current state of an important topic in the field of survey statistics and methodology. The paper reflects the mixture of theory and practice that characterized Joseph Waksberg’s work.

The author of the 2024 Waksberg paper will be selected by a four-person committee appointed by Survey Methodology and the American Statistical Association. Nomination of individuals to be considered should be sent by email before February 15, 2023 to the chair of the committee, Maria Giovanna Ranalli (maria.ranalli@unipg.it).

Previous Waksberg Award honourees and their invited papers can be found at: https://www150.statcan.gc.ca/n1/pub/12-001-x/award-prix-eng.htm

Tim Holt – Obituary

I was very sorry to hear of the sad passing of our former colleague Tim Holt at the age of 79.

Tim was the first Director of the Office for National Statistics, overseeing the amalgamation of the Central Statistical Office and the Office for Population, Censuses and Surveys in 1996.

During Tim's leadership of the ONS, he instigated the formal work on census under enumeration and pushed forward developments to improve business surveys.

Tim dedicated his life to the improvement of statistics, not just here but across the world. Following his PhD in statistics at the University of Exeter, he worked with Statistics Canada to pioneer work on hot deck imputation as well as being one of the world's leading experts in survey sampling.

In the late 1980s he returned from Canada to become Professor of Social Statistics at the University of Southampton where he worked together with Professor Fred Smith. He led the development of one of the leading centres of excellence in survey sampling and social statistics globally.

I can honestly say that there are many national statistical offices around the world, as well as our own, whose work over the past four decades has been greatly influenced by Tim's work.

He will be greatly missed and our thoughts go out to Tim's family at this time.

Sir Ian Diamond, National Statistician

Call for papers to the special issue on integrating data from multiple sources for production of official statistics

The Journal of Official Statistics has the pleasure to announce an upcoming special issue on integrating data from multiple sources for production of official statistics from a methodological perspective. We welcome manuscripts on statistical methods related to incorporating data from new sources, such as:

- web-scraped data from online platforms and open data;
- travel surveys by GPS;
- smartphone data and data obtained by other handheld devices;
- data integration techniques for combining probability samples, non-probability samples, big data samples and similar;
- administrative data and data in public domain;
- methods for data integration such a small area & domain estimation, calibration mass imputations etc. ;
- building up infrastructure and frameworks for data integration;
- quality issues related to integrating data from multiple sources;
- and other related methods and topics.

The Guest Editors for the special issue are Johan Fosen (Statistics Norway), Anders Holmberg (Australian Bureau of Statistics), Ingegerd Jansson (Statistics Sweden), Danutė Krapavickaitė (formerly at Vilnius Gediminas Technical University), and Ton de Waal (Tilburg University).

Submission guidelines and deadlines

Manuscripts should be submitted through the manuscript management portal ScholarOne https://mc.manuscriptcentral.com/joffstats .
All manuscripts must adhere to the JOS submission and peer review rules and will go through the usual JOS review process. Instructions for authors are available at Author Guide (clarivate.com) .
JOS is an open access journal. For more information about JOS, see Journal of Official Statistics (JOS) (scb.se).
For all articles of JOS, see the JOS-archive at JOS archive (1985–2012) (scb.se)
The deadline for submission is June 30, 2023.

Promoting good survey theory and practice around the world

The International Association of Survey Statisticians (IASS) aims to promote the study and development of the theory and practice of sample surveys and censuses.

It also aims to increase the interest in surveys and censuses among statisticians, governments and the public in the different countries of the world.

Dear statistician,

Join the IASS and become a member of an association of 430+ survey statisticians!

To become a member (never before a member of the IASS nor of the ISI):

You have to register first at Login (isiwebshop.org), an activation link will be sent to the email address you entered. Note that you must activate the account by selecting the activation link in the email you receive. If you don’t see the email in your Inbox, please check your SPAM box or your other email boxes. After activation, you can log in to https://www.isiwebshop.org/ using the username (email address) and the password you entered during registration.

Current members can renew their membership/s and update their contact details via the webshop. The username is the email address you used for your contact details and the password is your membership number, that is if you haven’t customized it.

Should you require any assistance in becoming a member, renewing your membership/s, or forgotten your membership number please send an email to isimembership@cbs.nl

The Survey Statistician, 2023, Vol. 87, 12-26

Ask the Experts

Mixed mode official surveys. Current status and near future[1]

Barry Schouten[2], Jan van den Brakel[3], Deirdre Giesen[4(a)], Annemieke Luiten[4(b)] and Vivian Meertens[4(c)]

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Abstract

Recently, Schouten et al. (2022) synthesized literature and research on both design and analysis of mixed-mode surveys in the context of official statistics. The COVID-19 pandemic has pointed very clearly at the benefits and drawbacks of mixed-mode survey designs, especially when comparability over time is key. A brief account is given of the main themes in design and analysis of mixed-mode surveys, which may be seen as starting points for National Statistical Institutes trying to make their designs more robust.

Keywords: Online/web, telephone, face-to-face, mode effects.

1 Introduction

The rise of online surveys over the past two decades has kindled a strong interest in mixed-mode surveys. Web questionnaires are cheap and fast, but have a lower response rate than traditional interviewer-based or mailed-out paper questionnaire modes. Combining web surveys with another survey mode like telephone or face-to-face interviewing is thus an obvious way of boosting low web response rates. In 2018, a survey was held among European National Statistical Institutes (NSIs) on their (mixed mode) practices. At that time, all but one country used mixed-mode designs for some or all of their surveys, and about half said web surveys were one of the design modes (Murgia, Lo Conte and Gravem, 2018). The COVID-19 crisis of 2020 and 2021 gave a strong impulse in NSIs' thinking about web and mixed-mode surveys, as face-to-face interviews were no longer possible. The new situation gave rise to a new inventory among European NSIs as to their experiences during the COVID crisis (Beck et al., 2022). The inventory showed that mixed-mode expanded rapidly, although face-to-face interviewing was mostly replaced with telephone interviewing, while the level

[1] This article is based to a large extent on the book written by the authors: Schouten, B., Van den Brakel, J., Buelens, B, Giesen, D., Luiten, A. and Meertens, V. (2022): Mixed-Mode Official Surveys. Design and Analysis. Boca Raton: CRC Press.

of web surveys remained stable. It appeared far more complicated to introduce new modes, than to expand the use of modes that were already familiar. Although mixing modes allows more flexibility in unforeseen circumstances, not all countries envisage continuation of the new mixed mode designs after COVID. Flexibility comes with added complexity, both in designing questionnaires, fieldwork logistics, adjustment and analysis. On the other hand, rising fieldwork costs and coverage problems in single mode surveys force others to embrace mixed mode solutions, and include web into the mix. If countries do consider the continuation of the new mode design, it is primarily for reasons of cost-effectiveness (Beck et al., 2022).

The use of mixed-mode designs is not new, but the current emphasis on the effects on analysis and estimation is. The effects of modes on non-response and measurements errors have long been known and have been the subject of research for decades. See for example Groves (1989) and Toepoel et al. (2020) for an older and a more recent discussion of mode effects: the combined effects of mode specific measurement error and mode-specific selection error. The web mode has completely different characteristics than the interviewer-based telephone and face-to-face modes. In addition, the web mode is diverse, as many devices can access the Internet. Desktops, laptops, tablets, smartphones, smart TV's and even some wearables can go online. In recent years, survey methodology conferences such as AAPOR and ESRA held many sessions solely on mixed-mode survey design and its impact on survey errors, survey costs, and survey estimates.

In this article, we give a short summary of recent insights into some of the most challenging aspects of mixed mode data collection. Section 2 describes data collection and questionnaire design. Section 3 describes how to test the impact of mixed mode surveys and how to adjust for mode effects. Finally, in section 4, we take a look at the future and the possibilities and challenges of the use of smart devices like smartphones, wearables and other sensor systems.

2 The design of mixed mode surveys

When designing a survey strategy, there are several aspects to consider: which modes to choose, in which sequence to apply them, and what communication strategy to apply. Underlying are considerations of costs, the prevention of nonresponse and selection bias, and the optimisation of data quality. In addition, mixed-mode questionnaire design plays a very important role in preventing mode-specific measurement errors.

To date, all four modes (mailed-out paper questionnaires, web, telephone and face-to-face interviewing) may appear, even in a single survey. Schouten et al. (2022) distinguish six features of survey modes: intimacy, interaction, assistance, speed and pace, presentation (aural or visual) and timing. These features impact the survey taking experience and differ to a large extent between the modes. The largest difference comes from interviewer versus self-administered modes, which show disparity on all mode features. In addition, modes may also introduce specific answering behaviours and response styles. For example, interviewer modes, through their higher intimacy, interaction and assistance, may help avoid errors, but may on the other hand introduce socially desirable answering. Bais et al. (2017) studied mode as a source of differential measurement error. They use a scoring of survey item characteristics, to predict measurement error risk. The score for one of Statistics Netherlands' surveys was such that a large-scale experiment was set up to estimate mode-specific measurement biases relative to face-to-face (Schouten et al., 2013).

Schouten et al. (2022) show that various modes and mode combinations may exist within one and the same NSI. A specific mixed mode survey design will be determined by aspects like the complexity of the subject matter (that may warrant interviewer assistance), the survey length (long surveys are less suitable for web and telephone), whether or not measurement differences are to be expected (e.g., for sensitive or attitude questions), and whether or not longitudinal measurements are foreseen (investing in the relation with respondents pays off if they are to be interviewed several times). Different surveys within one NSI may warrant different designs as a result of these considerations.

The choice of a mixed-mode design also depends on the motives for mixing them: minimizing total survey error, reducing costs, or increasing the speed of data collection. If speed is the main consideration, one could offer all modes at the same time, in a so called concurrent design. If costs are the main consideration, one should employ a consecutive design, starting with the cheapest mode (web), and only introducing other modes after a period of time. In inventories among European NSIs in 2013 (Blanke and Luiten, 2014) and 2018 (Murgia et al., 2019), costs appeared to be the main driver for the introduction of web surveys. For fieldwork costs, this is evident. Web interviews may be 50 to 100 time less expensive than face-to-face interviews. However, introducing web may have negative cost implications for other aspects of fieldwork, like longer travel times for the remaining sample persons, or higher interviewer turnover because of the more difficult job.

The sequence of offering modes and the implication on response rates and costs has been the subject of many studies. Medway and Fulton (2012) showed in a meta-analysis, that offering sample persons a choice of paper or web questionnaires leads to slightly lower response rates than just offering a paper questionnaire. In addition, this kind of concurrent mixed mode design limits the possibility of saving costs, as a large majority of persons will choose the paper option. Careful design could counteract this tendency. Biemer et al. (2018) show that offering persons an incentive to choose the web option substantially increases the web uptake and is even costs effective. Whether or not concurrent designs have different implications for response rates than sequential designs is unclear (Patrick et al., 2018). There are studies showing that the one leads to higher response rates, but there are also studies showing the opposite result.

The inventory by Murgia et al. (2019) showed that web surveys have been introduced in a large number of surveys in most European countries. They occur in four kinds of designs:

1. As the first mode in a sequential design. Nonrespondents are followed up in other modes. This design offers opportunities for large costs savings, but runs the risk of lowering response rates.

2. As a concurrent mode, offered at the same time as other options. This design is most often used when the other option is a paper questionnaire, but combinations between web and telephone and/or face-to-face interviewing exist as well. Web as concurrent mode was the most commonly used mixed mode design in 2013 in Europe, and still was in 2018.

3. Web is offered to nonrespondents of earlier telephone or face-to-face approaches. This design is chosen when the aim is to improve response rates over the initial mode. This design is used but only rarely.

4. Web is offered in subsequent waves, when respondents in a previous wave can indicate their willingness to fill in a web questionnaire, and give their email address.

What mode or what sequence of modes is offered does not need to be uniform for all sample persons. Adaptive or responsive survey designs target different approaches to specific groups. A simple version would be to offer the web survey only to younger persons. More advanced versions use insight into response and measurement errors per group per mode to fine-tune mode allocation. Calinescu and Schouten (2016) illustrate an adaptive mixed-mode design for the Dutch Labour Force Survey, where mode switches depend on response probabilities of different subsamples.

2.1 Communication strategy

Most NSIs, including Statistics Netherlands, do not have access to registries of telephone numbers or email addresses. That means that, even if sample persons are invited to participate in a web survey, the most common means of letting them know of the request is by letter. There is an ever-increasing host of research into the best way of 'web-push' designs (Dillman, 2017). Elements of this communication strategy are how to describe the task of logging on to the web, how to remind the respondent and how often, how to convey trustworthiness, and if and how to offer incentives. Dillman, Smyth and Christian (2014) developed guidelines to increase web response rates:

Use multiple contact modes to increase the likelihood that invitations are received and heeded by sample persons.

Make contact by a mode different from the response mode to increase trust that the survey is legitimate and useful. So, even if email addresses or cell phone numbers are available, it is good practice to also send an invitation letter alongside emails or text messages.

Send a small cash incentive with an initial postal mail contact to increase trust in the survey. Dillman, Smyth and Christian (2014) also suggest a second cash incentive in a later contact. However, differential incentives between early and later respondents may be an (ethical) issue here.

Try to obtain contact information for more than one survey mode.

Statistics Netherlands has found that offering incentives when inviting people to a web questionnaire is a cost-effective way of increasing web response rates. Depending on the specific survey design, both unconditional incentives (5€ gift card included in the invitation letter), conditional incentives (10 or even 20€ gift cards upon completion of the survey) or lottery incentives will be effective. See Schouten et al. (2022) for an overview of the communication and incentive experiments that were performed by Statistics Netherlands, and their effect on response rates and sample composition.

The COVID crisis that pressed NSIs to rethink their data collection strategy, also invited rethinking the communication strategy. Beck et al. (2022) describe that NSIs made changes in their contact channels, for example by including a QR code in the invitation letter, or by using e-mails and text messages. The latter channels are especially used for reminders and additional information. In some cases, national legislation was adapted to give NSIs the right to access telephone numbers and email addresses that were available in other public administrations (like the tax authority). But getting the number or the email address from the respondent, by either requesting it in the invitation letter, or visiting (without entering) the household was also frequently employed.

2.2 Questionnaire design

Administering questionnaires in different modes runs the risk of introducing measurement differences. The way that respondents understand and answer questions can be affected by characteristics like the presence or absence of an interviewer, whether questions are heard or read, and the way questions are visually presented on a screen. Mixed mode questionnaire design is an important tool in preventing or reducing mode-specific measurement effects.

Ideally, the properties of the questionnaire would play a role in the design of the survey. For example, if it is identified in the conceptual phase that mainly sensitive questions will be asked, it is wise not to mix interview modes with non-interviewer modes. An alternative could be to mix the non-interviewer mode with face-to-face, where the sensitive questions can be completed by the respondents themselves (CASI, Computer Assisted Self Interviewing).

Mixed mode questionnaires can be designed with a focus on minimizing measurement differences between modes by presenting a unified stimulus in all the modes used. This is called the unified mode approach (e.g., Dillman, Smyth and Christian. 2014, Dillman and Edwards, 2016). Alternatively, the 'best practices approach' focusses on minimizing error within each mode, even if that means using different stimuli in different modes.

Tourangeau, Conrad and Couper (2013) and Tourangeau (2017) argue that the best practice approach will best estimate the 'true value', and is thus preferable if an overall point estimate is the main goal of a survey. On the other hand, if comparison between groups is important, the unified approach is better suited. As mode distribution in the response can change over time, comparability over time is an additional reason to prefer unified mode design.

In practice, comparisons between groups and over time are paramount for most surveys. Therefore, mixed mode questionnaire design generally focuses on minimizing measurement differences between modes, i.e. the unified mode approach. Also from a practical and costs efficiency point of view it is preferable to design questionnaires for various modes as identical as possible. Mind, however, that some differences between modes must of necessity exist, even in a unified approach (e.g. "press enter to continue").

Schouten et al. (2022) advise to not just add a new mode like web to an existing survey, but to do a total redesign of the questionnaire if a mode is added. They also advise that mixed mode requirements should be considered in each stage of the questionnaire design process, e.g. the pre-testing of the questionnaire and the evaluation of the field work. If web is part of the mode mix, and the web questionnaire may be accessed by smartphone, consider designing the questionnaire for the smartphone. The next section is on this topic.

2.3 Smartphone questionnaires

If one of the modes is web, mixed mode questionnaire design will also entail mixed device design. Increasingly, respondents will access the web with a smartphone. This poses additional challenges to the design as it forces the developer to design for the smallest device. Figure 1 depicts how in continuous Statistics Netherlands' web surveys, the percentage of smartphone logins has increased to 35%, while both tablets and PC logins are on the decline.

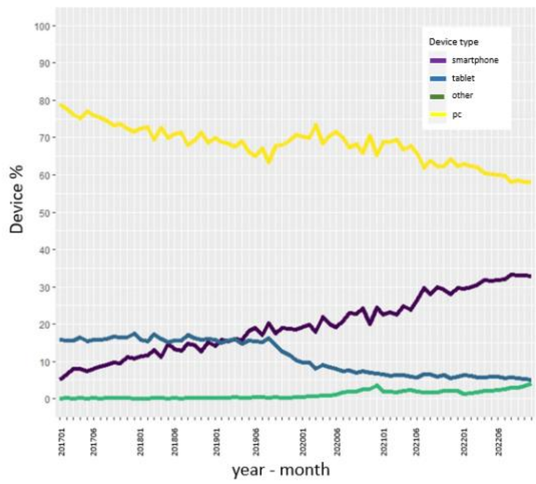

Figure 1. Device use (smartphone, tablets, PC, other) from 2017 to 2022 in percentage of number of first login attempts.

