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Stimulators of innovation in official statistics

1. Introduction

It is worth considering what factors stimulate innovation in official statistics. The interaction of these factors causes official statistics to provide users with more accurate and user-friendly information.

Innovation is a concept that has become commonplace. It is used in mass media, e.g. when advertising various products, and there are numerous scientific surveys and research work on this subject, pertaining to various fields. The term 'innovation' comes from the Latin word 'innovatio', which means renewal. Its meaning comprises everything that is new, from technical improvements, through technological advancement and organisational changes in various structures, local and global communication, media and fashion, to new ways of thinking.

The term was defined and introduced into economics by Schumpeter (1912), thus indicating five instances of the occurrence of innovations:
- creating a new product;
- application of new technology, production methods;
- creating a new market;
- acquiring unknown raw materials;
- reorganisation of a specific branch of the economy.

2. What is innovation, how to measure and use it?

In modern economy, there are three key factors which foster competitiveness and contribute to raising the standards of living and welfare. They are: knowledge, research and innovation. The role of knowledge in the above-mentioned processes can only be thoroughly demonstrated and understood with the help of reliable statistical information, which is also necessary for wise policy planning and its effective evaluation. Research and development activity, another pillar of the economic and social advancement, was expanded and harmonised in the 1960s. In the 1970s and 1980s, due to further progress in this area, researchers were able to create more complex analytical models and tools, which made it possible to measure innovation. However, to fully understand what leads to innovation and how to create policies encouraging it, it was necessary to analyse innovation processes at the level of individual companies, where again, statistical data proved indispensable.

The above-mentioned efforts resulted in the creation of the *Oslo Manual* in 1992, a publication which has become the international standard in the field of the conceptualisation and measurement of innovation. The manual has been updated three times since its publication, which was necessitated by the technical and technological advancement and the changing needs of users (OECD, Eurostat, 2018). The publication contains guidelines on the collection, presentation and interpretation of data on innovation, which is useful for national statistical offices (NSO) and other data producers. It also facilitates international comparisons and serves as a platform for research and experiments in measuring innovation. In addition, *The Oslo Manual* reviews several issues related to the use of innovation data for the construction of indicators and for carrying out statistical and econometric analyses. But nevertheless, its recommendations are addressed not only to those who develop indicators of an official nature, but to all those interested in innovation data. The book manages to meet the needs of a wider range of users, which the indicators cannot do on their own. It is also designed to encourage future experiments that would improve the quality, visibility and usefulness of data on innovation.

The *Oslo Manual* provides the following definition of the phenomenon (OECD, Eurostat, 2018, p. 20): 'An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes, and that has been made available to potential users (product) or brought into use by the unit (process).'

This definition uses the generic term 'unit' to describe the actor responsible for innovations. It refers to any institutional unit in any sector, including households and their individual members.

Despite the subjective nature of the concept of innovation, measuring it can be relatively objective, as it is possible to compare innovation levels using common reference points for novelty and usability. This enables comparisons of the degree of innovativeness among firms that are of different sizes and structures and which operate in different parts of the world.

3. Innovation in official statistics

Innovation in official statistics is crucial to keeping one step ahead of the changing demands. Only with creativity can statistical offices constantly improve their efficiency and the quality of their product. Innovations influence any aspect of the activity of a statistical office, bringing about the following: cutting-edge ways of gathering information; state-of-the-art technologies and statistical techniques to process data and generate statistics; new approaches to recruitment and structuring an organisation, and inventive ways of publishing data and reaching all kinds of audiences.

Innovations can also be found in statistics at the organisational level, e.g. in the form of various solutions which improve the work of an institution or office, the improved organisation of statistical surveys, more effective methods of data collection, analysis, presentation, dissemination and publication, and providing wider access to data.

