Uncertainty in Population Projections: The State of the Art

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Abstract

In this paper I critically review the state of the art in population projections, focusing on how uncertainty is handled in three approaches: the classical cohort-component, the frequentist probabilistic model and the Bayesian paradigm. Next, I focus on recent developments on mortality, fertility and migration projections under the Bayesian setting, which have been clearly in the frontier of knowledge in demography. By evaluating the merits and limitations of each framework, I conclude that the Bayesian paradigm will offer in near future the most promising approach to population projections, since it combines expert opinion, information that demographers have readily available from their empirical analyses and sophisticated statistical and computational methods to deal with uncertainty. Hence, the availability of population forecasts that take uncertainty carefully into account may enhance communication among demographers by allowing for greater flexibility in reflecting demographic beliefs. Also, improvements in demographic forecasts can definitely contribute to better policy decisions.

Keywords: Population Projections; Uncertainty; Cohort-Component Model; Frequentist Approach; Bayesian Approach.

Resumo

Neste artigo, apresento uma revisão crítica do estado da arte em projeções de população, focando em como a incerteza é tratada em três abordagens: no modelo clássico de coorte-componente, no modelo probabilístico frequentista, e no paradigma bayesiano. Em seguida, me concentro sobre desenvolvimentos recentes nos modelos de projeções bayesianos de fecundidade, mortalidade e migração, os quais tem claramente se destacado na fronteira do conhecimento em demografia. Ao avaliar os méritos e limitações de cada abordagem, concluo que o paradigma Bayesiano irá se destacar no futuro próximo como a abordagem mais promissora para as projeções de população, uma vez que combina a opinião de especialistas, as informações que os demógrafos têm disponíveis a partir de suas análises empíricas, assim como métodos estatísticos e computacionais sofisticados para lidar com a incerteza. Assim, a disponibilidade de previsões demográficas acuradas que leve em conta a incerteza pode melhorar a comunicação entre os demógrafos, permitindo uma maior flexibilidade na determinação das previsões demográficas. Além disso, melhorias nas previsões demográficas podem definitivamente contribuir para melhores decisões de políticas públicas.

Palavras-chave: Projeções de População; Incerteza; Modelo de Coorte Componente; Abordagem Frequentista; Abordagem Bayesiana.

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1 Introduction

The field of population projections is probably one of the richest in demographic research. Keyfitz (1972) defines demographic forecasting as “the search for functions of population that are constant through time, or about which fluctuations are random and small.” According to the same author, the uncertainty around the population estimates should be expressed in the form of a probability distribution (KEYFITZ, 1972).

Notwithstanding the desire of Keyfitz, demographers have traditionally conducted population forecasts using the cohort-component model from a deterministic perspective. In short, the cohort-component method involves a number of steps, each of which utilizes the demographers’ expert opinion. Uncertainty is introduced into the projections at all phases of the process by means of the demographers’ judgment and experience. Based on their opinion and on past data analysis, a single-variant deterministic projection is built upon the most reasonable future behavior of the demographic components: fertility, mortality and migration. Hence, “projecting a population becomes an art influenced by scientific techniques” (DAPONTE et al., 1997, p. 1257).

In terms of the uncertainty of the population estimates, the standard population projection approach does not allow demographers to state, in an explicit manner, the probability that demographic events will occur. In order to overcome this limitation, demographers began projecting the population using different sets of variants, reflecting the uncertainty in their estimates and leaving it to the user to choose the projection that would best fit his or her needs. This is the so-called variant approach to population projections. Up to the 2010 Revision, this was the standard approach used by the UN Population Division to produce population estimates (UN POPULATION DIVISION, 2009). Even though the variant approach provided an advance in demographic forecasts,
some authors have argued that it has no probabilistic basis, resulting in inconsistencies in the demographic estimates (GIROSI; KING, 2008; LEE, R. D.; TULJAPURKAR, 1994).