Note: The 'other' devices are mostly new smartphone types but some respondents do login with smart watches

Smartphones can impact the questionnaire experience, as the size of the screen is much smaller, potentially influencing how much text is visible and how easy it is to read the text. In addition, while respondents can use their keyboard on a PC, they need to use the touch screen for the smartphone. Open answers may be far more difficult to type in as a result. Respondents may also be less focused on the task, as the chance of distractions while answering the questions is highly probable (Couper, Antoun and Mavletova, 2017). However, well-designed questionnaires can prevent device-specific measurement errors (e.g., Tourangeau et al., 2017).

The European MIMOD – Mixed Mode Designs for Social Surveys – project (Schouten et al., 2018, Schouten et al., 2022) developed a list of indicators to assess if questionnaires are 'smartphone fit', or if device-related measurement risks can be expected. The first indicator counts the question length, presence of instructions, horizontal answer scales or matrix questions and the number of answer categories, to determine if the question will fit on a small screen. The second indicator evaluates the necessity of screen navigation, for example as a result of open questions and items with many answer categories. The third indicator is about response burden: the number of questions, the number of household members who need to respond, and 'underwater' interaction with databases, e.g., for the classification of occupation. The fourth is on task complexity. Persons may need to look up information in their administration, a task that may be incompatible with the location in which the respondent fills in the questionnaire. The final indicator is on perceived enjoyment or burden. These indicators may help making surveys more smartphone friendly or may even suggest a smartphone first design in a mixed mode context. Less enjoyable surveys may be extra susceptible to break-off or sub-optimal respondent effort if the smartphone does not facilitate a smooth respondent experience (Gravem et al., 2019).

Adapting questionnaires for mixed-device data collection is still a relatively new field. This list of indicators will be further developed and adjusted as more research into device effects become available.

3 The design of mixed mode surveys

3.1 Field tests

In survey methodology literature many references to experimental studies on improving the quality or efficiency of survey processes can be found. For example studies to compare the effect of different questionnaire designs, data collection modes or approach strategies on the main outcomes of a sample survey, with the purpose of reducing measurement errors, nonresponse bias or improving response rates. Many experiments conducted in this context are small scaled or conducted with specific groups. The value of empirical research into survey methods is strengthened as conclusions can be generalized to populations larger than the sample that is included in the experiment. This can be achieved by selecting experimental units randomly from a larger target population and naturally leads to randomized experiments embedded in probability samples, Fienberg and Tanur (1987, 1988, 1989). This enables the generalization of conclusions observed in an experiment to larger target populations and is particularly important if experiments are conducted to improve survey methods or to obtain quantitative insight in different sources of non-sampling errors in survey research. From this point of view they complement the insights obtained with small scale cognitive and usability testing strategies.

In an embedded experiment a probability sample is drawn from a finite target population, which is randomly divided into two or more subsamples according to a randomized experiment. In survey literature, such experiments are also referred to as split-ballot designs or interpenetrating subsampling, and date back to Mahalanobis (1946), but see also Cochran (1977, section 13.15), Hartley and Rao (1978). Designing and planning a randomized experiment embedded in a probability sample requires a careful preparation and planning of the fieldwork of the survey organization. Besides the standard decisions on the minimum required sample size to observe pre-specified treatment effects that should at least result in a rejection of the null hypothesis at pre-specified levels of significance and power, many considerations and decisions on how to implement and conduct the field work of the experiment have to be taken. Chapter 7 in Schouten et al. (2022) provides a discussion of the aspects of designing large scaled field tests. See also the edited volume by Lavrakas et al. (2019) for an extensive overview of experimental methods in survey research.

An important issue in the analysis of such experiments is to find the right inferential framework. The standard literature on design and analysis of experiments applies model-based inference procedures for the analysis of experiments. The observations obtained in the experiment are assumed to be the realization of a linear model. To test hypotheses about treatment effects, F-tests are derived under the assumption of normally and independently distributed observations. Inference in survey sampling is traditionally design-based, which implies that the statistical inference is based on the stochastic structure of the sampling design. Approximately design-unbiased parameter and variance estimators are derived under the concept of repeatedly drawing samples from a finite population according to the same sampling design, keeping all other population parameters fixed. If experiments are embedded in probability samples with the purpose to generalize conclusions to larger target populations, a design-based inference framework might be more appropriate than the model-based approach traditionally used in the analysis of randomized experiments. Van den Brakel and Renssen (2005) and Van den Brakel (2008, 2013) developed such a design-based framework for the analysis of a large range of randomized experimental designs embedded in probability samples.

3.2 Discontinuities and survey redesigns

Implementing a mixed-mode design in a repeatedly conducted survey, generally has systematic effects on the sample estimates. Survey samples contain besides sampling errors different sources of non-sampling errors that have a systematic effect on the outcomes of a survey. As long as the survey process is kept constant, this bias component is not directly visible. If, however, one or more components of the survey process are modified, these non-sampling errors are changed. Modifications in the survey process therefore generally have systematic effects on the survey estimates, sometimes called discontinuities, which disturb comparability with figures published in the past. To avoid confounding real period-to-period change in the parameters of interest with change due to alteration in the survey process, it is important to quantify the effect of changing the field work strategies and data collection modes.

Van den Brakel, Zhang and Tam (2020) propose a framework of statistical methods to measure discontinuities, depending on the type of change in the survey process. In the case of changing field work strategies or data collection methods, it can be expected that the micro data are not consistent under the old and new approaches. In such situations, a straightforward and reliable approach to quantify discontinuities is to collect data under the old and new approach alongside of each other at the same time. This is referred to as parallel data collection. Redesign of long-standing surveys like e.g. the US Current Population Survey and the US National Crime Victimization Survey are accompanied with a parallel run, (Dippo, Kostanich and Polivka, 1994, and Kindermann and Lynch, 1997). A parallel run is preferably designed as an embedded randomized experiment. The design-based inference approach, discussed at the end of Subsection 3.1, is particularly appropriate for the analysis of such parallel runs as it tests hypotheses about treatment effects on the sample estimates for the finite population parameters of the survey, accounting for both the sample design and the experimental design.

A strong point of parallel data collection is the low risk level to the regular publications during the changeover to the new design. Through a well-designed experiment the risk of failing to detect a discontinuity is minimized since the design of an experiment gives full control over the minimum detectable difference at a pre-specified significance and power level. A disadvantage of a parallel run is that extra cost is required for additional data collection.

If, due to lack of budget or fieldwork capacity, the new survey process is implemented without parallel data collection, discontinuities can be quantified using time series methods. Van den Brakel, Zhang and Tam (2020) discuss the use of structural time series models (STM). Under this approach, an appropriate STM is proposed for the population parameter of interest, for example with an appropriate model for the trend, the seasonal component and the unexplained population variation. This model is extended with a component that models the sampling error and a level intervention that changes from zero to one at the moment that the new mixed-mode design is implemented in the survey process. An estimate of the regression coefficient of the level intervention, usually obtained with the Kalman filter, can be interpreted as an approximation of the discontinuity. See for example Durbin and Koopman (2012) for details of STM and the estimation via the Kalman filter.

A major advantage of the time series approach is that no additional data collection is required, which makes this approach very cost-effective. Skipping a period of parallel data collection and relying on a time series model to estimate discontinuities also has several disadvantages and risks. During the period directly after the changeover, estimates for the discontinuities are prone to large revisions, each time new observations under the new survey become available. As a consequence, revisions must be accepted and final estimates are not timely. Another important drawback of this approach is that real developments and estimates for the discontinuities are confounded if the real evolution of the population parameter deviates from the assumed time series model. This situation can occur, for example if the changeover of the survey coincides with the start of the Global Financial Crisis in 2009 or the corona crisis in 2020. Finally, under the time series modelling approach there is no control over the precision and size of the minimum observable differences, resulting in an increased risk of failing to detect relevant discontinuities.

There might be budget or capacity to conduct a parallel run with a limited sample size, for example large enough to obtain sufficiently precise direct estimates for discontinuities at the national level, but not at the level of the planned domains of the regular survey. In that case small area estimation techniques (Rao and Molina, 2015) might be considered to obtain sufficiently precise discontinuity estimates at domain levels. Van den Brakel and Boonstra (2021) proposed a hierarchical Bayesian bivariate level model to combine direct domain estimates obtained from the old and new design for estimating domain discontinuities.

3.3 Re-interview designs to disentangle and adjust for mode effects

Survey methodology offers three options to make data collection strategies robust against mode effects. The first option is to reduce or minimize measurement effects by good questionnaire design, see, e.g., Dillman et al. (2014) and Schouten et al. (2022), Chapter 6. The second option is to avoid mode effects by adapting the choice of survey modes to the sample units using adaptive mixed-mode survey designs, see, e.g., Schouten, Peytchev and Wagner (2017) and Schouten et al. (2022), Chapter 11. The third option is to adjust mode effects by some form of weighting or matching afterwards, which will be explained in Subsection 3.4. Mode effects are the net result of multiple sources of non-sampling errors in the data collection phase of a survey process and can be divided in mode-specific selection effects and mode-specific measurement effects. In order to decide which of the aforementioned options need most attention and are most promising, it is crucial that mode effects are decomposed in relative selection bias and relative measurement bias.

Selection and measurement effects are typically strongly confounded when survey outcomes obtained under different modes are compared. Separation of selection effects from measurement effects in empirical studies requires carefully designed experiments in combination with weighting or regression based inference methods to control for selection effects, see, e.g., Jäckle, Roberts and Lynn (2010). As an alternative, Vannieuwenhuyze, Loosveldt and Molenberghs (2010, 2012) propose to disentangle measurement and selection effects using instrumental variables; they use a single-mode comparative survey that is assumed to be equally representative of the population and that has the same measurement effects. In Vannieuwenhuyze, Loosveldt and Molenberghs (2013) they compare this method to the generally applied backdoor method that assumes ignorable mode selection given a set of auxiliary variables. Biemer (2001) proposed a test-retest study and assumed a latent class model to separate selection bias and measurement bias in face-to-face and telephone modes. All these methods require auxiliary information that is strongly related with the target variables to separate mode-dependent selection effects from mode-dependent measurement bias. Available auxiliary information generally concerns standard socio-demographic variables, which are only weakly related to the target variables of a survey.

Schouten et al. (2013) proposed an experimental design to disentangle mode effects into mode-specific coverage effects, mode-specific nonresponse effects and mode-specific measurement effects using four modes, i.e. face-to-face interviewing (CAPI), telephone interviewing (CATI), web questionnaires and mailed-out paper questionnaires. The experiment, illustrated in Figure 2, consists of two waves. First a probability sample is drawn from the target population. In the first wave of the experiment, the sample units are randomly assigned to one of the four survey modes. The full sample, i.e. the respondents and the non-respondents of the first wave, is approached once more in the second wave using the benchmark mode, which is the face-to-face mode in this example. Based on the observations obtained in this experiment, estimates for mode-specific coverage effects, mode-specific nonresponse effects and mode-specific measurement effects are derived in Schouten et al. (2013).

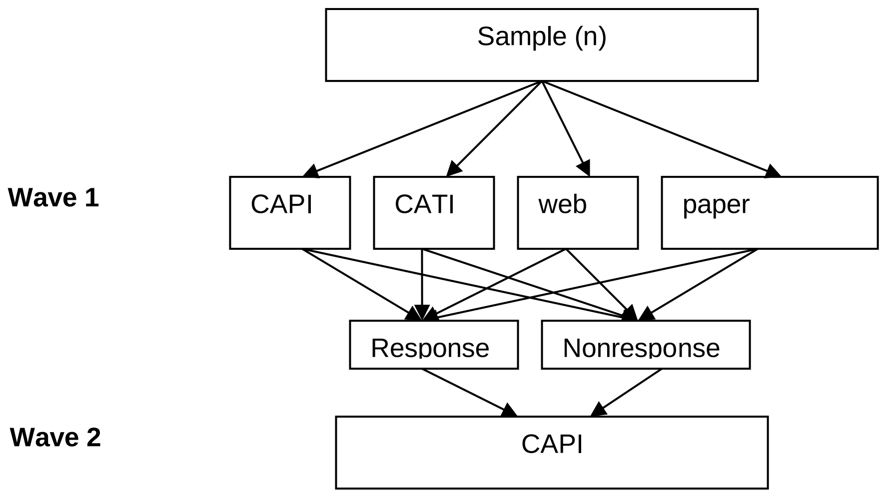

Figure 2: Repeated measurement design

Klausch et al. (2017) explored an estimation approach to adjust for measurement bias in sequential mixed-mode designs. The method is based on a re-interview approach. The idea behind this is to collect auxiliary information that is strongly correlated with benchmark variables to correct as best as possible for mode-dependent selection bias. Consider a sequential mixed mode design that starts with a data collection mode, say m_1, in the first round. In a sequential mixed mode design, the nonresponse of mode m_1 has a follow up using another mode, say m_2. To obtain strong auxiliary information for measurement bias adjustment, a random part of the response under mode m_1 is re-interviewed in the follow up using mode m_2. Estimators that adjust for mode-dependent measurement bias based on the re-interview data, are proposed by Klausch et al. (2017) and Schouten et al. (2022), Chapter 8.

3.4 Weighting methods for mixed-mode surveys

Survey sample estimates are generally based on calibration or generalized regression estimators, see, e.g., Särndal, Swensson and Wretman (1992). These techniques take unequal inclusion probabilities and selective nonresponse into account, and are aimed at correcting selection bias that could otherwise be present. Researchers and analysts working with mixed-mode data should not proceed carelessly as if analyzing single mode survey responses. When comparing survey estimates for population subgroups, observed differences could partially be the result of the fact that the groups were measured using different combinations of data collection modes. In a similar way, period-to-period changes in a repeated survey can partially be the result of different compositions of the respondents over the modes in both periods. When applying standard weighting methods to mixed-mode mode data, the resulting estimators consist of weighted combinations of observations collected through different modes. As a result, these traditional estimators contain components of differential measurement errors.

Regression, imputation and prediction techniques that attempt to remove measurement bias from the observations are developed by Suzer-Gurtekin, Heeringa and Vaillant (2012), Kolenikov and Kennedy (2014) and Park, Kim and Park (2016). Instead of correcting for mode dependent measurement bias, Buelens and Van den Brakel (2015, 2017) attempt to balance the response to neutralize adverse effects of varying response mode compositions. This is achieved by extending the calibration model with one or more components that assume a fixed distribution of the population over the data collection modes. In this way the measurement bias between domain estimates or between different survey editions is kept constant, such that differences are not affected by fluctuating measurement bias. Pfeffermann (2017) described a unified approach to handle inference from non-representative samples. Section 8.1 of that article suggests an extension from the essentially Bayesian approach to include measurement error arising in mixed-mode designs. The target of inference is the posterior probability distribution of the variable of interest, which is free from measurement bias, and corrected for selection effects.

4 The future of mixed mode surveys

The handbook Mixed-Mode Official Surveys (Schouten et al., 2022) was completed just before the COVID-19 pandemic. In its final chapter, Future of mixed-mode surveys, it is proclaiming that the face-to-face mode, while becoming more and more expensive, still is an important and stable mode in terms of coverage and response. Although only temporarily, the pandemic proved the authors wrong and pointed at the necessity of employing multiple modes. Or more specifically, at the necessity not to be dependent on one single mode. However, even with multiple modes, the impact of strong interventions such as COVID-19 is not to be underestimated. Interviewer modes, in particular face-to-face, are added because they bring in new types of respondents. Their addition does lead to shifts in statistics, and consequently, their omission to breaks in time series. Schouten et al. (2022) devote considerable attention to discussion of methodology for the estimation of such shifts accounting, if possible, for confounding with mode-specific measurement biases. The pandemic, thus, taught us that NSIs should have at least a basic understanding of the shifts in statistics that come from the inclusion of modes. This understanding must be updated on a periodic basis and ideally in such a way that it allows for some generalization across survey topics.

Surveys will undoubtedly continue to be very important tools in the production of official statistics for policy-making purposes. Surveys provide coherence and specificity in collected information and control over definitions and implementation. Given the increasing diversity in communication channels, there is also no doubt that surveys will keep using different modes to contact target populations and to administer data collection. But what will these surveys look like?

A clear trend that affects surveys in general, and mixed-mode surveys in particular, is the steady, gradual decline in response rates (Luiten, Hox and De Leeuw, 2020). It is not possible to attribute this trend to less willingness to participate in surveys alone; declining response rates have led to increasing costs per respondent which in turn have induced cost reductions through different mixes of modes. In other words, there is an interaction between the type of survey design and the response rates. Nonetheless, the prospect for future survey response rates is relatively grim. This prospect has already been forcing survey designers to tailor and adapt design features, and the survey mode is the most powerful of features. It is likely that a range of communication channels will remain to be needed in order to attract and recruit a diverse set of respondents, but in an adaptive, cost-effective fashion.

Face-to-face becomes less and less attractive from the cost perspective. To date, face-to-face often is a mode that is added in sequence to cheaper modes. This means the relatively hard cases are sent to interviewers, leading to lower interviewer response rates and thus higher costs per respondent. Furthermore, due to the unpredictable topographical variation in interviewer workloads, clustering of addresses within interviewers is complicated and face-to-face travel times may increase. These two consequences of mixed-mode surveys make face-to-face even more expensive, and may be the start of a downward spiraling of face-to-face. When face-to-face becomes more expensive then it may only be affordable for certain surveys or certain underrepresented population subgroups. This then leads to a smaller number of interviewers as workloads get smaller. Smaller numbers of interviewers lead to larger interviewer travel distances and travel costs, which in turn make face-to-face again more expensive. At Statistics Netherlands, this downward trend in face-to-face is already visible, despite being the most powerful mode still to recruit respondents.