The innovative process is a sequence of successive phases, from the creation of an innovative idea to its implementation and commercialisation; in other words, it is a set of activities leading to the implementation of new solutions in the technical, technological, organisational and social spheres (Alleva, 2017; Baldacci, 2017; Daas, Puts, Buelens and van den Hurk, 2015; Dillman, 1996; Lehtonen, Pahkinen and Särndal, 2002; Lehtonen and Särndal, 2009; Pfeffermann, 2015; Szreder, 2017). More particularly, in statistics, the innovative process is a sequence of procedures related to the formulation of the objective of the study, justification of its theoretical foundations, selection of appropriate methods for its implementation, and, finally, dissemination of its results.

Data collection, and especially business data collection performed by National Statistical Institutions (NSIs) has been the area where several new and innovative tools have been implemented. These include utilising administrative data, developing web-based questionnaires, automatic retrieval of data from companies' data systems or adopting new data collection methods based on combined sources. Increasingly often, the NSIs collaborate with other data providers in order to get 'raw-material' for statistical compilations. The business sector, in addition to providing valuable data to official statistics, also inspires the latter to look for new innovative solutions and supports its efforts to this effect.

A big advantage of administrative registry data is their integration. Survey and census data should be integrated in a similar way in order to obtain a wider scope of information and improve their quality. This, however, gives rise to numerous new challenges, which are of a different character than traditional problems related to survey sampling (Pfeffermann, 2015; Szreder, 2017).

The ongoing technological progress and the wide availability of big data create a demand for more detailed, more accurate, and up-to-date statistics. The new methodological challenges which can be mentioned in this context include: IT-integrated collection of big data and production of official statistics from it, increasing data availability, while at the same time ensuring their confidentiality, potential use of web panels as data source for official statistics, dealing with mode effects, measuring the scale of error in small area estimation, also in combination with censuses, and integration of statistics with geospatial information.

4. Stimulators of innovation in official statistics

Specific stimulators of innovation in official statistics include developments in statistical theories the increasing the role of information technology (IT) in statistics, and globalisation.

4.1. Innovation in scientific research and thought

The concept of paradigms, which illustrates the development of scientific ideas, was introduced by Thomas Kuhn (1962). Kuhn believed that scientific research and thought are determined by paradigms, i.e. conceptual worldviews. His theory assumed that scientific disciplines emerge in the pre-paradigmatic phase, and then progress to periods called 'normal science', during which they relatively quickly achieve a high degree of advancement and precision. During the normal science phase, the performed research adds to the previous knowledge, thus forming a cumulative whole, where new discoveries and experimental results contribute to the development of more accurate or comprehensive theories.

In other words, Kuhn argued that for the phase of normal science to occur, it is crucial that it is based on a universally accepted paradigm, which identifies research problems, enables the researcher to formulate rational expectations, and provides him or her with tools to carry it out successfully. The term 'paradigm', as used by the author, has two different meanings: a set of beliefs, values, techniques, etc., held by the scientific community, or just a specific solution/group of solutions, on which solving the problem in question could be modelled in the phase of normal science. The author referred to the former meaning of the term 'paradigm' as sociological, in the sense that it is what the scientific com-munity share (Kuusela, 2011).

4.2. Stimulators of innovation in statistical theory

The concept of statistical inference was introduced by a French statistician Pierre-Simon Laplace (1781). He published a plan for partial research where he defined the size of a sample which guaranteed achieving the necessary accuracy in estimation. He devised that plan following his Principle of Inverted Probability and his Central Limit Theorem. In 1774, he published these concepts in a memoir which revolutionised statistical thinking at the time (Laplace, 1774). The inference model developed by Laplace used Bernoulli's concepts related to binomial probabilities and corresponding trials. One of Laplace's most valuable contributions into the statistical thought was the assumption that populations constantly change, which he signified by assuming an *a priori* distribution of parameters. His method required a purposive selection of samples for research.

Laplace's inference model considerably influenced statistical thinking for a whole century. A Norwegian statistician, Anders Kiaer, and his work *The Representative Method of Statistical Surveys* (1897), serves as a good example here. Kiaer presented his method, which drew heavily upon Laplace's concepts, at the meeting of the International Statistical Institute in 1895. His method, introducing a novel idea that a research sample should reflect the structure of a population, i.e. be this population's 'miniature', became an instant success (Kiaer, 1895, 1897, 1905).

