Government Office for Science

Foresight

Migration and Global Environmental Change

MR8: Model specification and results of Bayesian forecasts of total and environmental immigration to the United Kingdom, 2010–2060

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October 2011

This review has been commissioned as part of the UK Government's Foresight Project, Migration and Global Environmental Change. The views expressed do not represent the policy of any Government or organisation.

Contents

Executive summary

This report presents and discusses Bayesian forecasts of international immigration to the UK until 2030 and 2060, with a focus on environmental mobility. The forecasts are based on available data series, and on a Delphi survey of experts undertaken in the previous stage of the research project ('Delphi Survey and Projection of Immigration to the UK with Particular Reference to Environmental Mobility') commissioned by the Government Office for Science (GO-S).

In this part of the project, two types of models were considered. First of all, multivariate – vector autoregressive – (VAR) models were estimated, based not only on immigration, but also on four demo-economic determinants: global population growth, global old-age dependency ratio, gross national income (GNI) per capita in less developed countries, and GNI ratio between the richer and poorer countries of the world. The VAR models served as a basis for producing conditional forecasts of immigration, under four scenarios of the above-mentioned determinants adopted from another study (GO-S 2011). The second modelling approach comprised an ensemble of univariate – autoregressive – models (AR), which relate immigration to its past history. In this case, formal methods of averaging forecasts yielded by various models were applied. In both approaches, forecasts of environmental migration were obtained as a fraction of the total immigration to the UK, and were fully expert-based.

In terms of central (median) tendencies, both models predict a decline in total immigration to the UK, from the current levels of 567,000 a year to either about 210,000–220,000 (VAR model) or about 332,000 (averaged AR forecasts) by 2060. The former result, however, involves extremely large predictive uncertainty and is therefore problematic in the context of policy planning. By contrast, the uncertainty of the averaged AR forecasts is much less, although still substantial. Clearly, however, the prediction error of such uncertain processes as migration when looking 50 years ahead would be expected to be large.

The most important output from the current forecasting exercise for the GO-S is a probabilistic estimate and forecast of environmental migration to the UK, with the surrounding uncertainty, the large magnitude of which is one of the key findings of this study. The univariate model presented in this paper suggests that there is a high likelihood that environmental immigration may increase slightly over the next few decades, but that the trend is less likely to be one involving ever-increasing numbers.

If policy makers were to use the median univariate forecast, then they would be thinking of the UK receiving between 25,000 and 27,000 people annually for environmental reasons between 2030 and 2060. Compared with the average expert estimates from the Delphi survey for current environment-linked mobility to the UK, this would represent a relatively small increase on the present day, and would still remain only a small percentage of the total immigration flow. Despite the surrounding – immanent and inescapable – uncertainty, which needs to be borne in mind when interpreting the results, we believe that this median estimate is useful to policy makers, providing the first serious attempt to quantify levels of environmental migration to the UK. Nevertheless, as researchers, we also recommend that policy makers pay attention to other possible futures, given the great uncertainty associated with forecasting environmental mobility. We believe that planners 'with foresight' should also consider the implications of the possible departures from the median trajectory, also presented in this report, even though some might interpret them as less probable. In terms of further applications of the results presented in this report, we argue that they can be useful both for scenario setting, as well as for a cost-based decision analysis of environmental immigration to the UK from now until 2060.

1. Introduction: aim and scope

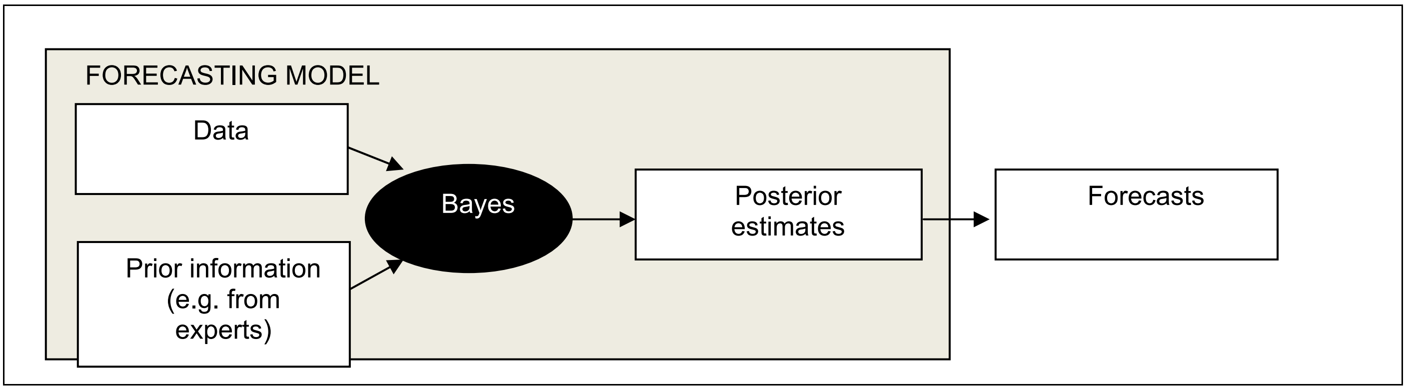
This report constitutes one of several outputs from the research project entitled *Delphi Survey and Projection of Immigration to the UK with Particular Reference to Environmental Mobility*, commissioned by the Government Office for Science (GO-S). Its aim is to present and discuss Bayesian forecasts of international immigration to the UK until 2030 and 2060, with a focus on environmental mobility, based on the Delphi survey of experts undertaken in the first stage of this project (Findlay *et al*., 2011). A brief introduction to the Bayesian approach in the context of estimation and forecasting is presented in Box 1 below.

Box 1. Introduction to Bayesian estimation and forecasting

Bayesian statistics, dating back to the seminal work of Reverend Thomas Bayes on his famous theorem (Bayes 1763), is characterised by a joint treatment of all quantities of interest in a statistical model – parameters, as well as processes under study – as random variables. For this reason, Bayesian statistics naturally incorporates the analysis of uncertainty surrounding the estimates or forecasts, which is being described in terms of probability distributions, either discrete or continuous.

One of the key attributes specific for Bayesian inference is the presence of *prior distributions*, related to the parameters of the statistical model, which are independent of any data. These prior distributions can be subjective – based on the expert judgement – or even 'non-informative', if no reliable expertise is available. Importantly, all Bayesian inference is based on a subjective definition of probability – which is treated here as a measure of belief. This does not necessarily match other definitions, such as the one that relates probability to the frequency of events.

The Bayesian inferential and forecasting mechanism, summarised in the scheme below, comprises updating the prior information in the light of new evidence, which becomes available from the data. By the means of the Bayes theorem, the prior distributions are combined with the data, to produce *posterior distributions* of the parameters. These can in turn be used, together with the historical series of past data, to produce forecasts – extrapolations of the past into the future. Notably, Bayesian forecasts are not only conditional on the past history, but also on the subjective elements – the expert judgement embodied in the prior distribution, and on the formulation of the forecasting model itself.



For a more detailed introductory-level exposition of Bayesian statistics, see for example Bernardo (2003).

By bringing together both expert knowledge and historical data, this study aims to provide more reliable measures of uncertainty associated with immigration forecasts. Additionally, an attempt is made to inform the forecasts using four scenarios of the Foresight Panel (Foresight, *forthcoming*), taking into account, in particular, global economic and demographic developments. It should be noted that this report deals with immigration to the UK only, rather than net migration, and therefore no comparison can be made between the resulting predictions and the assumptions of net long-term migration used in producing the official population projections for the UK (ONS 2008: 81–82).

The Bayesian approach has two main advantages over other approaches to migration forecasting. First, it uses probability distributions to handle uncertainties associated with the estimates and projections or forecasts. This produces forecasts that go beyond the normal presentation of one number predicted for each year. Instead a probability fan indicates the degree of uncertainty around the mean or median (see Abel *et al*., 2010). Second, Bayesian models have the capacity to formally allow expert opinions to be built into the projection in the form of the prior distributions[1]. In this paper, expert views were sought concerning the possible target values of immigration (both overall and environmental), as well as other statistical characteristics associated with their estimates, such as forecast errors. By combining this expertise with information from historical data series, the Bayesian approach produces forecasts of overall future total and environmentally induced immigration, together with appropriate confidence levels around these estimates.

This report is structured as follows: in Section 2 the three main sources of information used in this study are discussed – historical data, expert opinion, and the four GO-S scenarios (Foresight, *forthcoming*). Subsequently, Sections 3 and 4 deal with the specification of Bayesian forecasting models and results of forecasts of total and environmental migration to the UK, respectively for multivariate (taking into account demographic and economic drivers of migration), as well as univariate models (based only on immigration series). Finally, Section 5 contains conclusions and the main recommendations resulting from the study.

The report is accompanied by four appendices. Appendix A lists the OPENBUGS program code used to derive the forecasts described in Sections 3 and 4. Appendix B provides numerical results of averaged univariate forecasts of both total, as well as environmental immigration to the UK, presented on an annual basis for the period 2010–60. Appendix C lists summary statistics of the estimated univariate forecasting models, together with selected measures of their goodness-of-fit. Finally, Appendix D presents the operationalisation of four future scenarios of the GO-S for two demographic and two economic drivers of migration, complementing material presented in Section 2, as well as the resulting median scenarios of immigration to the UK, discussed in Section 3.

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[1] More details on Bayesian methods, specifically in the context of migration forecasting, can be found in Bijak (2010).

2. Sources of information

2.1. Caveats and health warnings

This report comes with a series of – inevitable – caveats and health warnings. First of all, as mentioned in the Introduction, Bayesian forecasts are by nature partially subjective, combining the quantitative data with the expert information. The output of forecasts is therefore conditional on the input – previous distributions constructed using expert insights, as well as on historical data, and specification of the forecasting model. An additional difficulty is the nature of expert judgement, which can be largely qualitative, yet still has to be translated into prior probability distributions. This task is by no means trivial and there is no single established set of guidelines on how this should be done – the approach taken in the current study, discussed in Section 2.3, is only one of many possibilities here.

Second, there are ambiguities surrounding certain terms used in this study, especially the definition of 'environmental migration'. Defining this term properly and operationalising it formally remained beyond the scope of the current study (see Findlay *et al.*, 2011, for discussion), and would need a separate enquiry. Besides, no time series of data on environmentally induced immigration to the UK are available, either. However, as the aim of this research was to construct forecasts that might offer some – even approximate – insights into the possible futures of environmental migration, we have decided that the environmental component would rely entirely on the expert opinion. Hence, throughout this report, 'environmental migration' is roughly understood as a type of human migration, which is caused by predominantly environmental factors. The considerations that gave grounds to this working definition – with all its imperfections – are mentioned in Findlay *et al.* (2011), in which the experts' answers and exchange of knowledge surrounding migration-related and environmental issues are discussed in more detail.

2.2. Data

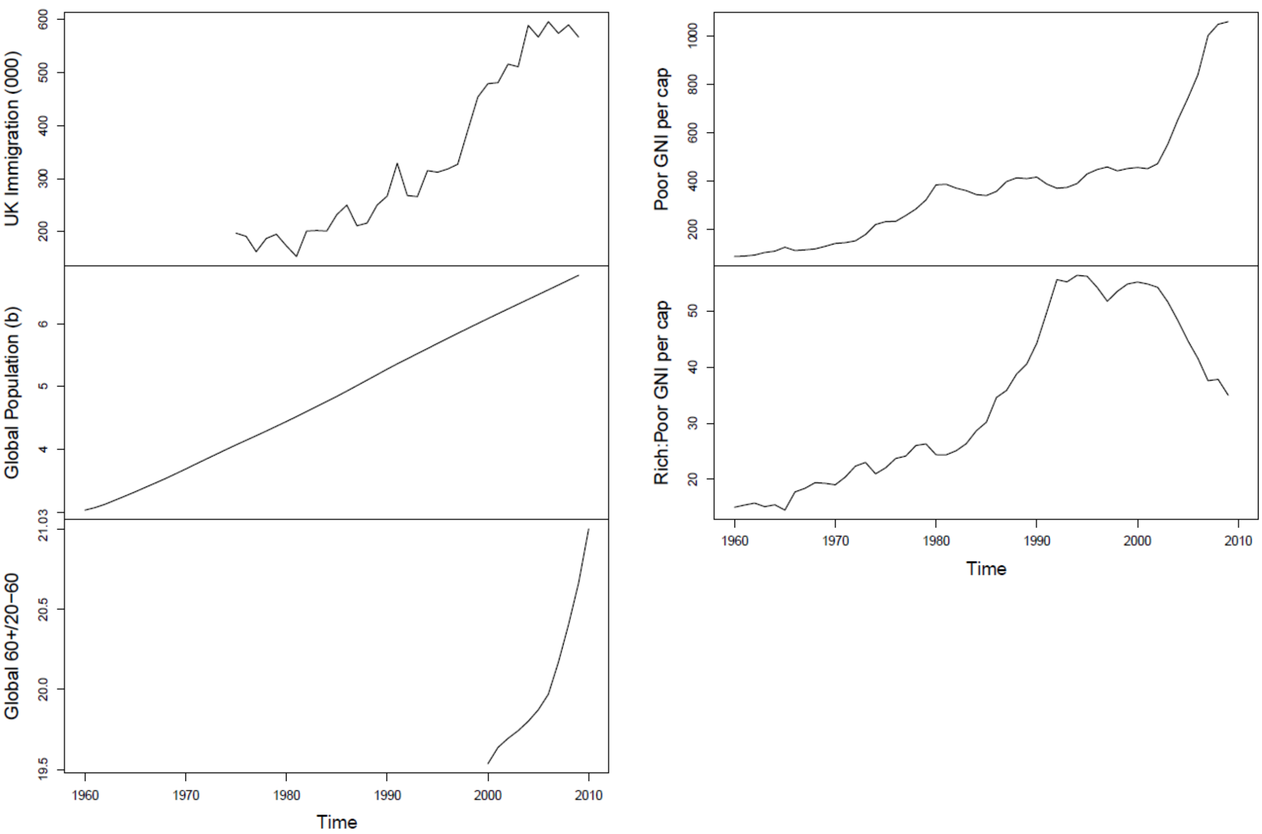
The data series used in this exercise come from a variety of sources. The series on total immigration, dating back to 1975, have been obtained from the Office for National Statistics (ONS). This series uses the United Nations definition of an international migrant as someone who changes his or her country of usual residence for a period of at least a year so that the country of destination effectively becomes the country of usual residence. As mentioned before, no data on environmentally induced immigration to the UK are available, which precluded the formal inclusion of the related time series in the forecasting model. Instead, only some basic socioeconomic determinants of migration have been used.