The online mode is likely to undergo further changes as new and more powerful devices may emerge. Currently, the small screen sizes of mobile devices are still a barrier and a challenge in designing surveys and user-friendly user interfaces. It is foreseeable, however, that the drawback of small screens may be overcome by clever design, new navigation options or speech-to-text and other forms of additional communication. If so, these developments will force questionnaire designers to rethink how they construct question-answer processes. Although, universally, survey target populations have become more and more active online, there is likely to remain some digital divide that forces the same designers to align the potential of devices with more traditional modes.

Finally, it seems a natural avenue that surveys will more and more make use of existing data and of other means of collecting data besides asking questions. Existing data may be added in the estimation stage to strengthen time series. Existing data may also be added by respondents themselves as a form of data donation. Other forms of measurements, in particular data coming from mobile device sensors and other sensor systems, offer powerful options to further enrich survey data. Such surveys have been termed smart surveys. They are promising from the respondent perspective when they are not intrusive or burdensome, when respondents can access and control data and/or when respondents can learn about themselves. Nonetheless, smart surveys are likely to have a mixed-mode design as response rates to web invitation is often too low for official statistics. Consequently, such surveys require a renewed look at total error frameworks and demand for extension of existing methodology and development of new methodology. One of most crucial choices when including new types of data is between active (with explicit respondent involvement) and passive data collection (without a strong involvement of respondents). Making these choices, surveys move towards big data and big data move to surveys, creating hybrid forms of data collection in which the respondent still is a key person.

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New and Emerging Methods

Using Social Media to Enhance Survey Data

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Abstract

This article provides an overview on the roles of social media (SM) in survey research. After examining the characteristics and challenges of using social media data in statistical research, we discuss recent approaches on ways SM have been used to enhance survey research. We then introduce a general modular framework for producing statistics taking advantage of the two data sources. Finally, we highlight important questions for future research.

Keywords: Augmenting information, Smart surveys, Smart statistics, Data integration.

1 Introduction

Probability sample surveys have been considered the gold standard for inference for many years, but they are facing difficulties related mainly to declining response rates and related increasing costs (Luiten et al., 2020; Brick and Williams, 2013). At the same time, an acceleration of technological advances has occurred, with the use of mobile phones and online social networks, specifically social media (SM), leading to the availability of vast amounts of new data. This is coupled with the development of new tools by computational social scientists to collect, process, and analyse digital trace data.

All this has led to an extensive use of SM data in research to better understand attitudes and behaviours with reference to socio-economic phenomena. SM data has been used, for instance, to examine political attitudes (Bail et al., 2020) and emerging political trends (Rill et al., 2014), active citizenship (Rosales Sánchez et al., 2017) and well-being (Luhmann, 2017; Iacus et al., 2022). A number of experimental statistics have been developed by Official Statistics using such textual data to study social tensions[2] and consumers' confidence in the economy, among other applications (Daas and Puts 2014; Istat's Social Mood on Economy Index[3]). For a complete overview on the use

[2] https://www.cbs.nl/en-gb/about-us/innovation/project/social-tensions-indicator-gauging-society
[3] https://www.istat.it/en/experimental-statistics/experiments-on-big-data

of SM and digital trace textual data in Official Statistics, please refer to Japec and Lyberg (2020). Over the last few years, an increasing amount of applied and methodological research has been conducted to understand how this new paradigm can leverage SM in different ways to advance survey research. In this respect, one important and promising direction consists in the combination of survey and SM data (Hill et al., 2019; Stier et al., 2020). This needs to take into account pitfalls inherent in SM data, including self-selection, limited demographic information about users, data accessibility, volatility, and coverage among others. Stier et al. (2020) advocate for the need to develop a conceptual and theoretical framework tailored toward the multidimensionality of such data, guiding researchers through the benefits and pitfalls of different approaches to data linking.

This paper first examines some of the challenges associated with the use of SM data. In light of these challenges, we present and provide a critical analysis of the potential roles of SM data to enhance survey research. Finally, we propose a novel modular framework for the construction of smart statistics integrating the two data sources, that could serve as a reference framework enabling to compare different applications and provide a common information basis.

2 Characteristics and challenges of using social media data for statistical research

There is a broad definition of SM which includes all websites and apps that allows users to share messages and digital contents (photos, videos, articles, etc.). Social networking, blogs/microblogs, content sharing, and virtual world applications and websites fall into this category. Their use is widespread among people, and they are also well integrated in the business strategy of small and big enterprises. However, SM coverage and usage differs worldwide.

According to the Global Digital Report 2022, released by We Are Social and Hootsuite (2022), the number of worldwide active users of SM, i.e., those who logged-in in the reference period of 30 days, follows an increasing trend and is equal to, on average, 58.4% of the world population. SM audience and rate of usage varies according to regions, age groups, gender and other socio-demographic characteristics. For example, Auxier and Anderson (2021) discuss the use of SM in the Unites States (U.S.). From this study it emerges that some SM are more common among adults under 30 (Instagram, Snapchat and TikTok), Pinterest is more popular among females and the proportion of Instagram users is higher among Hispanic and Black Americans rather than White Americans. Similarly, U.S. Twitter users are younger, more educated, and more likely to be Democrats than the general public (Wojik and Hughes, 2019). In the same report, the authors argue that the majority of tweets is posted by a small share of users.

Thus, a coverage issue in SM data is evident. In addition, users self-select themselves and the data generation process is out of the researcher's control. SM users can be both real persons, organizations, or Internet robots (BOTs). BOTs are used to automatically publish content online (e.g. advertising) but their use can also be malicious (e.g. spam, fake news, or comments to influence public opinion). Also, the problem of multiplicity of accounts should be taken into consideration when analysing this type of data. For instance, individuals and organizations can have multiple accounts with different purposes.

When retrieving SM data, Application Programming Interfaces are generally employed. Together with data, a set of metadata is delivered with additional information about the content and the user. However, complete socio-demographic information is usually not provided. Data retrieval can be performed through a search query with relevant keywords related to the topic of interest, or the full set of data for a given user can be retrieved. It should be noted that SM posts can be modified or deleted over time, and related metadata can also change (e.g., likes, replies, and shares). Therefore, the results may differ based on the timing of retrieval. Similarly, different formulation of the search query in terms of the specified keyword can result in the delivery of different data.

Once data are retrieved, it is necessary to transform the unstructured data into structured data in order to obtain the information of interest. This transformation can be performed in different ways (e.g. sentiment analysis, topic modelling, supervised classification and clustering, among others). However, the final results might be influenced by the data cleaning, pre-processing and analyses choices (Denny and Spirling, 2018). Thus, it appears evident that also the analysis of SM is susceptible to errors.

Opposite to survey, where the Total Survey Error framework allows the identification and allocation of errors during the whole process, for SM data such a rich and comprehensive framework does not exist. SM sources have different characteristics, which require different quality frameworks. For example, Salvatore et al. (2021) discuss several quality issues related to SM and propose a quality framework for the analysis of Twitter data, and Amaya et al. (2021) describe specific features and issues related to the analysis of Reddit data.

When the objective of the analysis is the integration or augmentation of surveys with SM data, these aspects are even more important. Indeed, it is crucial to understand how errors arise, accumulate, and interact during the entire integration process (De Waal et al., 2019). Biemer and Amaya (2020) propose an error framework to evaluate the quality of integrated datasets generated using survey and non-survey data, and of the resulting hybrid estimates. In understanding the roles of SM in survey research, such characteristics and statistical challenges should be taken into account.

3 The roles of social media in survey research

The roles of SM in survey research have evolved through the years. In this respect, we could identify three main approaches on ways SM can enhance survey research to augment and improve the available information, namely, SM can be used as a replacement for surveys, as a supplement for surveys adding to the richness of the data, or to improve survey estimates.

First, as recently as ten years ago, when research on SM for social sciences began spreading, there was a lot of excitement about the possibility of replacing surveys with the study of SM. In many studies, correlations and alignment between indexes and statistics obtained from traditional surveys and from SM data have been demonstrated. For example, one of the most influential applications is the study by O'Connor et al. (2010), where the authors show that their novel and SM-based consumer confidence index was aligned with traditional indexes including the Gallup's Economic Confidence Index and the University of Michigan's Index of Consumer Sentiment. Similarly, Antenucci et al. (2014) construct an index of job loss showing that it was aligned with the Department of Labor's Initial Claims for Unemployment Insurance. Ceron et al. (2014) demonstrated the ability of SM to forecast electoral results.

Despite the initial promising results, issues underlying SM data made it clear that using SM data as a replacement for surveys is very difficult. For instance, Conrad et al. (2015) replicated the analysis by O'Connor et al. (2010) until 2014 showing a degradation of the relationship between SM and traditional indexes after 2011. Similarly, the Social Media Job Loss index (Antenucci et al., 2014), starting from mid-2014 began to diverge to the actual claim for unemployment[4].

As a consequence, researchers started investigating conditions under which alignment is possible. Conrad et al. (2021), after several experiments on the original O'Connor et al. (2010) analysis, conclude that the relationship between the data was "more than a chance occurrence". More

[4] http://econprediction.eecs.umich.edu/

importantly, they demonstrated that micro-decisions in the analysis can potentially strongly affect the results. In a similar direction, Pasek et al. (2018) argue that at the current time SM data may “only be fit for purpose in replacing survey data under very limited conditions”.

Hence, if considering SM as a substitute for traditional surveys may be ambitious, a more plausible scenario is their use as a supplement. This is a quite recent and growing research area. In this respect, SM data can be collected passively and analyzed to investigate content shared by users on SM platforms and also uses of SM (connections, activities, etc.). This approach involves the inclusion of SM derived variables into statistical models based on traditional data (Bughin, 2015) or the linkage between survey units and SM-accounts (Al Baghal, 2020, Al Baghal et al., 2021). Referring to the case of linking survey respondents’ SM profiles to their survey responses, Murphy et al. (2019) supplement survey data with respondents’ Twitter postings, networks of Twitter friends and followers, and information to which they were exposed about e-cigarettes, finding the combined data to provide broader measures than either source alone. Recently, Salvatore et al. (2022) use Twitter data to augment traditional data on businesses to study Corporate Social Responsibility (CSR), by adding variables related to Twitter communication of CSR and building indicators based on the two data sources. A related concern is that such approaches could be used for a limited part of the sample, namely for respondents having SM, consenting to link these data, and providing correct SM handles to correctly link the data. In this direction, Al Baghal et al. (2020) explore the feasibility of linking Twitter SM data to survey responses in three British representative panels, with findings suggesting that consent rates for data linkage are relatively low and depend on mode. It is worth noticing that, in case of businesses, identification of accounts through the websites is much easier compared to individuals.

Another interesting and novel potential of SM as a supplement in survey research, is their use in generating qualitative insights. We could think at SM datasets as similar to data gathered from a huge focus group, in that there are comments generated by a broad range of stakeholders who have self-selected into discussing the topic and may display a broader range of opinions than a small focus group (Chen and Tomblin, 2021). In this respect, one also needs to consider that people posting on SM differ in many ways from a focus group that is moderated, topic-focused, and co-present.

Regarding the third approach, namely to use SM data to improve estimates, SM data can be used to combat nonresponse or to improve measurement. With respect to possible use for combating nonresponse, SM accounts represent a stable point of contact for an individual which tends not to change over time. Thus, linking survey respondents to their SM profiles makes them very attractive in longitudinal surveys. In such cases, when a respondent drops out of the study, some information can be retrieved from passive data collection from her/his SM profile. Again, innovative methods of participant engagement and tracing can take advantage of SM networking services, particularly Facebook (AAPOR, 2014; Calderwood et al., 2021). As for item nonresponse, adjustment methods can exploit data from linked SM accounts. Further, this additional data sources can be used as a way of completing otherwise missing items from surveys or to reduce response burden.

With respect to measurement error, Burnap et al. (2016) infer that SM very likely reduce the social desirability bias that affects respondents in a formal survey interview setting. In forecasting the outcome of 2015 UK General Election, the authors find significant support for right-wing parties on Twitter, contrasting the typical underestimation regarding the right-wing vote in the UK. This suggests that linkage of the two data sources can be used to improve measurement in surveys. In the longitudinal context, SM data can provide further information to the nature of change between panel waves, which is of particular interest and likely spurious. Further, SM data can be used to evaluate survey responses. In this direction, Henderson et al. (2021) use tweets to validate survey responses, comparing survey responses to observed behaviour in order to assess the validity of self-reported frequency of posting to Twitter, retweeting content, sharing photos, sharing videos, and sending direct messages. They find variation in the quality of self-reports across types of Twitter activity concluding that relying on self-reported SM behaviour distorts inferential results from what is found when relying on observed SM behaviour. Guess et al. (2019), linking survey data collected during U.S. 2016 election campaign with respondents' observed SM activity, validate self-reports of SM activity, finding that they are correlated with observed behaviour. However, they also find substantial discrepancies in reporting at the individual level.

Given the different possible uses of SM data in survey research, a common underlying conceptual and theoretical framework to guide enhancement of survey research through SM data could be extremely useful to provide a common and comparable basis of information.

4 A modular framework to produce smart statistics

In this section we present a modular framework that can be applied to produce smart statistics and indicators, i.e., generated by augmenting traditional data with SM data. The same approach is discussed in greater detail and applied in the specific field of smart business statistics in Salvatore et al. (2022).

We propose a modular methodological framework organized into three layers, each of which defines the tasks and the outputs. In this paper, we focus on the case of composite indicators as the basis for augmentation. Its structure has been inspired by the modular organization into three layers introduced by Ricciato et al. (2020).

The first layer involves the collection and transformation of data into structured data. Such data and their relative metadata represent the input for the second layer. This second block consists of extracting innovative statistical information and indicators. Using new elementary indicators based on textual unstructured data, the first and second layers enhance the statistical information. In the third layer, innovative statistics and indicators can be used to complement traditional source datasets through linkage and/or statistical integration or combined with existing indicators. As a result, Smart Statistics are produced. Figure 1 summarizes the framework.

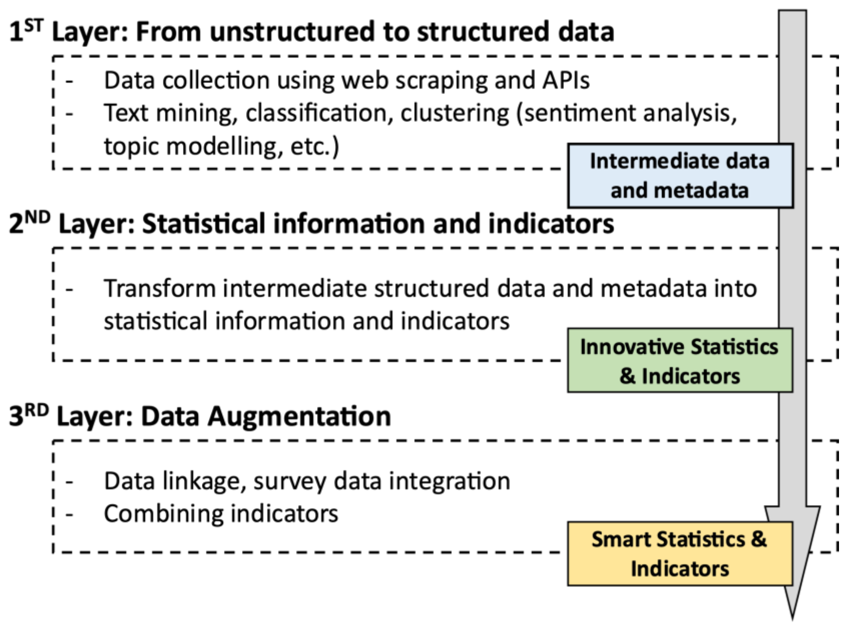

Figure 1. Modular methodological framework for producing smart statistics and indicators

As new and complex data sources are integrated with traditional ones, the modular approach can be followed. Modularity also facilitates exploration of other methodological variants (instances) within the same methodological architecture, plus possible improvements to specific modules or testing of the sensitivity of the results. As an added benefit, when enhancing survey data with SM data, the researcher may proceed across all three layers or may only refer to specific layers depending on information already available.

5 Discussion

The use of SM data to enhance survey research is a recent field of study with a wide range of prospective applications. We have provided considerations on the current state of research. Overall, the results are promising and the potential of these approaches is evident. In this respect, we envision a future survey world "that uses multiple data sources, multiple modes, and multiple frames" to enhance research (Lyberg and Stukel, 2017). SM data will clearly be part of this process, leveraging different ways to advance the survey research paradigm.

Many open problems remain, related to issues inherent in SM data and its data generation process, particularly selectivity, coverage, availability of information about users producing the data, data accessibility and volatility among others. Further, besides ethical and privacy considerations, linking survey and SM data about individuals requires identification of the accounts of interest and obtaining consent to collect and use this data. Also, understanding what questions may be more easily answered by passively collected SM data can help supplement traditional methods of survey data collection. The research agenda will have of course to deal with these issues, keeping quality considerations at pace of the developments.

A lot of experimentation is still needed to provide concrete results and to further explore the extent of the benefits of the use of such data. In this direction, the proposed modular framework will be very useful in structuring experimentations in a stepwise and common way so as to facilitate comparisons and have a broad common base of experimental reference results. Modularity will even allow experimentation focusing also only on a single module benefiting with already known results about other modules. We thus advocate the adoption of such modular framework in future experimentations.

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Book and Software Review

Multiple Imputation of Missing data in Practice Basic Theory and Analysis Strategies

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Abstract

The book *Multiple Imputation of Missing Data in Practice - Basic Theory and Analysis Strategies* is a recent piece of literature on multiple imputation methods. It constitutes a very complete contribution in the field, providing a methodological and applied point of view on the topic and facing several real situations in which imputation is non-negligible. The authors deal with a variety of complex problems, such as, among others, how to apply multiple imputation with survival, longitudinal and survey data, without losing rigor and making this book useful both for scientists and practitioners.

