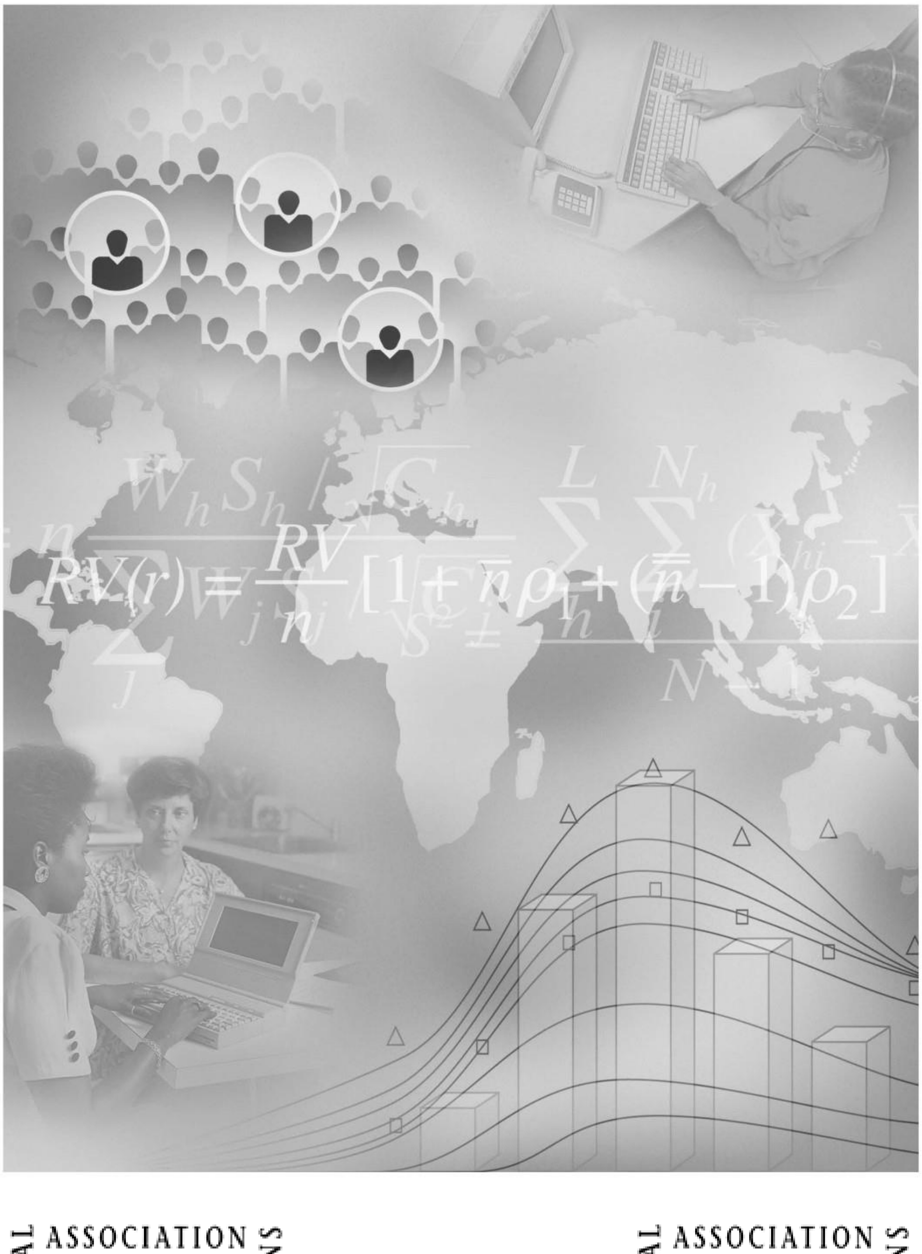
the Survey Statistician

The Newsletter of the International Association of Survey Statisticians

No. 82 **July 2020**



INTERNATIONAL ASSOCIATION OF SURVEY STATISTICIANS

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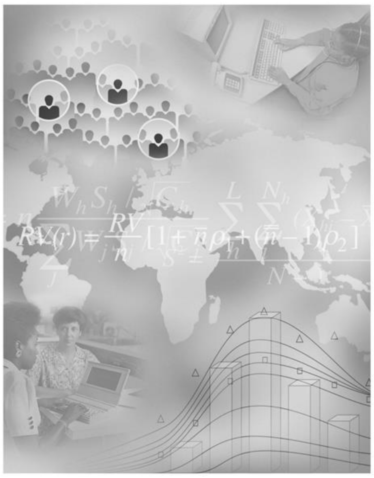

The Survey Statistician No. 82, July 2020

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In this Issue

Letter from the Editors

The 82nd issue of The Survey Statistician (TSS) starts as usual with a kind letter from the IASS President where she presents IASS activities in presence of the COVID-19 pandemic. The Scientific secretary pursues this topic, explaining postponements in the planned arrangements in the Report from the Scientific Secretary. Information about celebrations of two survey statisticians, Ray Chambers and Luigi Biggeri is then presented. The events took place in the beginning of the year. The editorial board of TSS congratulates Ray and Luigi and wishes good health and continued high achievements in statistics for them and for their followers.

Despite the fact that the planning of this issue started in 2019, it so happens that it perfectly meets the needs of survey statisticians in the world changed by the Covid-19 virus. The topics of papers included in the *Ask the Experts* and *New and Emerging Methods* sections cover the use of alternative data sources that can be used to eliminate survey data collection in business, agriculture and population surveys. Also, mobile devices have become an important part of people's lives, and it makes sense to consider using them in statistical data collection to replace face-to-face and other ways of data collection. Challenges for survey statisticians in the changing data environment are described. The global pandemic modified people's lifestyles, and the *Country Reports* show how it influences the work of National Statistical Offices around the world. The review of the Seppo Laaksonen's book *Survey Methodology and Missing Data* reminds that classical problems and their solutions should not be forgotten even in non-traditional situation.

We thank everyone who supplied the current issue with information, starting with the IASS president Denise Britz do Nascimento Silva for her strong support and activities towards TSS' benefit. This first 2020 issue of TSS is now presented on the web in a split version by papers and supplied with the information about the open source publication.

There are some changes in the editorial board. Olivier Dupriez, from the World Bank, completed his work as a webmaster of IASS. We thank him for his contribution and inputs over the years and wish him success in his other roles. The role of the webmaster has now been given to Melini Cooper and Harry Raymond from *Australian Bureau of Statistics*. They are both welcomed.

James Chipperfield is now responsible for the section *New and Emerging Methods*. Please let James Chipperfield (james.chipperfield@abs.gov.au) know if you would like to contribute to the *New and Emerging Methods* section in the future. Also, if you have any questions which you would like to see answered by an expert, please send them to the new *Ask the Experts* section editor Ton de Waal from Statistics Netherlands (t.dewaal@cbs.nl). If you are interested in writing a book or software review or suggesting a source to be reviewed, please get in touch with the *Book & Software Review* section editor Emilio López Escobar from the *Quantos Investigación Cuantitativa* in Mexico (emilio@quantos.mx). Finally, the country reports should be sent to Peter Wright from Statistics Canada (peter.wright2@canada.ca).

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 IASS members

Since the last TSS edition in January, much has changed in our lives due to the pandemic situation that is affecting all of us. I wish this letter finds you and your families safe and healthy.

The need to adjust to a remote working environment demanded emergency changes on teaching, research, conferencing, and survey processes. All over the world, National Statistical Offices and survey institutions are dealing with methodological and operational challenges to maintain continuity of their statistical programmes. Survey statisticians are involved in several initiatives to meet the new data demands to promptly respond to the pandemic crisis, such as pulse surveys to monitor its impact on population well-being and the economy, surveillance surveys, and projects related to the integration of survey data and alternative data sources. The current unique events present plenty of complex and urgent problems to be addressed, and surveys keep playing an important role in providing evidence for informed decisions.

In this unsettling time, IASS is actively engaged in fulfilling its mission. President-elect Monica Pratesi motivated discussion regarding application of the best survey methods to support COVID-19 surveillance. We contacted IASS country representatives to obtain information on sample surveys being planned or taking place across the world to deal with this issue and we thank them for their responses. Gaia Bertarelli and Pedro Silva organised the material that will soon be communicated via the IASS website. We also planned some webinars to share this information and to discuss related matters. The first of the series, “Sample Surveys on Covid-19 Pandemia Around the World”, was held in June. I celebrate its success and congratulate the invited speakers: Monica Pratesi, Linda Sabbadini, Bruce Fraser, Danny Pfeffermann, Luis Carlos Silva Aycaguer, Salah Merad and Pedro Silva. We are really motivated to organise the following ones and to engage the IASS community in this activity.

Although many conferences have been cancelled or were postponed to 2021, one of the IASS supported conferences took place in Nigeria in February. A report is available in this TSS edition. As I informed in January, we are liaising with ISI and other ISI Associations to enhance collaboration and to participate in working groups. I attended an IAOS council meeting in which we discussed some ideas to promote joint IASS-IAOS activities. In addition, during the first semester of 2020, IASS appointed the following representatives to committees/working groups: Isabel Molina – ISI Data Science Working Group, James Chipperfield and Danutė Krapavickaitė – ISI Publication Committee, Solange Correa-Onel – ISI Working Group for the International Year of Women in Statistics and Data Science, Peter I. Ogunyinka – ISI Young Statisticians Committee, Monica Pratesi – Programme Committee of the World Statistics Conference 2021 (WSC2021) and Maria Giovanna Ranalli – Short Course Committee of the WSC2021. I am grateful for their contribution.

Also, we welcome Emilio López Escobar and Ton de Waal in the TSS team to contribute to the Book and Software Reviews and Ask the Experts sections. Regarding our website, Melini Cooper and Harry Raymond, of the Australian Bureau of Statistics, have agreed to jointly hold the IASS webmaster role. We thank them and the ABS for the collaboration. Very special thanks are due to Olivier Dupriez for being our webmaster for many years.

Unfortunately, one of our distinguished members, Prof. Chris Skinner, passed away this February. His impressive academic carrier and generosity to share his knowledge impacted the development of survey methods and the lives of many students and collaborators. I was one of them. Chris was interviewed by David Haziza and Paul Smith in 2019 for the International Statistical Review (https://onlinelibrary.wiley.com/doi/full/10.1111/insr.12356). A conference to honour him and Fred Smith, both having served on the IASS Executive Committee, will take place in Southampton in July 2021, and is planned to be a satellite meeting of the WSC2021.

When reading TSS, it is inevitable to notice many names as well as information about research and activities that involve several people (including the production and circulation of TSS). Well, this is us. IASS community, collaborators and sympathisers who share interests and care for IASS. If you are reading this letter, keep connected with IASS and invite colleagues to join the association. Let us increase and enhance this invaluable network.

I hope that you, and those around you, remain safe. I keep positive for the end of this difficult period.

"What we call the beginning is often the end and to make and end is to make a beginning. The end is where we start from." (T.S. Eliot, *Little Gidding*)

In the meantime, I want to express my commitment to IASS and will be happy to receive your feedback and suggestions on how we can best work together.

Denise Silva

(denisebritz@gmail.com)

Report from the Scientific Secretary

It has been a busy first 6 months for me in the role of Scientific Secretary. It has been great making connections with other statisticians across the world and trying to make a difference.

In this report I introduce the article in the *New and Emerging Methods* section, request members input on IASS webinars, mention plans to update the IASS website, mention how the IASS EC is responding to the Covid-19 pandemic, and provide an update on upcoming conferences. We are also looking to email IASS members directly with important updates (e.g. IASS monthly newsletter).

I encourage you to share your views on the functions of the Scientific Secretary with me.

New and Emerging Methods

The article in the New and Emerging Methods section is written by participants of a workshop that was held in Sydney (Australia) during February 2020 with the theme *Using administrative data, along with or in place of a traditional census, to count a countries' population size*. The article is called Exploring developments in population size estimation. It explores the replacement of traditional census with administrative data sources. A main motivation for this work is cost reduction- Censuses are expensive. This article is timely as many countries have decided to delay their traditional Census due to the Covid-19 pandemic and will be considering administrative sources as a replacement. The article has contributions from over 4 countries and 9 individuals.

The format of The New and Emerging Methods articles is 8-10 pages and should cover the presenting challenge, the methods and their application, and the relevance to the development of survey methods. Please contact me if you are interested in writing such an article for future editions of The Survey Statistician.

Webinars

The IASS EC is considering holding a series of webinars. If you would like to contribute to the webinar series or would like to suggest a topic, please contact me. The first series of webinars will be on Covid-19 surveillance surveys (see below).

IASS and Covid-19

The Covid-19 pandemic has had a major impact on our societies and on how our statistical agencies collect survey data for decision-making. Statistical agencies have postponed Census collections that were planned to take place during 2020 and are using alternatives to face-to-face interviewing. Agencies are measuring the prevalence of Covid-19 in their populations and its impact on well-being, so called Covid-19 surveillance surveys. The World Health Organisation released guidelines for Covid-19 surveillance surveys. The IASS EC feels that the IASS can play a role here as well.

First, as mentioned in the May 2020 IASS newsletter, the IASS EC and the Italian Statistical Society are collating information about Covid-19 surveillance surveys that are being conducted by statistical agencies across the world. We plan to share the information with IASS members (via IASS website). If you can contribute to this, please contact Gaia (gaia.bertarelli@ec.unipi.it) and Denise (denisebritz@gmail.com). Pedro Luis do Nascimento Silva has kindly helped with the collation.

Second, the IASS EC is planning a series of webinars during 2020 on Covid-19 surveillance surveys. Information about this will be emailed to members and appear on the IASS website in due course. Please contact me if you would like to present such a webinar.

IASS Website

There are few items the IASS EC plan on uploading to the IASS website during 2020. These include:

- a list of all past IASS presidents and vice presidents since inception (1973) and a list of council members since 2000. If you can help complete the list of council members prior to 2000 please let me know!
- monthly IASS newsletters.
- links to IASS webinars
- statistical agencies' plans and progress in the design of Covid-19 surveillance surveys

Collaboration with IAOS

The IASS EC is looking to work collaboratively with the International Association for Official Statistics. As part of this we will promote its statistics journal, SJIAOS (https://officialstatistics.com/), by linking it to the IASS monthly newsletter We are also planning a joint activity for the 2020 World Statistics Day on 20th October. Details will be announced soon.

WSC 2021

The IASS EC is finalising its proposal for 2-3 short courses which will be forwarded to the WSC Short Course Committee. The committee emphasises the need for short courses that promote continuing professional development and go beyond our usual statistical capacity building.

As a result of the recent Covid-19 pandemic, the ISI is considering options to have part of the WSC programme available online. Updates will be announced via https://www.isi2021.org/ and via e-mail to ISI members.

The submission system for IPS Proposals is not yet open. Further announcements will again be made via their website and via email to ISI members. If you are considering such a proposal see https://www.isi-web.org/images/news/2019-12_ISIWSC2021-Pre-announcement-call-for-proposals.pdf.

Other News

A conference in honour of Fred Smith & Chris Skinner, both of whom had served on the IASS Executive Committee, will take place 8-10 July in Southampton 2021. It will likely finish at lunchtime on 10th, allowing people to travel to the Hague, Netherlands for the start of the WSC 2021. More details will be announced at a later date.

On 12 May at 13:00 (CEST), the ISI celebrated the International Year of Women in Statistics and Data, the ISI's 135th anniversary (which falls on 24 June), and the official welcome for the 63rd ISI World Statistics Congress in The Hague in July 2021. To mark the celebration the ISI posted presentations on the above three topics on its website https://www.isi2021.org/international-year-of-women-in-statistics-and-data-science.html.