Since the 1990s, demographers have attempted to incorporate uncertainty in population estimates in the form of probability distributions using the frequentist paradigm. I call this the frequentist probabilistic projection approach. This work was pioneered by Lee and colleagues to project mortality trends by extrapolating time series parameters (LEE, R. D.; CARTER, 1992; LEE, R. D.; TULJAPURKAR, 1994; LEE, R. D., 1992), and later by scholars from the IIASA team aiming to derive projections based on expert judgment (LUTZ; SCHERBOV, 1998; LUTZ et al., 1998). The frequentist probabilistic projections provide a useful approach for assessing change and deviations of population outcomes from the most likely scenario by quantifying the uncertainty in terms of probability. However, this approach has some problematic issues that still remain to be solved. For instance, Girosi and King (2008) argue that the properties of the model developed by Lee and colleagues will not fit demographers' beliefs about the future patterns of mortality. Also, it is argued that the frequentist probabilistic approach does not address the uncertainty of confidence intervals (BIJAK, 2011).

Recently, Bayesian statistics has been raising interest in a variety of scientific fields as a result of the development of analytical tools and methods and the advancement of computational techniques. In demography forecasting, the Bayesian theory provides a clear framework to deal with uncertainty, the use of subjective assumptions as well as straightforward tools for predictions (ALKEMA et al., 2011; BIJAK, 2011; DAPONTE et al., 1997; GIROSI; KING, 2008; PEDROZA, 2006). In this context, there is an
increasing view in the mainstream of population forecasting that the future belongs to Bayesian probabilistic predictions (BIJAK, 2011; GIROSI; KING, 2008).

While in academic research there are clear advancements towards sophisticated population forecasts, the same advancements are still incipient in the demographic practice. For instance, the UN Population Division started in 2010 to develop probabilistic projections for the total fertility rate (TFR) in their 2010 Revision of the World Population Prospects in collaboration with researchers from the Center for Statistics and the Social Sciences (CSSS) at the University of Washington (ALKEMA et al., 2011; CHUNN et al., 2010; RAFTERY, A. E. et al., 2012). In Brazil, population forecasts are developed by the National Institute of Geography and Statistics (IBGE) following the most likely scenario for total fertility rates, life expectancy and child mortality rates, and no uncertainty measure is provided with their estimates (IBGE, 2008).

Given the promising advances in Bayesian population projections and the fact that improvements in demographic forecasts can definitely contribute to better policy decisions, my goal with this paper is to critically revise the state of the art in the population projections field. My focus, however, is to revise how uncertainty is incorporated into the derivation of population estimates, and also to evaluate the merits and limitations of each framework in demographic applications. Also, I focus on a detailed explanation of the research on Bayesian formulations for mortality, fertility and migration projections. I believe that the Bayesian paradigm will offer in near future the most prominent approach to population projections, since it combines expert opinion, information that demographers have readily available from their empirical analyses and
sophisticated statistical and computational methods to deal with uncertainty. Furthermore, the Bayesian framework offers elegant and appropriate solutions to missing data problems.

I expect that this paper will increase the awareness of the demographic scholar community on the importance of the availability of forecasts with their respective uncertainty to improve policy planning and evaluation. Also, the concern on the development of robust population forecasts will enhance communication among demographers by allowing a clear and exact observation of the sources of uncertainty in the estimates.

2 Population Projections: State of the Art

In this section I provide a brief overview of the advancements in the population projections field. I describe the classical cohort-component model. Next, I present the frequentist probabilistic projection model. Finally, I discuss the Bayesian projection model.

2.1 Classical Cohort-Component Model

The cohort-component method is widely used among demographers to carry out population projections (ARRIAGA et al., 1994). This method is based on the demographic balancing equation, which states that the future population is a function of the previous population plus the number of births and the number of immigrants, minus the number of deaths and the number of emigrants. In short, this method is applied for
each sex and age group and relies on separate models for the demographic components – fertility, mortality and migration – which are later combined using the balancing equation to derive population totals (PRESTON et al., 2000).

