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When will European Muslim population be majority and in which country?

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Abstract

Purpose – The purpose of this paper is to estimate the years the European Muslim population will be majority among 30 European countries.

Design/methodology/approach – The methodology/approach is to forecast the population of 30 European countries with wavelet analysis combined with the Burg model which fits a *p*th order autoregressive model to the input signal by minimizing (least squares) the forward and backward prediction errors while constraining the autoregressive parameters to satisfy the Levinson–Durbin recursion, then relies on an infinite impulse response prediction error filter. Three scenarios are considered: the zero-migration scenario where the authors assume that the Muslim population has a higher fertility (one child more per woman, on average) than other Europeans, mirroring a global pattern; a 2017 migration scenario: to the Muslim population obtained in the zero-migration scenario, the authors add a continuous flow of migrants every year based on year 2017; the mid-point migration scenario is obtained by averaging the data of the two previous scenarios.

Findings – Among three scenarios, the most likely mid-point migration scenario identifies 13 countries where the Muslim population will be majority between years 2085 and 2215: Cyprus (in year 2085), Sweden (2125), France (2135), Greece (2135), Belgium (2140), Bulgaria (2140), Italy (2175), Luxembourg (2175), the UK (2180), Slovenia (2190), Switzerland (2195), Ireland (2200) and Lithuania (2215). The 17 remaining countries will never reach majority in the next 200 years.

Originality/value – The growing Muslim population will change the face of Europe socially, politically and economically. This paper will provide a better insight and understanding of Muslim population dynamics to European governments, policymakers, as well as social and economic planners.

Keywords European population, Muslim population, Forecasts, Wavelet analysis, Burg model

Paper type Research paper

1. Introduction

This paper presents estimates of the years the European Muslim Population will be majority in 30 European countries using spectral analysis. Europe's population represents about 10 per cent of the world population and about 5 per cent of Europe's population is Muslim. Europe has experienced a refugee crisis that reached a peak in 2015 with an influx of refugees coming mainly from Muslim countries across the Mediterranean Sea or overland

JEL classification – C53, E37

No potential conflict of interest was reported by the authors.

through Southeast Europe. Refugees have come primarily from Syria, Afghanistan, Iraq and Eritrea. In all, 86 per cent of them are Muslims based on the top ten origins of refugees from 2010 to 2016 (Pew Research Centre, 2017). Refugees include two main groups: asylum seekers and economic migrants.

The growing Muslim population has already changed the face of Europe socially, politically and economically. Socially, the Muslim community experiences more communitarianism than the Christian community does; the latter being more fragmented in terms of churches, beliefs and practice. Muslims are strongly attached to their beliefs and their roots and keep usually a relationship with their country of origin if they are migrants. Politically, the Muslim community includes more left-wing voters, leftist political parties being usually in favor of integrating Muslims migrants to the European society (Dancygier, 2018). Economically, Muslims are less educated than non-Muslims are, a majority of them work in the construction and the manufacturing sectors. The second or third generations of Muslim migrants may have access to education, get diplomas and occupy white-collar employments. They can also be involved in politics. There have been many examples of Muslim citizens having succeeded in politics where they have occupied key political roles of deputies, ministers or mayors of large cities, for example the current mayor of London, UK, Mr Sadiq Aman Khan, a practising Muslim of Pakistani origin who took up office in 2016 or Mrs Aygül Özkan who served as Minister of Social Affairs, Women, Families, Health and Integration between 2010 and 2013, being the first ever German politician of Turkish descent and a Muslim serving as minister. The greater the proportion of Muslims in a country, the faster the change will be in the society: construction of mosques, prayer calls from loudspeakers, open air worships, halal products available in supermarkets and produced locally, compatible workload and adjustable working hours with Ramadan constraints are examples of such changes in Europe. In recent years, new laws targeting Muslims have been voted such as laws to ban Burqa, headscarves and veils in public (Weaver, 2017) or laws against family reunification to limit people's ability to reunify to control immigration in Denmark, The Netherlands, Germany, Norway or the UK.

European political decisions may also be more and more subject to foreign governments' intrusion. For example, most of the Turkish migrant associations in Germany, religious, political and business-oriented, are characterized by transnational linkages where they maintain contacts to political representatives in both countries, Germany and Turkey (Amelina and Faist, 2008). Another example is the regular interference of the prime minister of Turkey telling Turks living in Europe that they do not need to assimilate into their host societies, urging them to make more babies, advising them to become more engaged in society and more influential in politics (Press, 2018). Funds from the Kingdom of Saudi Arabia (KSA) which have financed the construction of mosques and the spreading of Wahhabism in Europe have also come with the cost of a swelling influence of KSA on worshipers and domestic affairs. Wahhabism is the radical ideology dominating KSA, freely preached by government-backed clerics. Belgium has voiced concerns over the spread of KSA-backed Wahhabism throughout the country and the rest of Europe (PressTV, 2017) and has terminated KSA's half-century old lease of the Grand Mosque in Brussels over concerns it was promoting radicalism. France and Germany have also shut mosques suspected of radicalizing and encouraging young Muslims to travel to war zones including Syria and Iraq (AFP, 2018). Finally, anti-Islam political parties have gained support in many European countries in reaction to the uncontrolled wave of refugees flooding Europe where most governments have been overwhelmed by the influx of migrants, situation exacerbated by a string of terror attacks undertaken by radical Islamists in the UK, Belgium, France, Russia and Germany that have pressured European governments to bolster security measures and to deal with a very angry local population. All these social, political and economic changes will bring periods of adjustment that may be painful for the European society – some talk of shock of civilizations – and will depend on the degree of openness and tolerance of the communities toward each other and their willingness to build a balanced European society enriched with a diversity of beliefs and cultures.

2. Literature review

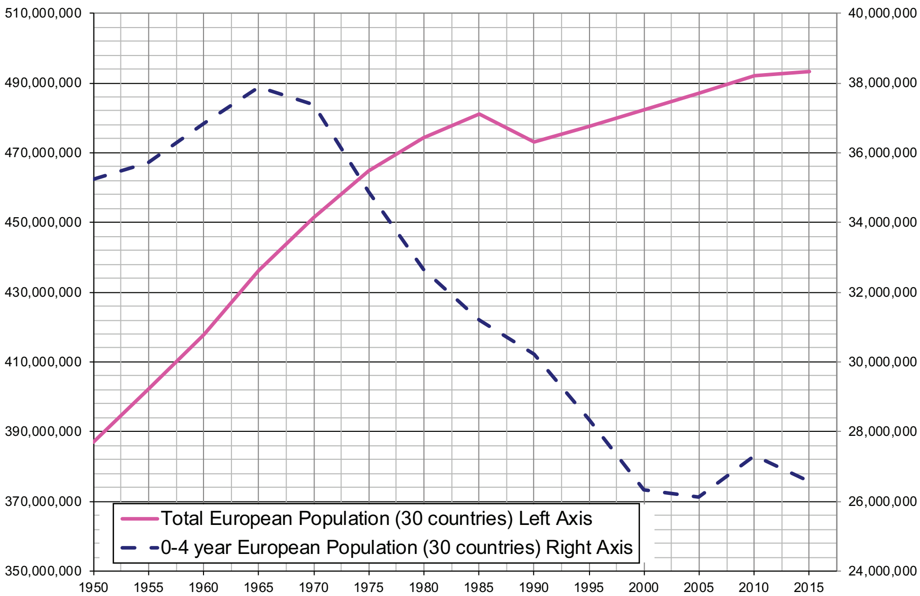
Wavelet analysis, a tool of signal processing, is used in Physics to model physical phenomena such as electrical, audio or seismic signals which propagate through space in waveforms. Wavelets mimic signals with specific properties that make them useful for signal processing. Signal processing focuses on the analysis, synthesis, and modification of signals. Spectral (or spectrum) analysis focuses on data analysis of signals. From a finite record of a stationary data sequence, spectral analysis estimates how the total power is distributed over frequency (Stoica and Moses, 2005). Spectral analysis may reveal hidden periodicities in data, which are to be associated with cyclic behavior or recurring processes in the field of meteorology or astronomy, for example.