James Chipperfield

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News and Announcements

Advances in Statistical Methodology: A symposium to celebrate the career of Professor Ray Chambers

To celebrate the career of Professor Ray Chambers a symposium on advances in statistical methodology was held on Thursday 6 February 2020 at the National Institute for Applied Statistics Research Australia, University of Wollongong.

The symposium considered some of the important areas of statistical methodology in which Ray has extensive interests. Ray has made significant contributions in a range of areas, including Sample Survey Design and Analysis, Robust Statistical Methods, Small Area Estimation, Graphical Methods in Statistics, Computer Intensive Statistical Methods, Statistical Modelling and Inference, Longitudinal Data Analysis, and Analysis of Computer-Linked Data.

Over 40 people attended the workshop including many from overseas, reflecting the high regard in which Ray is held internationally and his involvement in research, collaboration and consulting in many countries. Ray's career includes senior appointments at the Australian Bureau of Statistics, Australian Bureau of Agricultural and Resource Economics, The Australian National University, the University of Southampton, and the University of Wollongong.

Speakers included: Roberto Benedetti, James Brown, Robert Clark, Alan Dorfman, Paul Smith, Siu-Ming Tam, Nikos Tzavidis, Suojin Wang, Alan Welsh, and Li-Chun Zhang.

To mark the occasion Ray was presented with a case of Coonawarra Cabernet Sauvignon, labelled "The Robust Statistician".

Further details can be found at:

https://niasra.uow.edu.au/content/groups/public/@web/@inf/@math/documents/doc/uow263248.pdf

Luigi Biggeri's 80th birthday
Organized by the Department of Statistics, Computer Science, Applications "Giuseppe Parenti" University of Florence

Last January 30, 2020 many colleagues from our national and international scientific community met in Firenze to celebrate Luigi Biggeri's 80th birthday attending a workshop organized by the Department of Statistics, Computer Science, Applications "Giuseppe Parenti" University of Florence. The workshop was focused on the main research fields in which Luigi was a precursor at least in Italy.

In the last 30 years, he has made pioneering and highly influential contributions to a uniquely wide range of topics in applied statistics: price indices and PPPs, efficiency and effectiveness in university education, official statistics, poverty and well-being, statistics and society and statistics for citizens. His teaching has inspired generations of students, and many well-known researchers have begun as his graduate students or have worked with him at early stages of their careers. Many statisticians have been stimulated and enlightened by his many books, papers, and lectures about and more than 100 participants animated the event. Luigi was IASS president in 2003-2005.

Many IASS and ISI members sent their greetings: among the others we recall Jon N. K. Rao, Partha Lahiri, Natalie Shlomo, Colm O'Muirchertaigh, Danny Pfeffermann, Cynthia Clark, Ray Chambers, Prasada Rao and many fellows from World Bank. Monica Pratesi, President of the Italian Statistical Society and IASS President-elect together with Walter Radermacher, President of the FENSTAT, wished to Luigi all the best from the Italian and European communities. Denise Britz do Nascimento Silva, IASS President, sent the wishes of all the IASS members and Steve Penneck, President-elect of ISI, talked of Luigi as active and loyal ISI member.

Report on the IASS–Sponsored Event: Conference for Population Surveys, Data Users and Producers, 5-6 February 2020, Nigeria, Africa

The conference was held at the Federal University of Agriculture and was organised by the Royal Statistical Society Nigeria Local Group. The theme of the conference was *Population data for informed national planning and development*. Fifty-two papers were accepted and forty-six were presented at the conference. Over 350 participants attended from universities, the National Bureau of Statistics, the National Population Commission, the Central Bank of Nigeria, and the Ministry of Finance. Keynote speakers were Professor T. A. Bamiduro and Professor Kayode Ayinde who addressed the core conference theme of the statistics, planning and development. The conference allowed participants to share their research ideas and promote collaboration and networking.

The Important Role of Surveys during the COVID19 Pandemic

A recent issue of the free, open-access, journal *Survey Research Methods* is devoted to the impact of the COVID19 pandemic on survey research. Papers from several countries describe how surveys have adapted their methodology to be able to continue during the pandemic, and how survey research can contribute to understanding of the spread and the impacts of the virus. The issue can be found at https://surveymethods.org/issue/view/221.

Also, the Societal Experts Action Network (SEAN) of the American National Academies has set up a COVID-19 Survey Archive that contains survey questions, results, reports and related materials from hundreds of probability-based surveys on aspects of the pandemic from around the world. The archive is expanding daily and can be found at https://covid-19.parc.us.com/.

Corona Virus and National Statistical Offices

The United Nations is collecting information from countries to assess the impact of the corona virus pandemic on Census collection that was planned in 2020.
https://unstats.un.org/unsd/demographic-social/census/COVID-19/

The United Nations has also created a website to share best practice between National Statistical Offices on mitigating the impact of the corona virus pandemic on its business.
https://covid-19-response.unstatshub.org/

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Ask the Experts

Why machine learning and what is its role in the production of official statistics?

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Abstract

To remain competitive, statistical organizations need to move quickly to adopt and take advantage of machine learning and new digital data sources. Machine learning is not fundamentally new, and statistical agencies have been using modelling techniques for a very long time. Why do National Statistical Organizations require machine learning in their toolbox and what is its role in the production of official statistics? These are some of the questions discussed in this paper, along with examples of machine learning use in official statistics.

Keywords: machine learning, official statistics, artificial intelligence, open source

What is Machine Learning?

"Machine learning is the science of getting computers to automatically learn from experience instead of relying on explicitly programmed rules, and generalize the acquired knowledge to new settings." [1]

In essence, Machine Learning automates the analytical model building through optimisation algorithms and parameters that can be modified and fine-tuned.

1 Why do National Statistical Organizations require machine learning in their toolbox?

National Statistical Organizations (NSOs) are data-driven organizations, and data are at the centre of today's digital revolution. Data and technology are transforming our society and the way we consume information. The vast amount of digital data available is also transforming the role of NSOs as the premier information providers for evidence-based decision making.

New alternative data sources are already showing many benefits, including: providing faster and timelier products, reducing response burden on households and businesses, producing more accurate results and lowering costs. This is fundamentally changing the way statistical agencies operate. Many of these new opportunities require the use of machine learning methods. In fact, machine learning is the main computation tool for big data processing.

2 Is machine learning new?

Machine learning, and artificial intelligence, are not fundamentally new [4]. Statistical agencies have been using modelling techniques and data analytics for a very long time. Examples include modelling for stratification, imputation, and estimation purposes. [2] and [3] are excellent references in this context.

What makes today's machine learning methods different than the ones used five or ten years ago is their evolution within the big data processing space. This evolution has been enabled by:

- better computational capacity,
- along with developments in the algorithmic space and applications to unstructured data (text, images, video, censor, etc.)
- more efficient data ingestion
- increased access to structured and unstructured data
- more capabilities offered by big data processing platforms to efficiently manage RAM and CPU, and, when required, GPUs, both in the cloud and on-premises [5]

Another major factor driving this shift in methods is collaboration, especially in the open source community. Using R and Python for machine learning and having an open source first approach are accepted standards today. While previously development of data processing systems has been done independently by organizations, today users can benefit from open source code that results from years of effort, and has been tested at a scale that was not previously feasible. The implementation of open source tools can accelerate development, reduce project costs and result in faster turnaround times, allowing projects to move from development mode to production mode more quickly.

3 Machine learning use in official statistics: examples and benefits

3.1 Machine learning applied to retail scanner data

Statistics Canada receives point of sale data from large retailers. This provides a complete census data for volume and price statistics from the participating businesses. In the short term, the agency reduces reporting burden by eliminating survey collection for the participating businesses, which also reduces collection efforts. Statistics Canada is providing participating businesses with custom user-defined statistics based on their data. In the long term, as more businesses provide scanner data, the agency will be in a position to release local-level data (city and postal code), along with commodity data at a far more granular level. Whereas previously data was produced on a few hundred commodities, based on the North American Product Classification Standard (NAPCS), now it will be possible to potentially release data at the Universal Product Code level, i.e., thousands of different commodities. Another potential output is weekly publications on the value, amount, and average price of each NAPCS product sold at retail by detailed geographic area. A machine learning classifier, XGBoost, with linear base learners using character n-grams and bag of words based approach, is used to associate the presence of substrings in the data with certain NAPCS codes.

3.2 Satellite images use in agriculture

Currently, Statistics Canada has three machine learning projects in the space of agriculture that use satellite images. The in-season crop identification project, for instance, aims at predicting crop type proportions within an image. Landsat-8 satellite images of two census agricultural regions within Alberta are used. The labelled data are derived from crop insurance data. Using this dataset, a state-of- the-art deep learning model is built. This new model is expected to produce real time data and reduce the cost of crop production data collection. Other examples of machine learning use include the estimation of the area of land covered by greenhouses from satellite images, as well as the area covered by solar panels.

3.3 Automation

A broad range of tasks exist where analysts can extract information from unstructured data sources, such as the extraction of financial variables from annual financial reports; financial statements; company information forms; legal reports; news releases; acquisition and merger of assets of publicly traded companies; and financial statements received from federal, provincial and municipal organizations. Many of these tasks can be automated using machine learning, resulting in much more efficient processes.

Closing. Challenges and opportunities

The machine learning context is highly dynamic—which can be both an advantage and a challenge. This type of environment requires an ever-learning mindset. To remain competitive within this transformed data modelling space, statistical organizations need to move quickly to adopt and take advantage of machine learning and new digital data sources. Survey statisticians offer advanced expertise in statistical methods and data quality, and are well positioned to contribute to and benefit from the larger machine learning community. Survey statisticians will play a key role in the algorithmic space by identifying the standards of rigor, ensuring statistically sound methods are used, promoting quality and valid inference when it is needed, and abiding by ethical science practices when deriving insights from data [6]. While new technologies are creating amazing opportunities, these opportunities come with responsibilities. New algorithms and model assessment guidelines will have to be developed, and their monitoring and maintenance in production will pose new type of challenges.

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Active and passive measurement in mobile surveys

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Abstract

In this paper we discuss the implications of using mobile devices for online survey completion. With more and more people accessing online surveys on mobile devices, online surveys need to be redesigned in order to be able to meet the characteristics of mobile device usage, such as small screens and short messaging. We discuss mobile friendly design by focussing on survey layout, the length of the survey, special features, and the decision of making the survey app or browser based. Further, we discuss the different sensors that can be used to augment or replace survey questions, and respondents' willingness to share sensor data. We end with three examples of surveys conducted by Statistics Netherlands, where sensors are used for active and passive measurement in mobile surveys.

Keywords: sensor data, mobile surveys, passive measurement, data collection, data sharing

Introduction

The increasing abundance and commodification of data has caused a shift in survey research in the past two decades, reflecting how societies understand and make use of data. Some people are suggesting the eventual demise of social surveys in favor of new and innovative methods for social or human data collection (Savage & Burrows, 2007). However, most survey methodologists seem to believe in a future that harnesses a plurality of data sources, combining survey data with organic data such as web data, administrative data, or data collected through sensors and the Internet of Things. (Couper, 2013). Given the fact that traditional surveys require more and more effort and suffer from increasing costs (de Leeuw, Hox, & Luiten, 2018), new and supplemental data collection methods are very welcome to potentially improve data collection methods. In an era with an abundance of organic data, survey research has begun to explore the opportunities and challenges of augmenting survey data with organic data sources.

One area of new developments in survey research is the use of sensors in mobile devices to capture new types of data. Mobile devises have become an important part of people's lives, and it makes sense to use them for research purposes. Mobile devices have functions such as sensors that can be used to collect data in addition to asking questions. Wenz, Jackle and Couper (2019) divide these sensors into passive and active sensors. Passive sensors include device usage tracking apps, an accelerometer, GPS and the Bluetooth linkage to external devices; active sensors include camera use, text messages and the use of apps to answer questions. Mobile devices give researchers the opportunity to ask new types of questions, because most individuals are acquainted with the smartphone and its functions. Also, since the use of sensors in mobile devices have become normal and easy for many people (e.g. the use of camera, GPS), it might prove beneficial to use sensors for respondents who struggle to answer survey questions such as people with low cognitive ability (Sauer, Auspurg, Hinz, & Liebig, 2011). While many more organic data sources are available, one key advantage of mobile devices is that they can potentially be used by respondents to answer survey questions as well as provide other big data, such as sensor data at the level of the individual. Link et al. (2014) reported in their study on the possible implications of smartphone sensors as research tools that in addition to using sensors to augment or replace survey questions, the use of sensors can add context to survey data.

In this paper we discuss the implications of using mobile devices for online survey completion. We first focus on the design of mobile surveys. Online surveys have traditionally been designed for desktop PC completion. With more and more people accessing online surveys on mobile devices, online surveys need to be redesigned in order to be able to meet the characteristics of mobile device usage, such as small screens and short messaging. In addition, surveys designed for mobile devices can make use of sensors in order to augment or replace survey questions. We discuss mobile friendly design by focussing on survey layout, the length of the survey, special features, and the decision of making the survey app or browser based. Further, we discuss the different sensors that can be used to augment or replace survey questions, and respondents' willingness to share sensor data. We end with three examples of surveys conducted by Statistics Netherlands, where sensors are used for active and passive measurement in mobile surveys.

Mobile friendly design

Online surveys are mixed-device surveys in the sense that they are being completed on a range of different devices, such as desktop PCs, tablets, and smartphones. There are several ways to structure the survey with the goal to create an optimal experience for any device. In a device-agnostic approach, the survey will be the same on all devices. In a device-adaptive approach, one can distribute longer surveys on devices with large screens, and shorter surveys or the use of sensors on smaller devices. There are several ways to design a device-agnostic survey. Traditionally, surveys have been designed with a traditional desktop PC in mind. However, more and more surveys use a mobile-first survey design, where the survey is optimized for mobile phones. The rationale behind this is that if it looks good on a small mobile phone screen, it looks good on all devices. Most software for online surveys uses a responsive design, where the questionnaire layout is adapted to the device being used. User agent strings (UAS) can be used to detect the operating system and device. This can be enhanced with JavaScript to capture additional information such as screen size and browser. Some software uses real-time coding, while others use post-survey analyses (e.g. Rossman, Gummer & Kaczmirek, 2020).

Layout

With a mobile-first design perspective in mind, Antoun et al. (2017) have summarized the literature on mobile and mixed-device research and suggest the following guidelines on how to optimize for mobile:

- Use large fonts
- Content should fit to the width of the screen (no horizontal scrolling)
- Response options should be displayed as wide buttons or tiles
- Pictograms can be used for visual relief
- Avoid grid or matrix layout
- Use an auto-advance option

- Eliminate unnecessary elements such as images, progress bars, etcetera, to reduce visual distractions and reduce page-load delays.

Grid questions – were several items are place in the same grid or matrix- are difficult to design for small screen sizes. There are several ways to design grid questions. Some survey software uses a one-item-per-screen format for mobile surveys and a grid or matrix for desktop computer surveys. Some software changes the orientation of the scale to vertically aligned answer categories for mobile devices while retaining horizontally aligned answer categories for grid questions on desktop computers. This is problematic since research has shown response effects due to scale orientation as well as higher inter-item correlations when items are presented on a single screen (e.g. see Toepoel, Das & van Soest, 2009). It is therefore important to make sure that the layout of the survey is similar across devices when respondents use different devices to complete a survey. Alternatives to a grid design are a carousel format (where items fly by with an auto-advance function) and an accordion format (unfolding design, where questions are collapsible and a new question automatically unfolds when a question has been answered). By using an auto-advance function, the efficiency gain for grid questions can be mimicked.