In particular, two demographic variables from two historical series were applied in the model – (a) the global population growth rates, and (b) the global old-age dependency ratio, being a proxy measure of the population ageing process – the source of data was the US Census Bureau (www.census.gov). The old-age dependency ratio was defined here as a ratio of population over 60 years of age to the population aged 20–60 years. Such a definition was adopted to match the future scenarios of demographic developments, described briefly in Section 2.4. Whereas the data on global population size (and hence growth rates) were available back to 1960, the old-age dependency ratio defined as above was calculated only for the most recent decade. All five series of data used in this study (immigration, two economic and two demographic variables) are illustrated in Figure 1.

Economic variables were considered as proxies for macro-level determinants of immigration to the UK. They include (c) GNI per capita in the less economically developed countries of the 'Global South', as well as (d) the ratio of GNI between the less developed ('poor') and more developed ('rich') countries. For both these variables (and the grouping definitions), data from the World Development Indicators database of the World Bank (2010) were used, which provided available past data series dating back to 1960. Classification of the countries follows the World Bank's distinction between high-income countries and the rest of the World (World Bank, 2010). GNI was measured using fixed USD amounts provided by the World Bank. These were preferred to purchasing power parity amounts for two reasons. First, the World Bank past time series of GNI in purchasing power parity is far shorter than the USD equivalent. Second, calculations of future purchasing power parity would involve future assumptions of population sizes, already included as a separate variable in our data.

With respect to the future developments of economic and demographic determinants of migration, discussed above, the information came mainly from the GO-S scenarios (Foresight, *forthcoming*), summarised briefly in Section 2.4, supplemented by the input from probabilistic population projections of the International Institute for Applied Systems Analysis (IIASA 2007).

Figure 1. Plots of historical data series used in this study



Source: Immigration – ONS; Demographic variables – US Census Bureau; Economic variables – World Bank (2010)

2.3. Elicitation of expert opinion

As mentioned in the preceding report (Findlay *et al.*, 2011) the elicitation of expert information to inform the model parameters was performed through a two-stage Delphi survey. Given the diversity of experience of the 27 members of the expert panel, a simple approach was adopted, not requiring too detailed statistical knowledge. The two-stage approach was intended to allow for a possible informed convergence of the expert opinion after a general discussion during the project workshop in London on 21 March 2011. Previously, the Delphi method has been applied to migration forecasting, either as a stand-alone tool (Drbohlav, 1996), or in a similar fashion to the current study, as a means of eliciting the information on forecasting models (Bijak and Wiśniowski, 2010). More details on the survey and its results can be found in Findlay *et al.* (2011).

From the point of view of forecasting, two groups of questions were most relevant. The first comprised questions aimed at eliciting target distributions of total immigration, as well as the shares of environmental migration, for 2030 and 2060. Additionally, one question dealt with the share of environmental migration in 2010, because no relevant data are currently available. The second group of questions dealt with the impact of particular demo-economic covariates, listed in Section 2.2, on immigration to the UK.

The questions on the target values of the immigration to the UK, as well as on the shares of migration related to environmental reasons, were elicited in a straightforward fashion. The indicated values were treated as means of respective probability distributions, which were assumed to be log-normal for total immigration volumes (allowing positive values) and beta for shares (allowing only values from the range between 0 and 1). Additionally, for each of the interim periods (2011–29 and 2031–59), the shares of environmental migration suggested by the experts have been linearly interpolated.

Both log-normal and beta distributions require two parameters to be specified, so the second of these were computed based on the answers to the questions about the confidence of experts about the values or shares quoted before. The measures of confidence were obtained on a 100-point scale, ranging from 1 (very unsure) up to 100 (very sure). These questions were asked for all point estimates of future levels of migration and percentages of environmental migrants, and have been subsequently judgmentally mapped onto the scale of the variables in question, to match either the order of magnitude of the total number of immigrants, or of the share of environmentally related migration.

The mapping procedure was as follows: first of all, in each case, a total variance was calculated. This was done initially by calculating the overall weighted average of the mean response of all individuals, where the respondent's confidence answers were used as weights. The total variance was then derived as the summation of the squared difference between this weighted average and each respondent's mean (scaled by the confidence level), divided by the total number of respondents. An individual's variance term, in its log-normal distribution, was then calculated by dividing the total variance by respondent's reported level of confidence. Individual means and derived variance were used as method-of-moments estimates (obtained by matching the empirical mean and variance with their analytical forms, depending on the parameters) to calculate the beta distribution parameter for the share of environmental immigrants.

The 100-point scale was an extended and adapted version of an 11-point scale used in earlier work (Bijak and Wiśniowski, 2010). This scale was intended to provide a subjective measure of uncertainty surrounding the future levels provided in the preceding questions. Note, that this question was not aimed at eliciting confidence intervals. Given the heterogeneity of the expert panel, we could not assume that a question requiring statistical background would be understood consistently across the respondents. Instead, a subjective score with a wide range of options (1 to 100) was intended to allow the experts more flexibility and scope for manoeuvre between both Delphi rounds.

During the second round of the Delphi some respondents raised issues with the use of the 1 to 100 scale, and the placing of their level of uncertainty, especially in the middle of the range. These concerns are legitimate; however, as pointed out by the literature on elicitation, obtaining information about uncertainty is universally difficult and so far no consensus has emerged in the academy as to the ideal solution. In addition, during the second round of the Delphi survey, when faced with all responses from the first round the participants were able to move towards a shared understanding of the scale and the underlying concept of subjective uncertainty. In some cases respondents may have also adjusted their uncertainty in light of discussions. In general, the aim of choosing a point scale subjective measure of uncertainty was therefore to obtain a shared understanding of its meaning by the second round of the Delphi survey, despite differences in the methodological background of the experts. Hence, the second round responses to questions on uncertainty reflect subjective views of individual respondents relative to the whole expert panel. It is worth stressing that, as mentioned in the Introduction, Bayesian forecasts are characterised by inevitably subjective elements, because they are conditional on expert opinion next to the past history obtained from the data series.

The ultimate distributions for the target parameters in question were derived by 'averaging' individual distributions – log-normal for volumes and beta for rates – obtained for particular experts. In formal probabilistic terms, the final distributions were mixtures of expert-specific ones, where each expert was given an equal weight (probability) of inclusion in the final output.

The second group of parameters that were elicited during the Delphi exercise consists of the parameters describing the direction of impact of immigration drivers on the actual inflows. Here, the impact was found to be positive, although the patterns of answers varied depending on the variable considered. Thus, the experts were mostly in agreement that this impact is strongest in the case of the ratio of GNI per capita between the less developed and more developed countries, followed by the global population growth and the GNI per capita in less developed countries. For the old-age dependency ratios, the experts identified a relatively weak, albeit still positive, association.

The distributions for these parameters have been assumed to be normal, with variance equal to 1, and mean calculated as a logarithm from an average answer over all experts. For the calculation of the averages, survey answers indicating 'steady growth' were given the value of 1, 'ever faster growth' of 1.5, 'slower growth' of 0.5, and 'decline' of – 0.5. The answers of 'no impact' were assigned a value of zero (Findlay *et al*., 2011).

2.4. GO-S scenarios

Computation of conditional forecasts of immigration to the UK, based on assumed trajectories of possible future developments of its four demo-economic determinants, mentioned in Section 2.2, considered four scenarios prepared by the GO-S. These scenarios were broadly referred to as:

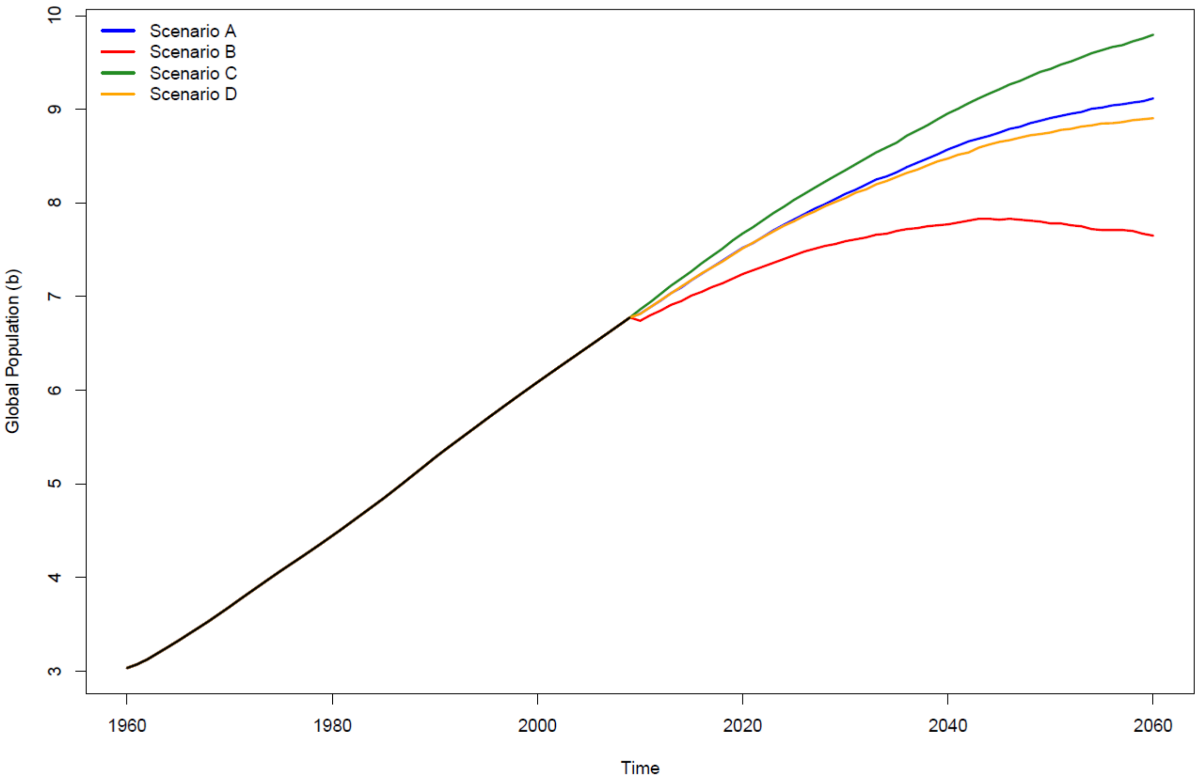
> ***Scenario A:*** High global growth, and exclusive local social, political and economic governance
>
> ***Scenario B:*** High global growth, and inclusive local social, political and economic governance
>
> ***Scenario C:*** Low global growth, and exclusive local social, political and economic governance
>
> ***Scenario D:*** Low global growth, and inclusive local social, political and economic governance
>
> (Foresight, *forthcoming*)

The scenarios A–D were originally formulated as narratives, with only a few pieces of numerical information provided, so their operationalisation was by necessity limited to quantifiable variables and additionally restricted by the availability of data – very limited in the case of environmental variables. The details of each scenario can be found in the dedicated report, and are therefore omitted from this study (Foresight, *forthcoming*).