Forecasters using wavelet analysis have focused on the Discrete Wavelet Transform due to several not tractable properties of continuous wavelet transform such as highly redundant wavelet coefficients (Valens, 1999), infinite number of wavelets in the wavelet transform and no analytical solutions found for most functions of the wavelet transforms. Renaud *et al.* (2002) proposed a wavelet-based forecasting method using redundant "à trous" wavelet transform and multiple resolution signal decomposition. Conejo *et al.* (2005) detailed a forecasting day-ahead electricity prices based on the wavelet transform and ARIMA models. Schlüter and Deuschle (2010) were able to capture seasonalities with time-varying period and intensity, incorporated the wavelet transform to improve forecasting methods. Tan *et al.* (2010) proposed a price forecasting method based on wavelet transform combined with ARIMA and GARCH models. Kao *et al.* (2013) integrated wavelet transform, multivariate adaptive regression splines (MARS), and support vector regression (SVR called Wavelet-MARS-SVR) to address the problem of wavelet sub-series selection and to improve forecast accuracy. Ortega and Khashanah (2014) proposed a wavelet neural network model for the short-term forecast of stock returns from high-frequency financial data. Kriechbaumer *et al.* (2014) showed the cyclical behavior of metal prices. With wavelet analysis, they were able to capture the cyclicality by decomposing a time series into its frequency and time domain. They presented a wavelet-autoregressive integrated moving average (ARIMA) approach for forecasting monthly prices of aluminum, copper, lead and zinc. He *et al.* (2014) proposed an entropy optimized wavelet-based forecasting algorithm to forecast the exchange rate movement. Rostan *et al.* (2015a) appraised the financial sustainability of the Spanish pension system using Spanish population forecasts. Berger (2016) transformed financial return series into its frequency and time domain via wavelet decomposition to separate short-run noise from long-run trends and assess the relevance of each frequency to value-at-risk (VaR) forecast. Rostan *et al.* (2017) applied signal processing to yield curve forecasting with a robust outcome when benchmarked to the Diebold and Li (2006) model. With a refined methodology using multiscale principal component analysis to take into account the co-dynamics of age groups, Rostan and Rostan (2017) forecasted European and Asian populations with signal processing. Rostan and Rostan (2018a) illustrated with market data the versatility of wavelet analysis to the forecast of financial times series with distinctive properties. Rostan and Rostan (2018b, 2018c) applied wavelet analysis to the forecasts of Spanish (2018b) and Greek (2018c) economies. Rostan and Rostan (2018d) applied signal processing to the forecast of the Saudi population.

Section 3 presents the five-step methodology. Section 4 gathers the results and Section 5 concludes.

3. Methodology

The objective of the paper is to present an application of wavelet analysis to the forecasts of Muslim population for 30 European countries. We estimate the future years when the Muslim population will be majority population for 30 European countries. The methodology, improved with a de-noising and compression step, is derived from Rostan and Rostan (2018a) and requires five steps illustrated with the time series of the Europe total population (30 countries). Figure 1 illustrates the series of the total population and the 0-4-year age group from 1950 to 2015 by step of Five years (14 data) released by the Population Division of the United Nations Secretariat. The 0-4-year age group is involved in the 5-step methodology since we assume that the 0-4-year age group is a good proxy (after adjustment for scale) of the fertility rate. Figure 1 illustrates two opposite trends, a growing European total population but a declining 0-4-year age group which, as a proxy of the fertility rate, is doomed to decline in the future. We clearly anticipate that the European population (30 countries) will get older in future years. However, there is an external factor not reflected by these historical data, the recent inflow of Muslim refugees following the European refugee crisis which has started in 2015 and that may revert the trend of the fertility rate, assuming that the Muslim population has higher fertility (one child more per woman, on average) than other Europeans, mirroring a global pattern (Pew Research Centre, 2017).



Sources: Population Division of the United Nations Secretariat. http://esa.un.org/unpd/wpp /DVD/

Figure 1.
The European total population and the 0-4-year age group (30 countries) for the 1950-2015 period obtained by census

3.1 Step 1: de-noising and compression of the first-order difference of the European total population time series

We compute the first-order difference of the European total population series to transform non-stationary series into stationary series. We apply the Augmented Dickey-Fuller test to the time series before and after differentiation: before differentiation, the time series are non-stationary (i.e. existence of a unit root) and after differentiation the time series is stationary (rejection of the existence of a unit root). The choice of this transformation relies on the fact that wavelet analysis presents a more accurate forecasting ability with stationary time series rather than non-stationary time series. Refer for example to Rostan and Rostan (2018a) for a demonstration.

We then de-noise the series using a one-dimensional de-noising and compression-oriented function using wavelets. The function is called "wdencmp" in Matlab (Misiti *et al.*, 2015). The underlying model for the noisy signal is of the form:

$$s(n) = f(n) + \sigma e(n) \tag{1}$$

where time n is equally spaced, e(n) is a Gaussian white noise $N(0,1)$ and the noise level σ is supposed to be equal to 1. The de-noising objective is to suppress the noise part of the signal s and to recover f.

The de-noising procedure proceeds in three steps:

(1) Decomposition. We choose the wavelet *sym4* and choose the level 2-decomposition. *Sym4* is a symlets wavelet of order 4 used as the mother wavelet for decomposition and reconstruction. It is a nearly symmetrical wavelet belonging to the family of Symlets proposed by Daubechies (1994). We compute the wavelet decomposition of the signal s at Level 2.

(2) Detail coefficients thresholding. For each level from 1 to 2, we select a threshold and apply soft thresholding to the detail coefficients.

(3) Reconstruction. We compute wavelet reconstruction based on the original approximation coefficients of level 2 and the modified detail coefficients of levels from 1 to 2.

Like de-noising, the compression procedure contains three steps:

1) Decomposition. 2) Detail coefficient thresholding. For each level from 1 to 2, a threshold is selected and hard thresholding is applied to the detail coefficients. 3) Reconstruction. The difference with the de-noising procedure is found in Step 2. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using a small number of approximation coefficients (at a suitably selected level) and some of the detail coefficients.

We illustrate in Figures 2 (appendix material) the European total population (14 data) before differentiation (top figure), after differentiation (middle) and after de-noising and compression (bottom).

3.2 Step 2: wavelet decomposition

We decompose the signal after being differentiated, de-noised and compressed. The signal, i.e. the time series of the European total population transformed at step 1 (13 data), is decomposed into decomposed signals *cAs* named approximations and *cDs* named details. The Discrete Wavelet Transform is a kind of decomposition scheme evaluated by passing the signal through lowpass and highpass filters (Corinthios, 2009), dividing it into a lower

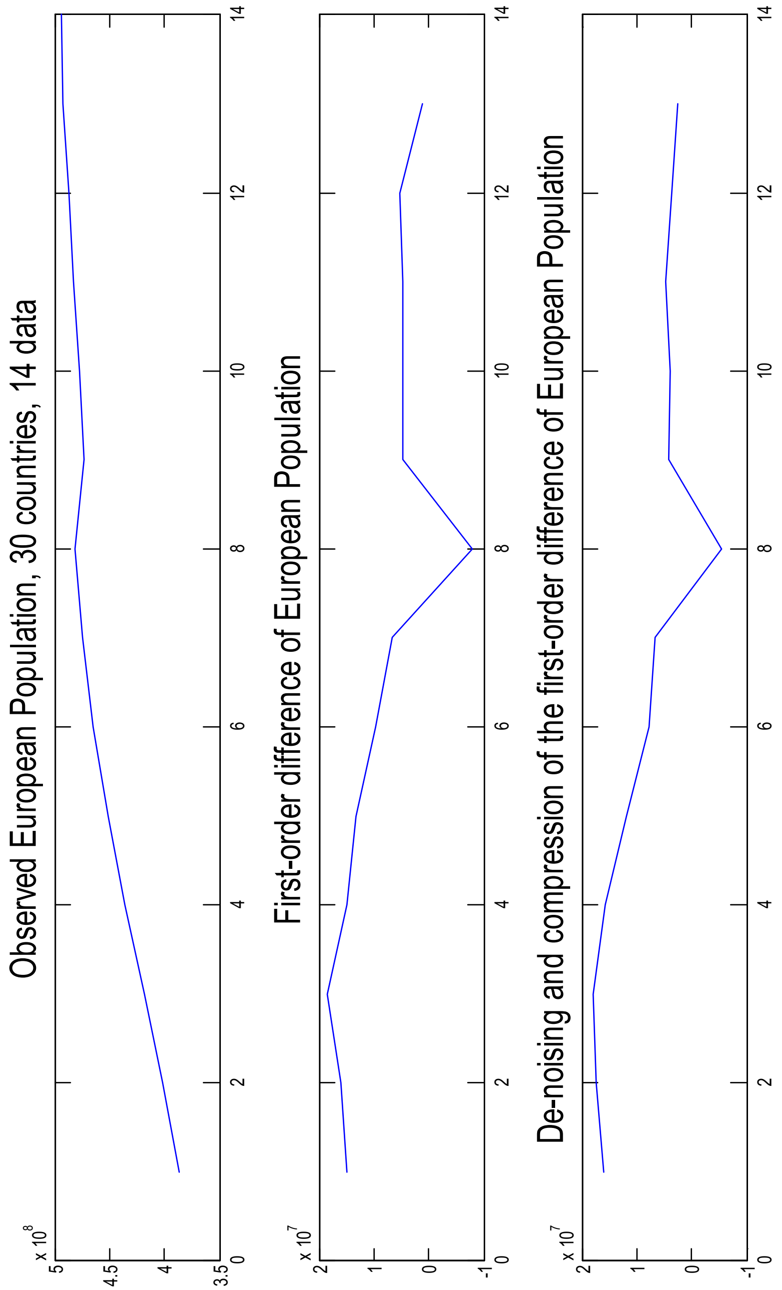


Figure 2.
Observed European total population (30 countries) from 1950 to 2015 (14 data, top), first-order difference of the European total population (middle), de-noising and compression of the first-order difference of the European total population (bottom)