Although dropdown menus are often used in mobile or mixed-device surveys since they save space on a screen, their use is not recommended. They look different on iOS and Android devices. In addition, long response options are sometimes truncated, and some browsers turn dropdown menus into scrolling wheels, whereby the first response option follows the last one on the wheel, affecting context effects.

Survey length

Kelly et al. (2013) show that a 20-minute survey is acceptable for 66% of PC users, while only 27% of smartphone users is willing to spend 20 minutes on a survey. In addition, only 73% of smartphone users is willing to spend 5 minutes on a survey, compared to 98% of computer users. Roberts and Bakker (2018) demonstrate that break off rate is on average 32% on mobile compared to 12% on tablet and 10% on PC for Statistics Netherlands. Reducing survey length seems important in an era where more and more surveys are being completed on mobile devices. The easiest way to accomplish this is to cut questions, but many researchers find it difficult to cut questions. An alternative is a split survey design, where a survey is chunked into smaller parts. Each portion can be fielded separately, and after the data collection, parts can be combined into one holistic data set again (stitching). This can be done across or within respondents. In within-respondent modularization, each respondent is offered all parts, but in several different chunks. Toepoel and Lugtig (2018) have demonstrated that this can increase response rates by about 10 percentage points, and although not all respondents may respond to all individual parts (wave nonresponse), the proportion of missing information can still be lower in the split survey design. Across-respondent modularization is more complex. One module typically contains all important (background) questions and goes to all respondents. Each respondent receives only a particular subset of the remaining modules. Whether modularization is a general solution for survey length is still very much a question, as there are also unsuccessful examples (Lips & Pollien, 2019; Andreadis & Karsounidou, 2020).

As mentioned in the previous section, another way to cut down on participant time to complete a survey is by using an auto-advance option. With this option, the respondent is immediately navigated to the next question without having to press a “next” button.

App Versus Browser based

Active and passive data collection in mobile surveys is possible via research apps or via the browser (JavaScript or HTML5). A research app is software that can collect data from the phone, which can then be used for data entry. Downloading an app can be an extra obstacle for participation, and may cause respondents to drop out. Apps have more possibilities than browsers, however, such as the use of camera or video's. An app runs in the background and can collect sensor data over a longer period than can a browser. In addition, reminders can easily be sent through an app as well as pop-up questions that need to be answered on the spot. Since programming an app is a lot of effort, apps are particularly suitable for long periods of data collection.

There is a large variety of devices, with (slightly) different operating systems, such as iOS and Android systems, and apps need to be developed for each platform. Different smartphone models include different sensors and displays, with different hardware specifications and software drivers. These specifications can largely influence the quality of the sensor data collected. For example, Read (2019) shows that device variation related to photo quality is very large, particularly due to the operating system and memory.

Technical limitations may constrain how many hours per day an app can gather data. Especially battery-intensive passive data collection like GPS tracking may drain the battery of a respondent's device. Respondents will need to charge their device regularly, which some might forget or perceive as burdensome, inducing nonresponse.

JavaScript may be easier to program than an app, but JavaScript cannot collect data for a long period of time (only for the time that the web-page is open). JavaScript is especially useful for single-time measurement—for example, to collect respondents' current location or when respondents are asked to take a picture. An example of a JavaScript tool is SurveyMotion (Höhne & Schlosser, 2019), that collects respondents acceleration data during an online survey.

Special features

Mobile phones bring new opportunities that are not possible or more difficult on computer devices. For example, push notifications can be sent in the moment. Location-based surveys or highly targeted mobile surveys can be used when people are on a specific premise or leaving a specific premise, such as a festival or business meeting. The notification can even be the question itself. Surveys might also become more conversational or gamified. For example, communicating through apps such as WhatsApp and Snapchat closely resembles natural turn-by-turn conversations between humans. Service chatbots try to mimic that communication style as well, turning a survey into a WhatsApp type of survey. One important feature of mobile surveys is the sensors that come with the mobile device.

Sensors in mobile phones

Smartphones incorporate a large number of sensors which can be logged passively, providing a large and detailed set of measurements about respondents and their environment.

Types of sensors

Based on Toepoel and Elevelt (2020) we discuss the most commonly used sensors for research purposes in social sciences.

Accelerometer: The rate of change of velocity of an object over time. It is measured in meters per second squared (m/s^2). Acceleration can occur on three different axes: the x-axis (i.e., left and right), the y-axis (i.e., up and down), and the z-axis (i.e., back and forth). In addition to the movement level on these three axes, the movement duration and stationary periods can be measured. Accelerometers are typically used to measure respondents' activity or motion level.

GPS Receiver: Respondents' geolocations can be determined both by the GPS receiver incorporated in smartphones or by cellular towers and Wi-Fi networks. All methods result in a GPS location, which is measured in a latitude and longitude. GPS measures can record a location accurately with a precision of about 5 meters (GPS/Wi-Fi), although precision is much lower when cellular networks are used. GPS location can be used to investigate mobility patterns such as respondents' duration of time spent at a specific location, the frequency of visiting locations, distances travelled, and routines in mobility patterns. GPS coverage varies and GPS accuracy depends on satellite geometry, signal blockage, atmospheric conditions, and receiver design features. One has to be cautious, since geographical location may be inaccurate as GPS trackers lose signal indoors or in areas with tall buildings causing positioning errors.

Bluetooth Scanners: Bluetooth is used for short-range communication between devices, including smartphones, hands-free headsets, tablets, and other wearables. A combination of Bluetooth and Wi-Fi can be used to determine whether devices (a.k.a. other respondents) are near. For example, Stopczynski et al. (2014) used Bluetooth sensors to determine whether schoolchildren are close to class mates (<10 meters) to determine their level of interaction.

Microphone: Microphones are high-fidelity sensors that can capture sound waves. FamilyLog (Bi et al., 2017) used the microphone to detect mealtime sounds, thereby determining the timing and frequency of family meals. They extracted clattering sounds, conversations and other sound sources from the recordings to detect family meal behaviour such as specific voices and conversations, speaking rates and turn-taking in conversation. As a more active task in self-administered surveys, researchers can ask respondents to make voice recordings in which respondents answer a question by dictating an answer instead of typing it.

Proximity Sensor: The proximity sensor combines an infrared LED and light detector. Proximity sensors can be used to detect whether a respondent's face is close to the phone.

Camera: The camera can be used for more active tasks in research, such as making photos or movies. For example, Kelly et al. (2015) asked respondents to take one picture every 10 minutes, to reconstruct a record of activities in time use research. Wenz et al. (2019) asked respondents to use the camera to scan receipts, in a budget study. In addition, a front camera can be used to track the respondent's eye movements across the phone's display, for example to investigate screen usage.

Other Logs: Other smartphone data that may be logged passively, although not through sensor data, are calls, app usage, and texts. Incoming and outgoing texts and calls may provide insights into the respondents' social interactions. App usage, or visited websites, can be tracked by having respondents install an app on their smartphone. The logs from this app may provide insight into mobile phone or web behaviour.

Respondents' willingness to provide sensor data

Sensor data are often perceived as intrusive and privacy-sensitive. Participants may not be willing to share sensor data, or willing respondents are specific socio-demographic subgroups, affecting response bias. Empirical studies on willingness to sharing sensor data have shown that hypothetical willingness tends to be higher than observed willingness (Struminskaya et al., 2018). In addition, willingness varies by task; for example, about 61% of the respondents of the Understanding Society Innovation Panel in the United Kingdom hypothetically consented to the collection of acceleration data, while 36.7% consented to sharing a GPS capture and 25.5% to installing a smartphone tracking app (Wenz et al., 2017). In the Netquest opt-in panel, 37.7% of the panel members hypothetically consented to the collection of acceleration data and 17.8% to installing a smartphone tracking app (Revilla et al., 2018). When looking at demographic or behavioural correlates of sharing sensor data, respondents with advanced smartphone skills and who use their smartphone for numerous activities are more likely to share sensor data (Elevelt, Lugtig & Toepoel, 2019; Keusch et al., 2019; Wenz et al., 2019). Willingness is higher for tasks where respondents have control over the reporting of the results (Revilla et al., 2018). Giving participants an option to review, edit, and delete specific data before transmitting may increase respondents' feelings of control and therefore their willingness to share sensor data (Keusch et al., 2019).

Confidentiality and privacy

Two important factors that influence willingness to share sensor data are privacy and confidentiality. High concerns about data privacy and/or security are associated with lower willingness to share sensor data (Jäckle et al. 2019; Sala et al., 2014; Wenz et al. 2019). The decision-making process of respondents to disclose personal information such as sensor data lies in the evaluation of perceived privacy risk and perceived benefits of disclosing that information (Majumdar & Bose, 2016). The decision to share sensor data is dependent on the type of data being shared, with whom and for what purpose. Also, expectations about intended use – depending on who is asking – can differ across tasks.

Struminskaya et al. (in press) conducted an experiment on factors that affect willingness to share information. In one condition they stated that the information that respondents provided would be treated confidentially and anonymously, and personal data could not be inferred from this information. The control condition did not include this text. Emphasizing privacy protection did not influence willingness to share data. Their results also showed that respondents' stated willingness is significantly higher for a university-sponsored study and lower for a market research sponsor compared to a statistical agency sponsor. The influence of the sponsor is more pronounced for sharing geolocation than for other sensors. In addition, respondents who indicated that they have a higher trust that the questionnaire guaranteed anonymity were more likely to be willing to share data. While the most named reason for non-willingness to share sensor data was privacy and anonymity concerns, the absence of an experimental effect of emphasizing privacy protection in question wording suggests that respondents' privacy concerns might be multifaceted.

It is difficult to grasp exactly what the intrinsic value of privacy is. Respondents do not only value privacy because they value the integrity and the protection of their own data, but also because they value having control over their data. Privacy, therefore, can be considered as something that not only ensures the protection of the information that is being provided by respondents, but also a concept that ensures that this information is collected, analysed and disseminated properly (Nissenbaum, 2010). Legal frameworks protect the privacy of respondents, such as the European Statistics Code of Practice and the European General Data Protection Regulation (GDPR). By stressing the importance of confidentiality and integrity in the data collection process, the Code of Practice focuses on the security of the respondent data from potential third-party intervention. The GDPR is more focused on how to deal with the collection of personal data. GDPR, therefore, focuses on various implications such as how to anonymize data in order to increase the protection of the respondent against the possible use of third parties, and how to be sure that data are going to be collected only with the consent of the respondent and cannot lead back to the respondent. To make the most of sensor data, confidentiality and privacy are central in the data collection process and harvesting new opportunities.

Active and passive measurement with sensors

New data collection opportunities such as the use of sensors (e.g., geolocation, physical movements, online behaviour, app usage, social media usage, text messages) and experience sampling methods (ESM), as well as wearables connecting with Bluetooth can increase data collection opportunities. These opportunities can replace or augment survey questions. Although surveys face difficulties and organic data is abundantly available, there have been few efforts to integrate surveys with organic data beyond ad-hoc methods.

A major advantage of combining sensor data with survey questions, is that it can simplify the response task for individuals. For example, in many surveys it is important that respondents report exactly what they do at what time. Estimates of time use (Fisher & Gershuny, 2013), consumption (Lagiou, & Trichopoulou, 2001) or travel behaviour (Axhausen et al, 2002) have long relied on diary studies that respondents have to complete for several days. Apart from issues of nonresponse, diary study data are often incomplete. Health surveys suffer from inaccurate statistics of how physically active people are. Respondents find it difficult to remember how much time they are physically active, let alone how intense these periods of activity are. A more general push factor of surveys is that they are hard to conduct due to increasing surveys costs and high nonresponse rates. A major pull factor of using sensors to collect data in addition to survey questions is the availability of sensor data. Furthermore, the costs of using sensors in mobile phones are low. Still, there are costs in terms of time and effort to access, process and store the data. A distinction can be made between active and passive tasks in smartphone research. Active tasks involve taking pictures, whereas passive tasks include sharing GPS locations or having an app that tracks mobile behaviour.

In the following section, we will provide three case studies of experimental surveys conducted by Statistics Netherlands where survey data are being combined with sensors from mobile phones. In each of the studies, the specific nature of the study topic and sensors used has led to different design decisions in how sensor data and surveys were integrated into the data collection instrument.

Examples of the use of active and passive measurement in surveys

Travel and mobility

Travel surveys are routinely conducted by official statistics agencies at the country and regional level to inform public policy makers on travel patterns, including travel modes, trip lengths and durations. Travel surveys typically rely on respondents either keeping a diary with them for a certain number of days and completing this whenever a trip is made, or to recall all trips for the period of the diary. In both situations, the underreporting of short trips in particular is a problem (Richardson, Ampt, and Meyburg 1995).

Figure 1 illustrates the approach taken by Statistics Netherlands, which has been taken by several other researchers as well. Respondents are invited by letter to install an app, allow location measures to be taken, and watch an instruction video of the app (upper panel). After this, a diary of visits and trips is automatically populated in the app, and the respondent is asked to label the visits (name, reason of visit) and trips (mode of transportation), and is asked some questions about the day generally (middle panel). The lower panel shows how the collected location information is fed back to respondents, and how the reason for a visit can be manually amended. For more information on how the app worked, please see McCool et al (2020) or Smeets et al (2019).

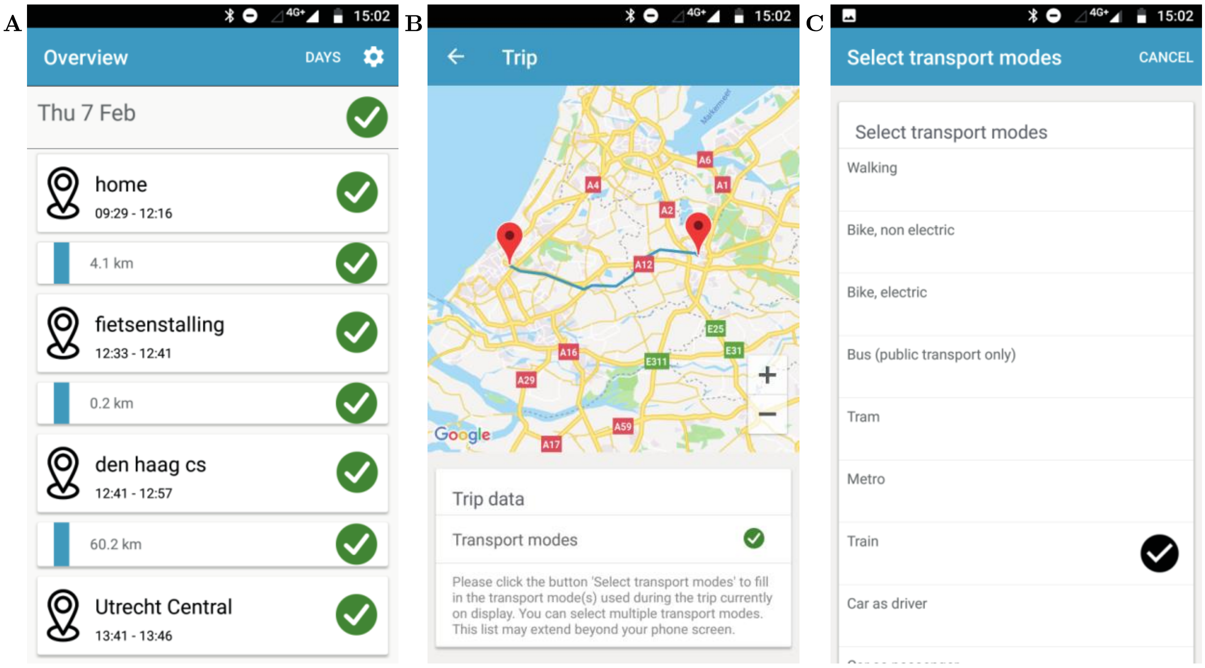

Figure 1: *Automatic trip detection with the CBS travel app and labelling by respondents. The left panel shows the daily diary that was automatically generated for respondents. Respondents could label the stops (locations) with names (left panel) When a respondent would click on a trip, he was presented with the trip trajectory (middle panel) and asked to indicate the transport modes used (right panel).*

Generally, we found the app was much better in detecting short trips than a comparative diary study that was conducted just 2 months prior to the app study, among partially the same respondents. The results in Figure 2 show all the data plotted geographically (left panel) and the amount of kilometres travelled per respondent per day in the travel app study, and comparative diary study (ODiN, short for Onderweg in Nederland). For more details, see McCool (2020) or Smeets (2019).