The first step of the cohort-component method is to derive a base mid-year population. By evaluating the quality of this initial measure through experience and scientific knowledge, the demographer may adjust this population for age-misreporting and under and/or over-enumeration (PRESTON et al., 2000). Next, the demographer works on assumptions with regards to fertility levels. In general, the total fertility rate is projected and, then, a set of age-specific fertility rates is assumed for the projection horizon. The same rationale is applied to the projection of mortality, in which the life expectancy is projected and a set of age-specific death rates is assumed. Then, based on empirical regularities and judgments, the demographer assumes a level and pattern of net migration rates. These three sets of age-specific rates - fertility, mortality and migration – are applied to the base population to derive the projected population in a given year.

The deterministic approach to the cohort-component model is currently the dominant forecasting practice in demography. In its deterministic version, uncertainty in the cohort-component model is usual incorporated through the demographer’s judgment of the most likely set of elements that would result in future changes in fertility, mortality and migration components. Generally, a single-variant deterministic projection is derived, that is, “a single, best guess population projection that assumes moderate levels of fertility, life-expectancy, and migration in the future” (O’NEILL, 2005, p. 231).

To allow for some degree of uncertainty, the UN approach developed multi-variant projections until the 2008 Revision (UN POPULATION DIVISION, 2009). In
this approach, various scenarios were developed to reflect uncertainty around fertility levels, although not in probabilistic terms. A clear limitation of the scenario approach resides in the lack of an integrated assessment. As Lee (1992) points out, UN medium variants receive a large degree of consideration from the specialists, while the high and low variants are a result of simplistic assumptions. Moreover, users may interpret that the interval between the high and low variants would contain the actual future values for the population size, when in fact this interval has no probabilistic meaning (LEE, R. D.; CARTER, 1992; LEE, R. D., 1992).

2.2 Frequentist Probabilistic Projection Model

As a response to the limitations of deterministic models in providing consistent measures of uncertainty to the demographic estimates, a probabilistic model for mortality projection was proposed by Lee and colleagues in the beginning of the 1990s. Known as the Lee-Carter model, it is now used by the U.S. Census Bureau as a benchmark for its population forecasts.

The Lee-Carter (LC) model allows the derivation of long-term forecasts of the level and age pattern of mortality and fertility and is based on matrix algebra. In this review I will develop the application of the LC model to project mortality rates. Consider $m$ as a matrix of log-mortality rates, $m = A \times T$, where $A$ refers to the number of age groups and $T$ to time periods. The LC model postulates a linear relationship between the log-death rates and a parameter $k$:

$$\ln(m_{a,t}) = \alpha_a + \beta_a k_t + \epsilon_{a,t}$$ (1)
Where the average shape of the age profile is given by the $\alpha_a$ coefficients and $\beta_a$ gives the deviations from the average age profile when $k$ varies. Since Eq. 1 is not estimable, a least-squares solution is found by using the first element of the singular value decomposition (LEE, R. D.; CARTER, 1992). Since the solution for this problem may not be unique, the authors impose two restrictions to the model:

$$\sum_a \beta_a = 1 \quad (2)$$

$$\sum_a k_t = 0 \quad (3)$$

From Eq. 2, it implies that $\alpha_a$ is the empirical average of the log-mortality rate in age group $a$. Since it is assumed that the disturbance term is normally distributed, it follows that:

$$m_{a,t} \sim N(\mu_{a,t}, \sigma^2) \quad (4)$$

In which the average estimator for $m_{a,t}$ is given by:

$$\mu_{a,t} = \bar{m}_a + \beta_a k_t \quad (5)$$

Hence, the LC method assumes the absence of age and time interactions, that is, $\beta_a$ is fixed over periods for all $a$, and $k_t$ is fixed by age groups for all $t$. After estimating the parameters using a single-value decomposition, forecasts are conducted assuming that $\beta_a$ is constant over time and employing an ARIMA model to the series of $k$. The authors found that a random walk with drift was appropriate for their data (LEE, R. D.; CARTER, 1992), and their model allowed the computation of confidence intervals for the projected life expectancies.
Besides pioneering in the application of a probabilistic method to demographic forecasts, the LC model presents considerable appealing characteristics. First, it is relatively simple and parsimonious, with a small number of parameters. Second, it relies on a relational model, preserving relevant features of the mortality pattern of the population of interest (LEE, RONALD; MILLER, 2001).