frequency band and an upper band. Each band is subsequently divided into a second level lower and upper bands. The process is repeated, taking the form of a binary, or "dyadic" tree. The lower band is referred to as the approximation *cA* and the upper band as the detail *cD*. The two sequences *cA* and *cD* are downsampled. The downsampling is costly in terms of data: with multilevel decomposition, at each one-level of decomposition the sample size is reduced by half (in fact, slightly more than half the length of the original signal, since the filtering process is implemented by convolving the signal with a filter. The convolution "smears" the signal, introducing several extra samples into the result). Therefore, the decomposition can proceed only until the individual details consist of a single sample. Thus, the number of levels of decomposition will be limited by the initial number of data of the signal. In this paper, we apply a level of decomposition that fits best the data of each variable as explained at the end of the Methodology section. Figures 3 (appendix material) illustrates the 4^{th}-level decomposition/reconstruction of the transformed European total population (after differentiation and de-noising/compression, 13 points). We observe in Figures 3 that details *cDs* are small and look like high-frequency noise, whereas the approximation *cA4* contains less noise than does the initial signal. In addition, the higher the level of decomposition, the lower the noise generated by details. For a better understanding of signal decomposition using discrete wavelet transform, refer to the methodology section of Rostan and Rostan (2018a).

3.3 Step 3: Burg extension of approximations and details

We apply Burg extension to *cA* and *cD*. To run the Burg extension, we apply an autoregressive *pth* order from historical data, in this paper we find the optimal *pth* order by minimizing the Root Mean Square Error for a given level of decomposition/reconstruction as explained in the last section "Identifying the optimal level of decomposition/reconstruction" of the methodology section. For instance, in 2015, when forecasting European total population for the subsequent years, the optimal *pth* order is 12. Given x the decomposed signal (which is *cA* or *cD*), we generate a vector a of all-pole filter coefficients that model an input data sequence using the Levinson-Durbin algorithm (Levinson, 1946; Durbin, 1960). We use the Burg (1975) model to fit a *pth* order autoregressive (AR) model to the input signal, x, by minimizing (least squares) the forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion. x is assumed to be the output of an AR system driven by white noise.

Vector a contains the normalized estimate of the AR system parameters, A(z), in descending powers of z:

$$H(z) = \frac{\sqrt{e}}{A(z)} = \frac{\sqrt{e}}{1 + a_2 z^{-1} + \ldots + a_{(p+1)} z^{-p}} \tag{2}$$

Since the method characterizes the input data using an all-pole model, the correct choice of the model order p is important. In Figure 4 (appendix material), the prediction error, e(n), can be viewed as the output of the prediction error filter A(z), where H(z) is the optimal linear predictor, x(n) is the input signal, and $\hat{x}$(n) is the predicted signal.

In a last step, the Infinite Impulse Response (IIR) filter extrapolates the index values for each forecast horizon. IIR filters are digital filters with infinite impulse response. Unlike finite impulse response (FIR) filter, IIR filter has the feedback (a recursive part of a filter) and is also known as recursive digital filter.

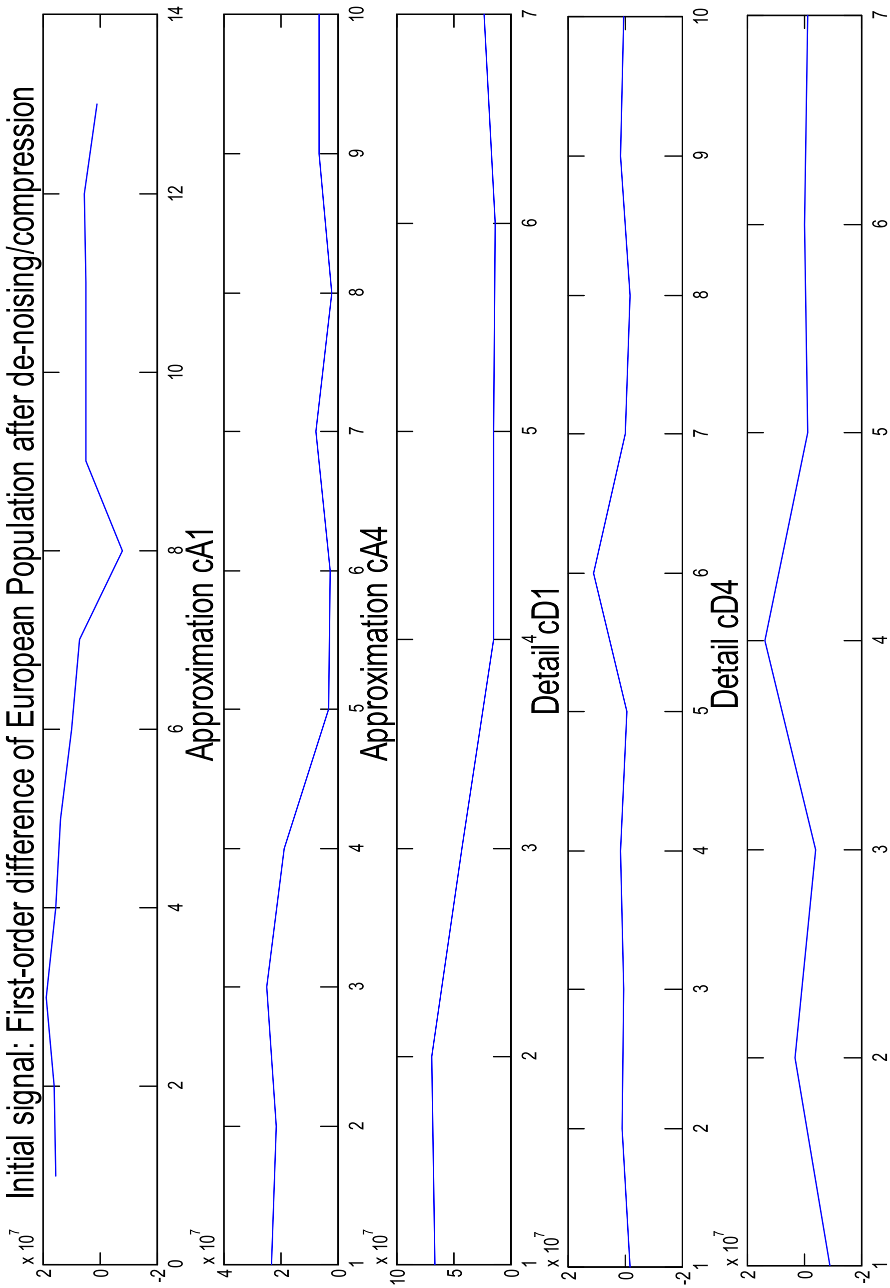


Figure 3.
4th-level decomposition of the transformed European total population, 30 countries, 13 data (after differentiation and de-noising/compression) using one-dimensional discrete wavelet analysis

3.4 Step 4: Wavelet reconstruction

We recompose the forecasted signals after Burg extension using the methodology illustrated in Figure 5 for the 3rd-level decomposition/reconstruction diagram. After reconstruction, we retransform the time series of the first-order difference of European total population into European total population absolute level.

Based on steps 1 to 4, we illustrate in Figure 6 the forecasts of the European total population and the 0-4-year age group (30 countries) for the 2015-2220 period with spectral analysis (4th level of decomposition/reconstruction, pth-order = 12). As expected the uptrend of the total population and the downtrend of the 0-4-year age group are confirmed, which will make the European population getting older.