Keywords: multiple imputation; missing data; complex surveys; imputed datasets.

Yulei He, Guangyu Zhang and Chiu-Hsieh Hsu released in 2022 the book *Multiple Imputation of Missing Data in Practice - Basic Theory and Analysis Strategies*, published by CRC Press. Since the beginning of its appearance in literature, multiple imputation techniques have been a topic of extreme interest and utility, experimenting in the last decades with a fast evolution due to the availability of new (and big) data sources that pose the attention to new challenges in missing data problems. This book fits into this context and covers a wide number of topics in the field of multiple imputation, maintaining a good balance between statistical methodology and its link with the real world. In fact, the approach of the book is really applied: every topic is presented, explained and contextualized through real examples and simulations, giving the chance, even for beginners, to approach the matter.

The book is designed in three parts, driving the reader through a path that includes the definition of the matter, the presentation of the main methods and their contextualization in several practical situations.

Following this road map, the first part is structured as follows: Chapter 1 consists of an introduction, Chapter 2 provides necessary statistical background and Chapter 3 introduces the basics in multiple imputation analysis.

The central part of the book discusses multiple imputation discriminating between techniques for univariate missing data and for multivariate missing data. In the first case, the authors define parametric methods (Chapter 4) and robust methods (Chapter 5), while in the second they present the joint modeling approach (Chapter 6) and the fully conditional specification approach (Chapter 7).

In the third and last part of the book He, Zhang and Hsu make a major contribution, proposing a very interesting discussion about the application of multiple imputation in real and complicated settings, such as for survival data analysis (Chapter 8), longitudinal data (Chapter 9), survey data (Chapter 10), measurement error (Chapter 11) and nonignorable missing data (Chapter 13). Chapter 12 and Chapter 14 deserve a special mention, due to the authors effort in offering insights on imputation diagnostics and on the combination of multiply imputed datasets. Along the entire book, examples are proposed in order to have a clear and immediate idea about the use of multiple imputation in practice.

As said before, a focus is proposed in Chapter 10 on multiple imputation analysis for complex data surveys. Since the 70s multiple imputation became a relevant topic in handle nonresponses in large surveys. Even if it has experienced advances in several fields of research, survey data remain the natural outlet for multiple imputation techniques. Herein, modeling and analysis techniques are discussed, together with the organizations point of view on data editing, processing and release. Usually data coming from complex surveys are managed by institutions for public use and their perspective is, even if too often ignored, undoubtedly relevant. The authors proposed instead an explanation of the different steps with which survey statisticians have to face in the pre-release phase of survey imputed data, such as for example the comparison with historical data, the consistency edits and the check with survey weights, in order to appropriately run the multiple imputation techniques. Interesting is also the paragraph devoted to the examples from previous literature related to imputed datasets for external users, since it helps the reader in understanding the problem in real situations.

Concluding, the book *Multiple Imputation of Missing Data in Practice - Basic Theory and Analysis Strategies* may be considered a quality reference book for those who are interested in, or have to deal with, multiple imputation in several applied contexts.

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Book and Software Review

Multiple Imputation of Missing Complex Survey Data using SAS®: A Brief Overview and An Example Based on the Research and Development Survey (RANDS)

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Abstract

Multiple imputation (MI) is a widely used analytic approach to address missing data problems. SAS® (SAS Institute Inc, Cary, N.C.) has established MI procedures including PROC MI and PROC MIANALYZE. We illustrate the use of these procedures for conducting MI analysis of complex survey data by an example from RANDS. Section 1 contains the introduction. Section 2 includes some necessary methodological background. Section 3 shows a MI example with an arbitrary missing data pattern. Section 4 concludes the paper with a discussion.

Keywords: Complex Survey, Missing Data, Multiple Imputation, SAS®.

1 Introduction

Population-based studies often rely on surveys to collect information and conduct data analysis. However, survey data are often subject to nonresponse or missing data problems. Multiple imputation (MI) is arguably one of the most popular statistical strategies to handle missing data issues in many fields (Rubin 1987; He et al., 2022) including survey nonresponse problems.

The default option in statistical software is to remove cases with missing values from the analysis (i.e., case-deletion). The practicality of MI sits on its successful implementations in some mainstream software packages (e.g., SAS® and R) so that practitioners can use straightforward programming statements to conduct the analysis. For example, Berglund and Heeringa (2014) provided an overview of MI and its applications, using SAS® for illustration. Similar research literature can be found for other software packages. In addition, practitioners can refer to the software documentation for guidance.

Missing data problems in complex surveys pose some unique challenges (Section 2). For survey item nonresponse problems, MI has been proven to be a useful analytical tool supported by a large body of literature (e.g., Rubin 1987; He et al. 2022, Chapter. 10). However, most of the literature has focused on the technical aspects of MI and yet touched less on the programming components. In addition, the relevant programming literature and documentation are largely targeted to non-survey types of data.

To fill this gap, the aim of this paper is to provide a brief overview and a real example of MI for complex survey data using SAS® programming statements (version 9.4; additionally, the users can also use the free cloud SAS platform on https://www.sas.com/en_us/software/on-demand-for-academics.html).

2. Method Background

2.1 Missing data mechanism

Briefly speaking, the missing data mechanism of an incomplete variable describes how the probability of its missingness (i.e., being missing) is related to the original data. In general, there are three types of missing data mechanisms: (1) Missing completely at random (MCAR): the missingness of a variable is not related to any variable in the data; (2) Missing at random (MAR): the missingness of a variable is only related to other fully-observed variables in the data; (3) Missing not at random (MNAR): the missingness of a variable is related to the missing values after controlling for other fully-observed variables.

2.2 Multiple Imputation

To conduct a MI analysis of a dataset, an appropriate missing data mechanism (e.g., MAR) is first assumed. Then a statistical imputation model is formulated to relate the missing variable(s) with observed variable(s) in the dataset. Next, missing values are imputed (i.e., replaced) by random draws from their posterior predictive distributions or their approximations derived from the imputation model. Such a procedure is independently repeated multiple (say M) times, resulting in M sets of imputed values. Early research (e.g., Rubin 1987) suggested setting M=5 is sufficient for regular analyses applied to datasets with a small or moderate amount of missing data. More recent research (e.g., He et al. 2022, Section 3.3.3) has shown that larger numbers (e.g., M > 5) might be desired when computing and data storage resources are available. After imputation, each of the M completed datasets, including both the observed and the imputed values, is analyzed separately and results in M sets of analysis results/estimates. Finally, these M sets of results are combined to yield a single set of statistical inference using the so-called Rubin's combining rules (Rubin 1987).

2.3 Multiple Imputation for Complex Survey Missing Data Problems

Most surveys are based on sample designs with one or more complex features such as stratification, clustering of sampled elements, and weighting to compensate for differential probabilities of sample inclusion or varying response rates. Therefore, it is essential to incorporate this design information for survey data analysis (Cochran 1977). Survey data analysis procedures accounting for the design information are readily available in SAS® (Section 3).

The above principle also holds for analyzing multiply-imputed complex survey data. Additionally, a principled MI procedure for complex survey missing data problems should also include the design information in the imputation process. However, there exist alternative practical options for incorporating the sample design (e.g., He et al. 2022, Section 10.3). Here we outline a hierarchical, trial-and-error strategy:

(1) Include the survey weight as a variable (predictor) in the imputation;

(2) To include information about the sampling strata and clusters:

(2.1) First, create a new categorical variable that combines the sampling strata and the nested clusters, and include this variable in the imputation;

(2.2) If the imputation model has some estimation issues due to a large number of categories from the above combining variable, then collapse clusters within a sampling stratum for clusters with small sample sizes or only includes the sampling strata variable in the imputation;

(2.3) If the model estimation issue still exists because some strata only have very few units then collapse these small-sample strata together to ensure each final stratum has a sufficient sample size, and then include the collapsed-strata variable in the imputation.

An additional major challenge for surveys is that missing data often happen for multiple variables, and this issue is usually coupled with another fact that survey variables are typically bounded. A feasible MI approach is the so-called "Fully Conditional Specification" (FCS) strategy, which imputes each incomplete variable based on a model that includes all other variables as the predictors and then cycles through all missing variables sequentially. FCS is arguably the most popular MI strategy for multivariate survey missing data problems (He et al. 2022, Chapter. 7).

3. A Multiple Imputation Example using SAS®

3.1 Major SAS® Procedures

The two main SAS® procedures for MI are PROC MI and PROC MIANALYZE. Other SAS® procedures and data steps are also often used, depending on the analytic goals and contexts. Here we outline five major programming stages in a typical MI analysis.

Stage 1 (processing): Processing data before imputation to construct the working dataset including both the target missing and fully-observed variables. Exploratory analyses are often conducted at this stage.

Stage 2 (imputation): Running imputation M times by applying PROC MI to the working dataset.

Stage 3 (analysis): Applying the planned (post-imputation) analysis to the completed datasets by running SAS® statistical procedures. In the context of complex survey data, these procedures typically include PROC SURVEYMEANS, PROC SURVEYREG, etc.

Stage 4 (combining): Combining the results to yield the final estimates with PROC MIANALYZE.

Stage 5 (evaluation): An evaluation analysis that typically compares results among different MI models and with the case-wise deletion method.

3.2 Data Background

The example is illustrated using a subset of Research and Development Survey (RANDS) (https://www.cdc.gov/nchs/rands/), a series of probability-sampled web-based surveys conducted by the National Center for Health Statistics (e.g., He et al, 2020). Specifically, we use some variables from the publicly released RANDS during COVID-19 data (the 3rd round), which is a special series of RANDS used to rapidly report on the impact of the COVID-19 pandemic (Irimata and Scanlon, 2022). The original dataset contains 5,458 records; it can be downloaded from (https://www.cdc.gov/nchs/rands/data.htm). Table 1 briefly describes the variables used in the example.

Table 1: Variables Used in the Example

Variable	SAS® name	Specifications
Age in years	AGE	18-70; Age ≥ 70 is top-coded
Sex	GENDER	Male/Female
Education	EDUC	High school diploma or less/ Some college/Bachelor's degree or higher
Marital status	MARITAL_NEW	Married or living with partners / Others*
Household internet use	INTERNET	Yes/No
Household size	HHSIZE	1-6; household size >=6 is top-coded
Household income	INCOME	1-16**
Sampling strata	S_VSTRAT	71 sampling strata in the original data
Sampling clusters	S_VPSU	2 to 7 clusters per stratum
Survey weights	WEIGHT_CALIBRATED	0.0096-17.6472***

Note: * collapsed from 6 categories in the original data; "Others" has four categories: widowed, divorced, separated, and never married.

** 1: < $5000; 2: $5000-9999; 3: $10000-14999; 4: $15000-19999; 5: $20000-24999; 6: $25000-29999; 7: $30000-34999; 8: $35000-39999; 9: $40000-49999; 10: $50000-59999; 11: $60000-74999; 12: $75000-84999; 13: $85000-99999; 14: $100000-124999; 15: $125000-149999; 16: > $150000.

*** normalized survey weights after calibrating to adjust for possible selection bias of RANDS.

3.3 Sample Code and Output

Stage 1: The selected variables contain no missing values in the original data. For illustrative purpose, we created around 20% missing values in both INCOME and MARITAL_NEW. The missingness of INCOME is related to AGE, GENDER, EDUC, and INTERNET; the missingness of MARITAL_NEW is related to AGE, EDUC, INTERNET, and HHSIZE. The missingness of both variables follows MAR (Section 2.1). For illustration, the key missing data-generating step for INCOME is included as follows (the initial dataset is called rands_covid3_new, while the new one is called rands_covid_missing):

```
 data rands_covid_missing;
    set rands_covid3_new;
    p_miss_INCOME = exp(-2+0.5*EDUC-0.5*GENDER-0.01*AGE+0.5*INTERNET)
                /(1+exp(- 2+0.5*EDUC-0.5*GENDER-0.01*AGE+0.5*INTERNET));
    rnumber_INCOME = ranuni(20110411);
    If rnumber_INCOME < p_miss_INCOME then R_miss_INCOME =1;
                else R_miss_INCOME=0;
    If R_miss_INCOME = 1 then INCOME=.;
run;
```

In SAS®, missing values are coded by "." (dot). In the code above, INCOME is set as missing if a uniform random number is less than a pre-specified missingness probability, which is related to other variables by a logit function. As outlined in Section 3.1, additional SAS® data steps and exploratory analyses can be done for the data processing stage of the MI analysis.

Stage 2: We first briefly discuss some possible modeling strategies. Since both INCOME and MARITAL_NEW have missing values, the desirable imputation strategy is FCS (Section 2.3). Under FCS, there exist alternative modeling options, some of which are included as follows:

(1) INCOME has 16 categories (i.e., 1-16) with an ordinal nature. Although each integer value does not represent the same dollar amount range, for simplicity we only consider these integers as our imputation and analysis metric. For convenience of illustration, this variable can be treated as a positive continuous variable and modeled via a linear regression model conditional on other variables. However, the imputed INCOME values can take fractional numbers. To preserve the integer format, a naive post-imputation rounding step can be taken; imputed values less than 1 can be set as 1 and those above 16 can be set as 16. Additionally, PROC MI has an option to force the imputed values being generated within a pre-specified range (e.g., [1,16]), and then rounding is only necessary for imputed values within the range. On the other hand, INCOME can also be imputed using the predictive mean matching (PMM) method (e.g., He et al. 2022, Section 5.5). Briefly, PMM can be viewed as a MI extension of hot-deck imputation, where each missing value is replaced with an observed response from a "similar" unit. In our example, PMM can naturally preserve the range and integer format of the imputations without the need of rounding.

(2) MARITAL_NEW has two categories, it can be modelled using a logistic regression conditional on other variables. Alternatively, binary or nominal variables such as MARITAL_NEW can be imputed via a discriminant analysis model. That is, stratified by MARITAL_NEW, other variables are assumed to follow a multivariate normal distribution (e.g., He et al. 2022, Section 4.3.2).

The sample code is as follows:

```
proc mi data =rands_covid_missing seed =197789 out= income_impute  nimpute =5
             min = 1 . . . . . . . .  max = 16 . . . . . . . .  ;
        class EDUC GENDER INTERNET MARITAL_NEW S_VSTRAT_COMBINE ;
        fcs nbiter=20 reg (INCOME/details) logistic (MARITAL_NEW / details likelihood=augment) ;
        *fcs nbiter=20 regpmm (INCOME/details) logistic (MARITAL_NEW/details likelihood=augment);
        *fcs nbiter=20 reg (INCOME/details) discrim (MARITAL_NEW/classeffects =include details);
        *fcs nbiter=20 regpmm (INCOME/details) discrim (MARITAL_NEW/classeffects=include details);
        var INCOME AGE WEIGHT_CALIBRATED EDUC GENDER INTERNET MARITAL_NEW HHSIZE
        S_VSTRAT_COMBINE;
run;
```

We provide some additional remarks about the above code.

(a) The input dataset is “rands_covid_missing”; the output dataset containing the multiple imputation results is “income_impute”; “nimpute=” specifies the number of imputations (we use 5 in this example); “seed=” specifies the initial random seed used in MI. Fixing the random seed can render reproducible results.

(b) The variables included in the imputation are specified after “var”. Among them, categorical variables are specified after “class”.

(c) To include the design variables, we initially include WEIGHT_CALIBRATED and the combined strata and PSU variable (S_VSTRAT and S_VPSU, respectively) in the model (after “var”). However, the model has estimation problems because some sampling strata have very few samples. As a result, SAS® would issue warnings in log files. They would also be noticed by checking the regression coefficients of the output. Therefore, we collapse some small strata so that each final stratum has at least 10 samples, which is coded by the new variable S_VSTRAT_COMBINE. We also exclude S_VPSU from the model.

(d) fcs nbiter=20 reg (INCOME/details) logistic (MARITAL_NEW/details likelihood=augment). This statement specifies that we use FCS to impute both INCOME and MARITAL_NEW. Specifically, “nbiter=20” specifies 20 iterations are to be used; “reg (INCOME/details)” specifies a linear regression model for INCOME, and the "details" option asks for outputting the regression coefficients of the model fit across all imputations; "logistic/details" specifies a logistic regression imputation model for MARITAL_NEW with coefficients output; "likelihood=augment" specifies a robust logistic regression to deal with possible data separation issues (e.g., He et al. 2022, Section 4.3.2.4).

(e) We can specify "min=1" and "max=16" after "proc" to force the imputed values of INCOME falling in this range. For the variables that do not need the bounds, their "min" and "max" are assigned as missing values.

(f) fcs nbiter=20 regpmm (INCOME/details) logistic (MARITAL_NEW/details likelihood=augment).

This statement (commented out with a "*") specifies another modeling option: a PMM imputation for INCOME and a logistic regression imputation for MARITAL_NEW.

(g) fcs nbiter=20 reg (INCOME/details) discrim (MARITAL_NEW/classeffects =include details). This statement (commented out with a "*") specifies another modeling option: a linear normal imputation for INCOME and a discriminant analysis model for MARITAL_NEW. For the latter, "classeffects=include" specifies that all of the remaining variables, both continuous and categorical, are included in the discriminant analysis.

(h) fcs nbiter=20 regpmm (INCOME/details) discrim (MARITAL_NEW/classeffects =include details). This statement (commented out with a "*") specifies another modeling option: a PMM imputation for INCOME and a discriminant analysis model for MARITAL_NEW.

We now include some output from the above code and provide remarks. For ease of illustration, we separate the output into four parts and then comment on them one by one.