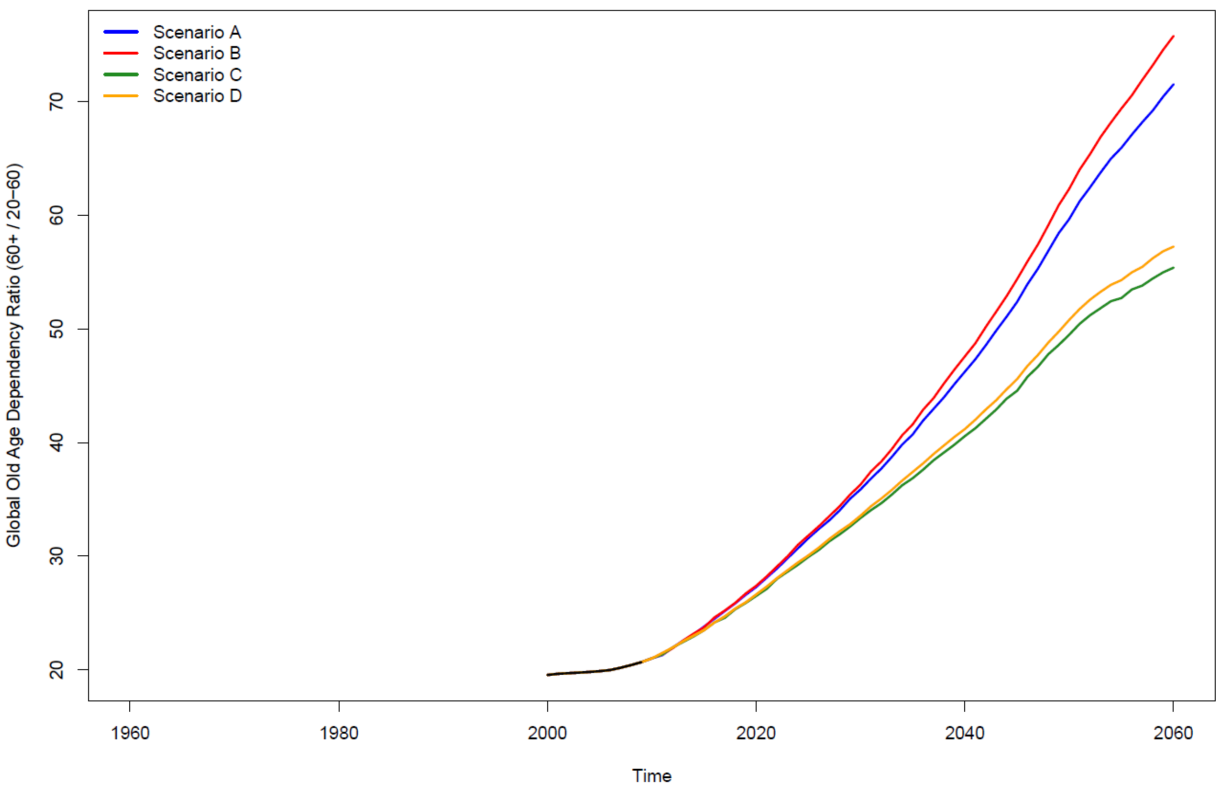
For these reasons, as well as to ensure coherence with the Delphi survey questionnaire, only the variables mentioned in Section 2.2 were operationalised. The target values of economic determinants of migration were taken directly from Annex B of the GO-S scenarios, and interpolated exponentially for the interim years (2011–59). For demographic determinants, the annual values have been taken from the probabilistic projections of IIASA (2007) following the hints included in Annex A of the GO-S report (Foresight, *forthcoming*), about which percentiles from the predictive distributions correspond to which scenarios. For regions of the world not explicitly specified in the scenarios, 'best guesstimates' based on the level of economic development were assumed. The values assigned to each variable in each of the scenarios are visualised in Figure 2, and listed in Table D.1 in Appendix D in 5-yearly intervals.

Figure 2. Operationalisation of GO-S scenarios A–D: demographic and economic drivers

Demographic driver 1: Global population (in billions)



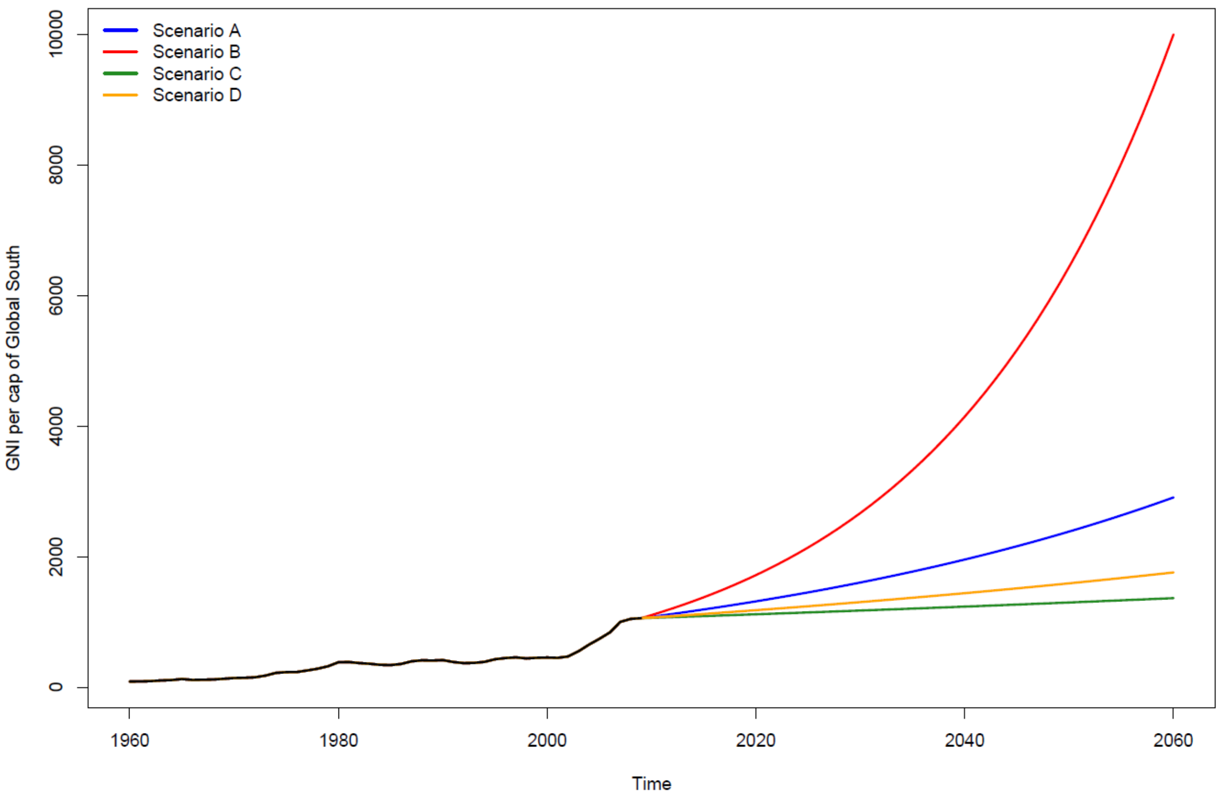
Demographic driver 2: Global old-age dependency ratio (population 60+ / population 20–60)



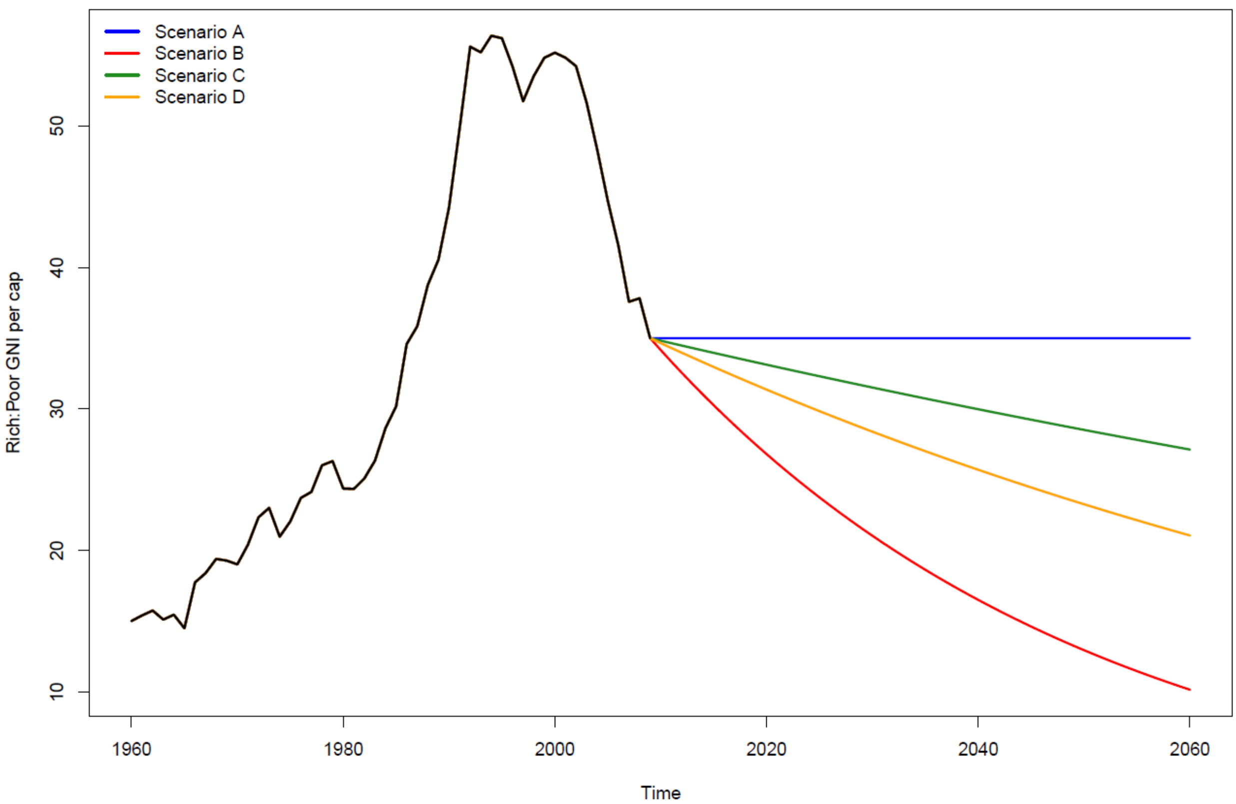
Source: Demographic variables – US Census Bureau; Scenarios – based on Foresight (*forthcoming*) and IIASA (2007)

Figure 2. (continued)

Economic driver 1: GNI per capita in the countries of the 'Global South'



Economic driver 2: Ratio of GNI per capita between the rich and poor countries



Source: Economic variables – World Bank (2010); Scenarios – own elaboration, based on Foresight (*forthcoming*)

3. Multivariate forecasts

3.1. General remarks

In general, the approach followed in this study is a hybrid between the full Bayesian approach and the probabilistic projection of IIASA (2007). The latter methodology was applied to use expert information on target values of volumes of the total and shares of environmental migration to the UK explicitly. The Bayesian statistical inference, in turn, was applied to update the experts' beliefs about the other parameters of the forecasting models, and in particular, the assessment of predictive uncertainty. The overarching framework was also Bayesian in spirit, in that all forecasts were computed within a joint probabilistic model, which treated both parameters, as well as the variables under study, as random quantities, estimated on the basis of data, expert opinion, or both. In the case of multivariate models, discussed in this section, the joint probabilistic model was also used to derive conditional forecasts of immigration, *given* various scenarios of its four determinants, discussed briefly in Section 2.4.

3.2. Modelling framework: vector autoregressive models

The joint modelling and forecasting of immigration and its determinants requires a multivariate model, capable of predicting all variables at the same time, to generate *unconditional* migration forecasts, including the full scope of future uncertainty. Such forecasts can then be fed with quantitative input from scenarios of migration determinants, such as those discussed in Section 2.4, to generate *conditional* forecasts, given specific assumptions. In such a way, conditional forecasts are devoid of the uncertainty of the prediction of the determinants – what is left is the uncertainty of migration, and inter-relations between the former and the latter.

One group of models which enable a coherent treatment of uncertainty at various levels, are VAR models, which are based on the past history of the variables under study. In migration studies, such models have been used for example by Gorbey *et al*. (1999) and Bijak (2010), with the level of success largely depending on the length of the time series. This approach has been adopted for the purpose of the current report. The advantage of using a VAR model in a Bayesian setting is that estimation and prediction can be performed at the same time, within the same joint probabilistic model encompassing the variables under study and model parameters.