3.5 Step 5: forecasting the Muslim population

3.5.1 Zero-migration scenario. Once we have forecasted the European total population (30 countries) and the 0-4 age group of the European population (30 countries) following the four-step methodology, we forecast the Muslim population in a zero-migration scenario: we assume that all refugee flows will stop after 2015, which is considered the most conservative approach. The reader may find this assumption surprising, knowing that more refugees arrived after 2015 but we adjust this additional inflow of refugees' post 2015 with the fact that we apply the 2016 proportions of the European Muslim population for the 30 countries collected by the Pew Research Centre (2017) to the 2015 UN data. The year 2015 is the base year of our forecasts. Assuming that the Muslim population has higher fertility (one child more per woman, on average) than other Europeans, mirroring a global pattern (Pew Research Centre, 2017), we will compute the newborn Muslim babies every five years. For example, assuming that in 2015 the proportion of Muslims is 5 per cent for the entire European Muslim population (30 countries), 5 per cent of 493,283,559 is 24,664,178, the total number of European Muslims in year 2015. In year 2020, five year later, 5 per cent of 498,585,190, the forecasted value obtained with spectral analysis, is 24,929,260. We assume that the proportion of Muslim babies between year 2015 and 2020 is also 5 per cent. Since Muslims have higher fertility (one child more per woman, on average), we assume that 5 per cent of the age group 0-4 years of the European population (30 countries) will be added to the Muslim population of 24,929,260, i.e. 5 per cent of 27,036,968 equal to 1,351,848 added to 24,929,260, equal to 26,281,108, or 5.27 per cent of 498,585,190. The proportion of 5.27 per cent will be applied to the computation of the estimated number of new Muslim babies for the period 2020-2025 and to the proportion of the Muslim population in 2025; the two numbers will be added to compute the estimated number of Muslims in 2025, we get 5.5 per cent of the total European population (30 countries) and so on. Therefore, we also apply the 4-step methodology to the forecast of the 0-4 age group of the European population (30 countries) as illustrated in Figure 6, because estimates of the 0-4 age group are needed to compute the number of new Muslim babies every 5 years. Finally, we illustrate the forecasts

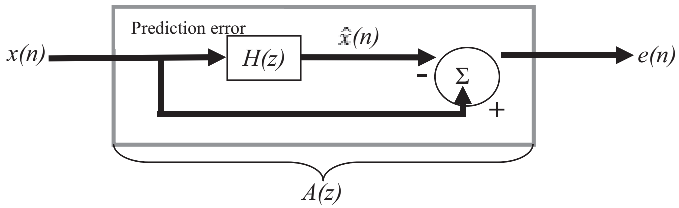
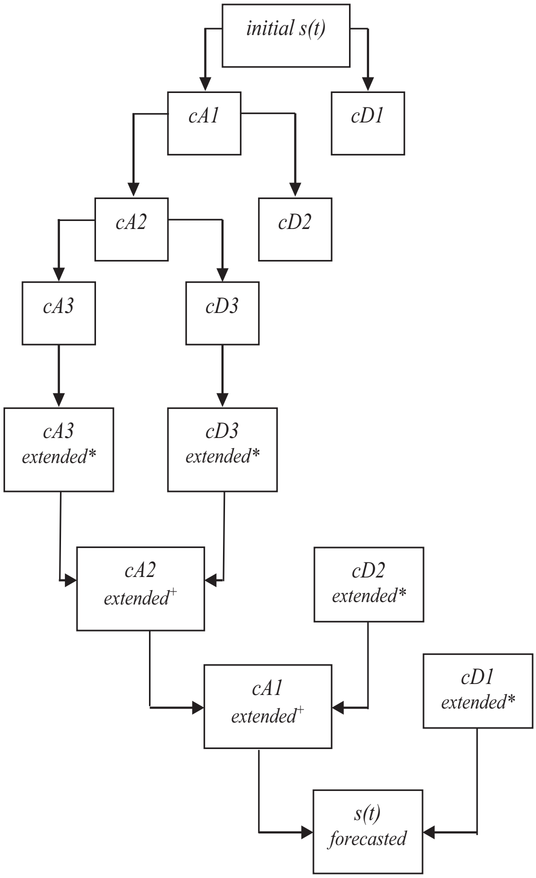


Figure 4. Prediction error filter to run the Burg extension



Notes: (*) Extended with Burg extension; (+) Extended by reconstruction of extended approximation and detail

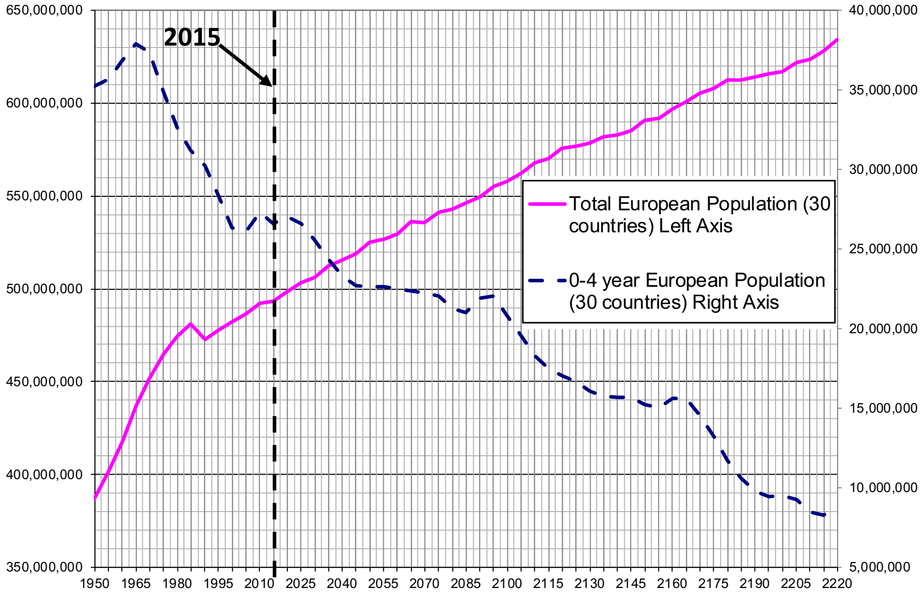
Figure 5.
Diagram of a 3rd-level wavelet decomposition/reconstruction tree to forecast the initial signal *s*(t)

of the European Muslim total population versus the European total population (30 countries) in Figure 7.

The European Muslim population should more than tripled (3.6 times) in the next 200 years, from 24,664,178 (5 per cent of the total population) in 2015 to 89,585,190 (14.13 per cent) in 2220.

3.5.2 2017 Migration scenario. To the Muslim population obtained in the Zero-migration Scenario in section 3.5.1., assuming a higher Muslim fertility rate, we add a continuous flow of migrants every year based on year 2017. Figure 8 illustrates the number of first-time asylum applicants in 2017 in 30 countries (Eurostat, 2017).

Germany (31 per cent of the total first-time asylum applicants), Italy (18 per cent), France (14 per cent) and Greece (8 per cent) received most of the first-time asylum applicants (70 per cent) and will therefore be the most impacted by this scenario. We use the 2017 number of first-time asylum applicants as a proxy of the annual flow of migrants, assumed to be continuous and constant in the subsequent years. Based on the



Sources: Population Division of the United Nations Secretariat. http://esa.un.org/unpd/wpp/DVD/

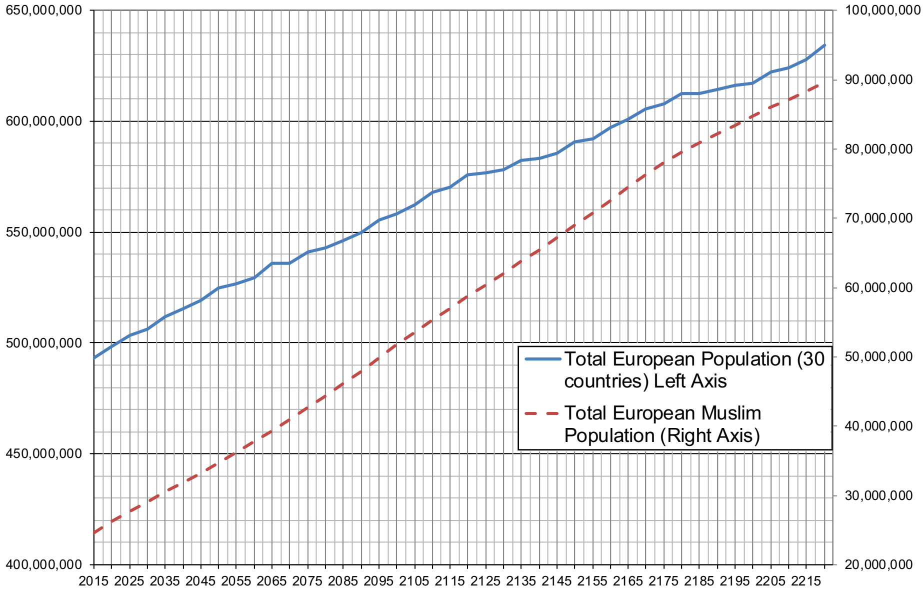
Figure 6.
Forecasts with spectral analysis of the European total population and the 0-4-year age group (30 countries) for the 2020-2220 period (4th level of decomposition/reconstruction, pth-order = 12). Historical data from 1950 to 2015 obtained by census