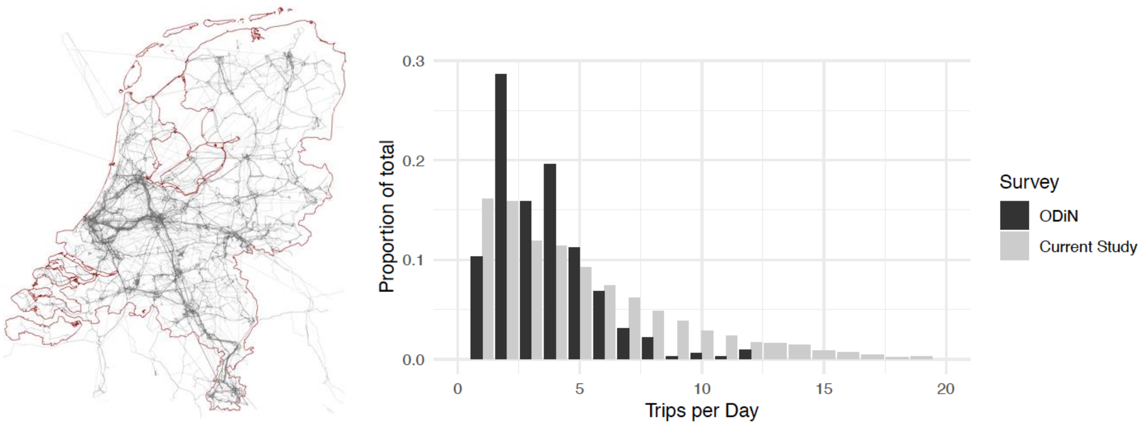

Figure 2: *All tracks collected with CBS Travel-app study among respondents in a 1-week period in November 2018 (left panel), and the number of trips per day in the diary study (ODiN, short for Onderweg in Nederland) and the travel app (current study) (right panel)*

The travel app generated precise location data over time. The app was much better in documenting very short trips made on foot or by bike. We also found however that some of the trips in the app were erroneous. The long right-tail in the number of trips sometimes is a sign of problems with signal loss or missing data more generally.

Household budget

Household consumption is typically measured through diary studies in which part or all purchases in a specified time period need to be reported. Such household budget surveys are known to be time-demanding and burdensome to respondents. To reduce respondent burden and to increase participation rates and quality of reported consumption data, there is a strong incentive to introduce smart features. See for example Jäckle (2019a; 2019b).

Smart features can be introduced in at least four ways: The first way is to assist respondents in searching for products through detailed search lists. Product search may be further enhanced by memorizing what products households have bought in earlier reporting days. The second way is by introducing data entry through scans of receipts. Receipts then go through text recognition and product classification steps either in-app or in-house. The third way is geo-fencing, where respondents consent to measure location and locations within certain geographical areas lead to in-app notifications or messages. The last way is data donation where respondents themselves request access to data about them that is stored by external parties. Examples of such parties are banks or supermarkets through loyalty cards or scanner transaction data. The different options have very different privacy and ethics consequences, and may not all be equally feasible in terms of respondent willingness and data protection legislation.

Figure 3 shows screenshots of the HBS app developed by Statistics Netherlands, partly funded by Eurostat, in which there are three options to include expenditures: through manual entry, through scans of receipts and through bank API's.

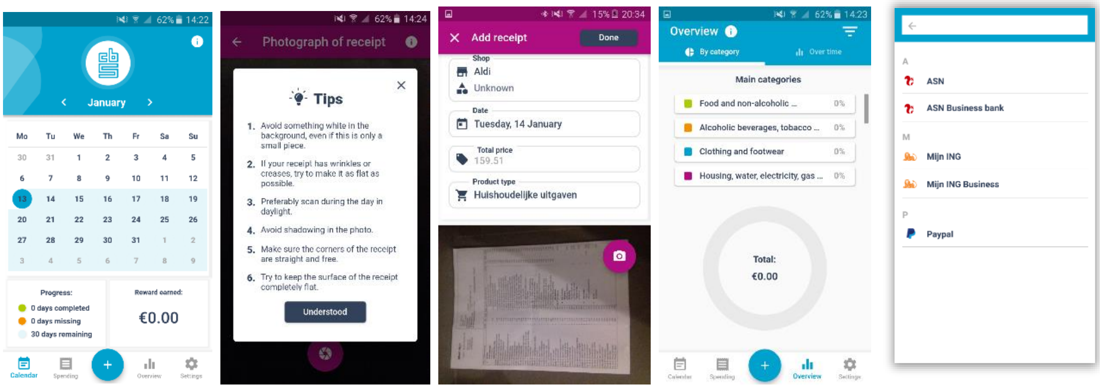

Figure 3: *Screenshots of the Household Budget Survey app developed by Statistics Netherlands. From left to right: Starting screen with calendar, tips to improve quality in scans, example of a scanned receipt, summary statistics, and selection screen of banks that can be consulted through an API after explicit consent*

First test results of the HBS app are promising and respondents are positive about the smart survey. In 2020 and 2021 large-scale field tests will be conducted.

Time Budget Study

A third area where official statistics might be improved is in the production of estimates of time use. As with travel and budget statistics, time surveys have relied on diary studies. Recall problems lead to respondents not reporting activities that were of short duration, or activities that were conducted as a secondary activity (e.g. reading a book while traveling to work). Another problem is the fact that respondents often complete a diary only once a day, implying that the start time, end time and duration of every activity may be off. There are a number of ways that mobile phone apps and sensor data can be used to improve these shortcomings.

First, respondents will carry their mobile phone with them most of the time, allowing them to complete the app more frequently. There is the possibility of sending respondents messages (a text message or push-notification) in case reports from respondents are believed to be missing, or if unclarities exist during the fieldwork period. Data can truly be collected in the moment (see Elevelt et al. 2019a for an example).

A second way to improve time use surveys is by the use of sensors. Chatzitheocari et al. (2017) link time use data to accelerometer data collected using smartwatches. Elevelt et al (2019b) link such data to GPS location data collected within the app. With both these kinds of data, it is possible to potentially understand in much better detail what kind of activity was conducted (accelerometers) and where this was done (GPS). These data may also assist the respondents to the survey in completing their diaries as they can reconstruct a basic day schedule based on detected stops and detected types of activity. Importantly, both types of data may help us to understand and improve our estimates of the start-, end time and duration of activities.

Discussion

Mobile phones may make it harder to conduct surveys due to constraints in how the survey should be displayed and how long it can be. However, mobile phones also offer exciting opportunities for data collection in official statistics and the social and health sciences. This paper has shown some examples of the possibilities that arise when sensor data are combined with surveys on mobile phones, either through browsers or mobile apps. We want to conclude this article with outlining several areas for future research.

1. How to make it work in the real world. Most examples published so far rely on volunteers and use small samples. There are a few examples that have shown that it is possible to achieve reasonably good response rates (>30%) when mobile phone app studies are conducted in the general population, but we need to test and experiment more.
2. Ongoing technical challenges. Mobile phone software, and the way the two main Operating Systems interact with apps changes continuously. App data collection is dependent on what Apple and Google allow for apps. Over time, the Operating Systems are becoming more restrictive in what they allow apps to do and what not to do. Because more and more apps are being developed and installed on mobile phones, there is an increasing need for security measures and battery-life saving settings. Also, users themselves may choose to restrict what data apps can (continuously) collect. It is unclear at this point in what direction the Operating Systems are heading and whether apps truly are the future of data collection.
3. Develop a framework for combining survey and sensor data. In the examples we outlined in this paper, we relied on methods from survey research to draw a random sample, and then for a subset of the sample, we collect additional sensor data. Such a ‘designed big data’ approach allows us to use traditional methods for inference to the general population. In many other examples where, mobile apps are being used, researchers rely on volunteers or ‘citizen science’ to collect data. Such samples will often suffer from selection bias. However, it may be possible to improve inference from such samples when data can be fused or combined with survey data collected from other (or partly overlapping) individuals. The challenge of improving inference for datasets that were not generated by probability sampling is not unique to mobile phone data. It is a general challenge in survey sampling, statistics and science in general.

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New and Emerging Methods

Exploring developments in population size estimation

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Abstract

This short paper covers some of the new and emerging research in the area of population size estimation in official statistics presented at a workshop in February 2020. It covers work exploring the replacement of traditional census with administrative data sources. These sources typically suffer from both under-coverage and over-coverage and this paper covers the application of dual- and multi-system estimation to tackle coverage errors. These estimation frameworks depend on linkage across different population lists and surveys, and the issue of adjusting for linkage error is also tackled. Finally, some discussion is given to current research in the context of population census for the 2020/21 round and the use of coverage surveys and administrative data to improve census outputs.

Keywords: dual-system estimation, record linkage, over-coverage, administrative data, census

1 Introduction

In February 2020, before the global pandemic, a group of 25 academic and official statisticians meet in University of Technology Sydney to share practical and methodological developments across several countries, as they prepare for the 2020/21 round of population censuses, and the future beyond. The workshop drew from Australia, Ireland, Italy, Netherlands, New Zealand, and UK. In this short paper, we discuss some of the emerging topics presented and discussed during the week.

It complements both the ‘ask the expert’ contribution by van der Heijden and Cruyff (2020) and the ‘new and emerging methods’ contribution by Tam and Holmberg (2020).

One focus is the increasing push to move beyond traditional census and utilise administrative data sources in countries where there is not a strong history of population registers and administrative data use in the compilation of population statistics. This creates a range of methodological challenges. A secondary focus is the desire to utilise administrative data sources within the traditional census framework.

2 Administrative-Based Population Counts

A common theme across several countries is the move for administrative lists to replace a traditional census in countries that do not have a national population register. The Office for National Statistics (ONS) is pursuing the production of Administrative data Based Population Estimates (ABPEs) by linking at a record level several broad coverage administrative data sources and applying rules to count individual records in or out of the ABPE. The focus in the ABPE construction and rules has been to remove as much over-coverage as possible and then to measure the under-coverage in the ABPE with an estimation methodology to produce population size estimates.

ONS plans to run a population coverage survey that will operate in a similar way to the traditional Census Coverage Survey (CCS), which enables the estimation of under-coverage in the traditional Census. A high-quality address frame is being developed which will be used as an address sampling frame for ONS surveys. The survey operation will be like the CCS with an emphasis on collecting variables useful for linkage to the ABPE (name, date of birth, address), ensuring that data are protected by appropriate privacy and security safeguards. However, it will be mixed mode with an online first, self-completion approach, followed by face to face or telephone where necessary. A similar response size to the CCS of around 300,000 addresses is required in order to provide sufficient sample to enable good quality local authority level estimates. The PCS will be a voluntary survey, in common with other social surveys in the UK, and from tests in 2018/19 ONS expect to achieve around 60% response rate. Consequently, the number of sampled addresses would need to be around 500,000 per year to provide the number of responses required to match CCS numbers. This represents a considerable ongoing data collection so the longer-term intention is to integrate the PCS with the Labour Market Survey (LMS) where the PCS questions will appear in a first wave along with some core LMS questions. A sub-sample of Wave 1 responses will be used for subsequent waves for labour market and other survey questions.

A particular challenge in the construction of linked administrative sources is working with hashed data. This is a requirement for some of the potential administrative data sources and creates a challenge from a linkage perspective. A clear recommendation coming from research presented by ONS is that data linkage is carried out using variables ‘in-the-clear’ wherever possible. However, for those instances where this is not possible, ONS presented the development a deterministic matching method, called “Derive and Conquer”, for linking hashed data. This method identifies pairs of matching records using the power of distributed computer processing and makes decisions based on derived agreement variables, which combine information on multiple derived variables. Work is ongoing to assess the quality of this method, but ONS anticipates that the results of linking hashed data will be of poorer quality compared with linking the data in the clear. However, if data suppliers are only willing to give us hashed personal identification data, then it is important to understand the changes in linkage rates, accuracy and bias. This will inform the decision on whether the linked data can be used in the production of official statistics.

Statistics New Zealand (SNZ) is working also towards an administrative-based census in the longer term. An administrative New Zealand resident population has been developed from linked administrative sources in SNZ's Integrated Infrastructure (IDI). Comparison with official population estimates shows that the administrative population is a good approximation (Stats NZ 2017), but includes some under-coverage and over-coverage. Over-coverage is dealt with through the application of rules relating to activity on the component administrative sources but that still leaves the under-coverage to be estimated.

As the work presented by ONS demonstrates, to estimate under-coverage the PCS needs to be very large, and even then, the provision of regular census-like population statistics will be limited by the level of disaggregation supported by the PCS. The concept of *Fractional counting* (Zhang, 2019a) presented at the workshop provides the theoretical foundation for a *system* of statistical data and estimation, which can accommodate all the relevant information and enables one to produce detailed statistics according to different definitions of the target population as required by users. The attraction is the starting point of an extended population dataset (EPD) that contains all possible individuals from linking across multiple administrative data sources, and therefore negligible population under-coverage. Such an EPD is already shown to be feasible in a number of countries, such as Estonia (Tiit and Maasing, 2016), Latvia (CSBL, 2019) and New Zealand (Stats NZ, 2018), but under-coverage is typically induced by the application of rules to remove over-coverage. In this case, rather than inducing under-coverage to target over-coverage, for every individual in the EPD, the following probabilities are applied. (i) the probability of belonging to the target population, (ii) the probability of correct 'official' address in EPD given (i), and (iii) the probability of being present at other addresses shown in the EPD given (i) and not (ii), including 'unknown' as a possible address. These probabilities are the *fractional counters* that are used to produce detailed population statistics, adjusting for over-coverage, rather than the removal of whole records with the risk of induced under-coverage.

3 Exploring the Dual-System Estimation Framework

Use of dual-system estimation is clearly still at the centre of approaches to estimate populations when faced with imperfect population lists, generated by census, administrative systems, and surveys. Below we have the simplest scenario estimating from two lists, A and B.

	In List B	Missed List B	
In List A	N_{11}	N_{10}	N_{1+}
Missed List A	N_{01}	??	
	N_{+1}		$\hat{N} = \frac{N_{1+}N_{+1}}{N_{11}}$

Zhang (2019b) reminds us of the crucial assumptions behind the dual-system framework but the dual-system approach remains attractive due to its simplicity. There is no model selection for relationships between lists, as independence is the only possible identifiable hypothesis. Even if one source has extremely heterogeneous capture probabilities, no bias is introduced (see Chao *et al*., 2011). The paper by van der Heijden and Cruyff (2020) explained how the framework could deal with missing covariates in its component lists. Contributions to the workshop particularly focused on the issues of linkage error and over-coverage in (administrative) lists.

