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Letter to the Editor

Probabilistic Population Forecasts for Informed Decision Making

Demographic forecasts are inherently uncertain. Nevertheless, an appropriate description of this uncertainty is a key underpinning of informed decision making. In recent decades, various methods have been developed to describe the uncertainty of future populations and their structures, but the uptake of such tools amongst the practitioners of official population statistics has been lagging behind. In this letter we revisit the arguments for the practical uses of uncertainty assessments in official population forecasts, and address their implications for decision making. We discuss essential challenges, both for the forecasters and forecast users, and make recommendations for the official statistics community.

Probabilistic Population Forecasts Revisited

Demographic forecasts are concerned with the future population size and structure by sex, age and possibly also some other attributes of interest, such as region of residence, marital status, household type, or other.

As stated by Jan M. Hoem (1973, 9), "the chief purpose of making a population forecast . . . is to contribute to improved planning and better decisions". However, the history of error in population forecasts is as old as the history of these forecasts themselves (Hajnal 1955). Hence, an appropriate description of the forecasting uncertainty is a key aspect of informed decision making. Recognising this, in the early 1970s a small, yet influential group of statistical demographers, becoming increasingly uneasy with the continuing use of deterministic variant 'projections', already suggested that probability distributions should be used to describe the forecast uncertainty (e.g., Keyfitz 1972). At that time, however, it was noted that the available technical resources would not stand up to the task in a general case (Hoem 1973).

The times have changed. Over the past four decades, the methods of statistical demography have been developing very rapidly, especially in the area of stochastic population forecasting at the national level. Increasingly, more arguments and suggestions have been put forward for applying these methods in practice. To mention a few examples: Alho and Spencer (1997) argued that probability distributions would allow the users to

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prepare appropriate contingency plans. Tuljapurkar (1992), de Beer (2000) and Bijak (2010) have recommended taking advantage of decision theory, allowing for different – possibly asymmetric – objective or loss functions of the forecast users. Lee (1998) added the possibility of making derived forecasts, where population predictions could be integrated with economic ones, as well as the analysis of conditional forecasts, with some sources of uncertainty removed.

Despite these methodological developments and recommendations, probabilistic population forecasting methods have been incorporated into official statistical practice only in a handful of countries – chiefly in the Netherlands and New Zealand. Ambitious plans laid out at the US Census Bureau a decade ago (Long and Hollmann 2004) have since been mothballed. Progress was additionally hampered by the lack of established methodology for forecasting subnational populations or disaggregating the forecasts by various groupings of interest (household position, labour market status, etc.). To our knowledge, there have been hardly any policy applications of formal decision analysis or similar techniques, with the notable exception of Alho et al. (2008).

However, a major step forward was taken on July 11, 2014 (World Population Day), when the UN Population Division for the first time issued official probabilistic population projections for all countries, using the methodology of Raftery et al. (2012). These were the basis for the article of Gerland et al. (2014), which argued that the world population is unlikely to stop growing this century – a probabilistic statement. This attracted considerable media coverage, much of which showed an understanding of the probabilities reported (e.g., Carrington 2014; Schiermeier 2014). We expect this to spur a revival of interest in official probabilistic forecasting of populations. Anticipating this revival, we want to reopen the discussion on the potential advantages and obstacles of producing and using the probabilistic population forecasts.

Challenges and Open Questions

Current practice in official population forecasting is not sufficient. Deterministic forecasts based on single numbers are bound to fail, and to surprise their end users time and again. Probabilistic forecasts, with probability distributions describing possible outcomes, can prepare the user for such outcomes. However, a very important aspect of the single-number forecasts is that they are easy to grasp in cognitive terms. Hence, to aid decisions, probability distributions need to be summarised in an appropriate way that will be useful for the users and correspond with their requirements.

Our basic premises are as follows. First, there is a need for an analytical framework for supporting policy and planning decisions under uncertainty, especially where there are some real concerns which can be expressed as losses – economic losses, or other, such as reputational. Second, deterministic scenarios can be misleading, have a zero probability under any continuous probability measure (or very close to zero in other cases), and are problematic to aggregate or compare with each other. They also attempt to answer a tautological question – what *would* happen under certain assumptions – when the real policy-relevant question is: what *will* happen (Keyfitz 1972; Hand 1994). Of course, a precise answer to this question is impossible, and probabilistic forecasts – similarly to deterministic scenarios – also depend on a number of assumptions, but they explicitly state the forecaster's belief as to how probable those conditions are. Third, probabilistic forecasts not only attend to the relevant question about the future, but also contain precise warnings about the uncertainty. We consider this to be an ethical virtue.