top ten origins of refugees from 2010 to 2016, 86 per cent of them are Muslims (Pew Research Centre, 2017). We will therefore assume that 86 per cent of the first-time asylum applicants are Muslims. We illustrate in Figure 9 the trend of the number of first-time asylum applicants for the 30 countries between 2008 and 2017. There is a net decline (-48 per cent) between year 2015 (the peak of the refugee crisis) and 2017 following drastic plans to stop the influx of refugees in many countries. These plans have involved the building of fences, stringent border controls and refusal from many countries of meeting the quotas of refugees instituting by the European Union's migration commission. The choice of the year 2017 as a proxy is explained by the fact that 1)it is the most recent known data and 2)the 2017 point is aligned with points 2008 to 2014 as illustrated by the dot line joining points 2008 and 2017 in Figure 9. 2015 and 2016 points are outliers. Although the trend of the number of first time asylum applicants is positive, we assume in this scenario a flat trend of the number asylum applicants in future years based on year 2017 data.

3.5.3 Mid-point migration scenario. The mid-point migration scenario data are obtained by averaging the data of the two previous scenarios.

3.6 Assessing the forecasting ability of spectrum analysis

An additional exercise is to assess the forecasting ability of spectrum analysis. We measure the forecasting error over the last five in-sample data of European total population time series for 30 countries for the years 1995, 2000, 2005, 2010 and 2015. We benchmark spectrum analysis to ARIMA(1,2,1) forecasting model (Box and Jenkins, 1976; Baillie and Bollerslev, 1992; Box *et al.*, 1994) applied to the absolute level of European total population



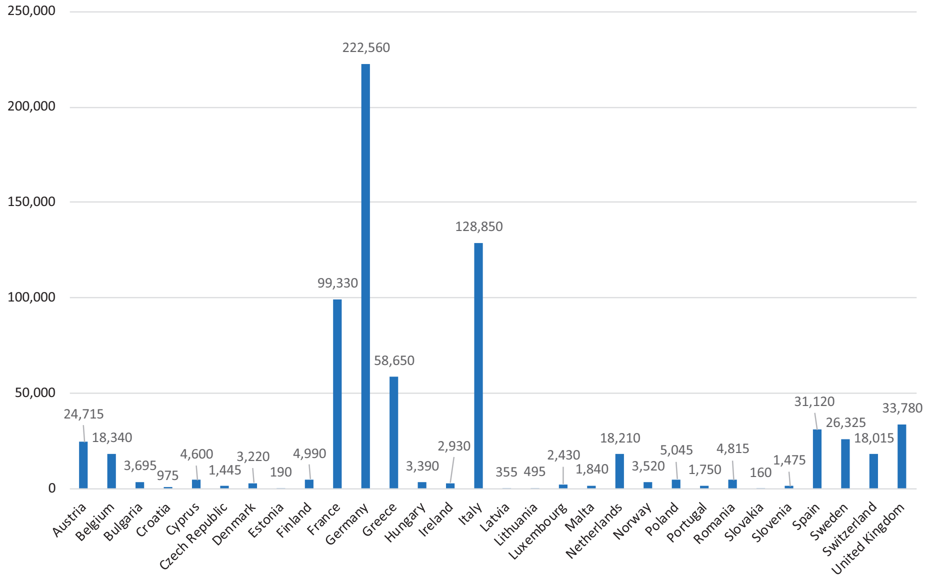
Sources: Population Division of the United Nations Secretariat. http://esa.un.org/unpd/wpp/DVD/

Figure 7. Forecasts of the European Muslim total population versus the European total population (30 countries) for the 2020-2220 period (4th level of decomposition/reconstruction, pth-order = 13). Historical data from 1950 to 2015 obtained by census

(i.e. no de-noising and no decomposition of the time series). We use the Root Mean Error Square criteria (forecasts versus historical data) to compute the error of forecasting. Spectrum analysis beats ARIMA(1,2,1) model with a RMSE of 5,341,392 versus 102,403,988 with ARIMA. Figure 8 illustrates the European total population forecasts with the two models.

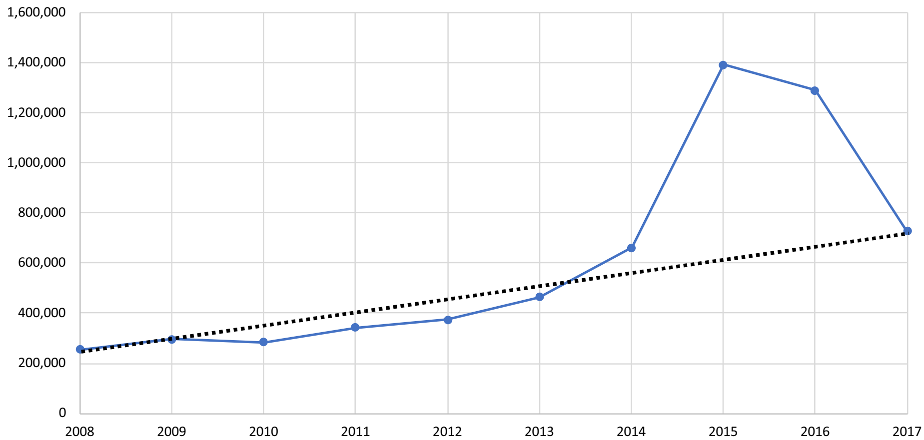
We choose the ARIMA(1,2,1) model since it best fits the data of the European total population (30 countries). We identify the ARMA lags $p = 1$ and $q = 1$ with the Bayesian information criterion (BIC) to the European total population time series (9 data). For this purpose, we estimate several models with different p and q values at different levels of differencing. For each estimated model, we compute the loglikelihood objective function value. Then, we input the loglikelihood value to compute the BIC measure of fit which penalizes for complexity. This methodology is implemented in MATLAB using the econometrics toolbox.

To formally identify the ARMA lags, we fit several models with different lag choices, making the degree of differencing (i.e. the "I" of ARIMA) varying from 0 to 2. We fit all combinations of ARMA(p,q) for $p = 1,\ldots,2$ and $q = 1,\ldots,2$ (a total of 4 models per degree of differencing). We store the loglikelihood objective function and number of coefficients for each fitted model. We calculate the BIC for each fitted model. We obtain four output BIC matrices for no differencing, the first, second and third order differencing. In the output BIC matrix below, the rows correspond to the AR degree (p) and the columns correspond to the MA degree (q). The best values in the BIC matrices are the smallest BIC value. The smallest value is obtained with the second order differencing:



Source: Eurostat (2017)

Figure 8.
Number of first-time asylum applicants in 2017 in 30 European countries



Source: Eurostat (2017)

Figure 9.
Total number of first time asylum applicants in 30 European countries between 2008 and 2017

$$\begin{array}{cc} & q \\ p & \begin{array}{cc} 314.7631 & 319.7855 \\ 318.2631 & 324.1994 \end{array} \end{array}$$

$$\text{Selected model: ARIMA}(p,d,q) = \text{ARIMA}(1,2,1)$$

3.7 Identifying the optimal level of decomposition/reconstruction

Finally, we focus on the optimal level of decomposition/reconstruction of our forecasting model. We make the level varying from 1 to 7. Levels 1, 2 and 3 return an error message. Figure 11 (appendix material) illustrates the RMSE computed on the last