Let a VAR model based on a one-period history, VAR(1), be defined as follows (cf Gorbey *et al*., 1999):

(1a)
$$\begin{bmatrix} m_t \\ pop_t \\ odr_t \\ gni_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} + \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} & \varphi_{14} & \varphi_{15} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \varphi_{24} & \varphi_{25} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} & \varphi_{34} & \varphi_{35} \\ \varphi_{41} & \varphi_{42} & \varphi_{43} & \varphi_{44} & \varphi_{45} \\ \varphi_{51} & \varphi_{52} & \varphi_{53} & \varphi_{54} & \varphi_{55} \end{bmatrix} \cdot \left(\begin{bmatrix} m_{t-1} \\ pop_{t-1} \\ odr_{t-1} \\ gni_{t-1} \\ rtp_{t-1} \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} \right) + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix},$$

or, in matrix notation:

(1b)
$$\mathbf{x_t} = \boldsymbol{\mu} + \boldsymbol{\Phi} \cdot \left(\mathbf{x_{t-1}} - \boldsymbol{\mu} \right) + \boldsymbol{\varepsilon_t},$$

where $\mathbf{x_t}$ is a vector comprised of total immigration in year t (m_t), followed by its four determinants in the order introduced in Section 2.2: global population growth (pop_t), global old-age dependency ratio (odr_t), GNI per capita in less developed countries (gni_t), and GNI ratio between the rich and poor countries (rtp_t). Here, all variables were transformed by taking natural logarithms (to ensure positivity), and then taking first differences (to eliminate trends). Elements of the vector μ denote the overall mean levels of such transformed variables, whereas matrix Φ is composed of elements linking the current values of the elements of $\mathbf{x_t}$, with the values from 1 year before, $\mathbf{x_{t-1}}$. Finally, $\varepsilon_\mathbf{t}$ are the error (random) terms, here in accordance with a common practice in VAR modelling, assumed to be independent and identically distributed, following a multivariate normal distribution with zero mean, and a variance–covariance matrix Σ, $\mathbf{N}(\mathbf{0}, \Sigma)$. The Σ matrix measures the instantaneous impact of changes in variables with each other, where as the Φ matrix measures the lagged impact on the mean level.

The previous distributions were assumed as follows: for the parameters of the matrix Φ it was assumed that the elements indicating impact of all variables on migration followed a normal distribution. For ϕ_{11} a stationary character of the first differences of log-transformed immigration volumes itself character was assumed a priori, with ϕ_{11} ~ N(0,1). For the remaining parameters from the first row of Φ, the assumptions followed the argumentation presented in Section 2.3, so that ϕ_{12} ~ N(0, 0.5833333),, ϕ_{13} ~ N(0.4736842,1), ϕ_{14} ~ N(0.5294118,1), and ϕ_{15} ~ N(0.6521739,1).

For $i \neq 1$ and all j = 1, ..., 5, it was assumed that ϕ_{ij}~ N(0,1). For the inverse of the variance-covariance matrix, Σ^{-1}, a Wishart distribution was assumed, with five degrees of freedom, and a diagonal parameter matrix **R**, with r_{ii} = 5 and r_{ij} = 0 for $i \neq j$. Such a construction assumes a priori that there is no instantaneous impact of demo-economic determinants on migration, only lagged, taking into account the length of the decision process leading to migration in ‘regular’ circumstances. All five elements of the vector $\mathbf{x_t}$ were also assumed a priori to have equal precision. The mean levels of the five variables modelled – elements of the vector μ – also were assumed to follow a normal distribution N(0,1).

As mentioned in Section 3.1, the forecasting approach adopted in this study can be seen as a Bayesian hybrid. The full mechanism of Bayesian inference, with data updating the previous information to produce *posterior distributions*, was applied for all parameters: Φ, Σ and μ. However, in the special case of μ_1, the forecasts of immigration were based on derived expert-based trajectories rather than the ones estimated from the model. Similarly, the share of environmental migration was assumed to follow a trajectory entirely based on the experts’ views, as discussed in Section 2.3. We believe that in these two cases the input from the expert information was crucial and therefore opted for its full, undistorted inclusion in the forecasting part of the exercise. Hence, we have estimated the parameters of the VAR model using past data of all available time series: migration, as well as its demographic and economic covariates, additionally augmented with the expert input.

After the parameters of the models were estimated, in the final stage of this part of the forecasting exercise, conditional predictions of immigration based on GO-S scenarios were computed. In this way, uncertainty of the extrapolation of four demo-economic covariates was removed from the overall forecasts, and what was left was only the uncertainty of immigration, as well as the uncertainty of parameters Φ, Σ and μ, depicting inter-relations between variables.

All Bayesian calculations were performed using computational, simulation-based methods, within the OPENBUGS 3.0.2 open-source environment, specifically devoted to Bayesian modelling (see Lunn *et al*., 2009). The results are based on the samples of 10,000 iterations of the estimation algorithm, with 1,000 initial run-up iterations discarded. The OPENBUGS programme code is provided in Appendix A.1, and more technical details on Bayesian VAR modelling in OpenBUGS are offered e.g. in Bijak (2010).

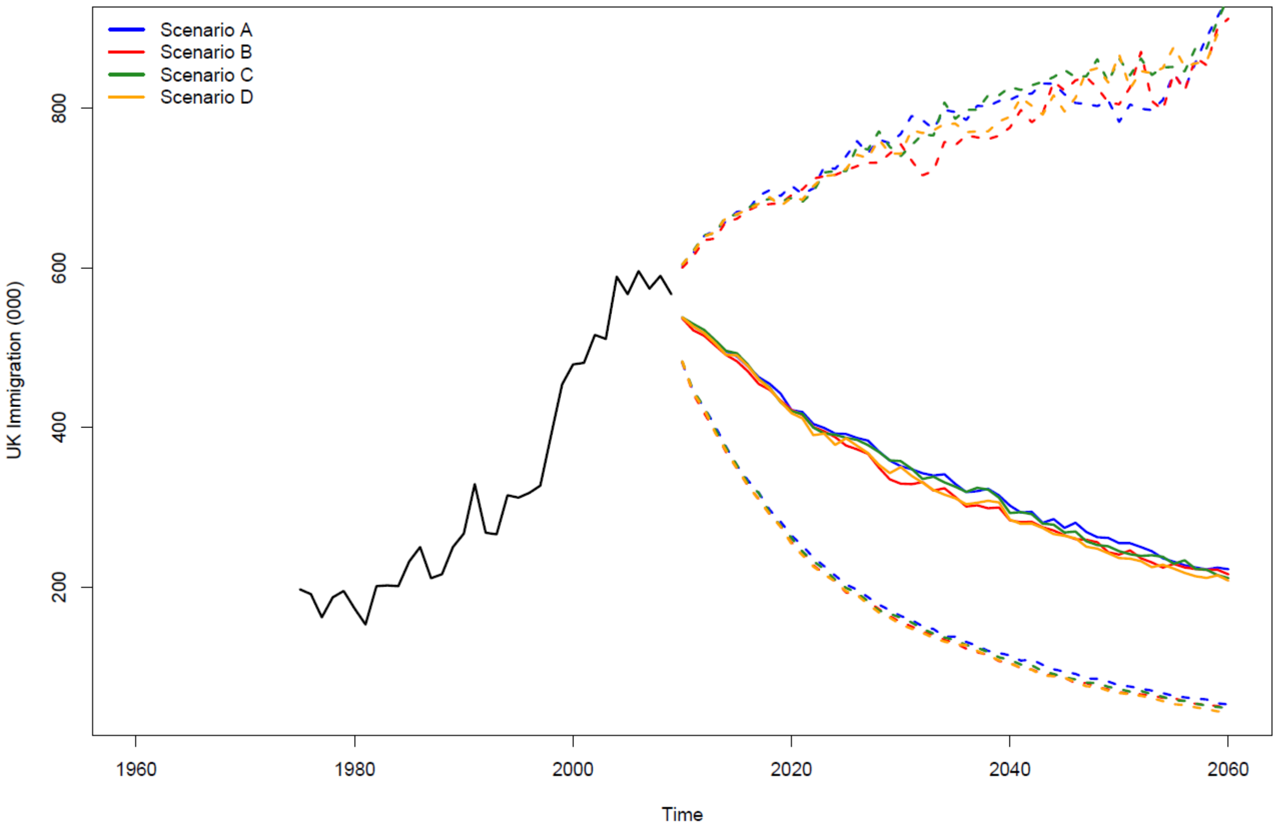
3.3. Results

Based on the conditional forecasts from the VAR models discussed before, and under four different assumptions on demo-economic covariates, four scenarios of total and environmental migration to the UK were obtained. These derived migration scenarios are based on median values from the predictive distributions and indicate a decline of the total immigration to between 329,500 and 357,800 immigrants by 2030, depending on the scenario. Of these between 4,700 and 5,200 will be related to environmental change. In the horizon of 2060, the overall number of migrants is expected to decline further to between 208,400 and 222,300, including between 10,800 and 11,300 environmental migrants. These declines result from both the expert-based input from the Delphi survey, as well as from the application of GO-S scenarios on demo-economic covariates of migration (Foresight, *forthcoming*), and from their inter-relations, embodied in the parameters of the forecasting model. Hence, the predicted total and environmental immigration levels differ from those produced by the Delphi results alone, the latter being more than twice as high, and exceed half a million immigrants on average (Findlay *et al*., 2011). More detailed numerical results are presented in Table D.1, in Appendix D. A lack of significant differences in terms of magnitude between the four scenarios is notable and is likely to be the result of poor associations between immigration and predictors that the VAR model was able to detect. In addition, the reduction in forecasted migration is predominantly the result of the influence of the expert based prior for the trajectory of forecasted immigration. This information dictated the estimate of the mean parameter for future immigration.

In terms of predictive uncertainty, even for conditional forecasts it proved to be too high to provide useful information to forecast users. The model tended to fit the observed values well. However, the associated variance estimates of the errors were, for some series, very large. Moreover, with respect to the uncertainty of the predicted immigration, there was hardly any difference between the scenarios A–D. Figure 3 illustrates the median conditional forecasts of total immigration, alongside their – quite wide – 20% predictive intervals. Note that the selection of 20% intervals in Figure 3 is arbitrary, and is intended to illustrate a trade-off between the assumed probability related to interval forecasts (in this case, 20% is rather low) and the associated uncertainty of the forecasts (already very high). Again, as suggested by other authors (Arango, 2002; Bijak, 2010) migration proved too difficult to be framed within a single theoretical framework with just a handful of macro-level drivers.

The findings presented in this report indicate two methodological issues: (1) the very large predictive uncertainty of migration, and (2) the rather vague evidence of demo-economic covariates impacting in a statistically significant fashion on immigration to the UK (at least in terms of the available datasets). These findings seem to point both to data deficiencies (especially to the shortness of time series) and limitations in migration theory informing analysts of relevant sociodemographic predictors of migration (Bijak, 2010). This is the main rationale for simplifying the approach and preparing forecasts based on univariate autoregressive time series models, where the predictions of migration are based on its own history rather than on a set of covariates. Such models and their results are briefly discussed in Section 4.

Figure 3. Scenarios of immigration to the UK under four sets of assumption, multivariate model



Notes: Solid lines depict total migration scenarios based on *median* conditional forecasts from the multivariate model. Dashed lines denote limits of 20% predictive intervals, based on quantiles of rank 0.4 and 0.6 of the distributions.
Source: Data – ONS; Forecasts – own elaboration in OPENBUGS/R.

4. Univariate forecasts

4.1. Modelling framework: autoregressive models and model selection

Another group of models, which can be used to predict immigration solely based on its past history, are univariate AR models (Bijak and Wiśniowski, 2010). An extensive treatment of suites of such models in the context of population predictions has been provided in Abel *et al.* (2010), where all methodological particulars underpinning the material presented in the current report are discussed in more detail. For the purpose of the current study, an AR model based on the *k*-year history if immigration, AR(*k*), is defined as:

(2) $$m_t = \mu + \sum_{i=1}^{k} \left[\phi_i \cdot (m_{t-i} - \mu) \right] + \varepsilon_t \, .$$

In equation (2), as before, m_t refers to total immigration in year t, again, taken as a first difference of the logarithms of migration volumes, for the reasons discussed in Section 3.1. Furthermore, μ is the overall mean level of m_t; parameters ϕ_i for $i = 1,\ldots, k$, refer to the ensemble of coefficients of autoregression of m_t with its past history up to k periods (years) before. Finally, ε_t denotes an error term, conventionally assumed to follow a univariate normal distribution with mean 0 and variance σ^2, N(0, σ^2). All ε_t are assumed to be independent and identically distributed.

In this study, migration history up to 8 years before was examined by way of a set of nine models, ranging from the independent normal (IN) model, equivalent to AR(0), through AR(1), etc. to AR(8). For every one of them, in terms of previous distributions, it was assumed that as well as μ, all relevant parameters ϕ_i follow a normal distribution N(0,1). Standard deviation of the error term, σ, was assumed to follow a normal distribution N(0,100), truncated at zero to ensure the positivity of the values of σ. This assumption is rather vague and reflects lack of strong beliefs a priori with respect to the error of immigration forecasts. As in Section 3, the full Bayesian inference was applied for all ϕ_i, σ and μ, although in the last-mentioned case, the forecasts drew on expert-based trajectories obtained from the Delphi survey, as described in Section 2.3. A fully expert-based approach was also applied to obtain the predictions of the share of environmental migrations. This was necessary in the absence of any systematic time series dataset on environmental immigration to the UK.

Given that in this exercise nine different models are considered, to allow for their goodness-of-fit with the empirical data, the procedure of Bayesian model selection and averaging were applied (Raftery, 1995). In this approach, models themselves are being assigned prior probabilities, adding up to unity, which are subsequently updated according to how much support from data a particular model has. The resulting *posterior probabilities*, also adding up to one, can then be used to select the best fitting model (i.e. the one with the highest probability), or to *average* forecasts yielded by different models, using these probabilities as weights. In the current example, the nine models were assumed a priori to be equi-probable, without preference to any one of them, so the prior probability of each of them equalled 11.1% (i.e. 1/9).