Output 1

The MI Procedure

Model Information

Data Set	WORK.RANDS_COVID_MISSING
Method	FCS
Number of Imputations	5
Number of Burn-in Iterations	20
Seed for random number generator	197789

FCS Model Specification

Method	Imputed Variables
Regression	INCOME AGE WEIGHT_CALIBRATED HHSIZE
Logistic Regression	MARITAL_NEW
Discriminant Function	EDUC GENDER INTERNET S_VSTRAT_COMBINE

Output 1 provides some general information about the imputation model setup and the variables included. For categorical variables, the discriminant analysis imputation model is the default option.

Output 2 shows the missingness pattern of the variables and some descriptive statistics of the associated subgroups. Specifically, Group 1 has all variables fully observed, denoted by 'X" for each variable; Group 2 has only MARITAL_NEW with missing values (denoted by "."); Group 3 has only INCOME with missing values; and Group 4 has missing values on both INCOME and MARITAL_NEW. The means of the continuous variables of each subgroup are also displayed. For instance, the average age from Group 1 (=53.386) is higher than those from the other three groups.

Output 2

Missing Data Patterns															
Group	INCOME	AGE	WEIGHT_CALIBRATED	EDUC	GENDER	INTERNET	MARITAL_NEW	HHSIZE	S_VSTRAT_COMBINE	Freq	Percent	Group Means			
												INCOME	AGE	WEIGHT_CALIBRATED	HHSIZE
1	X	X	X	X	X	X	X	X	X	3289	60.26	9.9811	53.386	0.9476	2.4387
2	X	X	X	X	X	X	.	X	X	948	17.37	9.9535	48.800	1.1708	3.9409
3	.	X	X	X	X	X	X	X	X	941	17.24	.	49.865	0.9972	2.5622
4	.	X	X	X	X	X	.	X	X	280	5.13	.	46.867	1.0469	4.2107

Output 2 also shows that the data have an arbitrary missing data pattern. On the opposite, a monotone missingness pattern is usually seen in longitudinal studies where once a subject drops out, his/her measurements at later times are always missing. Note that PROC MI has specific options for imputing monotone missing data. However, for brevity, they are not covered in this paper.

Output 3

Regression Models for FCS Method

Imputed Variable	Effect	EDUC	Imputation 1	2	3	4	5
INCOME	Intercept	.	-0.223674	-0.202220	-0.219967	-0.191550	-0.188843
INCOME	AGE	.	0.020476	0.029064	0.038018	0.022661	0.018259
INCOME	WEIGHT_CALIBRATED	.	0.042331	0.031441	0.069224	0.061784	0.034479
INCOME	EDUC	2.000	-0.377725	-0.396039	-0.394906	-0.384208	-0.329835
INCOME	EDUC	3.000	-0.036021	-0.014313	-0.023572	-0.011021	-0.077057

Logistic Models for FCS Method

Imputed Variable	Effect	Imputation 1	2	3	4	5
MARITAL_NEW	Intercept	-0.246513	-0.105072	-0.137450	-0.165294	-0.110486
MARITAL_NEW	INCOME	-0.885190	-0.903693	-0.923058	-0.902241	-0.809001
MARITAL_NEW	AGE	-0.524000	-0.520803	-0.542015	-0.571203	-0.524950
MARITAL_NEW	WEIGHT_CALIBRATED	-0.339081	-0.282057	-0.328680	-0.264126	-0.374018

Output 3 shows some details about the fit for each of the imputation models used in FCS. If we use the modeling option "fcs nbiter=20 reg (INCOME/details) logistic (MARITAL_NEW/details likelihood=augment)" in PROC MI, then the output contains the linear regression coefficients for INCOME and logistic regression coefficients for MARITAL_NEW across 5 imputations. For simplicity we do not include all coefficients here. Specifically, the results under "Regression Models for FCS Method" lists the coefficients for fitting INCOME. For example, the coefficient for AGE is 0.020476 for the 1st imputation, 0.029064 for the 2nd imputation, etc. The results under "Logistic Models for FCS Method" lists the coefficients for fitting MARITAL_NEW. For instance, the coefficient for AGE is -0.524000 for the 1st imputation, -0.520803 for the 2nd imputation, etc.

We previously discussed the need for collapsing some small strata and excluding clusters to achieve stable model estimates. If this was not implemented, in addition to seeing warning statements from SAS® log files, we would also see some very extreme logistic regression coefficients (e.g., outside the range [-5,5]) in Output 3.

Output 4

Variance Information (5 Imputations)

Variable	Variance Between	Variance Within	Variance Total	DF	Relative Increase in Variance	Fraction Missing Information	Relative Efficiency
INCOME	0.001115	0.003021	0.004360	41.96	0.443073	0.337540	0.936761

Parameter Estimates (5 Imputations)

Variable	Mean	Std Error	95% Confidence Limits		DF	Minimum	Maximum	Mu0	t for H0: Mean=Mu0	Pr > |t|
INCOME	10.014665	0.066028	9.881411	10.14792	41.96	9.974504	10.065734	0	151.67	<.0001

Output 4 shows some combined estimates after MI. It only displays simple means for continuous variables (e.g., INCOME) and some associated statistics. Note that it might be inappropriate to use this output as the basis for final results. For example, the mean estimation of INCOME here does not account for the complex survey design of RANDS.

Stage 3: we use the mean estimates as an analytical example. The example code is as follows:

```
proc surveymeans data=income_impute;
    weight WEIGHT_CALIBRATED;
    strata S_VSTRAT;
    cluster S_VPSU;
    var INCOME MARITAL_NEW;
    by   _imputation_;
    ods output  Statistics = mean_income_imp;
run;
```

For illustration, we estimate the overall mean of INCOME and MARITAL_NEW using PROC SURVEYMEANS, which uses the survey design information including strata, clusters, and weights. The working dataset “data=income_impute” reads the output dataset from PROC MI. In that dataset, a variable “_imputation_” is used to label the number of imputations (i.e., 1-5), and the dataset has 27,290 (=5458x5) records. A “by” option is used to run the analyses separately. Finally, the “ods output statistics = mean_income_imp” is used to store the output of the 5 analyses in the dataset “mean_income_imp” for carrying out the combining step in Stage 4.

Output 5 shows the means and standard errors of both variables from the 1st imputed dataset. It contains the default output from PROC SURVEYMEANS. For example, the mean of the completed INCOME is 10.161342 and the standard error estimate is 0.110726. The full SAS® output would include results from all 5 imputations and distribution plots of both variables (details not shown).

Output 5

The SURVEYMEANS Procedure
Imputation Number=1

Data Summary

Number of Strata	71
Number of Clusters	159
Number of Observations	5458
Sum of Weights	5457.99708

Statistics

Variable	N	Mean	Std Error of Mean	95% CL for Mean	
INCOME	5458	10.161342	0.110726	9.94129666	10.3813876
MARITAL_NEW	5458	0.646931	0.010449	0.62616660	0.6676959

Stage 4: We synthesize the results from the multiply-imputed datasets using PROC MIANALYZE. For example, the following code combines the survey mean estimates for INCOME.

```
proc mianalyze data =mean_income_imp edf=88;
   modeleffects mean;
   stderr  stderr;
   where varname = 'INCOME';
   ods output parameterestimates=MI_results_income;
run;
```

The procedure reads in the dataset mean_income_imp, which contains the separate estimates from the multiply-imputed datasets. The option “EDF= ” is not the default but necessary for complex survey data analysis because it specifies the degrees of freedom in the combining step. In this example, we specify the degrees of freedom as the number of clusters minus the number of strata in the dataset. The statement “modeleffects mean” specifies that the estimand for combining is the mean estimates. The statement “stderr stderr” lists standard errors associated with the means. “where varname = 'INCOME'” indicates that the combining step only applies to INCOME. Finally, “ods output parameterestimates=MI_results_income” saves the combined estimates to the dataset MI_results_income.

Output 6

The MIANALYZE Procedure

Model Information

Data Set	WORK.MEAN_INCOME_IMP
Number of Imputations	5

Variance Information (5 Imputations)

Parameter	Variance			DF	Relative Increase in Variance	Fraction Missing Information	Relative Efficiency
	Between	Within	Total				
Mean	0.000756	0.013659	0.014453	80.302	0.058117	0.055225	0.997246

Parameter Estimates (5 Imputations)

Parameter	Estimate	Std Error	95% Confidence Limits		DF	Minimum	Maximum	Theta0	t for H0: Parameter=Theta0	Pr > |t|
Mean	10.230448	0.120219	9.991217	10.46968	80.302	10.196713	10.294728	0	85.10	<.0001

Output 6 shows the results from PROC MIANALYZE. The combined mean estimate of INCOME is 10.230448, its standard error is 0.120219, and the 95% confidence limits are (9.991212, 10.46968). Detailed explanations of other statistics (e.g., between/within variance) can be found in the literature (e.g., He et al. 2022, Chapter. 3).

Stage 5: We conduct some diagnostics and evaluation. We have considered different modeling options for INCOME and MARITAL_NEW (Section 3.2.2). In this example, since we create the missing values, the imputation analysis results can also be compared with those from complete data as well as from the case-deletion method. The programming code for Stage 5 would be running different MI models and analyses (e.g., remark (d)-(h) after PROC MI in Section 3.3). Omitting the details, the evaluation results are summarized in Table 2.

Table 2: Mean Estimates of INCOME and MARITAL_NEW from Different Methods

Method	INCOME	MARITAL_NEW
Complete-data	10.38 (10.14, 10.62)	0.613 (0.592, 0.634)
Case-deletion	10.17 (9.91, 10.43)	0.589 (0.565, 0.614)
MI: linear+logit	10.36 (10.12, 10.59)	0.624 (0.600, 0.648)
MI: linear+discriminant	10.35 (10.13, 10.58)	0.620 (0.596, 0.643)
MI: (constrained) linear+logit	10.26 (10.03, 10.49)	0.621 (0.597, 0.644)
MI: (constrained) linear+discriminant	10.26 (10.03, 10.49)	0.623 (0.600, 0.645)
MI: PMM + logit	10.39 (10.17, 10.62)	0.621 (0.597, 0.644)
MI: PMM + discriminant	10.40 (10.16, 10.64)	0.620 (0.596, 0.644)

Note: 1. 95% confidence intervals are in the parentheses. 2. INCOME is modelled by either “linear” or “PMM”; MARITAL_NEW is modelled by either “logit” or “discriminant”. 3. “constrained” denotes imputed values for INCOME are forced to be in [1,16]. 4. Rounding is applied for fractional numbers when applicable.

The mean estimates from the case-deletion are considerably lower than the complete-data analysis due to MAR. In general, all MI methods correct for the biases somewhat. In addition, MI analyses yield generally narrower confidence intervals than the case-deletion method. Among different MI methods applied, it seems that when INCOME is imputed via PMM, the corresponding results are the closest to the complete-data analysis for both variables. Therefore, we would choose PMM+logit as the final MI modeling option.

4. Discussion

We provide some simple illustrations on how to use SAS® to conduct MI analysis for complex survey data. In addition to providing some sample code and output, we provide some general guidance on constructing imputation models and running some evaluations. The full programming code is available at https://github.com/he-zhang-hsu/multiple_imputation_book/tree/Survey_statistician. Additional references on SAS®-based MI applications can be found in Berglund and Heeringa (2014) and relevant SAS documentation. References on MI strategies and applications, including non-survey data and how they can be implemented using other software packages such as R (https://www.R-project.org/) package “mice” (see van Buuren and Groothuis-Oudshoorn, 2011), can be found in He et al. (2022).

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Country Reports

ARGENTINA

Reporting: **Verónica Beritich**

Closure of the 21st meeting of the CEA, presided over by Argentina for the first time in history.

The director of the National Institute of Statistics and Censuses (INDEC), Marco Lavagna, led the closing ceremony of the 21st meeting of the Executive Committee of the Statistical Conference of the Americas (CEA), an organization that Argentina chairs for the first time in history. The meeting was held the last week of August 2022 at the headquarters of the Economic Commission for Latin America and the Caribbean (ECLAC), in Santiago, Chile. The next edition of the CEA-CEPAL will be held at the end of 2023 in Argentina, at which time the presidency of our country in the Executive Committee will also end.

Representatives from the national offices of 28 member states of ECLAC and four associate members, along with members of different agencies, funds and programs of the United Nations, together with international organizations and academies participated in the working sessions.

Firstly, at the beginning of the Conference, the authorities of the national statistical offices of Argentina, Costa Rica, Brazil and Saint Lucia spoke about the recent advances in their population censuses, while the authorities of Paraguay, Jamaica and the Dominican Republic were part of a panel discussion on the challenges facing their upcoming population surveys.

Secondly, the seminar "Beyond GDP: statistical challenges for measuring development" was also held, with the participation of the director of the United Nations Statistical Division, Stefan Schweinfest, among other leaders in the region.

Thirdly, the delegations analyzed the progress in the execution of the Biennial Program of Regional and International Cooperation Activities 2022-2023.

Finally, the regional follow-up of the 2030 Agenda for Sustainable Development was carried out.

In the bilateral meetings that took place within the framework of the Conference, the Argentine delegation shared the experience of INDEC in the recent National Survey on Consumption and Care Practices, which is in the field until the month of November. Other outstanding presentations were made, such as the launch of the document "Breaking the statistical silence to achieve gender equality in 2030", carried out jointly between the Regional Conference on Women and the CEA, among other topics.

General information can be found at www.indec.gob.ar.

For further information, please contact ces@indec.gob.ar.

AUSTRALIA

Reporting: **James Chipperfield, Daniel Elazar, Anthony Russo and Joseph Chien**

Network reconstruction during a time of economic disruptions

Governments across the globe are increasingly interested in measuring resilience in the business supply chain network, forecasting the impacts of emerging or potential disruptions, developing effective mitigation strategies, and facilitating economic recovery. The Australian Bureau of Statistics (ABS) has been undertaking an innovation project to evaluate the feasibility of reconstructing the domestic business supply chain network and estimate the risks and likely impacts of economic shocks through the Australian economy. This is difficult to do with existing statistics that are not designed to capture the trading relationships between businesses and hence the dynamics of network interactions.

Following the methods of the Dutch Central Bureau of Statistics and in the emerging body of literature on network reconstruction, the ABS has utilised supply-use tables from the national accounts and tax data on business sales and purchases to construct a probabilistic prototype supply chain network. The ABS proof of concept (PoC) work currently focuses on the bread manufacture supply chain, from fertiliser production to wheat farms, to flour milling and finally to bread-making. The PoC can be extended to other parts of the economy to measure the extent and magnitude of disruptions throughout the supply chain. Network reconstruction presents new opportunities to quantify complex economic and social systems. A reconstructed network would enable the ABS to fill critical data gaps and provide new statistical tools in policymaking, macroeconomics and supply chain research.

For additional information on the exploration of network reconstruction at the ABS, see: https://www.abs.gov.au/statistics/research/supply-chain-network-reconstruction

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DataLab

The ABS DataLab provides a safe environment for researchers to access both household and business microdata to undertake complex research. The number of sessions has increased substantially since 2019–20, with 15,520 sessions accessed in 2020-21 and 24,037 sessions accessed in 2021-22.

To ensure privacy and confidentiality rules are followed, DataLab outputs need to follow strict procedures to minimise disclosure risks. Currently, output clearance is a manual checking process which is not scalable, cost effective or free from human error. There is also a risk that the increasing number of outputs from different projects could potentially introduce differencing risks even though these outputs have individually met the strict output criteria.

To automate the process, minimise differencing risks and reduce the costs, the ABS has prototyped an output protection tool that consistently applies the ABS perturbation methodology to aggregate outputs. The prototype is being trialled and feedback is being gathered to improve usability and expand on its methods. The tools are being developed further and being made more widely available in the DataLab.

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CANADA

Reporting: **Karelyn Davis and Joseph Duggan**

International Methodology Symposium series hosted by Statistics Canada

Statistics Canada began its International Methodology Symposium series in 1984 and has since hosted a total of 33 Symposia, having co-organized other large-scale methodology and statistical meetings in some years. The Symposium is a gathering of international experts to present their findings and exchange ideas on statistical methods and best practices, and has grown in interest and participation over the years. Symposium 2003 marked the first year of hosting the Waksberg Address, in honour of Joseph Waksberg's important contributions to survey methodology over his lengthy career. When the coronavirus pandemic forced a pause in gatherings, an on-line panel discussion was held instead, and it proved to be a pilot for Statistics Canada's entry to hosting virtual conferences. In each of the past two years, the Symposium has been entirely virtual, attracting close to a thousand participants from around the world.

For the 33rd edition of the Symposium in November 2022, the organizers chose a timely theme of **Data Disaggregation: Building a more-representative data portrait of society.** In many countries around the world, societal movements and change are leading to increased and growing demand for official statistics that help address gender gaps, racism and other systematic barriers. New methodologies are needed to break down data into sub-categories according to gender, race, age, sexual orientation and disability. For every person to reach their full potential, society needs to properly understand the circumstances in which people live and the barriers they face. As stated by Zeid Ra'ad Al Hussein, the United Nations High Commissioner for Human Rights: "Only if we track progress for different population groups, in all countries, can we ensure that no one is indeed being left behind."

The Keynote address for the Symposium was provided by Grace Sanico Steffan from the United Nations Office of the High Commissioner for Human Rights in Geneva. Ms. Steffan spoke on the topic of ''Breaking the Cycle of Invisibility in Data,'' with particular emphasis on the United Nations framework for human rights indicators and the Human-Rights Based Approach to Data. The Symposium also included invited and contributed sessions on the topics of data integration, sampling hard-to-reach populations, data access and confidentiality, record linkage, as well as two panel sessions: one on the emerging science of data equity and another on the important topic of collection for indigenous populations.