However, this model also has limitations. Girosi and King (2008) argued that the LC model tends to perform well in the short run, given slow changes in mortality, but it may lead to inconsistent long-run forecasts. Also, the LC model may produce implausible changes in projected age profiles given the independence of separate age-group forecasts. Furthermore, Thomas (2002) argued that the model tends to gradually forget the age pattern of the death rates when it approaches low levels of mortality, and nothing prevents death rates from becoming zero in the LC model. Lee himself recognized that the confidence interval for the forecasts tends to be narrow as a result of the low entropy of the survival curve in contexts of high-levels of life expectancy (LEE, R., 2000).

Despite its restrictions, the methodological coherence of the LC model was an important breakthrough in demographic forecasting. Since its proposal, several authors have worked to developed stochastic methods for projections (LEE, R. D.; TULJAPURKAR, 1994).

2.3 Bayesian Probabilistic Projections

Before introducing the Bayesian approach to demographic forecasting, I present a brief overview of selected aspects of Bayesian inference to provide background information for the purpose of this literature review.
The Bayesian inference obeys the subjectivist stance. By subjectivist stance, I mean a way of thinking in which a probability is assigned to uncertainty. If an individual is coherent, then uncertainty measures follow the laws of probability (FINETTI, DE, 1937). Second, a Bayesian statistician believes that empirical evidence is relevant to the understanding of a given phenomenon, but he or she also considers prior knowledge when conducting inferences.

Formally, the Bayesian paradigm postulates that, for an unknown quantity \( \theta \) and sample information provided in a vector \( x \), the likelihood function \( L(x|\theta) \) provides empirical information on \( \theta \): it is the probability of observing the sample given \( \theta \). The prior distribution \( \pi(\theta) \) represents the initial uncertainty on \( \theta \). Hence, the Bayesian inference on \( \theta \) is made in terms of the posterior distribution, \( \pi(\theta|x) \), where:

\[
\pi(\theta|x) \propto \pi(\theta)L(x|\theta)
\]

In short, the Bayesian approach assumes the existence of a probability distribution depicting the knowledge, intuition or belief of a researcher with respect to the possible values of \( \theta \), unconditional on the empirical evidence available from data. Hence, the essence of Bayesian inference is to transform prior beliefs and uncertainty about \( \theta \) and \( \pi(\theta) \) to the posterior knowledge, \( \pi(\theta|x) \), by incorporating empirical evidence, \( L(x|\theta) \).

The Bayesian paradigm offers appealing features for demographic forecasting. The issue of uncertainty in population forecasts requires the use of many subjective assumptions. To address this issue, the Bayesian framework is appropriate because knowledge and beliefs can be expressed in terms of the prior distribution. Also, forecasts are a natural analytical tool of Bayesian inference: the predictive distribution for \( \theta \) can be computed through the posterior distribution. In the past, Bayesian analysis was limited by
computational power. However, with recent developments in computing and analytical methods, complex tasks can be accomplished.

There is an increasing interest in conducting Bayesian demographic analysis, and studies have been developed to model fertility schedules in small areas (ASSUNÇÃO, R. M. et al., 2002; ASSUNÇÃO, R. et al., 2005; POTTER, J. E. et al., 2010). In the projections field, it is worth noting the work of Girosi and King (2008), which employed a Bayesian hierarchical model to predict mortality rates using information pooling from similar cross-sections (i.e., age groups, countries). Bijak (2011) applied the Bayesian paradigm to model and project the path of international migration in Europe. More details on the methodology of Bijak (2011) and Girosi and King (2008) are described in the next section, which is only devoted to Bayesian formulations.