In computing the posterior probabilities of particular models given the data, the *bridge sampler* algorithm was applied (Meng and Wong, 1996). Additionally, two measures of goodness-of-fit of models, also used in classical (frequentist) statistics, were calculated: the Akaike information criterion (AIC) and the Bayesian (Schwartz) information criterion (BIC). These measures are described in more detail in Congdon (2003: 32–33), whereas a discussion of the general methodology of Bayesian model selection in the context of a series of AR(k) models is provided in Abel *et al*. (2010).

As in the case of multivariate models, the Bayesian calculations were performed within the OPENBUGS 3.0.2 environment, and are based on 10,000 iterations of the estimation algorithm, with 1,000 initial iterations discarded. The generic programme template for AR models, as well as a specific example for the AR(8) model, are provided in Appendices A.2 and A.3, respectively. Programme code for the bridge sampling algorithm, written in the statistical package R, is available from the first author (GJA) upon request. More details on the approach and the technicalities are provided in Abel *et al*. (2010).

4.2. Results

By applying the methodology outlined above, univariate forecasts of total and environmental migration to the UK, based on AR models, were obtained. The forecasts of the total immigration are weighted averages (technically speaking, mixtures) of predictions yielded by particular models, from IN and AR(1) up to AR(8). The weights used were the posterior probabilities of particular models, obtained from the bridge sampler algorithm of Meng and Wong (1996). In this example, the averaged model was 58.5% influenced by the independent normal ['AR(0)'] model, 21.3% by AR(2), and 16.1% by AR(1), with a trace impact of AR(3) and AR(4). Notably, other goodness-of-fit criteria also pointed to models with high posterior probability: AIC to AR(2) and BIC to AR(1).

To derive forecasts of environmental migration, the expert-based predicted distributions of relevant shares were juxtaposed with the results for the overall immigration. The resulting forecasts of total and environmental immigration to the UK are illustrated respectively in Figures 4 and 5. The medial predictions, indicating that for 50% of the time higher values can be expected, and lower values for the remaining 50%, suggest an ever-slower-declining trend of total migration, and a long-term stability of environmental migration. Hence, in the median trajectory, overall immigration is expected to decline from the recent levels of 567,000 in 2009, to 411,000 in 2030, and then to 332,000 in 2060. At the same time, the median trajectory of the volume of environmental migration is expected first to increase slightly from the expert-based estimate of 19,600 in 2010, to 26,800 in 2030, and then decline to 24,900 by 2060. With respect to environmental migration, Figure 5 clearly shows a discontinuity of the trend around 2030, resulting from the values having to conform both to overall migration totals, as well as to the shares of environmental migration envisaged for 2030 by the experts. The lower values than those obtained in the Delphi survey alone (Findlay *et al*,. 2011, see also Section 3) are the result of the impact of the history of migration and its impact on the forecasts through the parameters of the forecasting model. In addition, respondent's answers for the mean levels are weighted by their associated uncertainty levels in the prior distributions.

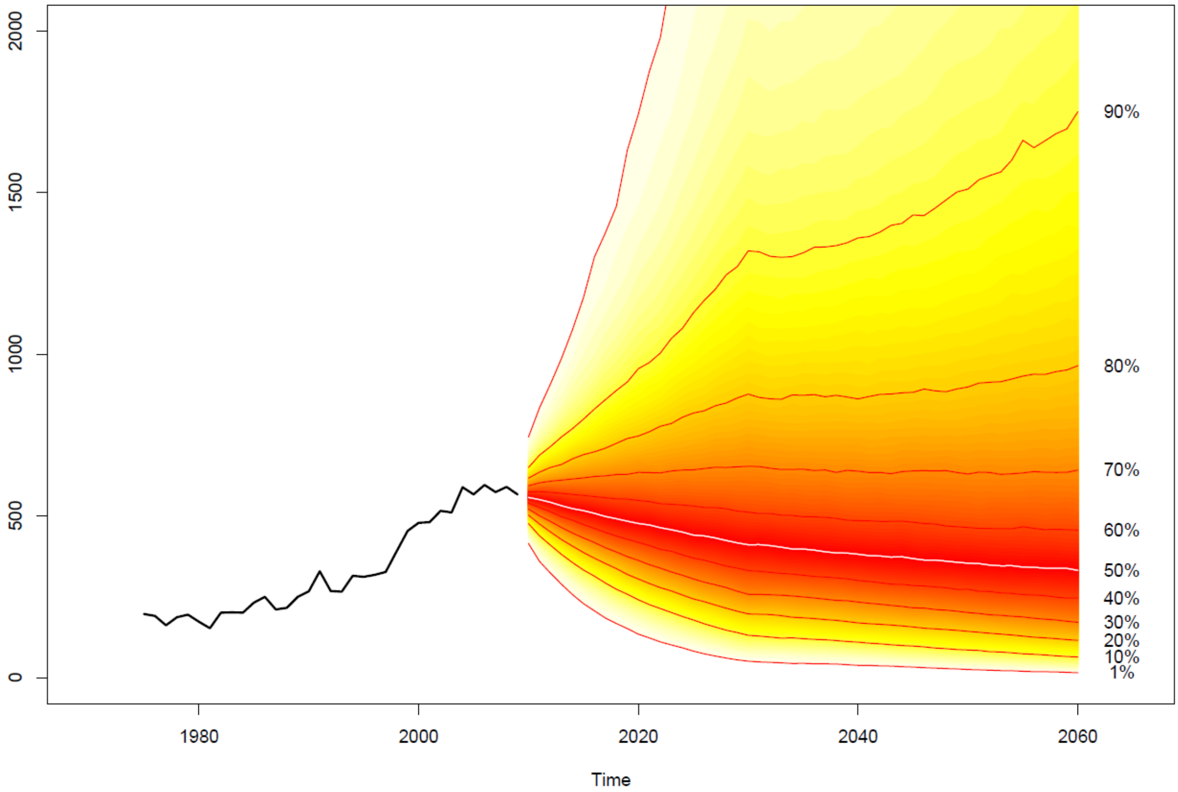
Figure 5 is ground-breaking in providing for the very first time some expert-based estimates of the volume of environmental migration to the UK that might occur year on year over the next 50 years. It not only shows the possible levels of environmental mobility, but perhaps more significantly it predicts that there will not be a continuous increase in the number of environmental immigrants, refuting the suggestions of some environmentalists of an exponential rise in environmental population movement by 2060. Needless to say, the caveats and health warnings made in Section 2.1 remain fully in force. As the authors of this report have been at pains to emphasise, the values shown in the diagram (while being the best estimate available to decision makers) are only as good as the knowledge base of the Delphi panel experts and the univariate modelling procedure that has been employed to generate this forecast. Nevertheless, by recognising that the panel of experts was selected to represent the best available knowledge on the topic in 2011, and that the model has taken into account the panellists self-defined uncertainty about future levels of environmental mobility, the forecast provides the best possible estimates ever generated of the possible scale of environmental mobility. This provides an important baseline for policy makers to work with until better estimates can be obtained.

The predictive uncertainty shown in Figure 4 is – as expected – quite high, although much lower than in the case of multivariate VAR models discussed in Section 3. For example, the

80% intervals[2], related to chances of one in 10 that in any particular year the actual total immigration to the UK will be above the given range, and one in 10 that it will be below, are estimated to be between 131,100 and 1.32 million immigrants in 2030, and between 64,000 and 1.75 million in 2060. By definition, the volume of environmental migration must fall within these ranges. Hence, in 2030 between 600 and 177,700 migrations could be caused by environmental drivers, whereas in 2060, this range would be between 600 and 312,700. In the short term, the uncertainty assessment seems plausible; however, because of the nature of the processes under study, as well as of the forecasting models, the intervals beyond 2020 or 2030 clearly become much wider, especially at the upper end.

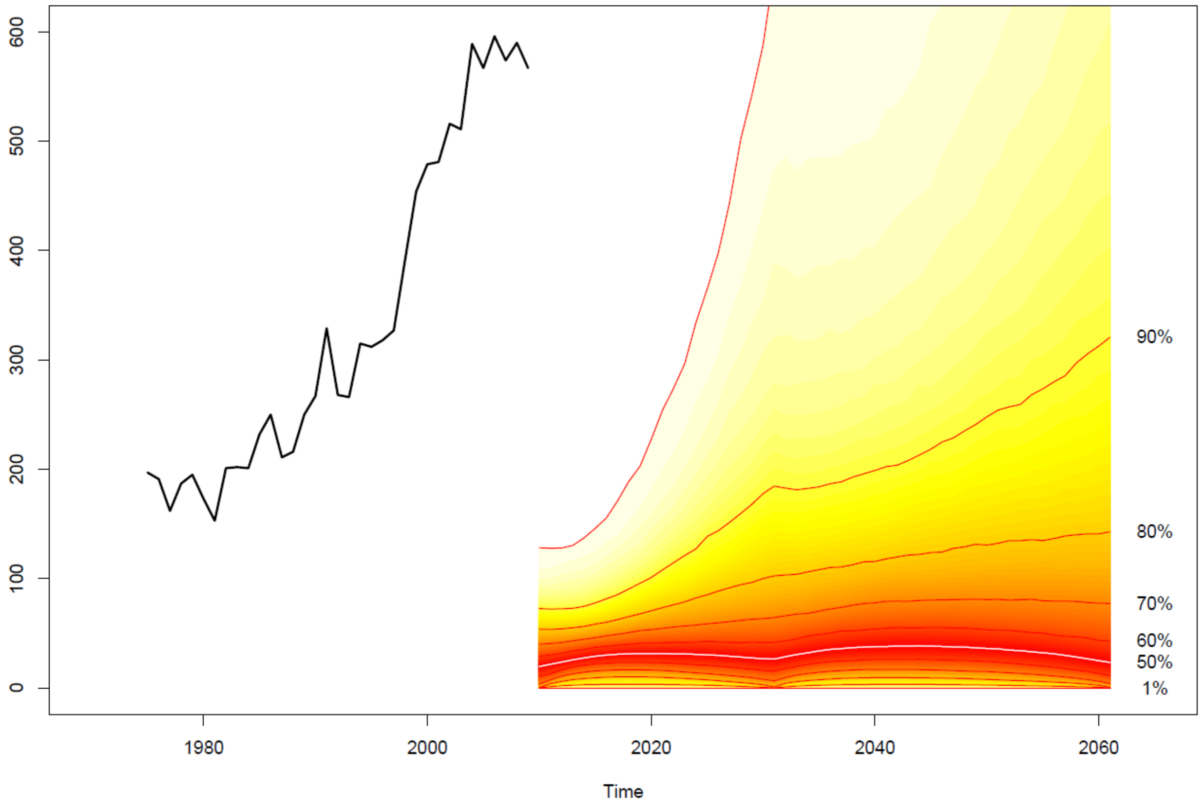
[2] Probabilistic population forecasters tend to prefer 80% predictive intervals over, for example, 95% ones, main arguments being that the former are more robust and less affected by the extremes, and do not unnecessarily amplify the impression of uncertainty (Lutz *et al.*, 2004: 37). Besides, as argued by Bijak (2010: 107), 'such intervals can also provide additional warning to the forecast users, as the probability that the process will fall beyond their limits from time to time cannot be neglected.'

Figure 4. Forecasts of total immigration to the UK, averaged univariate models (in thousands)



Note: White line on the forecast fan denotes the median forecast of total immigration to the UK.
Source: Data – ONS; Forecasts – own elaboration in OPENBUGS/R.

Figure 5. Forecasts of environmental immigration to the UK, averaged models (in thousands)



Notes: Black line denotes historical total immigration – the same series as in Figure 4 (rescaled).
White line on the forecast fan denotes the median prediction of environmental immigration to the UK.
Source: Data – ONS; Forecasts – own elaboration in OPENBUGS/R.

More detailed numerical results concerning the forecasts of total, as well as environmental migration to the UK have been provided in Appendix B, in Tables B.1 and B.2, respectively. The summaries of the estimated posterior distributions of model parameters – their posterior means and standard deviations – and three measures of goodness-of-fit: AIC, BIC and posterior model probabilities, are offered in Appendix C. More technical description of the procedures applied is available from Abel *et al*. (2010).

5. Conclusions

Figure 5 represents the most important output for GO-S from the current forecasting exercise. It suggests that environmental immigration may rise a little over the next few decades, but that the trend is less likely to be one involving ever-increasing numbers. Instead, the median forecast suggests that the total volume of environmental immigration (while hovering between 25,000 and 27,000 people between 2030 and 2060) is not set to expand exponentially as Britain moves into an era of significant climate change. If the views of the Delphi experts, fed into the Bayesian forecast, are correct, there is an approximately one in 20 chance of environmental migration rising to levels by 2060 that would equate with the total volume of all immigration to the UK in 2009. In addition, environmental migration will still most likely remain a small percentage of the overall migration inflow into the UK. The median environmental flows in 2030 and 2060 correspond to respectively 6.5% and 7.5% of the median total immigration flow. In addition to these estimates, Figure 5 provides policy makers with the challenge of considering how to respond to unlikely outcomes as well as to the more probable estimates around the median line.