3.1 Dealing with Linkage Error

Accurate record linkage is crucial for the reliable performance of the dual system estimator. It is arguably the most difficult and resource intensive stage prior to the population size estimation. There is a growing body of work looking at both the estimation of linkage errors (for example Chipperfield *et al*., 2018) as well as developing adjustments for estimated linkage error (for example Tuoto, 2016).

One approach to estimating linkage errors is to sample from the links and non-links. Sampling from the linked pairs, we can estimate the false linkage rate (FLR), and sampling from the non-linked pairs estimate the missing match rate (MMR). In both cases one only needs to verify whether the sampled pairs are true matches or not. However, a practical difficulty of such an approach to MMR is that the number of non-linked pairs can be enormous, while the true matches among them can be very few in comparison, such that the chance of observing a true match by random sampling is almost zero.

Returning to our linkage of list A of size N_{1+} to list B of size N_{1+}, the unknown set of true outcomes are the three cells N_{11} (true matches), N_{10}, and N_{01}; where records in N_{10} can never be correctly linked to records in N_{01}. One approach being developed to estimating the missing links presented at the workshop takes inspiration from the trimmed dual-system estimator (Zhang and Dunne, 2017) by repeating the linkage process under different structures and comparing results.

Taking linking strategy 1, the set of links D_1 contains L_1 links; while for strategy 2 the set of links D_2 contains L_2 links. The intersection of links, those linked pairs in both D_1 and D_2, contains L_{12}. We have two (under-)estimates of the total number of links that should exist between the two lists, so we can use dual-system estimation to estimate

$$\widehat{N}_{11} = \frac{L_1 L_2}{L_{12}} \tag{1}$$

However (1) is biased if there are false positive links in either L_1 or L_2, and if the two linkage procedures are not independent of each other. But estimating the FLR is possible by, for example, auditing from the linkages L_1 and L_2 and therefore we can adjust the number of linkages down to give $\tilde{L}_1$, $\tilde{L}_2$, and $\tilde{L}_{12}$. We trim the number of links to remove estimated false positives. The result is a revised estimate for the number of true links N_{11} given by

$$\widetilde{N}_{11} = \frac{\tilde{L}_1 \tilde{L}_2}{\tilde{L}_{12}}. \tag{2}$$

Insofar as linkage errors originate from the errors of linkage key variables, one can simply use *different* key variables for the two linkage processes, helping to approximate independence between the linking outcomes. At the workshop, simulations under the following three settings were presented by Zhang and Tuoto to demonstrate the approach:

- Setting 1: D_1 based on Name, Surname and Gender; D_2 based on Day, Month and Year of Birth.
- Setting 2: D_1 based on Name, Surname and Day of Month; D_2 based on Day, Month and Year of Birth, where the common linkage variable Day of Month is *not* affected by errors.
- Setting 3: D_1 based on Name, Surname and Gender; D_2 based on Name, Month and Year of Birth, where the common linkage variable Name is affected by errors.

As expected, estimator (2) of N_{11} is unbiased under setting 1, almost unbiased under setting 2 and biased under setting 3. Ongoing research aims to identify practical diagnostics for independence of linkage procedures, which can provide additional confidence to the prior choice of linkage variables.

Of course, the procedure one applies to link A and B in the end does not need to be the ones used for estimating the number of matches that one is targeting.

Presentations by Statistics New Zealand (SNZ) took a different route to estimating the missed matches. In the assessment of the 2018 Census, SNZ linked the Census to their administrative system. While the link rate is high with almost 98 percent of census responses linked to the administrative system, perfect linkage cannot be assumed. At the workshop, work was presented adjusting for linkage errors within the dual-system framework. Following the simplest model of Ding and Fienberg (1994), we assume no incorrect links (false positives), and estimate the rate of missed links (false negatives) within each stratum. In the case of the 2018 Census, the MMR was estimated by first restricting census returns to those that were very highly certain, based on their characteristics, to be in the administrative file. In other words if the census is list A then N_{10} is defined to be zero for this subset of returns. It is then trivial to estimate

$$\eta = \frac{\Pr(unlinked|match)}{\Pr(linked|match)}, \tag{3}$$

the ratio of linkage probabilities conditional on the true match status using this subset of the census returns. The overall rate of missed matches is estimated as 1.21 percent.

Missed links are added back into the N_{11} cell, and removed from the off-diagonal cells to preserve the marginal totals, leading to another adjusted dual-system estimator

$$\widehat{N} = \frac{N_{1+}N_{+1}}{N_{11}(1+\eta)}. \tag{4}$$

The results based on (4) presented at the workshop showed very plausible patterns of population structure and have given a valuable indication of the patterns of under-coverage remaining in the final 2018 Census dataset in the interim before official population estimates can be released.

An alternative approach to the linkage error problem presented at the workshop explores the theoretical and practical limits of the linkage free dual system estimation (Račinskij *et al*., 2019) The method utilises the parameters of the linkage error model directly in estimation, rather than attempting to resolve the linkage status of all possible record pairs. By exploring the close relationship between dual system estimation and record linkage, it shows that in certain cases the population size estimator can be expressed as a function of the estimated linkage parameters. This relationship allows, at least in theory, dual system estimation without the classification of record pairs into links and non-links. As a result, no one-to-one linkage or extensive clerical classification is required, but naturally, a certain loss of precision occurs, and a substantial modelling effort is needed.

Tam and Holmberg (2020) gives a method to integrate big data with survey data but this depends on high quality linkage. In the framework presented here, U is the population of interested with known size N. For units $i \in U$, y_i is the outcome of interest; and for a (large) subset of the population units $i \in B \subset U$ of size N_B, y_i is observed. Membership of this alternative data source is identified by the indicator $\delta_i = 1$. When you over-lay a sample A selected from U with inclusion probabilities $1/d_i$, Tam and Holmberg (2020) suggest one strategy is an approximately design-unbiased post-stratified estimator given by

$$\hat{Y}_{PS} = \sum_{i \in U} \delta_i y_i + (N - N_B) \frac{\sum_{i \in A} d_i (1-\delta_i) y_i}{\sum_{i \in A} d_i (1-\delta_i)}. \tag{5}$$

The population membership indicator δ_i for the units found in B is determined by a linkage process to a population frame, which under-pins the sample A. This facilitates the detection of duplicates in B as well as the removal or records that do not belong to U. However, in the presence of linkage errors, we observe $\hat{\delta}_i$ as the outcome of the linkage process and replacing δ_i with $\hat{\delta}_i$ in (5) results in a bias.

At the workshop, work presented the adjustment

$$\hat{Y}_{PS} = \sum\nolimits_{i\in U} \delta_i y_i + (N - N_B) \frac{\sum_{i\in A} d_i(1-\delta_i)y_i - (1-R)\sum_{i\in B} y_i}{\sum_{i\in A} d_i(1-\delta_i) - (1-R)N_B}, \tag{6}$$

where $R = Pr(\hat{\delta}_i = 1|\delta_i = 1)$. This returns (6) to an approximately unbiased estimator provided inclusion in the sample A is independent of inclusion in B, and further inclusion in the sample A is independent of the outcome of the linkage process given the true status of inclusion in B. Simulation results demonstrated R can be estimated using bootstrapping, using the methods outlined in Chipperfield *et al*. (2018).

3.2 Over-coverage with Two Lists

SNZ has been developing an alternative Bayesian model to estimate coverage of an administrative list using an Administrative Census Coverage Survey (ACCS), with early results presented at the workshop. The novelty of the proposed approach is in the simultaneous estimation of over-coverage and under-coverage of the administrative list in an extension of the dual-system estimation framework.

Specifically, the system in which the model operates is the union of the target population and the administrative list. Let N_U be the union size. Individuals are then either in both the target and the list (N_{11}), in the undercount of the target population (N_{10}) or the overcount (N_{01}), with $N_U = N_{11} + N_{10} + N_{01}$. Transforming counts into inclusion probabilities $\varphi = (\varphi_{11}, \varphi_{10}, \varphi_{01})$, which depend on individual covariates X (demographic and geographic characteristics), we have the following table of individual cell probabilities for a given x Є X:

		Admin list	
		1	0
target	1	$\varphi_{11}(x)$	$\varphi_{10}(x)$
	0	$\varphi_{01}(x)$	0

We now conduct the ACCS selecting areas from the target population, where λ(x) is the sample inclusion probability of an individual (given that the individual's target population area was selected in the ACCS), which we assume varies with X. Linking between the coverage survey and the administrative list, we now have the following cell probabilities:

		Admin list	
		1	0
ACCS	1	$\lambda(x)\varphi_{11}(x)$	$\lambda(x)\varphi_{10}(x)$
	0	$\varphi_{01}(x) + (1-\lambda(x))\,\varphi_{11}(x)$	$(1-\lambda(x))\varphi_{10}(x)$

In the inevitable case where λ(x)≠1 (due to both among- and within-dwelling non-response), the distribution of λ over X is unknown. Simulation experiments presented at the workshop showed that the model and data as currently set up provide no information to estimate λ simultaneously with φ.

Therefore, potential options to address the inherent limitations of 2-list population estimation in the presence of over-coverage still rest on refining rules and administrative record quality for inclusion in the administrative list to reduce over-coverage to a negligible level. The trimmed dual-system approach (Zhang and Dunne 17) offers a strategy provided multiple rules can be defined for implementing trimming from the administrative list.

3.3 Over-coverage with Multiple Lists

When more than two lists are available, log-linear models are the common choice to extend the dual-system framework, as they allow us to manage different capture probabilities in different lists, and to model the dependencies among captures of a same individual in different lists. The inclusion of a categorical latent variable constitutes a simple extension to account for unobserved (latent) individual heterogeneity in the capture probabilities, and log-linear latent class models are indeed successfully used in capture-recapture literature (see for example Biggeri *et al*., 1999; Stanghellini and van der Heijden, 2004; Thandrayen and Wang, 2010).

A different use of the latent variable discussed at the workshop is to model specific subpopulations, in the case of tackling over-coverage identifying the class out-of-scope units. The idea of using a binary latent variable to model over-coverage originates in various works of Biemer (see chapter 6.3 of Biemer *et al*., 2011), and has been explored in detail in Di Cecco *et al*. 2018 and Di Cecco (2019). We need at least four sources for any latent class model to be identifiable, but, in population count, it is not common to have more than three sources available. In cases where a certain number of administrative sources are used to produce a single statistical register, a simple way to increase the number of lists is to treat separately some of the sources composing the register. Another trick consists in including in the model some of the covariates such as gender, age and nationality of the units. In this way, we increase the number of manifest variables and we can tune the dependencies among all the variables as an alternative to simple stratification. Finally, we can include as capturing lists the so-called "signs of life", such as individuals' workplace or place of study, which will obviously come with a lot of over-coverage, but would provide useful information and contribute to the total number of lists and of identifiable models. In this case, some units have null probability of capture such as people outside working age. A way to overcome this problem is to treat the capture profiles of these units as partially observed, that is, to treat the information about the capturing status of certain units as missing at random (Di Cecco *et al*., 2018).

These approaches are being explored in the context of the Italian Permanent Census Strategy. The overall strategy integrates population registers and sample surveys so as to obtain the usual resident population counts at the reference date, while removing coverage errors from the register. Two sample surveys are carried out to integrate with the population register: an area sample survey mainly designed to estimate the under-coverage, and a register based sample survey mainly planned to integrate information not recorded in the population register. Dual-system estimation is used to evaluate the usual resident counts, after adjusting for people erroneously included in the register (over-coverage). The register-based sample provides the adjustment for over-coverage but this relies heavily on the field contact data, where non-response must be classified as either genuine non-response by a usual resident or non-response because the record on the register no longer relates to a current usual resident.

Research at the workshop presented a pilot using a latent class model, with full details reported in Fortini *et al*. (2020). The model integrates the 2018 register based survey data, affected by both missing values and response errors, with administrative signals of employment, school attendance and pension payments (signs of life) in order to estimate over-coverage rates for relevant profiles of statistical units for the 14 largest Italian municipalities. Manifest variables used for estimating the model parameters are: A, Age classes (4 classes); C, Citizenship (2); H, Household size (2); M, Municipality code (14); S, Sign of life (10) from administrative data and F, Field contact result (3). The first category of Field contact includes people confirmed as resident by interviewers during the survey, either as a respondent or direct non-respondent (refusal, unable). The second category consist of people checked as not resident, such as those moved or deceased, using proxy information collected by interviewers in the field or by municipal officers through local auxiliary data. The third class encompasses all other sampled individuals lacking evidence from the field to be classified. The Signs of life variable S collects information from many education, employment and welfare administrative sources in 10 classes with the aim to rank people according to whether or not their usual residence corresponds to their legal residence.

A two class latent variable (X) is defined to classify usual vs not usual residents and the following path analysis model with latent variables is used to fit the multivariate table of observed variables.

$$\Pr(F,S,H,A,C,M) = \sum_X \Pr(F|M,X)\Pr(S|A,X)\Pr(H,A,C,M,X). \quad (7)$$

Apart from conditional independence relationships induced by the factorization in (7) on the full, not observable table, this model relies on the following further assumptions:

1. the structural part of the model $\Pr(H,A,C,M,X)$ accounts for relationship between X and the other variables except for indicators S and F;
2. structural model assumes a hierarchical interaction configuration $\{XHM, XAM, XCM, HACM\}$;
3. in the observed table, structural zeros are considered in every cell where H*E combination is "0-19 years age" and "single-parent household" respectively, to consider that (almost) all Italian people dwelling in a household and falling in age class '0-19' actually live with their parents;
4. the measurement part of the model $\Pr(F|M,X)$ and $\Pr(S|A,X)$ consists in two logit functions between indicators F and S with the latent variable X respectively;
5. logit models regarding indicators F and S also consider variables M and A as predictors in addition to latent variable X, assuming only marginal effects to ensure model identification;
6. marginal probability $\Pr(F=1|X=1)$ to be classified as usual resident in the household by the interviewer during field contact (F=1) is fixed to zero given that person is actually a not usual resident (X=1). This assumption is made to force X into providing usual residence status, assuming that the status assigned during the interview is by far the most reliable information collected by interviewers. In this way, about 90% of the sample in assigned to usual residence (X=2) without error.

The presented model utilises 538 parameters leaving 6181 degrees of freedom.

Overall, the model provides coherent and reasonable results. This approach can help in understanding the strength and limitations of administrative signals and how they can be used to support statistical surveys. A key result is that the risk of over-coverage defined by the latent class model computed for each large municipality is often lower than the corresponding estimates obtained by simply leaving out people lacking field contact evidence (F=3), under the 'missing at random' assumption for missing information. Concerning the capability of Field contact (F) to identify over-coverage cases, while class 1 (people resolved as usual resident) is error free by design, class 2 and 3 show a probability to truly identify over-coverage between 50-60%, with little difference between them. This fact suggests that proxy information is in fact not much better than no contact for identifying over-coverage.

This application demonstrates that as we include more sources, we can use more complex models, but, in general, we face more methodological challenges. In particular, model selection is a notoriously challenging problem as different models with similar goodness of fit can lead to extremely different estimates of the population size. Results from both simulated data and real data shows that model misspecification can produce severely biased estimates, and classic tools for model selection like different information criteria (Bayesian, Akaike, Deviance) can indicate completely different models as preferable. However, a Bayesian approach to this class of models is relatively simple as outlined in Di Cecco *et al*. (2020). It allows the introduction of prior knowledge (on the capture probabilities of each source, or on the population size to be estimated) and leads to straightforward construction of interval estimates (HPD) of the population size, as well as of any other quantity of interest. In addition, it allows the implementation of model averaging techniques, which provides a natural way to address the problem of model selection, providing at the same time a robustification of the estimates to model misspecification (Di Cecco, 2020).