Various reasons have been put forward for a meagre uptake of probabilistic methods in official uses. Lutz and Goldstein (2004, 3–4) cite four arguments: a "misleading sense of precision" regarding probability ranges; the "mechanistic" nature of many forecasts, chiefly based on time series; technical and conceptual complexities and difficulties involved in making such forecasts; and a lack of skilled workforce at the statistical offices. Ten years later, however, while the official statistical agencies may still face technical, statistical, and computational challenges related to probabilistic forecasting, the goalposts have been moved. In our view, the above reservations can now be largely addressed, thanks to advances in methodology and statistical training, and the key contemporary challenges can be found elsewhere. Four of them are discussed in more detail below.

The first challenge is the user **attitude** towards forecasting uncertainty and towards risk in general. Uncertainty can be either perceived as a "curse" – lack of knowledge about the future; or as a "blessing" – if dealt with properly, this is additional information that can help us make better decisions. In particular, there is still a lack of clarity surrounding what can be gained – or lost – by using probabilistic forecasts in practice. Besides, the way uncertainty is dealt with also depends on the risk attitude of the users (Kahneman 2011), with options ranging from downplaying uncertainty for the sake of efficiency or potential gains, to preparing for the 'worst-case' scenarios under high risk aversion. As Kahneman (2011, 263) has put it, "an unbiased appreciation of uncertainty is a cornerstone of rationality, but it is not what people and organizations want."

The second challenge results from the **specificity** of various user needs and circumstances. The horizons for forecasts, projections, and decisions differ; so do the potential consequences of these decisions, as well as the level of risk aversion of the decision makers. The choice between a few predefined variants is not sufficient, as they are unlikely to correspond to user needs, especially if only offered at national level. On the other hand, offering decision support via probabilistic forecasts requires striking a delicate balance between what is needed by the users and what can be realistically offered by the forecasters. Examples range from local investment decisions, in the case of subnational forecasts (NZIER 2014), to macroeconomic policy issues, such as the sustainability of pension and other social security systems (Alho et al. 2008). Such decisions usually have long term and potentially very costly consequences, so it is all the more important to base them on a comprehensive analysis of potential forecast errors.

The third challenge is how to deal with **information** – specifically, statistical data and inferences made on their basis – which may be either incomplete or superfluous, and possibly conflicting. Here, the role of prior beliefs and expert judgement comes to the fore, and an appropriate approach to elicitation becomes crucial (O'Hagan et al. 2006). The same applies to eliciting from the users their attitudes to risk and loss or utility functions, which approximate the decision setting – the relative losses of underpredicting or overpredicting the parameters of interest (see Bijak 2010). The key questions are: what are the practical implications of probabilistic forecasts, and, if the forecasts are wrong, what is at stake? Elicitation requires caution, especially as the perceptions of concepts such as probability, utility, or loss are not uniform. Besides, cognitive biases have to be considered here – especially overconfidence and illusion of certainty, which are a subconscious way of avoiding the cognitive effort of processing more information than just single-point predictions or guesses (Kahneman 2011; Raftery 2014).

Finally, the fourth challenge is related to **validation**, the calibration and testing of probabilistic forecasts, chiefly through comparing them with known outcomes (Alho and Spencer 1997). Even though this aspect is more technical, it is a crucial complement for some other challenges, in particular attitudes: to appreciate the role of uncertainty, the users need to trust that it is calculated correctly. Here, the main question concerns the aim of probabilistic forecasting: is it to *describe* the predictive uncertainty, or to *minimise* it, which can be misleading? Alternatively, as suggested by Gneiting et al. (2007), a compromise could be to minimise uncertainty for a well-calibrated model, where the expected (*ex ante*) and observed (*ex post*) empirical frequencies of events match each other. In such models, events with predicted 50% probability would happen half of the time on average, the events with 90% probability would occur nine out of ten times, and so on.

Where Next? Practical Recommendations

To address the challenges mentioned above, the starting point could be to change the discourse about uncertainty from just a lack of knowledge, to a more realistic and nuanced view. In that regard, the discussion about uncertainty could be reframed as being about confidence, or *additional* knowledge or information. Besides, being explicit and transparent about the forecasting uncertainty can be also associated with such virtues as honesty, humility, and trust.

This approach has already proved successful in the aviation industry, contributing to a substantial increase in safety levels in the recent decades. One of the underpinning cultural changes that the aviation community has witnessed was a shift from a reactive and punitive blame-for-error model to a "just culture". This concept can be defined as "a culture in which front line operators and others are not punished for actions, omissions or decisions taken by them that are commensurate with their experience and training, but where gross negligence, wilful violations and destructive acts are not tolerated" (EUROCONTROL 2014), and explicitly recognises the role of uncertainty as an inherent part of operations. Importantly, by allowing an honest discussion about errors, this model allows for learning from the mistakes, and helps prevent them in the future.