Three virtual workshops were also offered to participants on the topics of: Disaggregating Racial-Ethnic Classification Systems to Improve Data Equity by Dr. Tara Becker from UCLA and the National Academies; Design and Analysis of Survey Data in Python by Dr. Mamadou Diallo of Samplics LLC; and a third detailed Methods for Multiple Frame Surveys by Dr. Fulvia Mecatti from the University of Milano-Bicocca. Finally, in continuing the tradition of the Symposium, the 2022 recipient of the Waksberg award, Professor Roderick Little of the University of Michigan delivered an invited presentation entitled "Bayes, buttressed by design-based ideas, is the best overarching paradigm for sample survey inference.''

The next iteration of the Statistics Canada International Methodology Symposium is planned for 2024, with a topic yet to be determined. Proceedings from the 2022 International Methodology Symposium will be available in mid-2023 from the website:

https://www.statcan.gc.ca/en/conferences/symposium2022/index

CROATIA

Reporting: **Ksenija Dumičić**

The Croatian Bureau of Statistics (CBS) published the final results of the Census 2021

In September 2022, the Croatian Bureau of Statistics (CBS) published the final results of the Census of Population, Households and Dwellings in the Republic of Croatia in 2021 (Census 2021) on the total population by gender and age and ethno-cultural characteristics of the population. The Census 2021 was conducted in two ways: From September 13 to 26, 2021, citizens could be registered independently using the census questionnaire in electronic form that was available on the e-Citizens portal, simultaneously listing the household and the apartment in which they live. From September 27 to November 14, 2021, enumerators used electronic devices to enumerate all census units that were not self-enumerated and controlled the data collected by self-enumeration (by downloading the control code from households that were enumerated in the e-Citizens system). According to Census 2021, Croatia has 3,871,833 inhabitants, 48.17% are men, and 51.83% are women. Compared to the Census 2011, the number of inhabitants decreased by 9.64%. CBS webpage: https://dzs.gov.hr/vijesti/objavljeni-konacni-rezultati-popisa-2021/1270. More Census 2021 data will be published successively.

SHARE Project survey, wave 9, in Croatia, conducted with F2F interviews, again

Research on Health, Aging and Retirement in Europe (SHARE) was launched in 2004 at the initiative of the European Commission to provide longitudinal microdata on population aging in 26 countries of the European Union, Israel, and Switzerland, https://www.share-project.hr/en/about-share/#vise. It was conceived as a multinational and interdisciplinary study intended to collect microdata and monitor changes in the economic, health and social situation of people aged 50+. The collected data are important for the reform processes of the government administration, when creating pension, health or social policies within individual ministries or special institutes. The SHARE project, which is based on a survey sample with personal interviews, has been implemented in Croatia since 2015. In 2020, SHARE's contribution to research on the social, health and economic impact of COVID-19, described at https://www.share-project.hr/hr/share-covid-19-research-project/, related to wave 8, was exceptionally done by telephone interviews with a special questionnaire "SHARE Corona 1", and was completed at the beginning of August 2020. At the beginning of summer 2021 using a questionnaire "SHARE Corona 2" the second survey of SHARE Corona, part of wave 9 of the SHARE study was conducted. In Croatia, 2,200 interviews were conducted in the first SHARE Corona survey, and around 2,000 in the second. Most of the respondents involved in it have been participating in the SHARE project since 2015. The data from the first SHARE Corona survey has been available to the scientific community since December 2020, while the data from the second survey SHARE Corona were published in early 2022. In wave 9 interviews reverted to face-to-face (F2F) mode, and the fieldwork was completed in September 2022, executed by Ipsos. The final result of wave 9 will be available in 2023.

ESTONIA

Reporting: **Imbi Traat**

Workshop on Survey Statistics 2022 in Tartu

The Baltic-Nordic-Ukrainian (BNU) network in Survey Statistics has organized annual workshops in the member countries since 1997. The 2022 workshop took place in August 23-26 in Tartu, Estonia. A special feature of the workshop was its hybrid mode. The group of 48 in-person participants in

Tartu was nicely supplemented by a total of 40 online participants from all over the world, as far as Ethiopia and India. Importantly, the hybrid mode enabled our partners from wartime Ukraine to participate in the workshop. However, meeting colleagues and friends in person and following the lectures on site in the auditoriums was very enjoyable after the tough years of the Covid pandemic.

The workshop was held in the newly built Delta Centre of the University of Tartu https://delta.ut.ee/en/ – the home of the local organizers from the Institute of Mathematics and Statistics. Delta Centre appeared ideal for hosting conferences due to its nice location on the river bank in the park in the centre of the city, and featuring auditoriums of different sizes equipped with modern digital technology.

The scientific program of the workshop was devoted both to innovations in the established methods on survey and official statistics and new and emerging approaches in the area. Non-probability sampling was one of the key topics. The first keynote speaker, Jean-François Beaumont, gave an online talk on inference from non-probability samples through data integration. The keynote speech by María del Mar Rueda addressed further challenges in inference with non-probability surveys. Unfortunately, she was unable to participate and her colleague Ramón Ferri-García delivered the talk. A PC lab on estimating with non-probability surveys using R was conducted by Luis Castro-Martín. Recent advances in population statistics were discussed by Li-Chun Zhang – the keyword was fractional counting. Among the invited papers on specific topical areas and country-specific invited talks, Oleksandr Gladun of the National Academy of Sciences of Ukraine presented Censuses in Ukraine: past and perspective. As with previous workshops, we had several contributed presentations. Abstracts are available in the electronic Proceedings on the BNU homepage. https://wiki.helsinki.fi/display/BNU/Home

Carl-Erik Särndal, the author of two milestone publications of 1992, the Springer book "Model-Assisted Survey Sampling" (with Bengt Swensson and Jan Wretman) and the JASA article "Calibration Estimators in Survey Sampling" (with Jean-Claude Deville), gave a keynote talk entitled "Progress in survey science, yesterday, today, tomorrow", followed by a round table discussion. This issue of *TSS* contains a short congratulatory text for Carl-Erik's 85th birthday.

Baltic-Nordic co-operation on survey statistics started in 1992 by the initiative of Prof. Gunnar Kulldorff and was developed as the Baltic-Nordic-Ukrainian Network on Survey Statistics from 1996 on. Today the BNU Network involves partners from Estonia, Finland, Latvia, Lithuania, Poland, Sweden and Ukraine. The participating institutions are universities, national statistical institutes and statistical associations. The University of Tartu, Statistics Estonia and the University of Helsinki had primary responsibility for organizing the Tartu 2022 workshop. The event was sponsored by the International Association of Survey Statisticians and Nordic Council of Ministers.

FRANCE

Reporting: **Philippe Brion**

The French Secure Data Access Centre (CASD), a Service for Datascience and Scientific Research

Giving researchers access to individual data collected by the Official Statistical System constitutes a major scientific challenge. This very detailed information requires a very high level of security to avoid any disclosure that would be prejudicial to the citizen, or any use by an unauthorised third party. To meet this security requirement, INSEE created in 2010 the Secure Data Access Centre (*Centre d'accès sécurisé aux données* in French, or CASD), whose teams have designed a secure device, allowing remote access while ensuring strong user authentication and confinement of the files.

CASD, now autonomous, has developed over time, extending its perimeters to other data producers than official statisticians and other types of highly detailed, sensitive data such as health data and administrative data. This service provides new solutions to the issue of record linkage and reproducibility of research work based on confidential data. CASD is increasingly used by the research community in France, and the originality of the experience, although relatively recent compared with that of its foreign partners, is enabling it to expand on an international level.

Technically, confidential data are hosted in the hermetic “secure bubble” of an integrated secure infrastructure with secure “sub-bubbles” for each research project accessing the data. Each of these sub-bubbles can only be accessed via dedicated client workstations (SD-Box) installed at the users’ offices in their institutions and directly managed by CASD. Researchers can work within their bubble in a high-quality research environment providing all the necessary software tools; over the whole lifecycle of their research project: from the data processing to the writing of their papers. Data cannot be downloaded, and results are exported once anonymized.

Such a large set of confidential data can be accessed remotely also across borders (at the moment, researchers can work from their universities in the EU and EFTA countries as well as in North America).

Today, CASD’s data catalogue pools together 367 confidential data sources (more than 3000 datasets). It has allowed over 3800 users from various domains and countries to securely access and jointly work with those data.

More information in: https://www.insee.fr/en/information/5014754?sommaire=5014796

For a demand of access to data : https://cdap.casd.eu/comite-secret-statistique

Contact : service@casd.eu

GERMANY

Reporting: **Dr. Jan Pablo Burgard**

The Census of Germany today and in the future

Due to the COVID-19 pandemic, the German Zensus 2021 was postponed to 2022, with the qualifying date being the 15th of May 2022. Like the German Zensus 2011, it combines the population register, the register of buildings and dwellings, and a regionally stratified random sample of residential buildings. Within the sampled buildings, all residents are surveyed. The sample is estimated to include about 10 million persons, a slight increase in comparison to the Zensus 2011. It is planned to finalize the survey in November 2022. By comparing the population register with the sample results, estimation of population figures as well as over- and undercoverage estimation is performed. The release of the first results is planned for the end of the year 2023. For more information, please visit the homepage at https://www.zensus2022.de

In parallel, the German Federal Statistical Office is pre-testing a new census strategy, which is based mainly on the use of registers, called Registerzensus. The aim is to reduce the survey burden for the population by making use of the information already available at the different institutions of the Federal Republic of Germany, and its federal states. At the same time, the automatization of processes could lead to more timely and regionally differentiated results. Depending on the success of these pre-test, the next census in 2031 could be almost purely register based. For more information, please visit the homepage at https://www.destatis.de/EN/Themes/Society-Environment/Register-census/_node.html

Also in 2022, the German Federal Statistical Office is conducting a time use survey on a voluntary basis. This survey is conducted every ten years. It will be very interesting to see the changes in time use, especially with the structural changes driven by COVID-19 in everyday work and leisure times. For more information, please visit the homepage at https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Einkommen-Konsum-Lebensbedingungen/Zeitverwendung/zve2022/_inhalt.html

THE NETHERLANDS

Reporting: **Arnout van Delden and Paul Smith**

European Establishment Statistics Workshop 2021

The seventh *European Establishment Statistics Workshop* (EESW21) was held 14-17 September 2021 as an online event, virtually hosted by Statistics Netherlands and by the Office for National Statistics. The programme, papers and presentations and a detailed report can be found at https://sites.google.com/enbes.org/home/home/news-and-events. The central theme of the workshop was 'adapting establishment statistics to new conditions'.

The first day we discussed adapting data collection to COVID-19, notably the move away from surveys sent by ordinary mail and toward other ways of data collection. Slovenia presented an example of using web portals and electronic questionnaires, for which a clear routing and careful testing are needed. In Portugal, lower survey response rates were a booster to use administrative data instead. That required correction for measurement and coverage errors. Canada presented a rapid way to collect business data by crowdsourcing, for which auxiliary data were used to correct for the selectivity.

The second day we discussed different forms of alternative data sources. Two presentations discussed 'System-to-System' data collection: one concerned bookkeeping software and the other one smart farming data. The transformation of the collected data into statistical variables poses a challenge. A third presentation concerned the use of website data to estimate social media usage. The next session looked at combining sources such as using job advertisement data to supplement survey data, and using combinations of administrative data to improve output on entrepreneurs. The day concluded with an ENBES general meeting which yielded various suggestions for common topics of interest.

The third day began with a session on quality aspects. Statistics Netherlands presented an approach to assess quality of imputations based on random forests. Canada presented an approach to combine multiple quality measures for administrative data into an overall indicator. Finally there was a paper on the way COVID-19 affected various processing steps in short-term statistics and consequently the quality of the output. This topic linked well to a session on how to produce new monitoring statistics. Portugal had launched a short survey which was put together in around 5 days; Serbia designed a flexible system that could launch several new surveys; Ireland used administrative data to produce new output.

Three presentations on seasonally adjusting series during the COVID pandemic took place on the final day. One focused on economic indicators, the next on how to react in real time to get a good seasonal adjustment, and the third on robust seasonal adjustment methods. The last session covered network analysis of enterprises, and began with an overview of company level production networks which are constructed in several countries using administrative data, primarily registers of VAT declarations. Further, a paper discussed how to assess the resilience of production networks. The third presentation discussed two approaches to reconstruct a business-to-business (B2B) trade network: one deterministic, the other a probabilistic entropy maximization approach. The final presentation described a research project to develop a firm-to-firm payments dataset based on payment systems data.

ENBES gratefully acknowledges financial support from the IASS towards holding this workshop.

NEW ZEALAND

Reporting: **Adam Tipper**

Quarterly greenhouse gas emissions

Stats NZ are now releasing quarterly greenhouse gas emissions statistics as official statistics. The quarterly publication complements Stats NZ's suite of System of Environmental-Economic Accounting (SEEA) based emissions statistics including annual industry and household production, consumption, tourism, and regional emissions statistics. Using the quarterly methodology also allows for provisional annual emissions statistics to be published approximately six months after the end of the year. These annual statistics are also being used to provide more up-to-date regional emissions which now have a lag of approximately 8 months as opposed to the previous lag of 21 months.

Quarterly production-based emissions were developed over 18 months, after identifying customer need for more timely emissions data. Quarterly estimates are calculated using the SEEA greenhouse gas (GHG) annual production estimates and activity indicators (e.g., energy statistics, card transaction data, transport data) to project emission trends beyond the latest GHG Inventory (compiled under UNFCCC guidelines) year. The quarterly emissions statistics use the proportional Denton indicator method which is used to compile quarterly gross domestic product. Using this indicator method, emissions can be estimated up to six months behind current time, allowing SEEA-derived emissions to be reported up to 18 months ahead of the GHG Inventory. This allows closer monitoring of emissions volumes, economic-environmental decoupling, and comparisons of emissions behaviour to economic recovery following disruptive events such as COVID-19.

While in development, the quarterly account was released with an 'experimental' label. Following international peer review and stakeholder feedback, it was released as an official statistic for the first time on 20th July 2022. This recognises that the statistics are considered by Stats NZ to have methods that are robust, accurate and fit for purpose. Currently, only two other National Statistics Offices (Statistics Sweden and Statistics Netherlands (CBS) and the IMF routinely produce quarterly SEEA greenhouse gas emissions estimates, while the UK's Office for National Statistics is currently investigating feasibility.

See Greenhouse gas emissions (industry and household): December 2021 quarter for key results from the series and for links to methodology.

For further information, please contact Adam Tipper, Stats NZ, email: adam.tipper@stats.govt.nz

PERU

Reporting: **Leonor Laguna**

Recent improvements to data quality and dissemination

The INEI (Instituto Nacional de Estadística e Informática) is using electronic devices to collect information in all the surveys they carry out. This practice was instituted about 4 years ago. This approach has had a positive impact on both the data quality and the data processing of surveys.

The INEI has also organized a Data Base of the main surveys it carries out. The Data Base contains the information collected and methodological documentation in support of the Data Base, all of which are made available to the public.

To access to the Data Base you may use the following link:

https://www.inei.gob.pe/bases-de-datos/

PORTUGAL

Reporting: **Almiro Moreira and Sofia Rodrigues**

WebInq - an electronic processes for Data Collection in Business Statistics

Statistics Portugal (INE) is aware of the effort required from the respondent units to answer its surveys. Therefore, INE has established the adoption of new processes for data collection as a priority, both to minimise the statistical burden imposed and to better manage the procedures and resources allocated to respond to the surveys it conducts.

WebInq was created in 2005 as an innovative service available on the Internet aimed to collect data electronically, reducing the effort required from companies to respond to official questionnaires, and aiming to improve the relationship with respondents by creating processes that reduce and speed up their work. The response to the INE surveys is available in a WebInq private area, after certification with a code and password. Companies may complete the online electronic form and upload XML files with the option “Upload XML file” or through a webservice available by INE. This option will gradually replace the previous one.

WebInq provides safety and confidentiality, as it uses a secure HTTPS (Secure Sockets Layer) connection protocol for transmitting private data over the Internet.

WebInq continues being a benchmark in terms of electronic data collection, as it constitutes a data provider communications channel involving 83 business surveys, more than 70,000 companies in surveys, and more than 870,000 collected questionnaires.

SWITZERLAND

Reporting: **Alina Matei**

Special honour bestowed by the University of Neuchâtel, and a seminar series on innovation in survey research and practice

Prof. Carl-Erik Särndal received on November 5, 2022 the title of Doctor Honoris Causa awarded by the University of Neuchâtel, Switzerland

Two important events related to survey statistics took place in Switzerland in 2022, initiated and supported by the Institute of Statistics of the University of Neuchâtel. The first one concerns the title of Doctor Honoris Causa awarded by the University of Neuchâtel in 2022.

We are very happy to announce that Prof. Carl-Erik Särndal received on November 5, 2022 this very prestigious title for all his contribution in science. With this occasion, Prof. Särndal gave a lecture entitled "Progress in survey science and practice: yesterday - today - tomorrow". Prof. Särndal presented personal reflections on the progress made in the field, and shared his thoughts on how progress can be made in survey statistics.