The use of a latent variable to model a specific subpopulation is not new, and is often open to criticism, as it is necessary to get some validation on its interpretation. A clear example of validation is given by inspecting the posterior probabilities of belonging to the two latent classes for those units captured in all lists. In the context of identifying over-coverage, if they have an almost equal posterior probability of belonging to the two classes, our interpretation will not be defensible. Conversely, if they belong with almost certainty to one class, that constitutes evidence in favour of our model. This approach is strengthened when one of the lists is a survey that explicitly identifies usual residents as in the application above.

4 Enhancements to the 2020/21 Round of Population Census

There is considerable ongoing work in preparation for upcoming censuses that looks to develop the coverage assessment of census, and utilise administrative data throughout the census process.

4.1 Census Coverage

Statistics New Zealand presented their work assessing the coverage of the 2018 Census by comparison to their Administrative Population (Stats NZ, 2019). Over-coverage in the administrative list is removed by applying stricter rules for being included in the administrative population, at the expense of removing true members of the population. However, increased under-coverage is not a problem in the dual-system context. The approach to dealing with potential heterogeneity is a classic post-stratification into small sub-populations based on an individual's location and characteristics. The dual-system estimator is calculated within strata defined by single year of age, sex, ethnic group, and an intermediate sub-national geography[1]. A limitation of this approach is that many small cells are created by these strata. One consequence is that estimation by ethnicity is restricted to only three ethnic groups: Maori, Pacific, and Asian. The Chapman correction factor[2] is applied to avoid a zero denominator and reduce bias due to small numbers.

[1] Territorial authority and Auckland Local Boards

[2] The Chapman correction factor $\widehat{N}_T = \frac{(N_{1+}+1)\,(N_{+1}+1)}{(N_{11}+1)} - 1$

ONS are exploring developing their 2021 coverage estimation to go beyond classic post-stratification in Brown *et al*., 2019 based on geography and age-sex for controlling heterogeneity. This is possible because the census data for the entire country will be available quicker than it was in 2011. This will result from increased electronic collection and less reliance on scanning for data capture. No batching into Estimation Areas (EA) is needed and the estimation can be carried out either at the national or at the regional levels, similar to the approach used for example in the 2010 US Census (US Census Bureau, 2008; US Census Bureau, 2012). A sufficiently large sample of data permits the census coverage for a reasonably large set of characteristics to be modelled using logistic or mixed effects logistic regression models as proposed in Alho (1990) and Alho *et al*. (1993). Estimated census non-response weights (reciprocals of estimated census response probabilities) can then be applied to each census observation with the corresponding characteristics (US Census Bureau, 2012). Similar to the concept of fractional counting for an administrative file, summing up all weighted census observations with the characteristic of interest will produce an estimated population size of units with the characteristic.

Research indicates that weights based on mixed effects logistic regression can achieve higher overall accuracy both at the national and subnational levels. Modelling census coverage this way, allows controlling for effects other than age, sex, hard to count defined on geographic areas; and therefore has the potential to deal with heterogeneity bias more efficiently. Research shows that, in the 2011 Census methodology, the lack of control for variables such as ethnicity and tenure could result in relative bias of at least -0.2% at the national level (with a target of the absolute relative bias at the national level not to exceed 0.5%). A second gain is that the coverage modelling naturally embeds different geographic levels such as Local Authority (LA) level, avoiding a direct synthetic assumption as in Baffour *et al*. (2018), that patterns of under-coverage for each LA within an EA were constant after just controlling for age, sex, and hard to count.

For estimated (net) under-coverage, ONS will again adjust the final census database. The adjustment will use a two-stage approach for 2021: 1) Impute missed households (and persons within them) and 2) Impute characteristic variables for the persons and households imputed in stage 1. In 2011, missed persons were also first imputed into counted households. While the 2011 Census adjustment methodology based on Steele *et al*. (2002) worked well to provide a census database that agreed with coverage estimates, the implementation was challenging. An evaluation of the methodology concluded that alternative approaches should be explored for the 2021 Census focusing on the selection of donor households for imputation and their placement within the adjusted database.

Combinatorial Optimisation (CO) (Voas and Williamson, 2000) is an integer programming method which involves finding the best (an optimal) combination from a finite set of combinations for a problem. In the context of the adjustment problem, CO involves the selection of a combination of households from the existing census database that best fit the coverage estimate benchmarks. As part of the 1st stage, the CO selection of donor households are placed in a geographic location. Administrative data sources are being considered here as they may be able to provide additional information about census dummy forms (forms for addresses where unable to enumerate, but only collecting basic information), which are used as placeholders for donors. Coverage estimates of the census population will be provided in more detail in 2021, so CO will constrain its selection to a wider range of key demographic characteristics at a lower geographical level, which would not be possible with the calibration approach implemented in 2011.

4.2 Improving Census Returns

Several presentations at the workshop looked at the integration of administrative data to enhance the the traditional census process. For example, Australian Bureau of Statistics (ABS) presented work exploring the use of administrative sources to help enhance fieldwork processes, as well as the potential to repair a census return. ONS are exploring variable replacement. For example, a new admin-based number of rooms variable will be produced from linked Valuation Office Agency (VOA) data, which similar to all other census variables will need to undergo edit and imputation. Recent research has therefore focused on whether the assumptions underpinning nearest-neighbour donor-based imputation, typically used for item imputation in census, are still valid when using linked administrative data. For example, although the reasons for missingness will be different to traditional surveys, missingness must still be predictable from the observed data for the method to be valid. Research so far supports the use of donor-based methods, so this will be implemented with linked admin-census data in 2021 for the first time.

The experience in New Zealand in 2018 demonstrates clearly that the common move towards a "digital-first" census impacts on census returns, and therefore on the design of the edit and imputation strategy. Research has shown that characteristics and non-response rates differ between online and paper respondents, which introduces a risk of bias during imputation. Imputation will therefore need to be conditioned by response mode to avoid propagation of characteristics from one mode to another. ONS are exploring the use of linked administrative data to allow for searching the census data for donors conditional on age, even when age is itself missing. The method involves using an 'admin age' variable from linked administrative data as an additional matching variable when searching census returns for donors during imputation. Proof of concept has so far been successful but further work is required around the practical implementation of this method before it can be applied in 2021.

5 Concluding Remarks

There is extensive research being undertaken across the world of offcial statistics to better enhance the use of administrative data in the efficient production of timely official statistics. The current pandemic only reinforces that need. The work presented at the workshop focused particularly on the production of population estimates in both the context of administrative data only and census enhamced with administrative data; demonstrating a range of exciting approaches, especially in the areas of linkage and over-coverage.

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Book and Software Review

Seppo Laaksonen (2018) Survey Methodology and Missing Data, Springer

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Abstract

We find that the book might be useful for a wide auditorium facing with sample surveys because the author explains all necessary steps in a simple way. Ideas on the use of auxiliary information, weighting, and imputation, which are presented by examples of real social surveys, might be interesting for experienced statisticians as well.

Keywords: survey statistics, handbook, social survey, sampling design data file

Implementation of a sample survey is a process of manifold tasks that requires specific knowledge. To organize, coordinate, and accomplish the steps of a new survey, a good idea is to follow the best practices of other surveys. For this purpose the survey statistician may look at publicly available documentation of well-established surveys, to search for books of a handbook type, or to read *Survey Methodology and Missing Data*, where Seppo Laaksonen systematically explains the main survey points using real examples. Choosing the latter option, we can see that the author has the mandate to teach the reader because of his huge experience accumulated when working with multinational and national surveys practically and from the theoretical side as well.

The book covers all stages that are necessary to implement a social cross-sectional survey: from the questionnaire design, sampling, and weighting to advanced weighting, non-response treatment, editing, and imputation. The presentation of all the topics is not based on strict mathematics, that is, ideas are explained in words rather than using formulas, but the references are given for further reading and technical details. That form extends the reader circle to that including survey managers and students of social sciences, and thus increases the popularity of survey statistics.

To explain the principles of sample surveys by example, the author mainly uses two surveys: European Social Survey and Programme for International Student Assessment, known also as PISA. As the multinational surveys, these two ones have rich methodologies and auxiliary information is exploited in different ways. Seppo Laaksonen demonstrates the importance of auxiliary data taken from administrative and other sources and promotes to use them to increase the quality of surveys.

The imputation is perhaps the main topic, but the book should be considered as a whole. That is, the reader is prepared to understand the imputation questions that are discussed in Chapters 11 and

12. As we know, the treatment of missing data is a hot topic in these times of low response rates, and therefore there are monographs devoted to imputation only. To handle missing data, the author presents an approach based on his own experience obtained in European Union research projects on survey methods. Another one original part of *Survey Methodology and Missing Data* is Chapter 6, where the new term ‘sampling design (data) file’ is introduced. The idea of that file is to describe the whole survey process by collecting information on the gross and net sample units that includes: sample data, auxiliary variables used at all survey stages, detailed sampling design information, weights, and so on. Some of us use similar files in practice, and now the name is proposed to them.

The book may serve as a good guide when carrying out the survey and can be useful for the experienced practitioner as well because the author gives a lot of useful advice born in real surveys.

ARGENTINA

Reporting: **Verónica Beritich**

Argentine time series treatment during COVID-19 pandemic

It is well known that the COVID-19 outbreak is having a severe impact on several economic activities. The main difference is that this time, the beginning of this outbreak can be clearly determined. On March 19, 2020, a quarantine due to the coronavirus pandemic was declared nationwide by decision of the Government of the Argentine Republic. Its official name is Social, Preventive and Mandatory Isolation (ASPO). Having started at March 20 at 00:00, ASPO was initially intended to run until March 31. At the time this report was prepared, ASPO had been extended a sixth time to continue running until June 28.

The announcement of the lockdown was generally well received, although there was concern about its economic impact on the already delicate state of the Argentine economy. Analysts predicted at least a 3% decrease in GDP in 2020.

The Eurostat methodological note "Guidance on time series treatment in the context of the COVID-19 crisis" is inspired by the *ESS guidelines on seasonal adjustment, (Eurostat, 2015)*, where in chapter 2.8 there is guidance about the "Treatment of outliers at the end of the series and at the beginning of a major economic change". In statistical terms, the current crises can be translated into the treatment of an end-point of the time series, in which major economic changes firstly appear as an additive outlier (AO) at the end of the series.

The Eurostat specific suggestion for crisis period data points, in most cases occurring in March/Q1 2020, is to model them as outliers. Depending on the expected impact on a specific domain, they should be treated at least as AO. The type of outlier will then be verified when new information will become available, and revising it to temporary change (TC) or to a level shift (LS) or staying with the AO using a comparison among the results of three options starting with the successive period. Using an AO to model the event is an implicit assumption that the trend-cycle is not affected.

It should be noticed that, since the seasonally/calendar adjusted results contain both the trend-cycle and the irregular component, the effect of the COVID-19 crisis on the data will always remain visible. The key question is to which component should be assigned the effect.

This methodological note was made under the assumption that the COVID-19 effect would lead to a major downturn in the economy. In the European Union and the Euro zone economies, this effect represents a turning point that could be correctly modelled by an additive outlier (AO) at the end of the series, prior to more data on the crisis period becoming available.

In contrast to most European economies, the Argentine economy shows a systematic decreasing pattern in many indicators since at least September/October 2019 but, in many others, since January/February 2018. These outliers shall be modelled at the end of a time series based on statistical criteria and economic information. In Argentine indicators, the implicit assumption that the trend-cycle is not affected seems rather unrealistic.

Before additional observations become available, the specific suggestion for the first crisis period data points was not to intervene, letting the automatic downweighting of the nonparametric X11-

ARIMA part in X13-ARIMA-SEATS to treat those values as extreme irregulars. This way, the outliers at the end of the series are reflected in the trend-cycle which seems more realistic than having impact only in the irregular.

When additional observations become available, the suggestion is to revise all adjustment options considering different scenarios:

1. Fit the RegSARIMA model to prior adjust the original series and to forecast one year in advance, having an out-of-sample of at most 15% error up to December 2019 (without the crisis observations).
2. Consider a ramp from January/February 2020 to March/April 2020.
3. During 2020, use automatic outlier detection procedures only based on statistical criteria, as available in X13-ARIMA-SEATS.

The gap/distance between real value and forecasted should be monitored in order to decide on the type of outliers; the options should take into account that negative values will be introduced neither in the seasonally adjusted series nor in the trend-cycle.

As the choice of the type of outlier can influence turning point identification, to avoid overfitting it is recommended to leave the last point of the series un-modelled, unless there is strong economic evidence about the direction of the change.

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BRAZIL

Reporting: **Andrea Diniz da Silva**

COVID-19 Surveillance in Brazil

Since the beginning of 2020, we have been witnessing a growing effort to monitor the COVID-19 outbreak. To understand the meaning of the figures coming from the growing number of register-based platforms, nonprobability sampling surveys, as well as new probability sampling surveys are now part of the daily teleworking routine of statisticians.

Following this trend, Brazil counts on a number of online register-based platforms for public use that show the progress of the disease and the availability of hospital equipment to help users and people prepare to face COVID-19 across the country. An important one is MonitoraCovid-19 platform, created by Oswaldo Cruz Foundation (Fiocruz) in partnership with IBGE. The platform shows the progress of the disease and its growth factor, in cities, states and across the country. It is also possible to compare data with those countries in more advanced stages of the pandemic.

An important nonprobability sampling survey, conducted by telephone, land lines and mobile phones, was implemented by the Ministry of Health. The survey aims to monitor the health of the population to identify vulnerable people in advance, with signs and symptoms of COVID, by triggering calls with automated attendance to find possible cases. An artificial intelligence system is managing to contact 125 million Brazilians and making questions on the general health and, if they belong to risk groups, with whom they live. Also, many nonprobability sampling web-surveys have popped up since we registered 100 cases, in March 18th. Most of them are conducted by accredited universities and researchers. Such surveys approach mainly the impact of COVID-19 on behaviour but also ask some questions on how the respondent is feeling towards health. “ConVid Survey on Behaviour” and “Lifestyle during COVID-19” are examples, both are still collecting information from volunteers.

The Brazilian Institute of Geography and Statistics (IBGE) has started, on 4th of May, the data collection of the PNAD-COVID. The survey is a version of the continuous national household probabilistic sample survey (PNADC). It is a partnership with the Ministry of Health to estimate the number of people with COVID-19 symptoms and the impact of the pandemic on the labour market. About two thousand IBGE agents have started calling 193,600 households in 3,364 municipalities in every State of the country. The sample is based on the 211,000 households in the sample of the PNADC in the first quarter of 2019. The households with no registered phone number will not be contacted.

Other sample surveys, targeting Brazilian population or subpopulations, have also been conducted, are being conducted or are planned. That is the case of EPICOVID19, a survey in the state of Rio Grande do Sul, conducted in April 2020 by the Federal University of Pelotas – RS. The University has also started, on 5th May, a national survey to test 99,000 people living in 133 cities. Also, FIOCRUZ is adding a module ELSI-COVID to a longitudinal survey on elderly health.