In order to convince the users and producers of population forecasts of the **added value** of an analysis of uncertainty, and to overcome some institutional inertia, the experience of other areas and disciplines could be looked at. Probabilistic forecasting has been successfully developed, for example, in some aspects of meteorology and climatology, aviation, and macroprudential economic regulation. In these areas, techniques of communicating uncertainty to the users and the general public are also being researched. This experience and expertise could be used in population forecasting. Similarly, population forecasts are a crucial input for many policy areas, for example with respect to such structural measures as pension reforms. Given that population is often used as an exogenous variable in the macroeconomic system, its forecasts will be helpful in supporting decisions regarding the endogenous policy variables, such as interest rates.

In particular, the meteorological community has been grappling with issues surrounding uncertainty in weather forecasts for over a century (WMO 2008). Unlike in the case of the aviation industry, with its high level of regulation and entry barriers, the users of weather forecasts are much more diverse. The recent *Guidelines on Communicating Forecasts Uncertainty* (WMO 2008) offer several arguments for communicating uncertainty to the users. Besides the clear applicability for decision making, increasing users' confidence that the forecasts are a result of an honest, objective, and scientific endeavour, and besides managing the users' expectations, it is also pointed out that uncertain weather forecasts simply reflect the state of the science (WMO 2008). This point is even more important in demography and other social domains, where, thanks to human agency and ingenuity, we do not know (and will be never able to know exactly) what drives the individual decisions on, for example, whether and when to have children or to migrate, or the reasons why some people die earlier than others, or why the different demographic processes change over time. In that sense, probabilistic forecasts provide an important epistemological statement about the limited state of knowledge in population sciences – and about the limits of forecasting more generally.

Addressing the second challenge requires **bespoke approaches**, with forecasts tailored to the specific needs of different types of users and different audiences (Raftery 2014). There are vast differences between high-level, longer-term, strategic decision making, and practical, more immediate, operational-level planning, which requires quantitative input for decisions (Bijak 2010). In that respect, full probabilistic forecasts offer a general solution, from which the specific options can be derived. Some users (and uses) may require no point forecasts or estimates at all. And if scenarios are needed, they can be obtained from trajectories based on quantiles from predictive distributions. Finally, conditional probabilistic forecasts, assuming that some variables are known, can help answer policy-relevant "what-if" questions. Interactive, versatile online tools might help the users here. In any case, the user appreciation of the benefits of probabilistic forecasts can help the official statistical agencies justify the resources needed for their development.

Tailoring the predictions, and eliciting the relevant information, such as prior beliefs, expert judgement, or loss functions, requires **interaction** with users. The prerequisites here involve an open, two-way dialogue, with frequent exchange of information between forecasters and users. This exchange can become routine if the forecasts are periodically updated, as is often the case with official population forecasts. Some of the related challenges can be overcome by appropriate methods of communication, such as the use of visualisations (Spiegelhalter et al. 2011). This aspect would benefit from wider insights from cognitive science on such issues as statistical literacy, education, and training, not only related to the end users of forecasts, but also the general public (see also Kahneman 2011). Similarly to the case of weather forecasting, this is especially important for nonspecialist users, who may benefit particularly from appropriate visualisations, interactive online tools, and similar materials.

Not surprisingly, more **methodological research** on a number of technical issues is required. In particular, there is need to design an appropriate framework for calibrating whole time series of observations. Besides, for rare events, there may not be enough observations to properly calibrate the extremes (tails) of the distributions (see e.g., Taleb 2007). In such cases, exploration of methods and techniques of risk management can be promising, whereby future events are classified according to a combination of their probability and impact. As mentioned above, there is also a need to develop a wider range of methods for the types of forecasts that play the greatest role in actual policy and expenditure decisions, for example at the subnational level.

However, in order to achieve a paradigm shift in practical applications of probabilistic population forecasts, the focus should not be on methods, but rather on possible impacts and consequences of decisions. In such a way, the ongoing change of methodological perspective in demographic forecasting, from deterministic point forecasts through variant scenarios to probabilistic predictions, would continue incrementally towards interactive decision support at a variety of levels of policymaking – from national to subnational, in parallel with the methodological developments for the latter. Of course, as a prerequisite, various sources of uncertainty need to be acknowledged and combined in the forecasts, ideally within a joint and coherent framework, such as the one offered by Bayesian statistics.

The challenges of the practical uses of probabilistic forecasts are important, but they are now well recognised and are not insurmountable. The methodology is ripe, and insights from other areas of application are encouraging. In many other areas, the concepts of uncertainty and risk have already entered the language and practice of the decision makers and other forecast users. As for population forecasts, several pioneer countries, as well as the United Nations Population Division, have also taken up to the challenge. We hope this trend continues – where there's a will, there's a way.

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