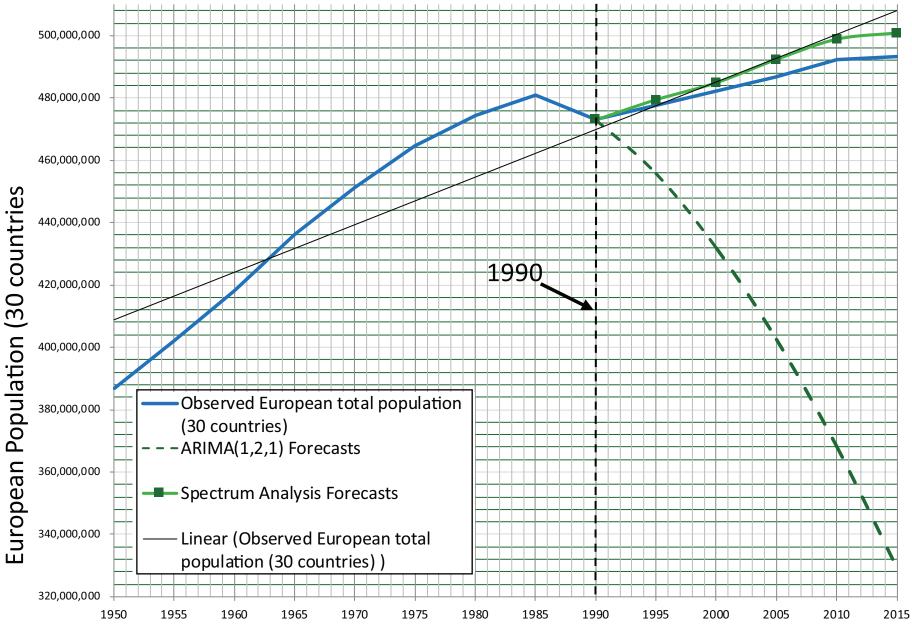


Figure 10. European total population (30 countries) forecasts for the in-sample years 1995, 2000, 2005, 2010 and 2015, ARIMA(1,2,1) versus Spectrum Analysis (level-4 decomposition/ reconstruction, *pth* order = 8)

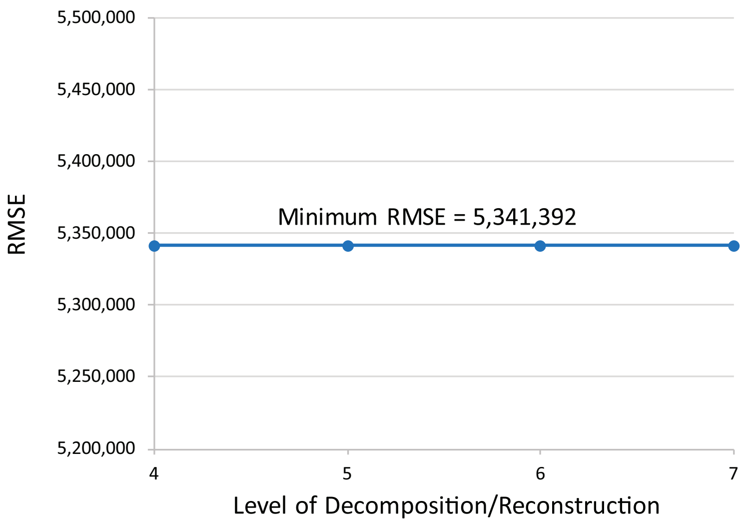


Figure 11. RMSE versus level of decomposition/ reconstruction

5 in-sample years of our database for the years 1995, 2000, 2005, 2010 and 2015 (forecasts versus observed data) of European total population (30 countries). Since the RMSE is constant for levels 4 to 7, we choose the 4th level of decomposition-reconstruction for our forecasts for simplicity.

4. Results

We apply the five-step methodology to each European country among the 30. We identify three tiers depending on the level of forecasted growth of the European Muslim population among the 30 countries, high-growth, medium-growth and low-growth and 3 scenarios, zero-migration, 2017 migration scenario, and mid-point scenario.

4.1 Zero-migration scenario

4.1.1 Tier 1: high-growth Muslim population countries. Among the High-Growth Muslim population countries, 6 of them will reach a majority of Muslim population in the next 200 years, Belgium (in 2175), Bulgaria (in 2160), Cyprus (in 2175), France (in 2165),

Tier 1: High-growtd Muslim population countries	>5%	>10%	>25%	>50%	>75%
Belgium	2015	2045	2120	2175	2205
Bulgaria	2015	2015	2130	2160	2180
Cyprus	2015	2015	2020	2175	N/A
France	2015	2030	2105	2165	2200
Ireland	2105	2140	2195	N/A	N/A
Norway	2015	2075	2175	N/A	N/A
Slovenia	2055	2110	2175	N/A	N/A
Sweden	2015	2040	2115	2170	2200
The UK	2015	2060	2135	2195	N/A
Tier 2: Medium-growth Muslim population countries	>5%	>10%	>25%	>50%	>75%
Austria	2015	2075	N/A	N/A	N/A
Denmark	2020	2090	N/A	N/A	N/A
Finland	2095	2200	N/A	N/A	N/A
Greece	2015	2095	N/A	N/A	N/A
Italy	2030	2105	2220	N/A	N/A
Luxembourg	2070	2145	N/A	N/A	N/A
The Netherlands	2015	2060	N/A	N/A	N/A
Spain	2090	2155	N/A	N/A	N/A
Switzerland	2015	2080	2200	N/A	N/A
Tier 3: Low-growth Muslim population countries	>1%	>2.5%	>5%	>10%	>15%
Croatia	2015	N/A	N/A	N/A	N/A
Czechia	2170	N/A	N/A	N/A	N/A
Estonia	N/A	N/A	N/A	N/A	N/A
Germany	2015	2015	2015	N/A	N/A
Hungary	N/A	N/A	N/A	N/A	N/A
Latvia	2145	2180	2210	N/A	N/A
Lithuania	2220	N/A	N/A	N/A	N/A
Malta	2015	2015	N/A	N/A	N/A
Poland	N/A	N/A	N/A	N/A	N/A
Portugal	N/A	N/A	N/A	N/A	N/A
Romania	N/A	N/A	N/A	N/A	N/A
Slovakia	N/A	N/A	N/A	N/A	N/A

Table I. Zero-migration scenario tier 1, 2 and 3, high-, medium-, low-growth Muslim population countries

Sweden (in 2170) and United Kingdom (in 2195) (Table I). None of the Medium-Growth Muslim population countries will have a majority of Muslim population in the next 200 years, the most will be more than 25 per cent of the population in Italy (in 2220) and Switzerland (in 2200). Low-Growth Muslim population countries will never count more than 10 per cent of Muslim population in the next 200 years.

4.2 2017 Migration scenario

Among the High-Growth Muslim population countries, all of them will reach a majority of Muslim population in the next 200 years. None of the Medium-Growth Muslim population countries will have a majority of Muslim population in the next 200 years, the most will be 49 per cent of the population in Spain in 2220 (Table II). Low-Growth Muslim population countries will never count more than 10 per cent of Muslim population in the next 200 years.

4.3 Mid-point migration scenario

The mid-point migration scenario data are obtained by averaging the data of the two previous scenarios (Table III). This is the most likely scenario. Among the High-Growth

Tier 1: High-growtd Muslim population countries	>5%	>10%	>25%	>50%	>75%
Austria	2015	2030	2065	2130	2200
Belgium	2015	2030	2075	2120	2150
Bulgaria	2015	2015	2095	2125	2145
Cyprus	2015	2015	2020	2065	2125
France	2015	2025	2070	2115	2145
Germany	2015	2030	2075	2180	N/A
Greece	2015	2025	2050	2085	2120
Ireland	2060	2095	2140	2180	2205
Italy	2020	2040	2085	2130	2165
Lithuania	2120	2135	2160	2180	2195
Luxembourg	2025	2035	2070	2120	2160
Norway	2015	2050	2125	2200	N/A
Slovenia	2035	2065	2120	2170	2195
Sweden	2015	2025	2060	2100	2125
Switzerland	2015	2035	2085	2150	2195
The UK	2015	2045	2110	2165	2200
Tier 2: Medium-growth Muslim population countries	>5%	>10%	>25%	>50%	>75%
Denmark	2020	2060	2160	N/A	N/A
Finland	2040	2075	2155	N/A	N/A
Malta	2025	2035	2075	N/A	N/A
The Netherlands	2015	2035	2110	N/A	N/A
Spain	2050	2090	2160	N/A	N/A
Tier 3: Low-growth Muslim population countries	>1%	>2.5%	>5%	>10%	>15%
Croatia	2015	2040	2105	N/A	N/A
Czechia	2065	2115	2160	2215	N/A
Estonia	2060	2100	N/A	N/A	N/A
Hungary	2035	2070	2125	N/A	N/A
Latvia	2055	2155	2185	2215	N/A
Poland	2100	N/A	N/A	N/A	N/A
Portugal	2050	2150	N/A	N/A	N/A
Romania	2040	2080	N/A	N/A	N/A
Slovakia	N/A	N/A	N/A	N/A	N/A

Table II. 2017 Migration scenario tier 1, 2 and 3, high-, medium-, low-growth Muslim population countries