When considering the forecasts from the multivariate and univariate models (averaged), the differences in the predicted magnitude of migration and the associated uncertainty at the first glance seem obvious. The VAR models produced conditional median trajectories that by 2060 are lower by about a third than those of the averaged ensemble of AR-based predictions: about 210,000–220,000 immigrants in total, as opposed to 332,000. The numerical differences between the median trajectories are the result of the impact of particular scenarios of economic and demographic drivers of migration, as well as the uncertainty of inter-relations between these drivers and migration, propagated into the forecasts.

On the other hand, uncertainty in the VAR models is far higher, and the median forecast is much less appropriate as an indicator of future migration developments. In fact, when uncertainty is taken into account, the picture looks quite different: conditional forecasts from the VAR, assuming any of the scenarios A–D, reach about 332,000 immigrants by 2060 already for the 53rd or 54th predictive percentile, so, in terms of probability, very close to the median. This indicates very high sensitivity of the conditional multivariate forecasts on the selection of the level of probability. On the other hand, forecasts from univariate models are far more robust, and hence seem more suitable for use as policy guidance than the mostly uncertain multivariate forecasts, even though based on well-defined scenarios. Still, even in the AR models the predictive uncertainty is substantial – its large magnitude is itself one of the key findings of this study.

Summing up, given the limitations of available data (short time series), simpler models such as the AR, proved to be more accurate *ex ante*, with lower, yet still considerable, uncertainty of predictions. It can be argued that, especially within a shorter horizon, uncertainty assessment of univariate models is more realistic, and definitely much more informative, than the one arising from the multivariate models. In the multivariate case, which combines the uncertainty of forecasting with the uncertainty of theoretical links between migration and its drivers (cf. Arango, 2002), and with the simplistic operationalisation of the latter using available macro-level indicators, the ultimate result is simply unknown.

Clearly, the current study has its methodological limitations, from the possible ambiguity of expert answers to the Delphi survey, to the insufficient availability of appropriate data, which rendered the multivariate forecasts too uncertain to be useful in their own right. In particular, despite a clear potential advantage of including environmental scenarios in the forecasts, we found them very difficult (if at all possible at this stage) to operationalise in quantitative terms. This is a clear limitation of our work, but given the lack of appropriate data series, or even a consensus on a definition, especially with respect to environmental migration – which would be needed to estimate the models – we have decided to apply a simplified approach and rely entirely on the expert-based elicitation.

In terms of the empirical results, wide predictive intervals, even for univariate forecasts, reinforce the caveats about the general unpredictability of migration when we look several decades into the future, and shortness of plausible forecast horizons (Bijak and Wiśniowski, 2010). Such outcomes might not be particularly welcome by all users of forecasts, but, given the nature of the phenomena under study, the results are intended to convey an honest message about the uncertainty, as well as possibility of providing forecast of environmental migration to the UK looking forward 50 years. The main point here is that the presence of high uncertainty is a warning sign of the caution required on the users' part (see e.g. Makridakis and Taleb, 2009).

In this respect, there are several ways of using the information embedded in the uncertainty of total and environmental migration forecasts. Trajectories based on various percentiles from the predictive distributions – not only median – can be helpful for planning, if the expected costs of under-predicting versus over-predicting migration are roughly known, or at least can be approximated. Median values are a special case, because they correspond to a situation with symmetric costs of over-prediction and under-prediction of migration, which does not need to be true in real-life situations. A detailed discussion of this issue, based on statistical decision theory, goes beyond the scope of the current report (Bijak, 2010). However, even without a formal decision analysis, various percentile-based trajectories can be used directly as numerical input to scenarios of total and environmental migration – in a similar fashion as that in which the IIASA (2007) predictions were used in the GO-S scenarios concerning global demography (Foresight, *forthcoming*). This would constitute yet another way of enhancing the scenario method by adding quantitative insights (Wright and Goodwin 2009).

As indicated by the recent economic crisis, ignoring the scope of predictive uncertainty can have severe consequences for public life. Hence, instead of striving for an unrealistic precision of forecasts, both forecasters and users of predictions should admit that uncertainty is inescapable, and plan with foresight for possible, yet less probable outcomes. As Figure 5 has shown, it is most likely that future environmental immigration to the UK in 2060 will not be much different from the current median estimate. However, the forecast shows that this outcome is not inevitable, and that by 2060 there is a one in 10 chance that the environmental immigration could exceed the total level of immigration experienced by the UK in 2010.

Acknowledgements

This study was funded by the Government Office for Science (GO-S) within the framework of its Foresight programme. The Centre for Population Change is a joint initiative between the University of Southampton and a consortium of Scottish Universities in partnership with ONS and GROS, funded by the ESRC Grant number RES-625-28-0001. The authors are grateful to the Expert Panel of the GO-S for sharing their views in the Delphi survey, which has substantially informed our work. We would also like to thank Jonathan J Forster, and Peter W F Smith (University of Southampton) for their help and advice on various aspects of modelling, as well as four anonymous reviewers for their comments and feedback that helped to improve the successive drafts. The findings, interpretations, and conclusions expressed in this study are those of its authors and should not be attributed in any manner to the GO-S, ONS, GROS, or any of the institutions with which they are otherwise affiliated. All the errors and omissions are exclusively ours.

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Appendix A. OPENBUGS code used in estimation and forecasting

A.1. Multivariate models

```
model
{
#data manipulations
for(t in na.imm:n){
	y[t,1] <- log(imm[t])-log(imm[t-1])
}
for(t in 2:N2){
	y[t,2] <- log(pop[t])-log(pop[t-1])
}
for(t in na.edr:N2){
	y[t,3] <- log(edr[t])-log(edr[t-1])
}
for(t in 2:N2){
	y[t,4] <- log(gni[t])-log(gni[t-1])
	y[t,5] <- log(rtp[t])-log(rtp[t-1])
}


#wccmcv
#overall likelihood
for(t in 2:N2){
	y[t,1:5] ~ dmnorm(y.mean[t,1:5], isigma2[1:5,1:5])
}
isigma2[1:5,1:5] ~ dwish(R[1:5,1:5],5)
R[1,1]<-5
for(i in 2:5){
	R[i,i]<-5
	for(j in 1:(i-1)){
		R[i,j] <- 0
		R[j,i] <- 0
	}
}

#full mean structure
#initialise
for(t in 2:2){
	for(i in 1:5){
		y.mean[t,i] <- mu[i]
	}
}
#rest
for(t in 3:n){
	for(i in 1:5){
		y.mean[t,i]<-mu[i]+
		phi1[i,1]*(y[t-1,1]-mu[1])+phi1[i,2]*(y[t-1,2]-mu[2])+
		phi1[i,3]*(y[t-1,3]-mu[3])+phi1[i,4]*(y[t-1,4]-mu[4])+
		phi1[i,5]*(y[t-1,5]-mu[5])
	}
}
#future
for(t in n+1:N1){
	for(i in 1:1){
		y.mean[t,i]<-nu1+
```

```
            phi1[i,1]*(y[t-1,1]-nu1)+phi1[i,2]*(y[t-1,2]-mu[2])+
            phi1[i,3]*(y[t-1,3]-mu[3])+phi1[i,4]*(y[t-1,4]-mu[4])+
            phi1[i,5]*(y[t-1,5]-mu[5])
      }
      for(i in 2:5){
            y.mean[t,i]<-mu[i]+
            phi1[i,1]*(y[t-1,1]-nu1)+phi1[i,2]*(y[t-1,2]-mu[2])+
            phi1[i,3]*(y[t-1,3]-mu[3])+phi1[i,4]*(y[t-1,4]-mu[4])+
            phi1[i,5]*(y[t-1,5]-mu[5])
      }
}
for(t in N1+1:N2){
      for(i in 1:1){
            y.mean[t,i]<-nu2+
            phi1[i,1]*(y[t-1,1]-nu2)+phi1[i,2]*(y[t-1,2]-mu[2])+
            phi1[i,3]*(y[t-1,3]-mu[3])+phi1[i,4]*(y[t-1,4]-mu[4])+
            phi1[i,5]*(y[t-1,5]-mu[5])
      }
      for(i in 2:5){
            y.mean[t,i]<-mu[i]+
            phi1[i,1]*(y[t-1,1]-nu2)+phi1[i,2]*(y[t-1,2]-mu[2])+
            phi1[i,3]*(y[t-1,3]-mu[3])+phi1[i,4]*(y[t-1,4]-mu[4])+
            phi1[i,5]*(y[t-1,5]-mu[5])
      }
}

#priors
for(i in 1:5){
      mu[i] ~ dnorm(0,1);
}
phi1[1,1] ~ dnorm(0,1)
phi1[1,2] ~ dnorm(0.5833333,1)
phi1[1,3] ~ dnorm(0.4736842,1)
phi1[1,4] ~ dnorm(0.5294118,1)
phi1[1,5] ~ dnorm(0.6521739,1)
for(i in 2:5){
      for(j in 1:5){
            phi1[i,j] ~ dnorm(0,1)
      }
}
i30.ind ~ dcat(i30.p[])
i30.ind.c <- cut(i30.ind)
nu1 ~ dnorm(i30.exp[i30.ind.c], i30.conf.exp[i30.ind.c])
i60.ind ~ dcat(i60.p[])
i60.ind.c <- cut(i60.ind)
nu2 ~ dnorm(i60.exp[i60.ind.c], i60.conf.exp[i60.ind.c])

#forecasts
imm.new[n] <- imm[n]
env.new[n] <- imm.new[n]*e10
for(t in n+1:N1-1){
      imm.new[t] <- exp(y[t,1]) * imm.new[t-1]
      env.new[t]<-imm.new[t]*et[t]
      et[t]<-e10+(t-n)*(e30-e10) / (N1-n)
}
imm.new[N1] <- exp(y[N1,1]) * imm.new[N1-1]
env.new[N1] <- imm.new[N1]*e10
for(t in N1+1:N2-1){
      imm.new[t] <- exp(y[t,1]) * imm.new[t-1]
      env.new[t]<-imm.new[t]*et[t]
      et[t]<-e30+(t-N1)*(e60-e30) / (N2-N1)
}
e10.ind ~ dcat(e10.p[])
```

```
e10.ind.c <- cut(e10.ind)
e10 ~ dbeta(e10.alpha[e10.ind.c], e10.beta[e10.ind.c])
e30.ind ~ dcat(e30.p[])
e30.ind.c <- cut(e30.ind)
e30 ~ dbeta(e30.alpha[e30.ind.c], e30.beta[e30.ind.c])
e60.ind ~ dcat(e60.p[])
e60.ind.c <- cut(e60.ind)
e60 ~ dbeta(e60.alpha[e60.ind.c], e60.beta[e60.ind.c])

#sims for visual of model fit
for(i in 1:5){
     for(j in 1:5){
           isigma2.c[i,j] <- cut(isigma2[i,j])
     }
}
for(t in 2:N2){
     for(i in 1:5){
           y.mean.c[t,i]<-cut(y.mean[t,i])
     }
     y.sim[t,1:5] ~ dmnorm(y.mean.c[t,1:5],isigma2.c[1:5,1:5])
     imm.sim[t]<-y.sim[t,1]
     pop.sim[t]<-y.sim[t,2]
     edr.sim[t]<-y.sim[t,3]
     gni.sim[t]<-y.sim[t,4]
     rtp.sim[t]<-y.sim[t,5]
}

}
```

A.2. Univariate models – general template[3]

```
model{

#data manipulations

for(t in 2:n){

     y[t] <- log(imm[t])-log(imm[t-1])

}



#likelihood

for(t in 2:N2){

     y[t] ~ dnorm(y.mean[t],isigma2)I(,5)

}
```