Recently, a team from the Center for Statistics and the Social Sciences (CSSS) at the University of Washington developed population estimates using Bayesian methods (ALKEMA et al., 2011; CHUNN et al., 2010; HEILIG, G. et al., 2010; RAFTERY, A. E. et al., 2012). Their approach followed the cohort-component model, but mortality and fertility were modeled using a Bayesian framework. Their Bayesian model used to project total fertility is composed of two steps. The first model attempts to project total fertility rates (TFR) in the first phase of the fertility transition, in which fertility decreases from high to low levels, reaching the replacement-level. They used a Bayesian approach to estimate the parameters of a bi-logistic function fitted for data for most countries worldwide, and the posterior distribution of the parameters for each country reflects its own fertility decline as well as the experience of all countries combined. A second model was used to project the second phase of fertility transition when low fertility prevails:
using a first-order autoregressive time-series frequentist model with a mean set at the replacement-level, they generated random fluctuations of the TFR around the mean. For the mortality projection, a Bayesian model was employed to predict future paths of male life expectancy and female life expectancy assuming country-specific sex differentials observed in the UN Population Division Projections. The CSSS team has not attempted to produce a probabilistic projection of international migration. From projected trajectories of future fertility and mortality, the scholars produced median population estimates with the paths corresponding to the 95 percent confidence intervals for all countries over the period 2010-2050.

From the description of the studies presented above, it can be inferred that the Bayesian paradigm provides a novel and promising framework for demographic projections.

3 Advancements in Population Projections using the Bayesian Approach

3.1 Mortality

The Bayesian model for mortality projections proposed here is inspired by the work of Girosi and King (2005). The authors presented a Bayesian hierarchical modeling approach for predicting mortality rates by pooling information from similar cross-sections (i.e., age groups, countries). By incorporating considerable information that demographers have about observed mortality data and future patterns, their model presents an outstanding performance.
Girosi and King’s model is formalized as follows. Consider $i$, $i = 1, \ldots, N$ cross-sections and $t$, $t = 1, \ldots, T$ time periods. We observe $d_{it}$, which is the number of deaths in the cross-section $i$ and time $t$. Define the log-mortality rate $m_{it}$ as:

$$m_{it} = \frac{d_{it}}{p_{it}}$$  \hspace{1cm} (6)

Where $p_{it}$ is the population at the cross-section $i$ and time $t$. We assume a linear specification for the log-mortality:

$$m_{it} \sim N(\mu_{it}, \sigma_i^2)$$  \hspace{1cm} (7)

$$\mu_{it} = Z_{it}\beta_i$$  \hspace{1cm} (8)

Where $\mu_{it}$ is the expected log-mortality rate, $m_{it}$ is assumed independent over $t$ conditional on $Z$. Girosi and King noted that $Z$ may include lagged terms of $m_i$.

The Bayesian model for the log-mortality rates assumes that the parameters $\sigma_i^2$ and $\beta_i$ are unknown and fixed quantities and that their uncertainty \textit{a priori} is expressed in terms of probability distributions. For $\sigma$, the prior distribution is $P(\sigma)$. For $\beta$, assume that its prior distribution is a function of hyperparameters $\theta$ and that its prior distribution is given by $P(\beta|\theta)$. In turn, $\theta$ has its own prior distribution $P(\theta)$. The functional form of $P(\sigma)$ and $P(\theta)$ are chosen to be non-informative (flat), whereas $P(\beta|\theta)$ is assumed to be highly informative. Assuming that \textit{a priori} $\sigma$ is independent of $\beta$ and $\theta$, the posterior distribution is given by:

$$P(\beta,\sigma,\theta|m) \propto P(m|\beta,\theta) [P(\beta|\theta)P(\theta)P(\sigma)]$$  \hspace{1cm} (9)

Where the prior distribution is $P(\beta,\sigma,\theta) \equiv P(\beta|\theta)P(\theta)P(\sigma)$. We can summarize updated information using the posterior mean (Bayes estimator):

$$\beta^{Bayes} = \int \beta P(\beta,\sigma,\theta|m) d\beta d\sigma d\theta$$  \hspace{1cm} (10)
Given this information, Girosi and King described three methods for forecasting: (i) forecasting covariates; (ii) autoregressive models, and (iii) lagged covariates. Based on experimentation, the authors emphasized that the third strategy is preferable because it allows for a combination of statistical methods and expert judgment.