Tier 1: High-growtd Muslim population countries	>5%	>10%	>25%	>50%	>75%
Belgium	2015	2035	2090	2140	2175
Bulgaria	2015	2015	2120	2140	2160
Cyprus	2015	2015	2020	2085	2210
France	2015	2025	2080	2135	2165
Greece	2015	2035	2075	2135	N/A
Ireland	2075	2110	2160	2200	N/A
Italy	2020	2055	2110	2175	N/A
Lithuania	2135	2155	2180	2215	N/A
Luxembourg	2030	2050	2110	2175	N/A
Slovenia	2040	2080	2145	2190	N/A
Sweden	2015	2030	2075	2125	2170
Switzerland	2015	2045	2115	2195	N/A
The UK	2015	2050	2120	2180	2210
Tier 2: Medium-growth Muslim population countries	>5%	>10%	>25%	>50%	>75%
Austria	2015	2035	2100	N/A	N/A
Denmark	2020	2070	2210	N/A	N/A
Germany	2015	2040	2130	N/A	N/A
Finland	2055	2105	2220	N/A	N/A
Malta	2030	2055	N/A	N/A	N/A
The Netherlands	2015	2045	2145	N/A	N/A
Norway	2015	2060	2145	N/A	N/A
Spain	2060	2110	2190	N/A	N/A
Tier 3: Low-growth Muslim population countries	>1%	>2.5%	>5%	>10%	>15%
Croatia	2015	2050	N/A	N/A	N/A
Czechia	2090	2150	2205	N/A	N/A
Estonia	2085	N/A	N/A	N/A	N/A
Hungary	2050	2110	N/A	N/A	N/A
Latvia	2075	N/A	N/A	N/A	N/A
Poland	N/A	N/A	N/A	N/A	N/A
Portugal	2075	N/A	N/A	N/A	N/A
Romania	2055	N/A	N/A	N/A	N/A
Slovakia	N/A	N/A	N/A	N/A	N/A

Table III. Mid-point migration scenario tier 1, 2 and 3, high-, medium-, low-growth Muslim population countries

Muslim population countries, all of them will reach a majority of Muslim population in the next 200 years. None of the Medium-Growth Muslim population countries will have a majority of Muslim population in the next 200 years, the most will be 49 per cent of the population in Austria and Norway in 2220. Low-Growth Muslim population countries will never count more than 10 per cent of Muslim population in the next 200 years.

4.4 Benchmarking the proportion of European Muslim population per country

We benchmark spectral analysis proportion estimates to the Pew Research Centre (2017) estimates in Table IV (appendix material) for year 2050.

Based on the two-sample *t*-test for equal group means, means of the 2050 spectral analysis estimates and Pew forecasts are not statistically different for the three scenarios. The benchmarking may confirm the reliability of spectral analysis forecast estimates as long as the benchmark is itself reliable.

Table IV. Benchmarking spectral analysis proportion estimates to the Pew Research Centre (2017) estimates

YEAR 2050	Zero-migration scenario, Spectral Analysis (%)	Zero-migration scenario, Pew Forecast (%)	Midpoint scenario, Spectral Analysis (%)	Medium-migration scenario, Pew Forecast (%)	2017 migration scenario, Spectral Analysis (%)	High-migration scenario, Pew Forecast (%)
Belgium	11.5	11.1	14.4	15.1	17.3	18.2
Bulgaria	14.1	12.5	15.3	9.2	16.4	11.6
Cyprus	33.7	25.5	39.1	26.6	44.5	28.3
France	13.5	12.7	16.3	17.4	19.1	18.0
Greece	7.7	6.3	16.7	8.1	25.7	9.7
Ireland	2.4	1.6	3.4	4.3	4.4	4.4
Italy	6.6	8.3	10.5	12.4	14.4	14.1
Lithuania	0.1	0.1	0.5	0.1	0.8	0.2
Luxembourg	4.6	3.4	11.1	6.7	17.6	9.9
Slovenia	5.5	4.3	6.8	5.0	8.1	5.2
Sweden	12.3	11.1	17.1	20.5	21.9	30.6
Switzerland	8.4	8.2	11.9	10.3	15.4	12.9
The UK	9.7	9.7	10.6	16.7	11.5	17.2
Austria	9.1	9.3	14.5	10.6	19.9	19.9
Denmark	7.7	7.6	8.7	11.9	9.6	16.0
Germany	7.7	8.7	12.5	10.8	17.3	19.7
Finland	3.9	4.2	5.5	11.4	7.1	15.0
Malta	3.2	3.2	9.9	9.3	16.6	16.2
Netherlands	9.9	9.1	11.7	12.5	13.5	15.2
Norway	8.5	7.2	9.6	13.4	10.8	17.0
Spain	3.7	4.6	4.8	6.8	5.9	7.2
Croatia	2.1	1.8	2.6	2.0	3.1	2.1
Czechia	0.3	0.2	0.5	1.1	0.8	1.2
Estonia	0.3	0.2	0.6	0.8	0.9	1.0
Hungary	0.5	0.4	1.2	1.3	1.8	4.5
Latvia	0.2	0.2	0.6	0.2	1.0	0.4
Poland	0.1	0.1	0.3	0.2	0.6	0.2

(*continued*)

Table IV.

YEAR 2050	Zero-migration scenario, Spectral Analysis (%)	Zero-migration scenario, Pew Forecast (%)	Midpoint scenario, Spectral Analysis (%)	Medium-migration scenario, Pew Forecast (%)	2017 migration scenario, Spectral Analysis (%)	High-migration scenario, Pew Forecast (%)
Portugal	0.5	0.5	0.8	2.5	1.1	2.5
Romania	0.5	0.4	1.0	0.8	1.5	0.9
Slovakia	0.1	0.1	0.2	0.6	0.2	0.7
AVERAGE	6.3	5.8	8.6	8.3	11.0	10.7
Standard deviation	6.8	5.7	8.2	6.8	10.0	8.6
Two-sample *t*-test for equal group means	H = 0; $p = 0.7459$; The logical value 0 indicates the null hypothesis is accepted at the default 0.05 significance level. The *p*-value for the test is high. There is sufficient evidence that the means are equal		H = 0; $p = 0.8637$; There is sufficient evidence that the means are equal		H = 0; $p = 0.9016$; There is sufficient evidence that the means are equal	

5. Conclusion

This paper presents estimates with spectral analysis of the years European Muslim Population will be majority among 30 European countries. About 5 per cent of Europe's population is Muslim. Two main factors are responsible of a growing European Muslim population, a higher fertility rate of Muslim population (one child more per woman on average) than other Europeans and a refugee crisis that reached a peak in 2015 with an influx of refugees coming mainly from Muslim countries across the Mediterranean Sea or overland through Southeast Europe. Refugees have come primarily from Syria, Afghanistan, Iraq and Eritrea. 86 per cent of them are Muslims based on the top ten origins of refugees from 2010 to 2016 (Pew Research Centre, 2017). We implement a five-step methodology (Rostan and Rostan, 2018a) based on spectral analysis which involves 1) de-noising and compression of the first-order difference of the population time series of each European country among the 30; 2) wavelet decomposition; 3) Burg extension of approximations and details; 4) wavelet reconstruction and finally 5) forecasting the Muslim population based on three scenarios: 1) a conservative zero-migration scenario; 2) a 2017 migration and a more likely 3) mid-point migration scenario. In the mid-point migration scenario, we identify 13 countries where the Muslim population will be majority between years 2085 and 2215 in order of occurrence: Cyprus (in year 2085), Sweden (2125), France (2135), Greece (2135), Belgium (2140), Bulgaria (2140), Italy (2175), Luxembourg (2175), the UK (2180), Slovenia (2190), Switzerland (2195), Ireland (2200) and Lithuania (2215). The 17 remaining countries will never reach majority in the next 200 years. The growing Muslim population will change the face of Europe socially, politically and economically. Examples of such changes will include proliferation of mosques, prayer calls from loudspeakers, commercialization of halal foods and products, compatible workload and adjustable working hours with Ramadan constraints, new laws in favor of the Muslim population and a growing meddling of foreign governments in European political decisions. At first, anti-Islam political parties may gain support in a xenophobic reaction to the rising contribution of the Muslim population to the life of the European society until the Muslim population be majority. Then negative reactions should fade away. These social, political and economic changes will bring periods of adjustment that would be painful for the European society -some talk of shock of civilizations- and will depend on the degree of openness and tolerance of the communities toward each other and their willingness to build a balanced European society enriched with a diversity of beliefs and cultures.