[3] R code for model selection, based on the bridge sampler, is available from the first author (Guy J. Abel) upon request.

```
for(t in 2:2){
     y.mean[t] <- mu
}
for(t in 3:n){
     y.mean[t] <- mu
     y.mean[t] <- mu + phi1*(y[t-1]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu) +
phi4*(y[t-4]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu) +
phi4*(y[t-4]-mu) + phi5*(y[t-5]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu) +
phi4*(y[t-4]-mu) + phi5*(y[t-5]-mu) + phi6*(y[t-6]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu) +
phi4*(y[t-4]-mu) + phi5*(y[t-5]-mu) + phi6*(y[t-6]-mu) + phi7*(y[t-7]-mu)
     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu) +
phi4*(y[t-4]-mu) + phi5*(y[t-5]-mu) + phi6*(y[t-6]-mu) + phi7*(y[t-7]-mu) +
phi8*(y[t-8]-mu)
}


for(t in n+1:N1){
     y.mean[t] <- nu1
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1)
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1)
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1)
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1) +
phi4*(y[t-4]-nu1)
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1) +
phi4*(y[t-4]-nu1) + phi5*(y[t-5]-nu1)
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1) +
phi4*(y[t-4]-nu1) + phi5*(y[t-5]-nu1) + phi6*(y[t-6]-nu1)
     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1) +
phi4*(y[t-4]-nu1) + phi5*(y[t-5]-nu1) + phi6*(y[t-6]-nu1) + phi7*(y[t-7]-nu1)
```

```
    y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1) +
phi4*(y[t-4]-nu1) + phi5*(y[t-5]-nu1) + phi6*(y[t-6]-nu1) + phi7*(y[t-7]-nu1) +
phi8*(y[t-8]-nu1)

}


for(t in N1+1:N2){

    y.mean[t] <- nu2

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2) +
phi4*(y[t-4]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2) +
phi4*(y[t-4]-nu2) + phi5*(y[t-5]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2) +
phi4*(y[t-4]-nu2) + phi5*(y[t-5]-nu2) + phi6*(y[t-6]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2) +
phi4*(y[t-4]-nu2) + phi5*(y[t-5]-nu2) + phi6*(y[t-6]-nu2) + phi7*(y[t-7]-nu2)

    y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2) +
phi4*(y[t-4]-nu2) + phi5*(y[t-5]-nu2) + phi6*(y[t-6]-nu2) + phi7*(y[t-7]-nu2) +
phi8*(y[t-8]-nu2)

}


#priors

mu ~ dnorm(0,1)

phi1 ~ dnorm(0,1)

phi2 ~ dnorm(0,1)

phi3 ~ dnorm(0,1)

phi4 ~ dnorm(0,1)

phi5 ~ dnorm(0,1)

phi6 ~ dnorm(0,1)

phi7 ~ dnorm(0,1)
```

```
phi8 ~ dnorm(0,1)

sigma ~ dnorm(0,0.0001)I(0,)

isigma2 <- 1/(pow(sigma,2))

i30.ind ~ dcat(i30.p[])

i30.ind.c <- cut(i30.ind)

nu1 ~ dnorm(i30.exp[i30.ind.c], i30.conf.exp[i30.ind.c])

i60.ind ~ dcat(i60.p[])

i60.ind.c <- cut(i60.ind)

nu2 ~ dnorm(i60.exp[i60.ind.c], i60.conf.exp[i60.ind.c])



#forecasts

imm.new[n] <- imm[n]

env.new[n] <- imm.new[n]*e10

for(t in n+1:N1-1){

     imm.new[t] <- exp(y[t]) * imm.new[t-1]

     env.new[t]<-imm.new[t]*et[t]

     et[t]<-e10+(t-n)*(e30-e10) / (N1-n)

}

imm.new[N1] <- exp(y[N1]) * imm.new[N1-1]

env.new[N1] <- imm.new[N1]*e30

for(t in N1+1:N2-1){

     imm.new[t] <- exp(y[t]) * imm.new[t-1]

     env.new[t]<-imm.new[t]*et[t]

     et[t]<-e30+(t-N1)*(e60-e30) / (N2-N1)

}

imm.new[N2] <- exp(y[N2]) * imm.new[N2-1]

env.new[N2] <- imm.new[N2]*e60
```

```
e10.ind ~ dcat(e10.p[])

e10.ind.c <- cut(e10.ind)

e10 ~ dbeta(e10.alpha[e10.ind.c], e10.beta[e10.ind.c])

e30.ind ~ dcat(e30.p[])

e30.ind.c <- cut(e30.ind)

e30 ~ dbeta(e30.alpha[e30.ind.c], e30.beta[e30.ind.c])

e60.ind ~ dcat(e60.p[])

e60.ind.c <- cut(e60.ind)

e60 ~ dbeta(e60.alpha[e60.ind.c], e60.beta[e60.ind.c])


#sims

isigma2.c<-cut(isigma2)

for(t in 2:n){

     y.mean.c[t]<-cut(y.mean[t])

     y.sim[t] ~ dnorm(y.mean.c[t],isigma2.c)

}


}
```

A.3. Univariate models – example of an AR(8) model

```
model{

#data manipulations

for(t in 2:n){

     y[t] <- log(imm[t])-log(imm[t-1])

}
```

```
#likelihood

for(t in 2:N2){

     y[t] ~ dnorm(y.mean[t],isigma2)I(,5)

}

for(t in 2:9){

     y.mean[t] <- mu

}

for(t in 10:n){

     y.mean[t] <- mu + phi1*(y[t-1]-mu) + phi2*(y[t-2]-mu) + phi3*(y[t-3]-mu) +
phi4*(y[t-4]-mu) + phi5*(y[t-5]-mu) + phi6*(y[t-6]-mu) + phi7*(y[t-7]-mu) +
phi8*(y[t-8]-mu)

}



for(t in n+1:N1){

     y.mean[t] <- nu1 + phi1*(y[t-1]-nu1) + phi2*(y[t-2]-nu1) + phi3*(y[t-3]-nu1) +
phi4*(y[t-4]-nu1) + phi5*(y[t-5]-nu1) + phi6*(y[t-6]-nu1) + phi7*(y[t-7]-nu1) +
phi8*(y[t-8]-nu1)

}
```

```
for(t in N1+1:N2){

     y.mean[t] <- nu2 + phi1*(y[t-1]-nu2) + phi2*(y[t-2]-nu2) + phi3*(y[t-3]-nu2) +
phi4*(y[t-4]-nu2) + phi5*(y[t-5]-nu2) + phi6*(y[t-6]-nu2) + phi7*(y[t-7]-nu2) +
phi8*(y[t-8]-nu2)

}



#priors

mu ~ dnorm(0,1)

phi1 ~ dnorm(0,1)

phi2 ~ dnorm(0,1)

phi3 ~ dnorm(0,1)

phi4 ~ dnorm(0,1)

phi5 ~ dnorm(0,1)

phi6 ~ dnorm(0,1)

phi7 ~ dnorm(0,1)

phi8 ~ dnorm(0,1)

sigma ~ dnorm(0,0.0001)I(0,)

isigma2 <- 1/(pow(sigma,2))

i30.ind ~ dcat(i30.p[])

i30.ind.c <- cut(i30.ind)

nu1 ~ dnorm(i30.exp[i30.ind.c], i30.conf.exp[i30.ind.c])

i60.ind ~ dcat(i60.p[])

i60.ind.c <- cut(i60.ind)

nu2 ~ dnorm(i60.exp[i60.ind.c], i60.conf.exp[i60.ind.c])



#forecasts

imm.new[n] <- imm[n]

env.new[n] <- imm.new[n]*e10
```

```
for(t in n+1:N1-1){

     imm.new[t] <- exp(y[t]) * imm.new[t-1]

     env.new[t]<-imm.new[t]*et[t]

     et[t]<-e10+(t-n)*(e30-e10) / (N1-n)

}

imm.new[N1] <- exp(y[N1]) * imm.new[N1-1]

env.new[N1] <- imm.new[N1]*e30

for(t in N1+1:N2-1){

     imm.new[t] <- exp(y[t]) * imm.new[t-1]

     env.new[t]<-imm.new[t]*et[t]

     et[t]<-e30+(t-N1)*(e60-e30) / (N2-N1)

}

imm.new[N2] <- exp(y[N2]) * imm.new[N2-1]

env.new[N2] <- imm.new[N2]*e60

e10.ind ~ dcat(e10.p[])

e10.ind.c <- cut(e10.ind)

e10 ~ dbeta(e10.alpha[e10.ind.c], e10.beta[e10.ind.c])

e30.ind ~ dcat(e30.p[])

e30.ind.c <- cut(e30.ind)

e30 ~ dbeta(e30.alpha[e30.ind.c], e30.beta[e30.ind.c])

e60.ind ~ dcat(e60.p[])

e60.ind.c <- cut(e60.ind)

e60 ~ dbeta(e60.alpha[e60.ind.c], e60.beta[e60.ind.c])


#sims

isigma2.c<-cut(isigma2)

for(t in 2:n){

     y.mean.c[t]<-cut(y.mean[t])
```

```
    y.sim[t] ~ dnorm(y.mean.c[t],isigma2.c)

}


}
```

Appendix B. Numerical results – averaged univariate forecasts

Table B.1. Total immigration to the UK: selected percentiles of forecasts

Year	1%	5%	10%	25%	**50%**	75%	90%	95%	99%
2010	414,900	453,700	476,590	512,300	**557,400**	604,400	650,000	677,115	744,408
2011	359,696	410,595	438,800	488,200	**550,650**	618,450	688,220	733,910	834,604
2012	323,298	376,400	409,790	467,475	**542,400**	627,600	714,910	773,000	908,410
2013	288,999	346,995	381,300	445,975	**531,900**	634,725	744,400	819,805	987,227
2014	257,297	317,700	356,200	427,975	**522,900**	644,100	770,110	865,805	1,076,020
2015	228,995	292,095	333,100	410,675	**516,600**	649,550	799,420	908,905	1,175,050
2016	206,796	272,585	313,900	394,900	**508,400**	658,300	830,800	952,525	1,301,000
2017	184,491	251,095	292,690	377,500	**498,550**	662,725	859,910	1,008,000	1,376,020
2018	167,493	231,100	273,600	364,875	**491,650**	670,250	888,300	1,048,050	1,458,060
2019	151,798	216,000	258,090	348,975	**484,000**	679,225	914,700	1,104,050	1,632,000
2020	134,595	198,700	240,900	334,500	**476,900**	685,700	955,710	1,171,100	1,743,060
2021	123,096	184,295	225,990	320,300	**472,350**	693,450	974,610	1,212,000	1,875,020
2022	110,697	169,595	213,790	308,400	**463,850**	697,500	1,004,000	1,268,100	1,980,010
2023	101,298	158,200	201,700	297,775	**457,600**	706,250	1,049,000	1,327,000	2,176,090
2024	92,500	146,400	189,500	286,575	**450,350**	709,900	1,080,000	1,401,200	2,305,030
2025	82,228	135,200	178,590	275,875	**441,100**	719,900	1,128,000	1,460,150	2,588,020
2026	73,708	124,200	166,590	262,775	**438,450**	724,950	1,167,000	1,540,050	2,709,080
2027	66,918	116,300	156,670	253,975	**432,200**	737,625	1,201,100	1,616,050	2,907,110
2028	60,650	107,900	146,790	245,800	**424,350**	738,550	1,246,000	1,688,050	3,088,070
2029	55,179	99,088	139,500	234,750	**417,100**	743,375	1,271,100	1,754,000	3,324,160
2030	51,079	93,278	131,100	226,800	**411,200**	751,975	1,320,000	1,858,200	3,647,050
2031	48,840	91,989	128,800	225,700	**411,650**	748,500	1,317,000	1,833,050	3,677,080
2032	47,519	90,984	125,700	225,175	**408,500**	743,600	1,303,000	1,808,050	3,640,050
2033	46,087	88,886	122,300	223,275	**403,700**	740,650	1,300,100	1,829,000	3,681,010

2034	44,010	86,807	123,400	219,900	**398,150**	741,550	1,302,100	1,838,000	3,719,100
2035	44,429	85,857	120,700	215,775	**397,850**	740,950	1,314,000	1,858,300	3,821,020
2036	43,089	83,659	118,590	214,375	**394,550**	739,950	1,331,000	1,889,000	3,954,030
2037	42,948	82,207	117,300	212,700	**389,350**	739,525	1,332,100	1,905,200	4,001,100
2038	42,380	80,670	114,890	209,875	**386,000**	741,500	1,336,000	1,906,100	4,236,170
2039	40,255	79,034	111,990	204,800	**385,350**	742,325	1,345,100	1,929,150	4,175,010
2040	38,160	76,747	109,900	201,675	**381,900**	741,675	1,360,100	1,950,450	4,127,030
2041	38,104	75,163	106,790	198,600	**377,450**	735,100	1,364,200	2,007,150	4,264,060
2042	36,509	73,397	104,800	195,175	**376,350**	735,525	1,378,200	2,014,100	4,441,250
2043	35,910	69,619	101,690	192,400	**372,850**	742,525	1,399,000	2,053,050	4,558,020
2044	34,019	66,828	99,510	187,600	**373,850**	743,975	1,405,100	2,098,150	4,650,400
2045	32,869	65,955	97,772	185,675	**368,350**	743,750	1,431,000	2,126,050	4,975,060
2046	31,027	63,636	95,302	183,575	**363,900**	747,125	1,429,000	2,130,100	5,035,230
2047	29,589	62,550	91,778	182,475	**363,850**	742,850	1,452,000	2,225,100	5,236,300
2048	28,180	60,552	89,723	179,975	**360,500**	748,225	1,477,300	2,247,150	5,370,000
2049	27,090	58,039	87,085	174,900	**357,100**	744,650	1,502,100	2,309,000	5,582,070
2050	25,249	56,470	85,606	172,200	**354,200**	749,250	1,511,000	2,307,150	5,617,150
2051	24,299	54,019	84,176	169,075	**353,000**	749,600	1,540,000	2,330,050	5,824,190
2052	23,049	52,470	80,274	167,175	**348,250**	756,075	1,553,000	2,366,200	5,936,090
2053	21,897	51,046	79,448	163,175	**346,100**	751,750	1,564,100	2,397,000	6,024,400
2054	21,519	49,580	76,854	159,875	**346,450**	756,175	1,601,100	2,408,100	6,327,140
2055	19,760	47,109	73,879	156,675	**342,100**	758,350	1,662,100	2,487,050	6,499,390
2056	18,648	45,170	72,394	152,400	**341,500**	761,400	1,639,100	2,622,050	6,690,210
2057	18,430	44,359	70,262	151,000	**338,800**	768,425	1,660,100	2,672,150	6,949,140
2058	17,840	42,217	67,614	148,600	**338,450**	764,500	1,682,000	2,787,150	7,131,140
2059	16,507	40,809	65,399	146,875	**338,200**	768,025	1,697,300	2,858,100	7,506,230
2060	15,269	39,449	64,047	142,675	**332,000**	771,900	1,750,000	2,908,050	7,897,280

Source: Own elaboration. Median forecasts in **bold**.