To gather information on initiatives and actions under development, such as studies and research, to support efforts to fight COVID-19, the Brazilian Institute of Geography and Statistics (IBGE) launched a hotsite. In addition to preliminary results on deaths (2019); displacement to seek health services (2018); data and interactive panels on Indigenous and Quilombola peoples (2019); research results, information on partnerships with other public bodies and changes in the Institute's routines and projects during the period of social distancing is made available at IBGE’s website.

Adapting our statistical programs

The Brazilian Institute of Geography and Statistics – IBGE, postponed the Population Census to 2021 and also suspended all face-to-face data collection, due to the new coronavirus outbreak. Nevertheless, dissemination on employment and inflation will not be interrupt. Data on employment and prices are being collected by telephone and on the Internet. To help fighting COVID-19, IBGE has been creating many new products such as the special edition of the main household survey on labour force which is fully dedicated to monitor COVID-19 cases and their impact on the labour market and also data on displacement to seek health services and vulnerable populations, among others.

CANADA

Reporting: **Eric Rancourt** and **François Brisebois**

A Framework for Privacy Protection and New Approaches to Collect Data

Adopting a New Privacy Protection Framework for Data ingestion

In October 2019, Statistics Canada adopted a new Necessity and Proportionality Framework to jointly maximize the production of information and privacy protection when developing data gathering approaches. This framework provides both a justification and a guide for designing strategies to gather sensitive data using surveys, administrative sources obtained from the public or private sector, or any other method. The approach is the result of consultations that were carried out with domestic and international experts and practitioners in the domain of official statistics, professional statistical associations, privacy experts, ethics experts, and the Office of the Privacy Commissioner. The Necessity and Proportionality Framework is an adaptation of the scientific approach (Rancourt, 2019) to the context of both statistical methodology and privacy protection. It rests on a solid description of why a given data source is needed and a thorough ethical assessment. To support this work, a secretariat operating under a Chief Ethics and Scientific Integrity Officer was set up. The secretariat’s work supports the activities of an internal Data Ethics Committee. Statistics Canada integrated the Necessity and Proportionality Framework into its data acquisition process such that the ingestion of any new data source has to follow the framework. More information can be found at https://www.statcan.gc.ca/eng/trust.

Three Rapid Data Collection Initiatives Implemented during the COVID-19 Pandemic

Within the first few weeks of the COVID-19 pandemic, three Statistics Canada initiatives have been added to existing social statistics survey options in order to produce even more timely statistics: the Fast Track Option, a web panel, and the use of crowdsourcing. This report provides a summary of these three initiatives focusing on methodological aspects such as sample selection and inferential capacity.

The Fast Track Option (FTO) consists of adding a short series of questions to the monthly Labour Force Survey (LFS) questionnaire. This additional content can be added to all or just a random subset of LFS respondents. Given its direct connection to the LFS, it relies on the same probabilistic survey design and therefore, FTO specific population representative weights can be calculated. A FTO survey was developed for April 2020 in order to measure impacts of the COVID-19 pan-demic in Canada.

For more information, consult https://www.statcan.gc.ca/eng/survey/household/3701, under *Labour Force Survey Supplement – Labour Market Impacts of COVID-19*.

Web Panel: The Canadian Perspectives Survey Series (CPSS) consists of a pool of people (a "panel") who had previously agreed to complete about six very short online surveys over a period of one year. This panel was created by randomly selecting one person aged 15 or older from a random subset of responding LFS households interviewed mid-2019, in all ten Canadian provinces. Given its connection to the LFS design and the randomness of the panel selection, this makes the CPSS a probability sample.

Of the 32,000 respondents asked to join the CPSS, just over 7,200 agreed to join and complete short online surveys. Survey weights were calculated for the web panel, adjusting their initial LFS selection weights to minimize the potential non-participation bias. Using the survey weights, representative estimates of those living in the Canadian provinces can be calculated. A first survey was administered through the web panel from March 29 to April 3, 2020, to address the COVID-19 pandemic. The response rate for the survey was 63.9%. The cumulative response rate is 14.6%, after accounting for non-participants of the CPSS. For more information, consult https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&Id=1280240.

Crowdsourcing involves collecting information from the online community. Publicity efforts are made to reach a wide portion of the target population but participants are self-selected and provide data on a voluntary basis, thus rendering this type of data collection exercise a non-probabilistic process. Given this non-probabilistic aspect and unknown population coverage, such a crowdsourcing cannot be used to make statistical inferences about the full Canadian population. Results are only reflective of the participants and extreme caution should be exercised when interpreting them.

Although statistical inference cannot be made using solely data obtained from crowdsourcing, these data could provide a valuable source of auxiliary information that might benefit modeling techniques aiming at improving the quality of statistics produced from other existing probabilistic sample data. Research on such methods are ongoing.

The crowdsourcing initiative, Impacts of COVID-19, was launched on April 3rd for Canadians to voluntarily provide data on how COVID-19 is impacting their lives. For more information about that initiative, consult https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=5311.

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NEW ZEALAND

Reporting: **Chen Chen** and **Patrick Graham**

A new monthly employment indicator series

On November 2019, Stats NZ introduced a new monthly employment indicator (MEI) series to provide an early indication of changes in the labour market. These indicators use a combination of administrative data from Inland Revenue (New Zealand's tax department), to produce timely filled jobs and gross measures for total NZ and three broad industry categories.

The MEI series are published four to five weeks after the end of the reference month. The measures are provisional and subject to revisions each month, with updated payday filing information received after publication.

The indicator series covers filled jobs and gross earnings belonging to

- full-time and part-time employees
- foreign residents and members of the permanent armed forces with wages and salaries
- self-employed people who pay themselves a wage or salary.

Filled jobs are output at the total New Zealand level and use the following broad industry categories based on the industry code assigned at the enterprise level:

- Primary industries: Agriculture, Forestry and Fishing and Mining
- Goods-producing industries: Manufacturing, Electricity, Gas, Water & Waste and Construction
- Services industries: Wholesale Trade through to Other Services

Gross earnings are output at the total New Zealand level.

The series was only ever intended to be an indicator series but with the growing need for frequent, timely measurements of the New Zealand economy during the COVID-19 pandemic we are continuing to refine the methods used.

For more information please contact chen.chen@stats.govt.nz.

In response to the COVID-19 pandemic

In response to the COVID-19 pandemic, Stats NZ acted as a data steward and facilitated access to data by the epidemic modelling team led by Prof. Shaun Hendy from the University of Auckland. Aggregated cellphone data has been analysed to study people movements. Stats NZ's Chief Methodologist, Vince Galvin, has been seconded to the National Crisis Management Centre (NCMC), as head of the modelling workstream. An informal internal Stats NZ COVID-19 modelling team has been established to review papers from the academic modelling group and may be involved in running some sensitivity analyses in support of Vince's work at the NCMC. Stats NZ also explored new data sources and methods to continue to produce key economic and social outputs amid the level 4 and level 3 lockdown.

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UNITED STATES

Reporting: **William J. Wiatrowski**

Reporting key economic data during the COVID-19 pandemic

The Bureau of Labor Statistics (BLS, https://www.bls.gov/) is the U.S. statistical agency responsible for measuring labor market activity, working conditions, price changes, and productivity in the U.S. economy. Despite the ongoing COVID-19 pandemic, BLS operations continue and economic data are being released on schedule. As a telework-ready organization for several years, BLS quickly transitioned over 2,000 staff from around the country to 100 percent telework. All work continues, albeit with some challenges, most notably related to data collection.

BLS employs a wide variety of collection modes to obtain information from businesses and households. In-person data collection is often used for initial appointments, to build relationships that allow for ongoing collection. To ensure the safety and well-being of both employees and respondents, BLS took immediate action to halt all in-person collection following reports about the virus's spread. Collection is now conducted by telephone, email, and the internet, as well as experimental collection by video – a BLS first.

Some unique data collection challenges

BLS gathers labor market and price information through many different means, each with its own unique challenges. Due to the pandemic, BLS made adjustments to continue operations. Here are a few examples:

- The BLS Electronic Data Interchange center in Chicago receives and processes large data files from employers. Since staff in this facility were already telework-ready, the transition to a 100 percent telework environment was smooth with minimal disruption in workflow.
- BLS uses four data collection centers located across the U.S. to contact employers and gather data. These offices are staffed by contractors who were generally not telework ready. To respond to the crisis, BLS closed the onsite centers and gradually shifted contractors to telework. Work slowed during the transition to telework, but is gradually improving.
- BLS has several cooperative programs with State agencies. Some States have closed their offices and furloughed their employees. Other States remain open for certain activities but have limited telework ability. BLS is adjusting deadlines, providing assistance through Federal staff (on telework), and assisting states to transition to telework environments.

In each of these changes, and in related adjustments to collection procedures, BLS continues to adhere to strict confidentiality requirements. The identity of survey respondents and the information they provide is never disclosed. Data are used for statistical purposes only. By maintaining this pledge of confidentiality, even during the pandemic, BLS upholds its reputation for producing gold standard economic data.

Response rates

The pandemic is also a challenge for businesses and households that provide data to BLS. Many businesses are closed and staff are not available; this is especially true for small to medium-sized companies. Collection from other businesses, such as hospitals and grocery stores, may be suspended in recognition of excessive workloads. For household surveys, there may be more people at home but they may not answer the phone or may have more pressing activities. For all of these reasons, response may be affected. BLS has encountered significant disruptions to data collection before, to include those following the 9/11 terrorist attacks and Hurricane Katrina. These experiences form a playbook that can help inform today's collection activities.

Response to the Consumer Price Index (https://www.bls.gov/cpi/) collection of prices for goods and services from businesses was about 20 percentage points lower in April 2020 than a year earlier; similarly, response to the Current Population Survey (https://www.bls.gov/cps/) collection of labor force information from households was about 13 percentage points lower in April 2020 than a year earlier. In contrast, response from businesses to the Current Employment Statistics (https://www.bls.gov/ces/) collection of payroll employment data in April was about three percentage points higher than a year ago, perhaps the result of considerable electronic collection. When data are not available, BLS uses traditional adjustment methods. To date, reductions in survey response have had only a limited effect on published statistics. Going forward, severe levels of nonresponse may lead to a reduction in the amount of published detail.

Keeping up-to-date with the latest information from BLS

BLS has a tradition of providing extensive information about the methods involved in producing economic statistics, and is transparent in identifying data limitations. This tradition is maintained during the COVID-19 pandemic, as the BLS website (https://www.bls.gov/) is frequently updated. A special page (https://www.bls.gov/bls/bls-covid-19-questions-and-answers.htm) devoted to COVID-19 Questions and Answers has been added to the website, with information on all BLS programs, information for survey respondents, and other announcements. In addition, BLS news releases are accompanied by explanatory material on the effect of COVID-19 on data collection, response, data processing, and other issues. Accurate and timely economic data are needed now more than ever, and despite collection challenges and a fully-remote workforce, BLS continues to meet that need.

Due to the corona virus pandemic some conferences have announced postponements, changes to format (from an in-person to a virtual conference) or suspended registration. Other conferences are in the process of doing so. Where this information is available, it has been noted below.

Late last year, the IASS Executive committee decided to provide monetary support to five conferences during 2020. As mentioned, due to the COVID19 pandemic some of these conferences have been postponed to 2021. When asked by conference organisers, the IASS committee has agreed to transfer that support to 2021.

IASS-Supported Conferences Planned for 2020

Conference for Population Surveys, Data Users and Producers, took place 5-6 February 2020, Nigeria, Africa.

ICES VI - The International Conference on Establishment Statistics is planned to take place 14-17 June, 2021 in New Orleans, U.S.

Website: https://ww2.amstat.org/meetings/ices/2021/

SAE2020 - BigSmall - Conference on Small Area Estimation was to be held 6-8 July in Naples, Italy, with the theme "Big Data for Small Areas". Due to the corona virus pandemic, the conference will be held 5-7 July in Naples as a satellite conference to the World Statistics Conference in 2021.

Website: https://sae2020.org/

Summer School on Survey Statistics 2020 was planned to be held 24-28 August in Minsk, Belarus but it has been postponed to 2021. Details to be announced.

Website: https://wiki.helsinki.fi/display/BNU/Events

11e Colloque International Francophone sur les Sondages - 11th International Francophone Conference on Surveys was planned for 13-16 October in Brussels, Belgium. It has been postponed. Details to be announced soon.

Website: http://sondages2020.sciencesconf.org

Other 2020 Conferences on survey statistics and related areas

17th IAOS Conference and the 3rd ISI Regional Statistics Conference due to be held 19-21 May 2020 in Livingstone, Zambia, has been postponed to a date to be confirmed.

Website: https://2020-iaos-isi.zamstats.gov.zm/index.php

12th International Conference on Transport Survey Methods was to take place May 31 – June 5 but due to the corona virus pandemic it is currently planned for 25-30 October at the Hotel Golf Mar in Porto Novo (near Lisbon), Portugal.

Website: https://www.isctsc2020.pt/

Australian and New Zealand Statistical Conference was to take place 6-10 July 2020, Gold Coast, Australia but is now postponed to 5-9 July 2021.

Website: https://anzsc2020.com.au/

Q2020 – 10th European Conference on Quality in Official Statistics was planned to take place 9-12 June in Budapest, Hungary. However, the conference will no longer take place during 2020.

Website: http://q2020.hu/

Joint Statistical Meeting with the theme Everyone Counts: Data for the Public Good will take place 1-6 August as a virtual conference.

Website: https://ww2.amstat.org/meetings/jsm/2020/index.cfm

Women in Statistics and Data Science Conference 2020 is planned to take place 1-3 October in Pittsburgh, USA.

Website: https://ww2.amstat.org/meetings/wsds/2020/

BigSurv20 – Big Data Meets Survey Science was planned to be held 4-6 November in Utrecht, Netherlands. This will likely not happen, and organisers are considering a virtual conference or postponement.

Website: https://www.bigsurv20.org

American Statistical Association Conference on Statistical Practice is planned to take place 18-20 February 2021 in Nashville, USA

Symposium on Data Science & Statistics is planned to take place June 2-5, 2021 in Missouri, USA.

Website: https://ww2.amstat.org/meetings/sdss/2021/

The Survey Research Methods Section (SRMS) of the ASA. Information on activities of the Survey Research Methods Section of the American Statistical Association (ASA) are available at https://community.amstat.org/surveyresearchmethodssection/home.

In Other Journals

Journal of Survey Statistics and Methodology

Volume 8, Issue 1, February 2020

Special Issue: Recent Advances in Probability-Based and Nonprobability Survey Research

https://academic.oup.com/jssam/issue/8/1

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A Statement from the Editors-in-Chief
Michael Elliott, Ting Yan

Editorial

Recent Advances in Probability-Based and Nonprobability Survey Research
Annelies G Blom, Carina Cornesse, Joseph W Sakshaug, Alexander Wenz

Survey Methodology

A Review of Conceptual Approaches and Empirical Evidence on Probability and Nonprobability Sample Survey Research
Carina Cornesse, Annelies G Blom, David Dutwin, Jon A Krosnick, Edith D De Leeuw ...