References

AFP (2018), "Will Saudi crown prince reform Wahhabism in Europe?", available at: www.dailymail.co.uk/wires/afp/article-5601565/will-saudi-crown-prince-reform-wahhabism-europe.html

Amelina, A. and Faist, T. (2008), "Turkish migrant associations in Germany: between integration pressure and transnational linkages", *Revue Européenne Des Migrations Internationales*, Vol. 24 No. 2, pp. 91-120, available at: https://journals.openedition.org/remi/4542

Baillie, R. and Bollerslev, T. (1992), "Prediction in dynamic models with time-dependent conditional variances", *Journal of Econometrics*, Vol. 52 Nos 1/2, pp. 1-113.

Berger, T. (2016), "A wavelet analysis: forecasting based on decomposed financial return series", *Journal of Forecasting*, Vol. 35 No. 5, pp. 419-433, doi: 10.1002/for.2384.

Box, G.E.P. and Jenkins, G.M. (1976), *Time Series Analysis: forecasting and Control*, Revised Edition, Holden Day, San Francisco.

Box, G.E.P., Jenkins, G.M. and Reinsel, G.C. (1994), *Time Series Analysis: forecasting and Control*, 3rd ed., Prentice Hall, Englewood Cliffs, NJ.

Burg, J.P. (1975), "Maximum entropy spectral analysis", available at: http://sepwww.stanford.edu/theses/sep06/ (accessed 30 December 2018).

Conejo, A.J., Plazas, M.A., Espinola, R. and Molina, A.B. (2005), "Day-ahead electricity price forecasting using the wavelet transform and ARIMA models", *IEEE Transactions on Power Systems*, Vol. 20 No. 2, pp. 1035-1042, doi: 10.1109/tpwrs.2005.846054.

Corinthios, M. (2009), *Signals, Systems, Transforms, and Digital Signal Processing with Matlab*, Taylor and Francis Group, LLC CRC Press, Boca Raton, FL.

Dancygier, R.M. (2018), "Muslim voters and the European left", *Foreign Affairs*, available at: www.foreignaffairs.com/articles/europe/2018-02-06/muslim-voters-and-european-left (accessed 30 December 2018).

Daubechies, I. (1994), "Ten lectures on wavelets", *CBMS, SIAM*, Vol. 61, pp. 198-202 and 254-256.

Diebold, F. and Li, C. (2006), "Forecasting the term structure of government bond yields", *Journal of Econometrics*, Vol. 130 No. 2, pp. 337-364.

Durbin, J. (1960), "The fitting of time series models", *Revue de L'institut International de Statistique / Review of the International Statistical Institute*, Vol. 28 No. 3, pp. 233-244.

Eurostat (2017), "Asylum and first-time asylum applicants by citizenship, age and sex annual aggregated data (rounded)", Last update: 26/04/17, available at: http://ec.europa.eu/eurostat/en/web/products-datasets/-/migr_asyappctza (accessed 30 December 2018).

He, K., Wang, L., Zou, Y. and Lai, K. (2014), "Exchange rate forecasting using entropy optimized multivariate wavelet denoising model", *Mathematical Problems in Engineering*, Vol. 2014, pp. 1-9, doi: 10.1155/2014/389598.

Kao, L., Chiu, C., Lu, C. and Chang, C. (2013), "A hybrid approach by integrating wavelet-based feature extraction with MARS and SVR for stock index forecasting", *Decision Support Systems*, Vol. 54 No. 3, pp. 1228-1244, doi: 10.1016/j.dss.2012.11.012.

Kriechbaumer, T., Angus, A., Parsons, D. and Casado, M. (2014), "An improved wavelet-ARIMA approach for forecasting metal prices", *Resources Policy*, Vol. 39, pp. 32-41, doi: 10.1016/j.resourpol.2013.10.005.

Levinson, N. (1946), "The wiener RMS (root mean square) error criterion in filter design and prediction", *Journal of Mathematics and Physics*, Vol. 25 Nos 1/4, pp. 261-278.

Misiti, M., Misiti, Y., Oppenheim, G. and Poggi, J.M. (2015), *Wavelet Toolbox for Use with Matlab, User's Guide*, The Mathworks, Natick, MA, available at: http://profesores.elo.utfsm.cl/~mzanartu/ipd414/docs/wavelet_ug.pdf.

Ortega, L. and Khashanah, K. (2014), "A neuro wavelet model for the short-term forecasting of high frequency time series of stock return", *Journal of Forecasting*, Vol. 33 No. 2, pp. 134-146. doi:10.1002/for.2270.

Pew Research Centre (2017), "Europe's growing Muslim population", available at: www.pewforum.org/2017/11/29/europes-growing-muslim-population/ (accessed 30 December 2018).

Press, E. (2018), "Turkish prime minister says 'assimilation is a crime against humanity", *The Local*, available at: www.thelocal.de/20080211/10293 (accessed 30 December 2018).

PressTV (2017), "Belgium voices alarm over spread of Saudi-backed Wahhabism", available at: www.presstv.com/detail/2017/02/08/509719/belgium-saudi-arabia-wahhabism-daesh (accessed 30 December 2018).

Renaud, O., Starck, J.L. and Murtagh, F. (2002), "Wavelet-based forecasting short and long memory time series", *Cahiers Du Département D'économétrie, Université De Genève*, Vol. 4.

Rostan, P. Belhachemi, R. and Rostan, A. (2015), "Appraising the financial sustainability of a pension system with signal processing", *Estudios De Economía Aplicada*, Vol. 33, pp. 1-16, available at: https://ideas.repec.org/a/lrk/eeaart/33_3_8.html (accessed 30 December 2018).

Rostan, P., Belhachemi, R. and Racicot, F.E. (2017), "Forecasting the yield curve with the Burg model", *Journal of Forecasting*, Vol. 36 No. 1, pp. 91-99, available at: http://onlinelibrary.wiley.com/doi/10.1002/for.2416/full (accessed 30 December 2018).

Rostan, P. and Rostan, A. (2017), *Population Projections and Pension System Sustainability*, Lambert Academic Publishing, Saarbrücken. ISBN 978-620-2-06479-8.

Rostan, P. and Rostan, A. (2018a), "The versatility of spectrum analysis for forecasting financial time series", *Journal of Forecasting*, Vol. 37 No. 3, pp. 327-339, available at: http://onlinelibrary.wiley.com/doi/10.1002/for.2504/abstract (accessed 30 December 2018).

Rostan, P. and Rostan, A. (2018b), "Forecasting Spanish and Euro area GDPs with spectral analysis", *Estudios De Economía Aplicada*, Vol. 36 No. 1, pp. 217-234, available at: https://dialnet.unirioja.es/servlet/articulo?codigo=6283924 (accessed 30 December 2018).

Rostan, P. and Rostan, A. (2018c), "Where is Greek's economy heading?", *International Journal of Management and Applied Science (IJMAS)*, Vol. 4 No. 3, pp. 28-31, available at: http://ijmas.iraj.in/paper_detail.php?paper_id=11490&name=where_is_greece%e2%80%99s_economy_heading?_ (accessed 30 December 2018).

Rostan, P. and Rostan, A. (2018d), "Will Saudi Arabia get older? Will its pension system be sustainable? Spectral answers", *PSU Research Review*, Vol. 2 No. 3, available at: https://doi.org/10.1108/prr-12-2017-0045; www.emeraldinsight.com/doi/full/10.1108/prr-12-2017-0045 (accessed 30 December 2018).

Schlüter, S. and Deuschle, C. (2010), "Using wavelets for time series forecasting: does it pay off?", Working Paper, IWQW discussion paper series, in cooperation with: Friedrich-Alexander University Erlangen-Nuremberg, Institute for Economics, Vol. 4.

Stoica, P. and Moses, R. (2005), *Spectral Analysis of Signals*, Prentice Hall, Upper Saddle River, NJ.

Tan, Z., Zhang, J., Wang, J. and Xu, J. (2010), "Day-ahead electricity price forecasting using wavelet transform combined with ARIMA and GARCH models", *Applied Energy*, Vol. 87 No. 11, pp. 3606-3610, doi: 0.1016/j.apenergy.2010.05.012.

Valens, C. (1999), "A really friendly guide to wavelets", available at: http://agl.cs.unm.edu/~williams/cs530/arfgtw.pdf (accessed 30 December 2018).

Weaver, M. (2017), "Burqa bans, headscarves and veils: a timeline of legislation in the west", *The Guardian*, available at: www.theguardian.com/world/2017/mar/14/headscarves-and-muslim-veil-ban-debate-timeline (accessed 30 December 2018).

Further reading

Cunningham, N. (2018), "The no. 1 challenge to the oil rally", *Oilprice.com*, available at: https://oilprice.com/energy/crude-oil/the-no1-challenge-to-the-oil-rally.html (accessed 30 December 2018).

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