Another influential 18th century statistician, Thomas Bayes, contributed the first mathematical approach to some non-trivial problems related to the analysis of statistical data, which was based on his concept of what is nowadays known as Bayesian inference. However, it was Pierre-Simon Laplace who both pioneered and popularised the ideas presently referred to as Bayesian probability.

The concept of Bayesian probability is based on logical expectations, formed according to the available knowledge or personal beliefs rather than on the frequency or tendency of a phenomenon. Probability as understood by Bayes is an extension of propositional logic that enables reasoning with hypotheses, and which involves propositions whose truth or falsity is uncertain. In the Bayesian approach, a probability is assigned to a hypothesis, whereas in the frequentist inference, the latter is often verified without any probability being assigned.

The Bayesian theory enabled obtaining the so-called predictive inference, thanks to which it is possible to predict the distribution of unobserved data. It is based on the posterior predictive distribution. This means that the prediction yields a distribution over possible points rather than over one fixed point. When we compare the Bayesian inference with its frequentist counterpart, we can see that the latter often involves finding an optimum point estimate of the parameter(s), mostly by means of the maximum likelihood or maximum posterior estimation, and then includes this estimate in the formula for the distribution of a data point. The shortcoming of this approach is that it does not make allowances for any uncertainty in the value of the parameter, and therefore underestimates the variance of the predictive distribution (Bayes, 1763, 1958).

It was not until the 1920s that another revolutionary theory came up in statistics. It was the work by Ronald Aylmer Fisher, who devised the estimation and inference theory. His model of statistical inference has remained the dominant paradigm until the present times. Its basis is repetitive sampling from the same population and assuming that population parameters are constant. He did not use *a priori* probabilities. His *Statistical Methods for Research Workers* (Fisher, 1925) has become a classic statistical textbook. It is often considered one of the 20th century's most influential books on statistics, along with his *The Design of Experiments* (Fisher, 1915, 1925, 1930, 1935, 1939, 1950 1956).

Fisher's inference model was further developed by Jerzy Neyman. Neyman adopted Fisher's model and used it for finite populations, with the difference that his model did not make any assumptions about the distributions of the study variables.

Fisher's fiducial argument helped Neyman develop the theory of confidence intervals. He also devised the concept of optimal allocation for stratification. Finally, he formu-lated a theory for double sampling, which was utilised by statisticians at the U.S. Census Bureau when they were working on a complex survey project for the Current Population Survey. What was also important for the Bureau, and what Neyman's method guaranteed, was to find a solution that would distribute workloads fairly equally among interviewers, while maintaining acceptable accuracy in estimation (Neyman, 1933, 1934, 1935, 1937, 1938, 1952, 1971).

4.3. Paradigms in statistics: Bayesian and Frequentist approaches

Thomas Bayes proved that an unknown event might be placed within probabilistic limits. However, as can be recalled from the previous chapter, it was Pierre-Simon Laplace who made Bayesian theory popular. Laplace applied what is nowadays called Bayesian theorem to problems in celestial mechanics, medical statistics, reliability, and jurisprudence. Early Bayesian inference, which used uniform priors according to Laplace's principle of insufficient reason, is presently referred to as 'inverse probability', because it goes backwards from observations to parameters, or from effects to causes.

After 1920, the concept of inverse probability was in a large part replaced after 1920 by a set of methods called frequentist statistics. In the 20th century, Laplace's ideas were further developed, but in two separate directions, referred to as 'objective current' and 'subjective current' in Bayesian inference. As regards the 'objective' or 'non-informative' current, the statistical analysis depends there only on the model employed, the data analysed, and the method assigning the prior. In the 'subjective' or 'informative' current, the specification of the prior depends on the belief, usually formed on the basis of information from experts, previous studies, etc.