The great challenge in Girosi and King’s approach is to define a prior distribution for $\beta$. Specifying a prior on the vector $\beta$ requires nonsample knowledge about it. Because $\beta$ refers to population measures, this vector does not always imply causal effects. The authors illustrated this issue assuming tobacco consumption as covariate to explain changes in mortality. Even though this relationship is clear at the individual level, the relationship between tobacco consumption and lung mortality may be confounded at the aggregate level by the country’s development level. Also, demographers may feel uncomfortable stating opinions about the similarity of coefficients. Rather, they may know fairly precisely how the expected value of mortality varies across cross sections.

To overcome limitations in the specification of a prior distribution of the coefficients, Girosi and King proposed a two-step strategy. First, they derive a prior density of the expected value of the mortality rates. Then, priors on the regression coefficients are specified. Priors on the expected value of the mortality rates are set based on genuine prior knowledge of age, time and country trends using a smooth approximation. As a result, posterior distributions are derived for the parameters using a Markov Chain Monte Carlo (MCMC) approach.

Finally, besides the inclusion of covariates, Girosi and King's model allows for five sources of prior knowledge: (i) the age profile toward which the forecasts will tend, due to the smoothing imposed; (ii) the cross sections across which the researcher expects
to see similar levels or trends in log-mortality; (iii) the degree of similarity and smoothing by setting the weight of the prior; (iv) the degree of smoothing imposed in different areas by choosing weights and relaxing the prior; (v) our ignorance, by setting the content of the null space, which is the portion of the forecasts that depend entirely on the data and are not influenced by the prior.

In summary, the appealing feature of Girosi and King’s model is precisely the incorporation of prior knowledge for the construction of projections within a sophisticated statistical framework. Thus, I believe that this method of projection of mortality seems to be quite adequate for demographic projections.

3.2 Fertility

The most known Bayesian model to project fertility was developed by the CSSS team to simulate future values of the total fertility rate (TFR) for all countries (ALKEMA et al., 2011). Their approach accounts for three stages of the fertility transition: Phase I, Pre-Transition with Stable and High-Fertility; Phase II, Fertility Transition; and Phase III, Post-Transition and Low Fertility. However, models were only developed for Phases II and III as all countries have begun their demographic transition, and only the Phase II model is adopted in a Bayesian paradigm. Hence, this description will only refer to the Bayesian model.

The model for the fertility transition can be briefly described as follows. Five-year decrements in the TFR are decomposed into a systematic decline plus random disturbances. The decline function is evaluated according to the level of the TFR at time \( t \) for country \( c \), \( f_{c,t} \), and to some country-specific parameters \( \theta_c = (\Delta_{c1}, \Delta_{c2}, \Delta_{c3}, \Delta_{c4}, d_c) \) using a double logistic specification:
\[ g(\theta_c, f_{c,t}) = \frac{-d_c}{1 + \exp\left(-\frac{2 \ln(9)}{\Delta c_1} (f_{c,t} - \sum \Delta c_i + 0.5 \Delta c_1)\right)} + \frac{d_c}{1 + \exp\left(-\frac{2 \ln(9)}{\Delta c_3} (f_{c,t} - \Delta c_4 - 0.5 \Delta c_3)\right)} \]

Where \( U_c = \sum_{i=1}^{4} \Delta c_i \) refers to different starting levels of the TFR decline, \( \Delta c_4 \) refers to the level at the end of the transition, \( d_c \) refers to the overall pace of the fertility transition and the ratio \( \Delta c_i/(U_c - \Delta c_4), \ i = 1, 2, 3, 4 \) refers to differences in the timing of acceleration or deceleration in the pace of decline. Hence, each value of the decline parameters, \( \theta_c = (\Delta c_1, \Delta c_2, \Delta c_3, \Delta c_4, d_c) \), refers to a special case of fertility decline.