The second one is the organization of the international Francophone webinar on survey statistics, in collaboration with the Group `Surveys, Models and Applications' of the French Statistical Society. The event takes place every two months, gathering survey statisticians from French speaking countries (Africa, Europe, and Nord America), and presenting recent and innovative developments in survey research and practice. The first webinar was held on October 20, 2022. For more information, please visit

https://www.sfds.asso.fr/fr/enquetes_modeles_et_applications/evenements/707-seminaire_en_ligne/

UNITED KINGDOM

Reporting: **Paul Smith and Simon Heckenmueller**

Initiatives at the ONS, and the Generations and Gender Survey

On 27 October, the Office for National Statistics (ONS) released a new and improved version of UK Climate Change Statistics Portal, ahead of COP27 which took place in Sharm El-Sheikh, Egypt. The new version built upon a prototype from October 2021, a cross-government project for analysts and policymakers to inform efforts to reach 'net zero' emissions by 2050 and adapt to climate change. It brings together relevant and timely statistics using a series of themed dashboards that visualise key data. The new version included improved display on mobile devices; enhanced interactivity; easier navigation; and a greater range of available visualisations. The portal is powered by the Integrated Data Service (IDS), an ONS-led and government-wide partnership. ONS also published a series of climate-related outputs around COP27, including people's climate worries and actions, business views on climate change impacts and actions, and excess mortality during heat-periods in England and Wales earlier in 2022.

The COVID-19 Infection Survey is changing: ONS plans several changes regarding the data collection and the sample size while preserving the value of the survey which includes insights into how the virus is spreading, the effectiveness of vaccines, and how symptoms may vary with different variants. Previously, survey workers visited people at their homes monthly but soon all this information will be collected online or by telephone. Participants will post their swab and blood samples, or these will be collected by a courier. And while the survey formerly collected samples and information from around 400,000 people across the UK every month, such a high level of precision is now less critical. The sample will be reduced to around 300,000 swab tests and around 120,000 blood tests each month, but can be adjusted in response to changing needs for information as the pandemic evolves.

The ONS is currently transforming the way it produces statistics on research and development (R&D): Comparing responses to the Business Expenditure on Research & Development (BERD) Survey with information from the larger Annual Business Survey, showed that more smaller businesses were undertaking R&D than was previously known. An article on Gross domestic expenditure on research and development provides more details about how this information was used to reweight the data. The recent annual releases of BERD and Gross Expenditure on R&D (GERD) outlines improvements, including a new, more comprehensive source of data on R&D in the Higher Education sector (TRAC). Longer-term redevelopment of R&D statistics will include developing an improved sampling frame to better take account of the types of businesses undertaking R&D.

The University of Southampton jointly with NatCen are currently collecting Generations and Gender Survey (GGS) data in the UK for the first time using a nationally representative sample of approximately 7000 people and employing complex online survey. It aims to better understand how young and mid-life adults in the UK are transitioning to adulthood, forming partnerships and families, and coping with recent economic, social and political uncertainty.

UKRAINE

Reporting: **Olga Vasylyk**

Special report from Ukraine

On the 24th of February, 2022, life in Ukraine changed dramatically. The full-scale Russian invasion caused deaths of thousands of civilians, the displacement of millions of refugees, and hundreds of destroyed settlements.

Since the start of the war, more than 7.2 million individual refugees from Ukraine have been recorded across Europe [1]. The majority of refugees are women, children, and men over 60. Around 84% of refugees are of working age, many of whom have lost their jobs or had to resign due to the war. The war has had a destructive impact on all spheres of our life, and, of course, on academic and scientific activities too. Many scientists, teachers and students have been forced to leave their homes, scattering around the world. Some of them continue their work or studies remotely, others have looked for a new job or study program. For the moment, staying in Ukraine, I can meet with my students only on-line.

Recently the team of “Kyiv Rysing” conducted a complex survey accompanied by many interviews with experts regarding the current situation in Ukraine (https://kyivrysing.kyivconsulting.com/present). They say: “our mission was to make a blurred window clear by processing piles of various multi-sectoral data on the country's Military, Social, Environmental and Economic domains and presenting it in a structured, clear and concise way.” According to the results of this survey, about one-third of

Ukrainians were forced to leave their homes to save their own lives, about 30% of employees in Ukraine have lost their jobs, over two million Ukrainian children were forced to move abroad, almost 22,000 Ukrainian teachers stayed abroad, and 69 education institutions moved their operations to the safer regions of Ukraine. In 2022, around 30% of Ukrainian students were expected to apply to European universities.

Despite the difficult circumstances, survey statistics institutions in Ukraine continue to provide up-to-date information. The State Statistics Service of Ukraine (https://ukrstat.gov.ua) monitors economic processes, macroeconomics indicators etc. as they did "before wartime". The Institute for Demography and Social Studies of the National Academy of Sciences of Ukraine (https://idss.org.ua) monitors migration processes, the demographic situation, and the labour market on a continuous basis. In September, the director of the Institute for Demography and Social Studies Dr. Ella Libanova at the seminar "Responsible leadership - the basis of building gender-oriented governance" said the following: "From February 24 to September 19, about 8.4 million people left Ukraine. During this time, 7.2 million people entered. Currently, 1.2 million people from Ukraine are abroad." She assumes that Ukraine may lose a further 500,000 to 600,000 people, up a maximum of 5 million, in the event of a prolonged war [2].

Kyiv International Institute of Sociology has resumed its work in May, 2022. You can find information about its recent surveys at https://www.kiis.com.ua. In October, 2022, the Faculty of Sociology of Taras Shevchenko National University of Kyiv announced its annual university survey UNIDOS, which monitors various spheres of students' life: satisfaction with studies, teachers, reasons for entering this particular university, plans for the future etc. (http://unidos.univ.kiev.ua/?q=en). In connection with the Russian invasion, this year's survey also includes a small psychological test. Recently the National Technical University of Ukraine «Igor Sikorsky Kyiv Polytechnic Institute» started its annual survey on the quality of education (https://dnvr.kpi.ua). Life goes on...

Writing these notes between blackouts, from time to time I was thinking "What do I feel now?" Fears, panic, confusion of the first months of war are already gone. Air raid alerts and blackouts mostly cause irritation and the question "Do the Russians really think they can break us with this?" It is not because I am so brave, it is just that a person – maybe unfortunately – gets used to everything. But we all believe that with the help of other countries that are on the side of good, Ukraine will win this terrible war, that we will be able to work in peace, our children will be able to go to school in peace, most of the refugees will return home and we will all rebuild our glorious Ukraine together.

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[1] United Nations High Commissioner for Refugees website: https://www.unhcr.org/ukraine-emergency.html

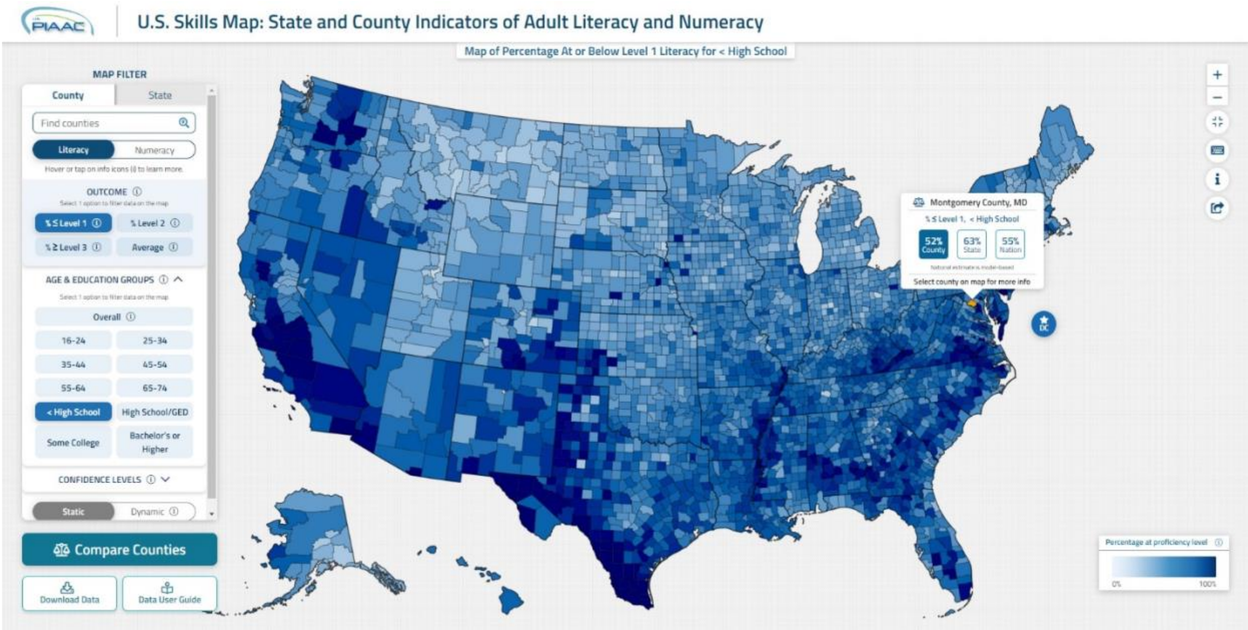
[2] https://nads.gov.ua/news/za-naihirshoho-stsenariiu-ukrainu-shche-polyshyt-do-5-mln-hromadian-ella-libanova-dyrektorka-instytutu-demohrafii-ta-sotsialnykh-doslidzhen-nanu

UNITED STATES

Reporting: **Andreea L. Erciulescu and Michael Wolf**

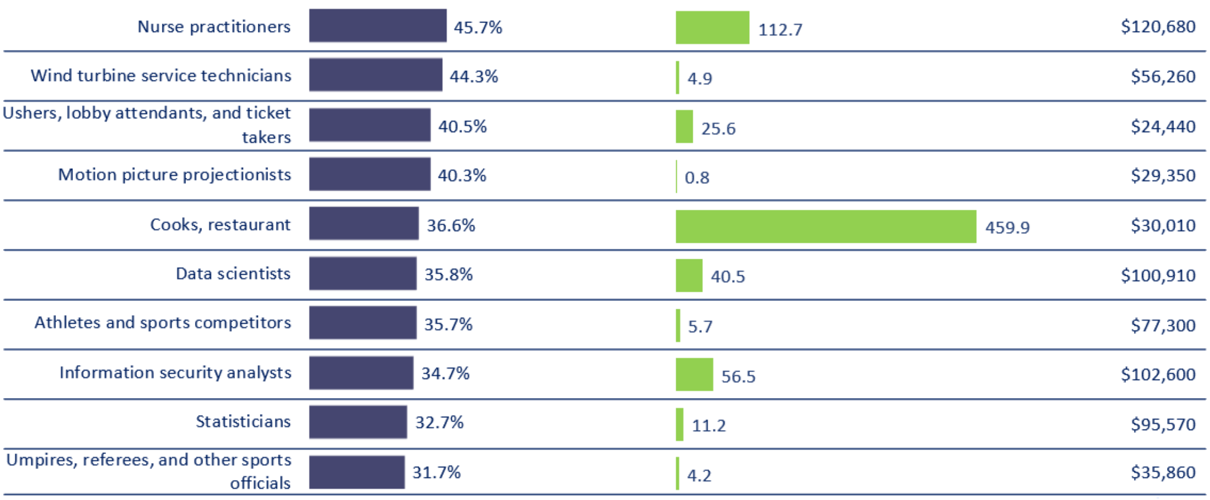
Model-based Adult Proficiency Official Statistics

The Program for the International Assessment of Adult Competencies (PIAAC) study is a multicycle international survey of adult skills and competencies sponsored by the Organization for Economic Cooperation and Development (OECD). The survey examines a range of basic skills in the information age and assesses these adult skills consistently across participating countries. The first cycle of PIAAC included three rounds: 24 countries participated in 2011-12 (round 1), 9 additional countries participated in 2014-15 (round 2), and 5 additional countries participated in 2017-18 (round 3). The United States (U.S.) participated in all three rounds of the first cycle of PIAAC and its combined 2012/2014/2017 sample was used to produce the county and state estimates, by age groups and by education groups, released in the U.S. PIAAC Skills Map. Recent model-based small area estimation developments have made it possible for the construction of reliable estimates at such fine levels of aggregation. The figure below provides an example of county-level estimates of proportion of adult individuals with less than high school education and with literacy at or below Level 1 (i.e., a score between 0 and 225). The U.S. PIAAC data are used by state and county adult education departments to plan interventions, allocate resources and provide information to the general public.



Publication of U.S. Occupational Employment Projections

On September 8, 2022, the U.S. Bureau of Labor Statistics (BLS) published long-term occupational employment projections for the period 2021-31. BLS releases new projections annually, with the goal of identifying long-run structural changes in the labor market.



Projections are a critical component of U.S. workforce development systems and help align education and training programs with the hiring needs of businesses. Projections also are used for making individual career decisions by students, parents, counselors, dislocated workers, jobseekers, and career changers.

Nurse practitioners are projected to experience the fastest employment growth of all occupations. Healthcare facilities are increasingly using team-based healthcare models, which utilize nurse practitioners, physician assistants, and other healthcare practitioners to provide patient care that would otherwise be provided by a doctor. Wind turbine service technicians are the second fastest growing occupation, reflecting the strong expected future demand for green energy sources.

The growth of the digital economy is reflected in the increased demand for data scientists and statisticians to collect, organize, and analyze the vast quantities of data now being generated to derive insights and aid decision-making processes, as well as in the growth of information security analysts to protect digital data and information systems. The residual impacts of the pandemic are also visible in the projections, with the fast growth in select leisure and hospitality occupations, such as motion picture projectionists, reflecting the recovery of these sectors of the economy after they experienced large employment losses during the early stages of the pandemic.

Further Information

In addition to occupational employment projections, the BLS projections program publishes data on projections for the labor force and labor force participation rates, the aggregate economy, industry output and employment, and education and training requirements.

Upcoming Conferences and Workshops

Conferences on survey statistics and related areas

12e Colloque Francophone sur les Sondages

The French National Institute for Demographic Studies INED will host les **12e *Colloque Francophone sur les Sondages*** from March 22-24, 2023, on Campus Condorcet at Aubervilliers. Tuesday 21 March 2023 will be devoted to training workshops.

Registration ends on January 30th!

For more information https://sondages2023.sciencesconf.org/

ITACOSM 2023 – The 8th Italian Conference on Survey Methodology

ITACOSM is a bi-annual international conference organized by the Survey Sampling Group (S2G) of the Italian Statistical Society (SIS) whose aim is promoting the scientific discussion on the developments of theory and application of survey sampling methodologies in the fields of economics, social and demographic sciences, of official statistics and in the studies on biological and environmental phenomena.

For the 8th edition of the conference the main title chosen by the Scientific Committee is ***New Challenges for sample surveys: innovation through tradition***. Contributions from survey practitioners, researchers, official statisticians and statistics stakeholders are welcome. **A prize for young researchers is established.**

ITACOSM2023 will be held in presence at the University of Calabria (Italy) from 7 to 9 June, 2023.

All updates are available on the website of the conference:

https://meetings3.sis-statistica.org/index.php/itacosm2023/main

SAE 2023

The ***Small Area Estimation, Surveys and Data Science*** international conference will take place at the Pontifical Catholic University of Perù, Lima, on **June 7 - 9, 2023**. This international conference will serve as a bridge among statisticians, survey methodologists, computer scientists, and others interested in combining information from multiple databases to develop reliable inferences at granular levels. In addition to traditional topics in SAE, the conference will cover a few emerging topics in surveys and official statistics. **All conference presentations will be strictly in-person. However, it will be possible to attend the conference virtually**. Currently, the Program Committee of SAE 2023 invites the submission of Invited Session and Contributed Session proposals. In addition to traditional topics in SAE, we expect to cover a few emerging topics in survey and official statistics (e.g., combining multiple sources of data, nonprobability sampling, probabilistic record linkage, data fusion, statistical disclosure control, etc.). Each invited session is expected to be 90 minutes long, with three speakers, or three speakers plus a discussant. The organizer could be one of the speakers. Please include the name of a session chair who should not participate as a speaker or the session's discussant. The proposal should include an outline/summary of the session and information (name, affiliation, email address) about the session organizer, speakers, discussant (if any), and session chair.

Relevant updated information about the conference, including abstract submission and registration, will be posted on the conference website

https://sae2023.pucp.edu.pe/.

If you have further questions, contact Mr Andrés Gutiérrez (andres.gutierrez@cepal.org), ECLAC's Regional Adviser on Social Statistics; or Mr Angelo Cozzubo (angelo.cozzubo@pucp.edu.pe), PUCP researcher.

WSC 2023

ISI2023 The ***64th ISI World Statistics Congress*** will be face-to-face and held in **Ottawa, Canada on July 16 - 20, 2023**.

OTTAWA 2023
64TH WORLD STATISTICS CONGRESS

https://www.isi2023.org/conferences/ottawa-2023/

Join the ISI WSC 2023 to celebrate the world of statistics and statisticians – there are some great reasons why you must not miss this edition of ISI WSC!

Return to Face-to-Face Meeting – Celebrate the work of the statistics and data science community in our first face to face meeting in four years

Keynote Speakers - ISI is very proud to announce that the President's Invited Speaker for WSC 2023 will be Professor Robert Groves, Provost of Georgetown University, Washington, D.C.

Networking – Collaborate and learn and enrich your thinking with colleagues from around the world.

BANOCOSS 2023

The 6TH BAltic-NOrdic COnference on Survey Statistics under the title

Survey Statistics meets Data Science will be held in Helsinki, Finland, in August, 21-25, 2023.

Webpage: https://wiki.helsinki.fi/display/BNU/BANOCOSS2023

European Establishment Statistics Workshop 2023

EESW23, the eight biennial European Establishment Statistics Workshop, is a prime European opportunity to follow developments and interact with like-minded official statistics methodologists, academic researchers and private sector professionals in the fields of business, economic and other areas of establishment statistics.

More information: sites.google.com/enbes.org/home/home/news-and-events/eesw23

BigSurv23

The third international conference on ***Big Data Meets Survey Science*** will be held on **October 26-29, 2023**, at Universidad San Francisco de Quito in Ecuador. It is currently accepting abstracts and session proposals on **Connecting Innovations in Data Science, Survey Research, and the Social Sciences**.

The call for abstracts and session proposals **closes on February 24, 2023**.