In the 1980s, research and applications of Bayesian methods increased significantly, mostly thanks to the *Markov chain Monte Carlo* methods, which greatly improved computational capacities of the former. In addition, that period saw an increased interest in non-standard, complex applications. But despite that, most undergraduate teaching has been, and even nowadays, is still based on frequentist statistics. This does not change the fact, however, that Bayesian methods are widely accepted and used, e.g. in the field of machine learning.

To sum up, Bayesian approach began to develop in the 19th century, contributing significantly to the advancement of mathematics and statistics – the process in which the role of the French scientist P.-S. Laplace could not be overestimated (Kuusela, 2011). In addition to developing the ideas of Bernoulli and Bayes, Laplace presented the principles of inverse probability, and, consequently, the idea of statistical inference. He also succeeded in specifying the size of a sample necessary to achieve a desired degree of accuracy of the result. The plan of Laplace's study was based on his principle of inverse probabilities and the central limit theorem. Published in 1774, it soon became exceedingly popular, and subsequently it has become one of the most revolutionary papers in the history of statistical inference.

Laplace's inference model was based on Bernoulli's tests and binomial distribution. He believed that the population was constantly changing, which was acknowledged by his assuming an *a priori* distribution for parameters. This model dominated the statistical thought throughout the 19^{th} century. Its further development was partially limited due to computational difficulties, which lasted for as long as until the 1980s, when modern computational technologies were introduced.

What is important to remember here is that his approach utilises all the available knowledge about an event, not only the knowledge resulting directly from the observed relative frequency of the event's occurrence in unchanged circumstances (as is the case with the frequentist interpretation). According to Laplace's interpretation, the probability of an event is assigned to a concrete person, and thus it is likely to be different for different people (experts), depending on their knowledge, experience or even intuition. For individual phenomena or the ones occurring rarely, this is the most effective and most commonly used probability interpretation. It also proves useful nowadays, when statisticians, interested in a given event or a population, have various sources of information at their disposal. The current abundant possibilities to collect, process, and send huge data sets make it very unlikely that a contemporary researcher would not have any prior knowledge about the studied phenomenon or population. Therefore, the problem is not whether to use this knowledge, but how to do it. This partially explains why contemporary statisticians are keen to use ever-bolder approaches and non-random samples in their research.

Frequentist inference is based on the frequentist interpretation of probability, and especially on its assumption that any experiment might potentially be a part of an infinite succession of its duplications, each of which could produce statistically independent outcomes. According to the frequentist approach, there is a high probability that the correct conclusion will be drawn from amongst the above-mentioned notional set of repetitions. However, it is also possible to adopt the same procedures with a slightly different formulation, i.e. taking a pre-experiment point of view into consideration. Under this formulation, before starting an experiment, the researcher should plan what exactly, step by step, will be done to draw a correct conclusion from data that have not yet been obtained. In such a case, the probability depends on a yet-to-occur set of random events, which is different from the frequentist interpretation of probability.

The value of a population according to the frequentist approach is a stable, unchanging (and unknown) quantity, without an assigned probability distribution. Next, confidence intervals for this quantity, or significance tests of hypotheses about it, are computed. At this stage, Bayesians argue, frequentists block off the possibility of utilising background knowledge about the problem, which leads to their inability to guarantee a satisfactory level of accuracy in their calculations. This, in turn, often results in other scientists' misinterpretations of the confidence intervals and significance tests which have been calculated by frequentists.

As all the above indicates, one can say that the 19th-century statistics belonged to Bayesians, whereas in the 20th century, it fell to frequentists. These sharp trends have been softened by technical improvements, but still the representatives of both approaches compete with each other for domination in the field of real-world applications. But this competition is not anything to worry about, because its outcome is that the ideas of Bayesians and frequentists are constantly developing and has come much closer to each other.

The main ideas of Bernoulli, Bayes and Laplace were subsequently developed by many mathematicians and statisticians, including de Finetti (1951), Jeffreys (1931, 1933, 1934), Kish (1995, 2002), Lindley (1958, 2004), Savage (1951, 1954, 1962), Stigler (1982, 1983) and Zellner (1971).