Relations Between Variables and Trends Over Time in Rdd Telephone and Nonprobability Sample Internet Surveys
Josh Pasek, Jon A Krosnick

A Process for Decomposing Total Survey Error in Probability and Nonprobability Surveys: A Case Study Comparing Health Statistics in US Internet Panels
Jennifer Unangst, Ashley E Amaya, Herschel L Sanders, Jennifer Howard, Abigail Ferrell, Sarita Karon, Jill A Dever

Total Error in a Big Data World: Adapting the TSE Framework to Big Data
Ashley Amaya, Paul P Biemer, David Kinyon

Survey Statistics

Integrating Probability and Nonprobability Samples for Survey Inference
Arkadiusz Wiśniowski, Joseph W Sakshaug, Diego Andres Perez Ruiz, Annelies G Blom

Big Data for Finite Population Inference: Applying Quasi-Random Approaches to Naturalistic Driving Data Using Bayesian Additive Regression Trees
Ali Rafei, Carol A C Flannagan, Michael R Elliott

Volume 8, Issue 2, April 2020

https://academic.oup.com/jssam/issue/8/2

Survey Statistics

Model-Based Screening for Robust Estimation in the Presence of Deviations from Linearity in Small Domain Models
Julie Gershunskaya, Terrance D Savitsky

Exact Adaptive Confidence Intervals for Small Areas
Kyle C Burris, Peter D Hoff

Comparing Alternatives for Estimation from Nonprobability Samples
Richard Valliant

Survey Methodology

Do Interviewers Moderate the Effect of Monetary Incentives on Response Rates in Household Interview Surveys?
Eliud Kibuchi, Patrick Sturgis, Gabriele B Durrant, Olga Maslovskaya

Do I Look and Sound Religious? Interviewer Religious Appearance and Attitude Effects on Respondents' Answers
Zeina N Mneimneh, Julie de Jong, Kristen Cibelli Hibben, Mansoor Moaddel

An Examination of an Interviewer-Respondent Matching Protocol in a Longitudinal CATI Study
Brady T West, Michael R Elliott, Zeina Mneimneh, James Wagner, Andy Peytchev, Mark Trappmann

Reading Fast, Reading Slow: The Effect of Interviewers' Speed in Reading Introductory Texts on Response Behavior
Michael Bergmann, Johanna Bristle

A Mixed-Mode and Incentive Experiment Using Administrative Data
Brian Bucks, Mick P Couper, Scott L Fulford

Modular Survey Design: Experimental Manipulation of Survey Length and Monetary Incentive Structure
Andy Peytchev, Emilia Peytcheva, Johnathan G Conzelmann, Ashley Wilson, Jennifer Wine

Using Response Propensity Modeling to Allocate Noncontingent Incentives in an Address-Based Sample: Evidence from a National Experiment
Michael T Jackson, Cameron B McPhee, Paul J Lavrakas

Volume 8, Issue 3, June 2020

https://academic.oup.com/jssam/issue/8/3

Conditional Bias Robust Estimation of the Total of Curve Data by Sampling in a Finite Population: An Illustration on Electricity Load Curves
Hervé Cardot, Anne De Moliner, Camelia Goga

Web Versus Other Survey Modes: An Updated and Extended Meta-Analysis Comparing Response Rates
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How Linkage Error Affects Hidden Markov Model Estimates: A Sensitivity Analysis
Paulina Pankowska, Bart F M Bakker, Daniel L Oberski, Dimitris Pavlopoulos

Panel Survey Recruitment with or Without Interviewers? Implications for Nonresponse, Panel Consent, and Total Recruitment Bias
Joseph W Sakshaug, Sebastian Hülle, Alexandra Schmucker, Stefan Liebig

Misreporting Among Reluctant Respondents
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The Effects of Survey Enhancements on the Quality of Reporting in the Medical Expenditure Panel Survey, 2008–2015
Samuel H Zuvekas, Adam I Biener, Wendy D Hicks

Comments on "How Errors Cumulate: Two Examples" by Roger Tourangeau
Kristen Olson

How Errors Cumulate: Two Examples
Roger Tourangeau

Discussion of "How Errors Cumulate: Two Examples" by Roger Tourangeau
Jill A Dever, Ph.D

Survey Methodology

Statistics Canada Statistique Canada Canadä

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https://www150.statcan.gc.ca/n1/en/catalogue/12-001-X

There were not any new issues published since the December 2019, Vol. 45, no. 3 issue.

Journal of Official Statistics

Volume 36 (2020): Issue 1 (Mar 2020)

https://content.sciendo.com/view/journals/jos/36/1/jos.36.issue-1.xml

A Framework for Official Temporary Population Statistics
Elin Charles-Edwards, Martin Bell, Radoslaw Panczak and Jonathan Corcoran

Identifying the Direction of Behavioral Dependence in Two-Sample Capture-Recapture Study
Kiranmoy Chatterjee and Diganta Mukherjee

The Joinpoint-Jump and Joinpoint-Comparability Ratio Model for Trend Analysis with Applications to Coding Changes in Health Statistics
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Statistical Challenges in Combining Survey and Auxiliary Data to Produce Official Statistics
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A Probabilistic Procedure for Anonymisation, for Assessing the Risk of Re-identification and for the Analysis of Perturbed Data Sets
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Can Interviewer Evaluations Predict Short-Term and Long-Term Participation in Telephone Panels?
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Fully Bayesian Benchmarking of Small Area Estimation Models
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Volume 36 (2020): Issue 2 (Jun 2020)

https://content.sciendo.com/view/journals/jos/36/2/jos.36.issue-2.xml

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Switching Between Different Non-Hierachical Administrative Areas via Simulated Geo-Coordinates: A Case Study for Student Residents in Berlin
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Controlling for Selection Bias in Social Media Indicators through Official Statistics: a Proposal
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Exploring Mechanisms of Recruitment and Recruitment Cooperation in Respondent Driven Sampling
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Explaining Inconsistencies in the Education Distributions of Ten Cross-National Surveys – the Role of Methodological Survey Characteristics
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Investigating the Effects of the Household Budget Survey Redesign on Consumption and Inequality Estimates: the Italian Experience
Nicoletta Pannuzi, Donatella Grassi, Achille Lemmi, Alessandra Masi and Andrea Regoli

On Accuracy Estimation Using Parametric Bootstrap in small Area Prediction Problems
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Book Review
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Survey Practice

Vol. 13, Issue 1, 2020

https://www.surveypractice.org/issue/1854

Articles

'You're Not My Friend': Communication Style, Sponsor Salience, and Gender in Recruitment Messaging
Joanna Woronkowicz, Jessica Sherrod Hale, Jesse Lynn Talley, Lilian Yahng

Sample size and uncertainty when predicting with polls: the shortcomings of confidence intervals
Robert Samohyl

Using Buttons as Response Options in Mobile Web Surveys
Christopher Antoun, Elizabeth Nichols, Erica Olmsted-Hawala, Lin Wang

Pre-Testing Establishment Surveys: Moving Beyond the Lab
Heather Ridolfo, Kathy Ott, Jeremy Beach, Jaki S. McCarthy

Cost effectiveness of pre- and post-paid incentives for mail survey response
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Interview the Expert

The Societal Experts Action Network (SEAN) COVID-19 Survey Archive, with Gary Langer
Eva Aizpurua

Survey Research Methods

Journal of the European Survey Research Association

Vol 14 No 1 (2020)

https://ojs.ub.uni-konstanz.de/srm/issue/view/219

Measuring geographic mobility: Comparison of estimates from longitudinal and cross-sectional data
Nicole Watson

Evaluating push-to-web methodology for mixed-mode surveys using address-based samples
Peter Lynn

The Impact of Splitting a Long Online Questionnaire on Data Quality
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Effects of Header Images on Different Devices in Web Surveys
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Attention Check Items and Instructions in Online Surveys with Incentivized and Non-Incentivized Samples: Boon or Bane for Data Quality?
Hawal Shamon, Carl Clemens Berning

The Impact of Mixed Modes on Multiple Types of Measurement Error
Alexandru Cernat, Joseph Sakshaug

Vol 14 No 2 (2020): Survey Research Methods During the COVID-19 Crisis

https://ojs.ub.uni-konstanz.de/srm/issue/view/221

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Investigating selection bias of online surveys on coronavirus-related behavioral outcomes
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Problems and pitfalls of retrospective survey questions in COVID-19 studies
Lena Hipp, Mareike Bünning, Stefan Munnes, Armin Sauermann

Unit nonresponse biases in estimates of SARS-CoV-2 prevalence
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Methodological Problems and Solutions in Sampling for Epidemiological COVID-19 Research
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Design for a Mail Survey to Determine Prevalence of SARS-CoV-2 (COVID-19) Antibodies in the United States
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Identifying impacts of COVID-19 pandemic on vulnerable populations
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Surveying Entrepreneurs' Perception of Society in Times of Corona: A proposal
Michael Weinhardt, Julia Bartosch

Using Difference-in-Differences to Identify Causal Effects of COVID-19 Policies
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Research initiatives

Partnering with a global platform to inform research and public policy making
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Combined mobile-phone and social-media sampling for web survey on social effects of COVID-19 in Spain
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High Frequency and High Quality Survey Data Collection
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Tracking the Effect of the COVID-19 Pandemic on the Lives of American Households
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Investigating the social, economic and political consequences of Covid-19: A rolling cross-section approach
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The Need for Household Panel Surveys in Times of Crisis: The Case of SOEP-CoV
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Can we directly survey adherence to non-pharmaceutical interventions?
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A Cross-National Design to Estimate Effects of COVID-Induced Non-Pharmacological Interventions
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Collecting survey data among the 50+ population during the COVID-19 outbreak: The Survey of Health, Ageing and Retirement in Europe (SHARE)
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The impact of Covid-19 on fieldwork efforts and planning in pairfam and FReDA-GGS
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Impacts of the COVID-19 Pandemic on Labor Market Surveys at the German Institute for Employment Research
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How Understanding Society: The UK Household Longitudinal Study adapted to the COVID-19 pandemic
Jonathan Burton, Peter Lynn, Michaela Benzeval

Effects of the COVID-19 Crisis on Survey Fieldwork: Experience and Lessons From Two Major Supplements to the U.S. Panel Study of Income Dynamics
Narayan Sastry, Katherine McGonagle, Paula Fomby

COVID-19 lockdown during field work
Gisela Will, Regina Becker, Dominik Weigand

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/toc/uasa20/current

Welcome New Members!

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

Title	First name	Surname	Country
MR.	Florian	Berens	Germany
MR.	Bo Robert	Beshanski-Pedersen	Bulgaria
MS	Elisabeth	Flittner	Finland
DR.	Dan Ion	Ghergut	Romania
MR.	Thomas	Krenzke	United States
DR.	Angelo	Moretti	United Kingdom
DR.	Damião	Nóbrega Da Silva	Brazil
DR.	Kazeem Adewale	Osuolale	Nigeria
PROF	Joseph	Sakshaug	Germany
PROF	Hussein Abel-Aziz	Sayed	Egypt
PROF. DR.	Alan M.	Zaslavsky	United States

IASS Executive Committee Members

Executive officers (2019 – 2021)

President:	Denise Britz do Nascimento Silva (Brazil)	denisebritz@gmail.com
President-elect:	Monica Pratesi (Italy)	monica.pratesi@unipi.it
Vice-Presidents:		
Scientific Secretary:	James Chipperfield (Australia)	james.chipperfield@abs.gov.au
VP Finance:	Lucia Barroso (Brazil)	lpbarroso@gmail.com
Chair of the Cochran-Hansen Prize Committee and IASS representative on the ISI Awards Committee:	Isabel Molina (Spain)	imolina@est-econ.uc3m.es
IASS representatives on the World Statistics Congress Scientific Programme Committee:	Cynthia Clark (USA) in 2017-2019	czfclark@cox.net
	Monica Pratesi (Italy)	monica.pratesi@unipi.it
IASS representative on the World Statistics Congress short course committee:	Nadia Lkhoulf (Morocco)	n.lkhoulf@hcp.ma
Ex Officio Member:	Ada van Krimpen	an.vankrimpen@cbs.nl

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

Institutional Members

International organisations:

- Eurostat (European Statistical Office)
- Observatoire économique et statistique d'Afrique subsaharienne (AFRISTAT)

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, Republic of Korea
- 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
- National Agricultural Statistics Service (NASS), United States
- National Center of Health Statistics (NCHS), United States

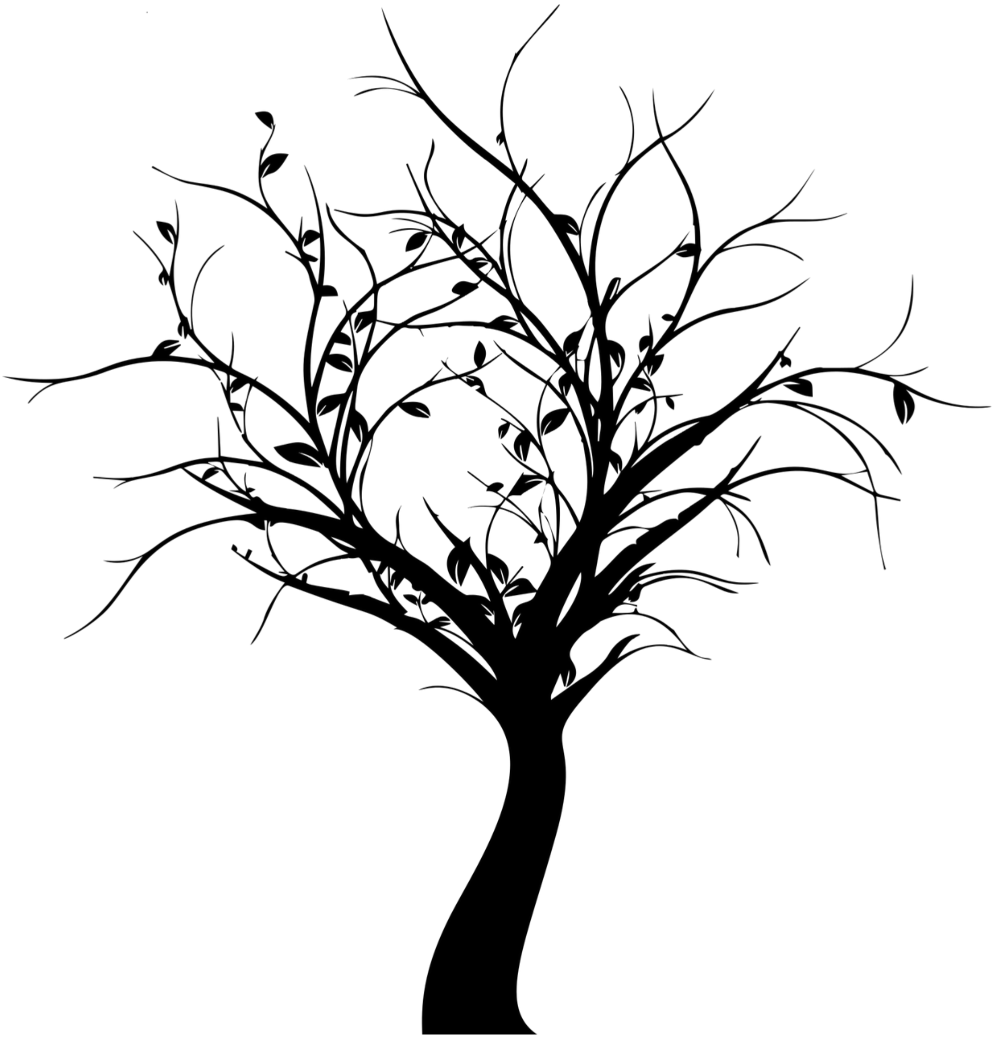
Private companies:

- Numérika (Asesoría estadística y estudios cuantitativos), Mexico
- RTI International, United States
- Survey Research Center (SRC), United States
- Westat, United States

Save a tree!

Read *the Survey Statistician* online!

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



Please contact Margaret de Ruiter-Molloy (m.deruitermolloy@cbs.nl)
if you would like to cancel receiving paper copies of this Newsletter.