As in Girosi and King’s model described previously, the CSSS team employs a Bayesian hierarchical model as a strategy to estimate the decline parameters \( \theta_c \) and their associated uncertainty. This model allows estimating the parameters for a given country \( c \) taking into account information from other countries. This is an appealing feature of their model, as there are few observations for each country and values for each country gravitate toward a world mean. In other words, the Bayesian hierarchical model assumes that the prior distribution for the decline parameters is best described by the range of the decline parameters for all countries. Next, the prior distribution is updated using a country's observed decline. Therefore, the posterior distribution summarizes information on a world pattern of fertility decline and the country's experience. Computations are performed using MCMC algorithms.

In sum, the approach to project fertility levels proposed by the CSSS team is promising. However, it is not completely grounded in the Bayesian paradigm – only the
demographic transition phase is modeled using a Bayesian hierarchical model. Further developments in this area are, therefore, strongly encouraged.

3.3 Migration

It is well recognized by demographers that migration is the most complex component of demographic change. As Coleman (2008) stated:

*Of the three components of demographic change, data on migration are far below the quality of those on birth and death. Of the three, its theory is the least satisfactory, its trend by far the most volatile, and its future by far the most difficult to forecast. It is the only demographic component, at least potentially, under substantial and direct policy influence, which adds to the difficulty of prediction. Even its definition is unsatisfactory (p. 453).*

Although clearly overstated, Coleman's argument summarizes some of the challenges involved in migration modeling and forecasting. Hence, future migration estimates are generally subject to considerable errors, which prevent derivation of accurate forecasts (KEILMAN, 2008).

Despite the difficulties described above, there is an increasing need for more accurate forecasts of migration flows. On one hand, policymakers are interested in numerical estimates of migrants to evaluate, for instance, their impact on labor markets. On the other hand, migration forecasts are inputs for population forecasts. Despite their importance and probably due to the challenges in measurement and modeling, future migration flows are generally: (i) projected using deterministic or scenario approaches, (ii) projected stochastically, but sometimes simplistically, or (iii) ignored (BIJAK, 2011).
However, uncertainty is definitely an important component in migration studies, perhaps more so than in fertility and mortality. To deal with uncertainty in migration projections, there are clear advantages of the Bayesian framework: as migration is a complex and multidimensional phenomenon and therefore is subject to a large amount of uncertainty, the Bayesian paradigm offers a suitable approach.

As far as I know, the work of Bijak (2011) is amongst the first attempts to summarize existing efforts to conduct migration forecasting and to compare different Bayesian models to derive migration estimates. Bijak’s Bayesian forecast averaging model drew my attention. The author claims that an averaging approach is desirable because there is no clear evidence towards a unique model that would better provide migration estimates. Hence, the Bayesian forecast averaging model allows for merging the features of various predictive models and providing an interesting strategy to account for the uncertainty. Because of space constraints, this method will not be formalized in this paper. Also, the application of Bayesian models for migration modeling is a very novel approach in demographic forecasting, which will require a great deal of research.

4 Conclusion

In this paper I critically review the state of the art in population projections, focusing on how uncertainty is handled in each approach. I gave a special focus to novel Bayesian Methods to produce population projections. I believe that conducting Bayesian demographic projections promises three important advantages for demographic research. First, it is a formal and probabilistic framework to deal with uncertainty; second, it will
improve communication among demographers by allowing for greater flexibility in reflecting demographic beliefs; and third, it will provide policymakers with better future estimates of the demographic components. This approach is certainly promising and is in the frontier of knowledge in demography.

References