4.4. Information technology

The term 'information technology' was used for the first time in an article by Harold J. Leavitt and Thomas L. Whisler published in *Harvard Business Review* in 1958, where the authors proposed this broad term as the name for 'the new technology [which] does not yet have a single established name.' In their understanding, the newly-coined name applied to three areas: data processing, statistical and mathematical support for decision-making processes, and using computer programs to simulate higher-order thinking.

Nowadays, information technology (IT) is associated with the use of computers and other electronic devices to store, retrieve, transmit and manipulate data or information, both for the needs of institutions (commercial or non-commercial) and individuals. It is seen as the section of a wider field of information and communications technology.

Although IT is most often associated only with computer systems and networks, it also refers to other channels of distribution of information, such as television, telephones and other devices enabling exchange of information. Numerous products and services available on the market fall within the IT category, e.g. computer hardware and software, electronic devices, semiconductors, telecom equipment, the Internet, including e-commerce, etc.

5. Globalisation and official statistics

Globalisation, as the name suggests, is a global process involving interaction and integration of people, companies, regions and governments of countries all over the world. It is fuelled by international trade. And while it is true that trade exchange has been developing among regions, countries and continents for centuries, or even millennia, it literally boosted in the IT era, greatly accelerating globalisation. In addition to trade exchange, globalisation is also synonymic with the exchange of ideas, practices and technologies.

Globalisation is an inevitable stage of development of the human society. It is a socio-historical phenomenon, which has become the practical necessity, and, subsequently, a strategy for the gradual building of a common market for ever-larger areas, and eventually, for the whole world. Globalisation is an ongoing process, taking place at the local, national, and regional levels. Its basis, as mentioned before, is social and economic interactions and mutual influence at all levels of societies' aggregation and in all aspects of social and economic life.

Globalisation has been the subject of intensified studies for official statistics. A good example is *The Statista Global Consumer Survey***,** which investigates consumption and media usage from a global perspective. The study has been designed to help marketers, planners and product managers understand consumer behaviours and trends. The *KOF Index of Globalisation* is a similar study, whose purpose is to measure the rate of globalisation in countries all over the world in economic, social, and political dimensions. These three dimensions facilitate the assessment of the current economic trends, level of information flow, intensity of social contacts, and cultural proximity among the surveyed countries.

6. Official statistics and big data innovation

Big data is presently considered a very promising source of data for official statistics. It potentially offers faster, cheaper, more detailed and relatively diverse statistical data. However, there are several challenges connected to the use of this kind of data, for example the non-probabilistic character of most sources of big data, which often results in a selectivity bias. This is because most big data sources have not been designed to produce statistics (Baesens, 2014; Beręsewicz, Lehtonen, Reis, Di Consiglio and Karlberg, 2018; Daas et al., 2015).

Recent years have seen an increasing amount of statistics describing different phenomena on the basis of big data. Not only are these data generated in completely new ways, but they also require new techniques of analysis and application. Adopting big data as one of its data sources means a fundamental change for official statistics, which necessitates a shift of paradigm for survey research. This demonstrates that, on the one hand, big data has a great potential for official statistics, but on the other, there are several challenges that have to be faced before this potential could be fully taken advantage of.

The paper by Beręsewicz and co-authors (2018) presents the statistical outlook on big data. The article tries to find a definition of big data which would identify its main statistical characteristics. The author asserts that big data sources are in many aspects similar to internet opt-in panel surveys, and suggests that this quality of theirs should be used to address the selectivity and coverage problems (also briefly addressed in the paper). Moreover, the article presents a selection of methods that can be used to deal with selectivity, and either to eliminate, or at least reduce the bias. This selection consists of both methods applicable at the individual level, i.e. the level of a statistical unit, and those applicable at the domain level, i.e. the level of produced statistics. Finally, the applicability of the methods to several big data sources is briefly assessed and a framework for adjusting selectivity in big data is proposed.