Additional information on the presentation formats and tracks can be found on the BigSurv23 website at https://www.bigsurv.org/abstracts

In Other Journals

Journal of Survey Statistics and Methodology

Volume 10, Issue 4, September 2022

https://academic.oup.com/jssam/issue/10/4

Editor's note

A Message from the Editors
Kristen Olson, Katherine Jenny Thompson

Survey Methodology

Using Smartphones to Capture and Combine Self-Reports and Passively Measured Behavior in Social Research
Florian Keusch, Frederick G Conrad

Exploring the Feasibility of Recruiting Respondents and Collecting Web Data via Smartphone: A Case Study of Text-To-Web Recruitment for a General Population Survey in Germany
Hannah Bucher, Matthias Sand

Increasing Participation in a Mobile App Study: The Effects of a Sequential Mixed-Mode Design and In-Interview Invitation
Annette Jäckle, Alexander Wenz, Jonathan Burton, Mick P Couper

Perceived Burden, Focus of Attention, and the Urge to Justify: The Impact of the Number of Screens and Probe Order on the Response Behavior of Probing Questions
Katharina Meitinger, Adrian Toroslu, Klara Raiber, Michael Braun

A Dynamic Survival Modeling Approach to the Prediction of Web Survey Breakoff
Felicitas Mittereder, Brady T West

Capture–Recapture Estimation of Characteristics of U.S. Local Food Farms Using a Web-Scraped List Frame
Michael Hyman, Luca Sartore, Linda J Young

Questionnaire Complexity, Rest Period, and Response Likelihood in Establishment Surveys
Joseph Rodhouse, Tyler Wilson, Heather Ridolfo

Survey Statistics

An Adaptive Mode Adjustment for Multimode Household Surveys
J Michael Brick, Courtney Kennedy, Ismael Cervantes-Flores, Andrew W Mercer

Benefits of Adaptive Design Under Suboptimal Scenarios: A Simulation Study
Shiyu Zhang

Testing for Phases of Dropout Attrition Using Change-Point Hazard Models
Camille J Hochheimer, Roy T Sabo

A Note About the Definition of Response Propensity for Survey Nonresponse
Roderick J Little

Reducing Variance with Sample Allocation Based on Expected Response Rates in Stratified Sample Designs
Blanka Szeitl, Tamás Rudas

Volume 10, Issue 5, November 2022

https://academic.oup.com/jssam/issue/10/5

Survey Methodology

Lack of Replication or Generalization? Cultural Values Explain a Question Wording Effect
Henning Silber, Endre Tvinnereim, Tobias H Stark, Annelies G Blom, Jon A Krosnick, Michael Bosnjak, Sanne Lund Clement, Anne Cornilleau, Anne-Sophie Cousteaux, Melvin John, Gudbjorg Andrea Jonsdottir, Karen Lawson, Peter Lynn, Johan Martinsson, Ditte Shamshiri-Petersen, Su-Hao Tu

Underreporting of Purchases in the US Consumer Expenditure Survey
Stephanie Eckman

A Simple Question Goes a Long Way: A Wording Experiment on Bank Account Ownership
Marco Angrisani, Mick P Couper

Assessing the Quality of Self-Reported Financial Information
Carlos Madeira, Paula Margaretic, Felipe Martínez, Pedro Roje

Using Visual Grouping to Improve Navigation of Skip Patterns in Mail Surveys: An Experiment
Rebecca J Powell, Jolene D Smyth

Split Questionnaire Designs for Online Surveys: The Impact of Module Construction on Imputation Quality
Julian B Axenfeld, Annelies G Blom, Christian Bruch, Christof Wolf

Survey Statistics

Optimality of the Recursive Neyman Allocation
Jacek Wesołowski, Robert Wieczorkowski, Wojciech Wójciak

A Cautionary Note on the Hanurav–Vijayan Sampling Algorithm
Guillaume Chauvet

Using Capture–Recapture Methodology to Enhance Precision of Representative Sampling-Based Case Count Estimates
Robert H Lyles, Yuzi Zhang, Lin Ge, Cameron England, Kevin Ward, Timothy L Lash, Lance A Waller

Prediction of Finite Population Proportion When Responses are Misclassified
Sumanta Adhya, Surupa Roy, Tathagata Banerjee

Estimating Population Size from a Privatized Network Sample
Ian E Fellows

Risk-Efficient Bayesian Data Synthesis for Privacy Protection
Jingchen Hu, Terrance D Savitsky, Matthew R Williams

Survey Methodology, December 2022, vol. 48, no.2

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Waksberg Invited Paper Series

Bayes, buttressed design-based ideas, is the best overarching paradigm for sample survey inference
Roderick J. Little

Special discussion paper

Statistical inference with non-probability survey samples
Changbao Wu

Comments on "Statistical inference with non-probability survey samples" – Non-probability samples: An assessment and way forward
Michael A. Bailey

Comments on "Statistical inference with non-probability survey samples"
Michael R. Elliott

Comments on "Statistical inference with non-probability survey samples"
Sharon L. Lohr

Comments on "Statistical inference with non-probability survey samples" – Miniaturizing data defect correlation: A versatile strategy for handling non-probability samples
Xiao-Li Meng

Comments on "Statistical inference with non-probability survey samples"
Zhonglei Wang and Jae Kwang Kim

Author's response to comments on "Statistical inference with non-probability survey samples"
Changbao Wu

Regular papers

Are deep learning models superior for missing data imputation in surveys? Evidence from an empirical comparison
Zhenhua Wang, Olanrewaju Akande, Jason Poulos and Fan Li

Multilevel time series modelling of antenatal care coverage in Bangladesh at disaggregated administrative levels
Sumonkanti Das, Jan van den Brakel, Harm Jan Boonstra and Stephen Haslett

Optimal linear estimation in two-phase sampling
Takis Merkouris

Bayesian spatial models for estimating means of sampled and non-sampled small areas
Hee Cheol Chung and Gauri S. Datta

Journal of Official Statistics

Volume 38 (2022): Issue 3 (September 2022)

https://sciendo.com/issue/JOS/38/3

Construction of Databases for Small Area Estimation
Emily Berg

Hierarchical Bayesian Model with Inequality Constraints for US County Estimates
Lu Chen, Balgobin Nandram and Nathan B. Cruze

Timely Estimates of the Monthly Mexican Economic Activity
Francisco Corona, Graciela González-Farías and Jesús López-Pérez

Small Domain Estimation of Census Coverage – A Case Study in Bayesian Analysis of Complex Survey Data
Joane S. Elleouet, Patrick Graham, Nikolai Kondratev, Abby K. Morgan and Rebecca M. Green

Identifying Data Quality Challenges in Online Opt-In Panels Using Cognitive Interviews in English and Spanish
Yazmín García Trejo, Mikelyn Meyers, Mandi Martinez, Angela O'Brien, Patricia Goerman and Betsarí Otero Class

Measuring and Mapping Micro Level Earning Inequality towards Addressing the Sustainable Development Goals – A Multivariate Small Area Modelling Approach
Saurav Guha and Hukum Chandra

Economic Nowcasting with Long Short-Term Memory Artificial Neural Networks (LSTM)
Daniel Hopp

Variable Inclusion Strategies through Directed Acyclic Graphs to adjust Health Surveys subject to Selection Bias for Producing National Estimates
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Pseudo Bayesian Mixed Models under Informative Sampling
Terrance D. Savitsky and Matthew R. Williams

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Special Issue on Respondent Burden
https://sciendo.com/issue/JOS/38/4

Preface Overview of the Special Issue on Respondent Burden
Robin L. Kaplan, Jessica Holzberg, Stephanie Eckman and Deirdre Giesen

Response Burden – Review and Conceptual Framework
Ting Yan and Douglas Williams

Testing a Planned Missing Design to Reduce Respondent Burden in Web and SMS Administrations of the CAHPS Clinician and Group Survey (CG-CAHPS)
Philip S. Brenner, J. Lee Hargraves and Carol Cosenza

Response Burden and Dropout in a Probability-Based Online Panel Study – A Comparison between an App and Browser-Based Design
Caroline Roberts, Jessica M.E. Herzing, Marc Asensio Manjon, Philip Abbet and Daniel Gatica-Perez

The Effect of Burdensome Survey Questions on Data Quality in an Omnibus Survey
Angelica Phillips and Rachel Stenger

Relationship Between Past Survey Burden and Response Probability to a New Survey in a Probability-Based Online Panel
Haomiao Jin and Arie Kapteyn

The Effects of Response Burden – Collecting Life History Data in a Self-Administered Mixed-Device Survey
Johann Carstensen, Sebastian Lang and Fine Cordua

Your Best Estimate is Fine. Or is It?
Jerry Timbrook, Kristen Olson and Jolene D. Smyth

Analyzing the Association of Objective Burden Measures to Perceived Burden with Regression Trees
Daniel K. Yang and Daniell S. Toth

Modeling the Relationship between Proxy Measures of Respondent Burden and Survey Response Rates in a Household Panel Survey
Morgan Earp, Robin Kaplan and Daniell Toth

Exploring Burden Perceptions of Household Survey Respondents in the American Community Survey
Jessica Holzberg and Jonathan Katz

Determination of the Threshold in Cutoff Sampling Using Response Burden with an Application to Intrastat
Sašo Polanec, Paul A. Smith and Mojca Bavdaž

A User-Driven Method for Using Research Products to Empirically Assess Item Importance in National Surveys
Ai Rene Ong, Robert Schultz, Sofi Sinozich, Jennifer Sinibaldi, Brady T West, James Wagner and John Finamore

Survey Practice

Vol. 15, Issue 1, 2022

https://www.surveypractice.org/issue/3951

Survey Research Methods

Journal of the European Survey Research Association

Vol 16 No 2 (2022)

https://ojs.ub.uni-konstanz.de/srm/issue/view/230

Boosting Survey Response Rates by Announcing Undefined Lottery Prizes in Invitation Email Subject Lines Evidence from a Global Randomized Controlled Trial
Syedah Ahmad, Robert Lensink, Annika Mueller

The Role of the Interviewer in Producing Mode Effects: Results From a Mixed Modes Experiment Comparing Face-to-Face, Telephone and Web Administration
Steven Hope, Pamela Campanelli, Gerry Nicolaas, Peter Lynn, Annette Jäckle

Answer Refused: Exploring How Item Non-response on Domestic Abuse Questions in a Social Survey Affects Analysis
Valeria Skafida, Fiona Morrison, John Devaney

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Comparing Probability-Based Surveys and Nonprobability Online Panel Surveys in Australia: A Total Survey Error Perspective
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The Blind Spot: Studying the Association Between Survey Nonresponse and Adherence to COVID-19 Governmental Regulations in a Population-Based German Web-Survey
Martin Wetzel, Bettina Hünteler

Survey Response in RDD-Sampling SMS-Invitation Web-Push Study
Sebastian Kocar

Choosing Who to Follow: The Long-Run Impact of Following Rules on the Sample Size and Composition of Household Panel Surveys
Nicole Watson

Adapting the Robust Effect Size Cliff's Delta to Compare Behaviour Profiles
Frank Bais, Joost van der Neut

Harmonizing Single-Question Instruments for Latent Constructs With Equating Using Political Interest as an Example.
Ranjit Konrad Singh

An Item Response Theory Analysis and Psychometric Properties of the Czech Version of the Satisfaction with Life Scale
Radka Hanzlová

How and Why Does the Mode of Data Collection Affect Consent to Data Linkage?
Annette Jäckle, Jonathan Burton, Mick P. Couper, Thomas F. Crossley, Sandra Walzenbach

Other Journals

- **Statistical Journal of the IAOS**
    - https://content.iospress.com/journals/statistical-journal-of-the-iaos/
- **International Statistical Review**
    - https://onlinelibrary.wiley.com/journal/17515823

- **Transactions on Data Privacy**
    - http://www.tdp.cat/
- **Journal of the Royal Statistical Society, Series A (Statistics in Society)**
    - https://rss.onlinelibrary.wiley.com/journal/1467985x
- **Journal of the American Statistical Association**
    - https://amstat.tandfonline.com/uasa20
- **Statistics in Transition**
    - https://sit.stat.gov.pl

Welcome New Members!

We are very pleased to welcome the following new IASS members!

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DR.	Med	Verma	India
DR.	Enrique	de Alba	Mexico
DR.	Steven B.	Cohen	United States
MR.	John R.B.	King	United Kingdom

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President-elect:	Natalie Shlomo (UK)	natalie.shlomo@manchester.ac.uk
Vice-Presidents:		
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VP Finance	Jairo Arrow (South Africa)	jairo.arrow@gmail.com
Liaising with ISI EC and ISI PO plus administrative matters	Natalie Shlomo (UK)	natalie.shlomo@manchester.ac.uk
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IASS representative on the ISI publications committee	M. Giovanna Ranalli (Italy)	maria.ranalli@unipg.it
IASS Webinars Representatives 2021-2023	Andrea da Silva (Brazil)	andrea.silva@ibge.gov.br
Ex Officio Member:	Ada van Krimpen	an.vankrimpen@cbs.nl

IASS Twitter Account @iass_isi (https://twitter.com/iass_isi)

IASS LinkedIn Account https://www.linkedin.com/company/international-association-of-survey-statisticians-iass

Institutional Members

International organisations:

- Eurostat (European Statistical Office)

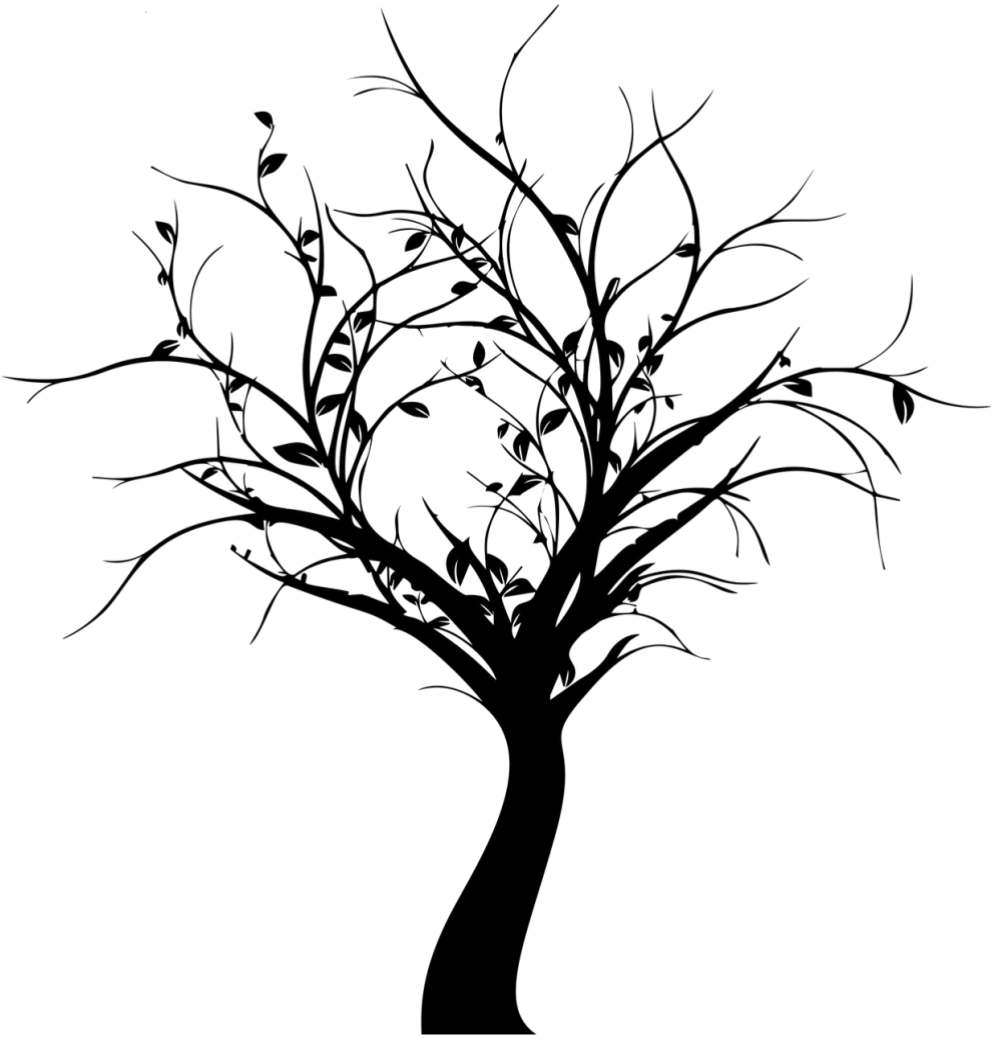
National statistical offices:

- Australian Bureau of Statistics, Australia
- Instituto Brasileiro de Geografia e Estatística (IBGE), Brazil
- Statistics Canada, Canada
- Statistics Denmark, Denmark
- Statistics Finland, Finland
- Statistisches Bundesamt (Destatis), Germany
- Israel Central Bureau of Statistics, Israel
- Istituto nazionale di statistica (Istat), Italy
- Statistics Korea (KOSTAT), Republic of Korea
- EC Eurostat – Unit 01: External & Interinst.
- Direcção dos Serviços de Estatística e Censos (DSEC), Macao, SAR China
- Statistics Mauritius, Mauritius
- Instituto Nacional de Estadística y Geografía (INEGI), Mexico
- Statistics New Zealand, New Zealand
- Statistics Norway, Norway
- Instituto Nacional de Estatística (INE), Portugal
- Statistics Sweden, Sweden
- Turkish Statistical Institute (Turkstat)
- National Agricultural Statistics Service (NASS), United States
- National Center of Health Statistics (NCHS), United States

Private companies:

- Westat, United States

Read *the Survey Statistician* online!



http://isi-iass.org/home/services/the-survey-statistician/