Table B.2. Environmental immigration to the UK: selected percentiles of forecasts

Year	1%	5%	10%	25%	**50%**	75%	90%	95%	99%
2010	0	0	0	1,210	**19,615**	46,528	72,631	89,771	128,201
2011	0	206	1,267	5,563	**21,715**	46,823	72,151	89,122	127,802
2012	0	297	2,068	8,309	**23,685**	47,745	72,377	89,723	128,001
2013	0	388	2,593	10,198	**25,750**	48,473	72,863	91,558	130,401
2014	0	428	3,024	11,510	**27,485**	50,313	74,640	93,923	137,300
2015	0	475	3,177	12,560	**29,005**	51,593	77,775	98,242	146,001
2016	0	505	3,365	13,260	**30,095**	53,363	81,622	103,310	155,504
2017	0	522	3,388	13,608	**30,845**	55,433	85,340	109,600	171,201
2018	0	519	3,412	13,608	**31,210**	57,123	90,552	115,300	188,900
2019	0	496	3,432	13,460	**31,505**	59,403	95,690	123,510	202,702
2020	0	496	3,395	13,220	**31,340**	61,160	101,010	133,705	227,220
2021	0	472	3,266	12,808	**31,325**	63,580	107,900	143,610	253,711
2022	0	450	3,075	12,310	**31,275**	65,365	114,600	153,300	274,110
2023	0	422	2,989	11,600	**31,110**	67,140	121,200	164,110	296,633
2024	0	396	2,718	10,830	**30,755**	68,513	127,210	178,705	334,208
2025	0	364	2,502	10,110	**30,235**	70,103	138,500	192,415	364,701
2026	0	317	2,276	9,383	**29,860**	71,713	143,900	204,905	397,904
2027	0	263	1,917	8,472	**29,035**	73,283	151,400	222,710	443,614
2028	0	210	1,515	7,444	**28,295**	75,113	159,600	235,010	501,809
2029	0	163	1,105	6,328	**27,450**	76,890	168,000	247,305	542,229
2030	0	100	648	5,060	**26,820**	78,495	177,710	263,535	587,943
2031	0	0	0	3,508	**26,415**	79,215	184,610	279,070	657,709
2032	0	230	1,078	6,695	**28,605**	81,230	182,820	275,100	640,804
2033	0	381	1,732	8,544	**30,585**	82,635	181,310	277,605	650,308
2034	0	485	2,229	9,852	**32,155**	84,235	182,510	279,810	666,549
2035	0	578	2,541	10,878	**33,910**	87,098	183,940	279,905	687,329
2036	0	635	2,798	11,660	**35,285**	87,793	186,830	284,000	688,173

2037	0	693	3,013	12,110	**35,990**	89,678	188,600	288,720	724,314
2038	0	763	3,162	12,650	**36,930**	91,545	192,810	288,730	689,051
2039	0	784	3,203	12,870	**37,355**	93,230	195,900	291,615	721,334
2040	0	752	3,303	13,188	**37,775**	94,695	198,940	301,455	727,523
2041	0	818	3,358	13,288	**37,895**	96,463	202,400	307,810	726,105
2042	0	829	3,337	13,180	**38,350**	97,103	203,800	312,000	791,346
2043	0	820	3,315	13,090	**38,330**	98,105	208,210	323,305	765,930
2044	0	841	3,281	13,018	**38,450**	98,045	213,250	327,210	832,216
2045	0	854	3,281	12,738	**38,290**	98,630	218,500	342,315	877,205
2046	0	816	3,182	12,488	**37,955**	99,340	224,960	356,050	931,664
2047	0	774	3,102	12,330	**37,530**	100,500	228,630	362,610	950,800
2048	0	787	2,990	12,005	**37,380**	100,850	235,090	373,305	1,039,040
2049	0	773	2,876	11,500	**36,695**	101,525	240,970	383,155	1,102,010
2050	0	722	2,701	11,205	**36,140**	102,200	248,000	398,910	1,137,010
2051	0	663	2,567	10,635	**35,770**	101,825	254,130	410,300	1,210,040
2052	0	635	2,399	10,278	**34,595**	102,600	257,110	428,115	1,235,250
2053	0	595	2,226	9,693	**34,145**	103,000	259,350	448,105	1,300,230
2054	0	551	2,029	9,196	**33,075**	102,800	268,230	465,445	1,359,060
2055	0	493	1,840	8,544	**32,225**	102,725	273,570	481,810	1,446,230
2056	0	452	1,658	7,997	**31,235**	103,500	280,000	496,250	1,499,080
2057	0	383	1,469	7,327	**29,825**	103,300	285,640	509,685	1,572,200
2058	0	315	1,223	6,446	**28,310**	102,700	297,270	536,825	1,668,030
2059	0	231	935	5,384	**26,680**	102,500	305,590	565,070	1,705,020
2060	0	140	603	4,121	**24,945**	102,800	312,740	583,335	1,772,300

Source: Own elaboration. Median forecasts in **bold**.

Appendix C. Estimation of univariate forecasting models

Table C.1. Estimates of model parameters (means and standard deviations) and measures of goodness-of-fit

Model	μ	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	ϕ_7	ϕ_8	σ	AIC*	BIC*	Probability**
IN***	0.03103	:	:	:	:	:	:	:	:	0.11560	–49.87	–49.31	0.5848
	(0.02003)	:	:	:	:	:	:	:	:	(0.01512)			
AR(1)	0.03130	–0.12382	:	:	:	:	:	:	:	0.11645	–48.82	–45.71	0.1607
	(0.01887)	(0.18694)	:	:	:	:	:	:	:	(0.01564)			
AR(2)	0.03367	–0.23133	–0.33718	:	:	:	:	:	:	0.10932	–51.94	–46.27	0.2125
	(0.01296)	(0.17593)	(0.17461)	:	:	:	:	:	:	(0.01469)			
AR(3)	0.03286	–0.19628	–0.30046	–0.00467	:	:	:	:	:	0.11360	–50.11	–41.89	0.0277
	(0.0176)	(0.22258)	(0.18978)	(0.19913)	:	:	:	:	:	(0.01587)			
AR(4)	0.03066	–0.18151	–0.25344	0.02871	0.13307	:	:	:	:	0.11463	–48.33	–37.56	0.0112
	(0.02561)	(0.22466)	(0.2197)	(0.20931)	(0.19936)	:	:	:	:	(0.01600)			
AR(5)	0.02958	–0.21601	–0.25265	–0.07706	0.12159	–0.04202	:	:	:	0.11842	–46.51	–33.18	0.0023
	(0.02643)	(0.22590)	(0.23619)	(0.25812)	(0.22427)	(0.21051)	:	:	:	(0.01667)			
AR(6)	0.02892	–0.28943	–0.32820	–0.08069	–0.00164	–0.03676	0.03016	:	:	0.11697	–44.51	–28.62	0.0008
	(0.03093)	(0.23621)	(0.24002)	(0.25957)	(0.26310)	(0.22600)	(0.20481)	:	:	(0.01735)			
AR(7)	0.03004	–0.18262	–0.25046	0.00207	0.00572	0.02529	0.07582	0.00126	:	0.12498	–42.59	–24.14	0.0000
	(0.02918)	(0.24052)	(0.24755)	(0.25958)	(0.24582)	(0.25635)	(0.22728)	(0.22145)	:	(0.01810)			
AR(8)	0.02770	–0.15459	–0.24801	–0.00933	0.02991	0.04648	0.07053	0.00922	0.07082	0.12743	–40.61	–19.61	0.0000
	(0.03155)	(0.25164)	(0.28357)	(0.28232)	(0.26305)	(0.25546)	(0.25658)	(0.22151)	(0.21499)	(0.01807)			

Notes: Colon (:) indicates 'not applicable'
* AIC – Akaike Information Criterion, BIC – Bayesian (Schwartz) Information Criterion;
** Probability – posterior probability of a given model, assuming equal prior probabilities of 1/9 for all of them, i.e. for $M_i \in$ {IN, AR(1), ..., AR(8)};
*** IN – Independent Normal model = AR(0);
For AIC, BIC and model probabilities, the optimal values have been underlined.

Source: Own elaboration

Appendix D. Operationalisation of GO-S scenarios and the resulting scenarios of immigration to the UK

Table D.1. Operationalisation of GO-S (2011) demo-economic scenarios and resulting scenarios of immigration to the UK (in thousands)

Year	2010	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
Scenario A											
- Global population (bn)	6.82	7.17	7.52	7.82	8.10	8.33	8.57	8.75	8.91	9.02	9.12
- Global old-age dependency ratio	21.00	23.80	27.28	31.57	35.87	40.71	46.23	52.37	59.67	65.94	71.53
- GNI per capita in 'Global South'	1080.57	1193.03	1317.21	1454.30	1605.67	1772.79	1957.30	2161.02	2385.94	2634.27	2908.44
- GNI per capita ratio (rich : poor)	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00	35.00
Result: Immigration to the UK (median)	**536.8**	**489.1**	**421.8**	**391.8**	**351.4**	**329.2**	**302.0**	**274.1**	**254.9**	**231.6**	**222.3**
- - of which, environmental (median)	**18.8**	**24.4**	**22.9**	**20.7**	**11.3**	**21.4**	**22.8**	**22.8**	**19.6**	**15.9**	**5.7**
Scenario B											
- Global population (bn)	6.74	7.01	7.24	7.44	7.59	7.70	7.77	7.82	7.78	7.71	7.65
- Global old-age dependency ratio	21.00	23.72	27.39	31.81	36.30	41.60	47.58	54.37	62.33	69.40	75.78
- GNI per capita in 'Global South'	1107.05	1379.59	1719.22	2142.46	2669.89	3327.17	4146.26	5167.00	6439.02	8024.19	9999.60
- GNI per capita ratio (rich : poor)	34.16	30.27	26.82	23.76	21.05	18.65	16.52	14.64	12.97	11.49	10.18
Result: Immigration to the UK (median)	**536.7**	**483.0**	**421.8**	**377.3**	**329.5**	**312.9**	**283.6**	**264.8**	**240.6**	**228.9**	**215.9**

- - of which, environmental (median)	**18.9**	**24.0**	**22.7**	**19.6**	**11.1**	**21.2**	**21.6**	**20.7**	**18.7**	**14.7**	**5.2**
Scenario C											
- Global population (bn)	6.82	7.17	7.52	7.82	8.10	8.33	8.57	8.75	8.91	9.02	9.12
- Global old-age dependency ratio	21.00	23.80	27.28	31.57	35.87	40.71	46.23	52.37	59.67	65.94	71.53
- GNI per capita in 'Global South'	1080.57	1193.03	1317.21	1454.30	1605.67	1772.79	1957.30	2161.02	2385.94	2634.27	2908.44
- GNI per capita ratio (rich : poor)	34.83	33.97	33.13	32.32	31.52	30.74	29.99	29.25	28.53	27.82	27.14
Result: Immigration to the UK (median)	**538.1**	**493.0**	**420.3**	**386.9**	**357.8**	**325.7**	**292.8**	**268.3**	**244.9**	**229.1**	**211.1**
- - of which, environmental (median)	**19.0**	**24.0**	**22.6**	**20.3**	**10.8**	**20.9**	**22.0**	**20.4**	**18.4**	**14.5**	**5.1**
Scenario D											
- Global population (bn)	6.81	7.18	7.51	7.80	8.05	8.28	8.47	8.65	8.75	8.85	8.90
- Global old-age dependency ratio	21.00	23.47	26.63	30.06	33.56	37.41	41.18	45.57	50.79	54.29	57.24
- GNI per capita in 'Global South'	1069.97	1124.55	1181.92	1242.21	1305.57	1372.17	1442.16	1515.73	1593.05	1674.31	1759.71
- GNI per capita ratio (rich : poor)	34.65	32.97	31.37	29.85	28.40	27.02	25.71	24.46	23.28	22.15	21.07
Result: Immigration to the UK (median)	**538.0**	**490.2**	**417.9**	**386.4**	**350.4**	**311.2**	**284.4**	**264.2**	**236.3**	**223.3**	**208.4**
- - of which, environmental (median)	**18.9**	**23.9**	**22.5**	**19.7**	**10.8**	**20.8**	**20.8**	**20.2**	**17.6**	**14.5**	**4.7**

Source: Own elaboration, based on GO-S (2011) and IIASA (2007) [See Section 2.4]

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