Big data, also understood as the way of gaining knowledge and learning about the latest possibilities of collecting and processing large data sets, has changed decision-makers' assessment of the usefulness and usability of information sources. Lack of information ceases to be a major problem, while selection, quality assessment, and aggregation become challenging. The greatest advantage of big data as a data source is that it gives access to large databases, including administrative data, to the extent never seen before. This advantage is not limited to the possibility of obtaining these data, but it also includes already-devised methods and tools for their processing, as well as tracking updates in real time (without delays). Administrative data, due to various formal requirements and restrictions that apply to the entities which produce them, are usually a reliable and good-quality source of information. Their growing role in exploring reality can be demonstrated by the fact that nowadays administrative data are an indispensable part of important projects undertaken by official statistics. Data from official registers are increasingly often used in statistics interchangeably with full surveys (censuses) or sample surveys. Nowadays even national censuses use administrative data in the cases where census representatives cannot obtain data directly.

In situations where traditional surveys/sources cannot provide reliable or complete data, the use of all the available and relatively reliable information seems a reasonable option. Big data's entry into domains previously reserved for statistical (complete or sample) investigations does not have to be seen as competition between these two data sources. Big data, just like administrative registers mentioned above, can – and in practice often already constitute – a valuable complement to sample-based research. In particular, big data can provide useful information in situations where a sample survey is liable to serious non-random errors, e.g. coverage errors or missing responses. In other words, additional population information needed for the effective application of sample weighing or data calibration mechanisms can be derived from big data. However, big data's impressive capabilities of providing large amounts of information do not change the fact that information obtained in this way always has to be critically evaluated, as this kind of data usually has a more complex and disorderly structure than data obtained in more traditional ways. It is important to remember that quantity cannot compensate for questionable or poor quality when any data is to be used by statistics (Alleva, 2017; Baesens, 2014; Baldacci, 2017; Daas et al., 2015; Dillman, 1996; Lehtonen et al., 2002; Lehtonen and Särndal, 2009; Pfeffermann, 2015; Szreder, 2017).

Taking into consideration all the above, official statistics is currently facing three main questions as regards big data, namely: whether big data is a domain worth expanding, monitoring and improving to better adjust it to the needs of official statistics; if so, then to what extent should official statistics become involved in this process; and finally, which types of partnerships should be formed for this purpose.

7. Concluding remarks

The paper demonstrates that successfully applied innovations have enabled the improvement of the quality and accuracy of data and have made it possible to utilise administrative data, which is especially important in the context of the pressing need for the diversification of data sources. Thanks to innovations, data acquisition methods as well as data dissemination channels have been modernised. Official statistics have also undergone the restructuring of their organisation and management, both nationally and internationally, thus achieving the level of efficiency much higher than any time before. Innovation has also been encouraged and fostered through international statistical cooperation, and especially due to the expansion of international networks established for this purpose.

However, despite several milestone achievements, statisticians cannot stop on their way towards the faster, more accurate and more useful data. They have to constantly pay the highest attention to optimal ways in which their products and services are disseminated within the society. It is also essential that management systems and strategic competence, as well as vital statistical activity, research and procedures are steadily developed and enhanced within institutions of official statistics. Moreover, official statistical services cannot forget an absolute necessity in the contemporary, network-operated environment: to foster partnerships with their foreign counterparts and other institutions. Last but not least, reasonable cost management must also be seriously regarded.

The 21st century poses huge challenges before statisticians, including complex problems which often comprise millions of data units and thousands of parameters. Which statistical method will prove the most effective in such complex cases? According to some statisticians, it will probably be a combination of Bayesian and frequentist ideas. It looks very likely that the near future will be a challenging period for both statisticians specialising in practical applications and those investigating the theory of statistics, but on the other hand, these challenges might open a fertile land for statistics, rivalling the era of Fisher, Neyman, and other luminaries of statistical research of the early 1900s (Pfeffermann, 2015).

New data sources, i.e. big data and the Internet, are viewed by official statistics as very promising and potentially highly useful. However, before they could be fully utilised, it is necessary to thoroughly verify them from the point of view of non-representativeness.

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