HUMAN MORTALITY EFFECTS OF ECONOMIC GROWTH FLUCTUATIONS

of Austrian population based on 1960-2017 data

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ABSTRACT

Recently, researchers have seen the need to study the increase in life expectancy and thus, mortality decline throughout the years in order to understand population structure for policymakers, individuals, governments, pension funds and insurance companies.

The first and most accepted mortality model is the one of Lee and Carter (1995) and has been widely used in different papers in order to fit and forecast mortality. The main objective of this research is to study the effects of macroeconomic factors on human mortality. For this reason, the GDP (Gross Domestic Product) per capita parameter, considered as a good indicator of a country's economic growth, will be added into the model as proposed by Niu and Melenberg (2014) in order to allow for more precise interpretations of the model.

This paper will analyze Austrian population for the years 1960-2017, and its parameters will be estimated by Singular Value Decomposition (SVD) and finally Autoregressive Integrated Moving Average (ARIMA) procedure will be used in order to forecast mortality for the next 10 years with 95% confidence intervals.

TABLE OF CONTENTS

1. INTRODUCTION

According to the World Health Organization, global average life expectancy increased by 5.5 years between 2000 and 2016, the fastest increase since the 1960s. Life expectancy is the key metric for assessing population health as it captures the mortality across all age groups, hence these two variables are closely linked to each other.

Even though for individuals might be of good news that life expectancies increase, decrease in mortality might not always have a positive impact on the society as it can raise problems for governments that struggle to pay for retirement pensions or even for social security administrations that want to price financial instruments properly. Not only policymakers envision complications but also life insurance companies strive against the longevity risk uncertainty. Even for citizens the study of mortality modeling is important as they need to plan for future retirement income, which affect their savings. The implications and concerns of a mortality rate change explain the importance of mortality model studies.

Some researchers state that mortality rate decline has been mainly affected by economic growth (Brenner, 2005), and thus showing a strong negative relationship with GDP per capita (Seklecka et al., 2018). This brings us to the main question that will be explored in this paper:

Is economic growth related with human mortality?

Throughout the years many different researchers have tried to fit and extrapolate mortality models in order to explain the trend and to forecast it. The first stochastic mortality model was proposed by Lee and Carter (1992) and since then it has been one of the most used and recognized mortality models due to its accuracy and simplicity. Some years later, Niu and Melenberg (2014) in order to study social development and public policy, added the GDP (Gross Domestic Product) per capita variable into the Lee-Carter model. This new approach was named LC-GDP model.

Following this line of reasoning, this paper will therefore be divided into three different sections; the first one will discuss and analyze the Lee-Carter mortality model on Austrian population from 1960-2017 explained by both genders, the second part will add the economic growth variable in order to explain the same model with an economic factor, and finally mortality will be forecasted for the next 10 years.

This paper is intended to answer the main question, analyze the impact macroeconomic factors have on human mortality and foresee what will happen in the future. The main objective is to warn governments and policymakers about the positive effects of health improvements on the economy as it is often underestimated. Therefore, suggesting a more efficient spending and a deeper focus on a better public health system for individuals. Giving a different insight into the economic effects of a decrease in mortality rate will point out the economic boost that reductions in mortality can cause, which far outweighs the retirement pay problems that the government may encounter.

To give a general overview, the findings from academic literature on mortality modeling will be presented and discussed in order to establish foundation in which the research will be built on. Furthermore, Austrian data from the Human Mortality Database and The World Bank Group for the years 1960-2017 will be analyzed using the Lee-Carter model applying SVD (Singular Value Decomposition) for the parameters' estimation, and ARIMA models for forecasting. The results of this data will be presented and discussed, and the findings will be finally summarized.

2. CONCEPTUAL FRAMEWORK

Mortality data is an important issue in many fields such as health, epidemiology or national planning and it is used to indicate the level of a country's welfare and quality of life. In order to improve health, reduce mortality or social index it is crucial to study mortality models for the social development and public policy.

Regarding the economic impacts from human health, there are many studies that focus on studying the impacts of change in mortality rates to economic growth while others only focus on fitting and forecasting human mortality. This research is intended to analyze both approaches. Thus, this section is going to be divided into two main parts: why is fitting and forecasting mortality so important and the second one, how does mortality relate to economic growth.

2.1. Mortality modeling

Since the increase experienced in the past years of life expectancy, there has been an increased need for the proper study of mortality models. Increase in life expectancies, which is closely linked with a decrease in mortality rates, it is of huge importance for many organizations such as pension funds, life and health insurances, and individuals (Seklecka *et al)*. While for individuals life expectancies increase might be of good news, for governments can be challenging as they have to finance aging population.

Mortality can differ among countries where lifestyles (eg. tobacco and alcohol consumption, physical activity level, etc.), nutrition (eg. diet), health system and environment (eg. climate change) is different. Nevertheless, mortality is still of main concern for all governments and it is for a fact that life expectancies are increasing globally. There are many authors who try to explain why this happens, but according to Preston, life expectancies increase due to income levels and technology (Preston, 2003).

Fitting mortality was first modeled by Lee and Carter (1992), who introduced a time dependent factor to the model and because of its simplicity of the parameters estimation by SVD, this model has been one of the most used and accepted in the community. There are many previous studies that test the Lee-Carter model in different populations: Italy (Maccheroni and Nocito, 2017), Peru (Cerda-Hernández & Sikov, 2018), Nordic countries (Koissi et al., n.d.) and even comparing different countries such as Central East European countries (Rabbi & Mazzuco, 2018) or selected Eurozone countries (Secklecka et al., 2018). These studies assert that this model is reliable and from them, it comes its popularity.

This model is widely used due to its simplicity when making long-run forecasts of times series using SVD parametrization because it accounts for almost all the variance over time in age-specific death rates (Lee and Carter, 1992). Lee and Carter found that the mortality parameter (k_t) decreased at a constant rate and due the fact that this model is very precise it is the main reason why this method is chosen.

Forecasting is the main objective of the stochastic mortality modeling, so once the time-dependent parameter k_t is fitted, Lee and Carter estimate their data with Autoregressive Integrated Moving Average (ARIMA). This model is used in order to reduce the maximum residual autocorrelation and therefore forecast with best estimates the mortality rates of the following years. There are previous studies that also use this approach to forecast mortality estimates such as the study for Indian population (Chavhan & Shinde, 2016) or for Eurozone countries (Seklecka et al., 2018). Given that both show future decreasing trends, similar results are expected to show in this study.

Governments are not only interested in the future trends of mortality but also on how these trends are affected by the economy. In the next section, how to analyze the relationship between mortality and economic factors is going to be discussed.

2.2. Mortality rates and economic growth

Understanding how does the economy contribute to changes in health indicators is crucial for analyzing the relationship between the decrease in mortality and related improvements in the economy.

As already observed by previous studies, there are many factors that influence mortality such as GDP, inflation and unemployment rate, which affect public policies, countries' welfare, etc. Therefore, in this study the GDP per capita growth is going to be analyzed as one of these factors.

There are vast amounts of literature discussing mortality models, but Niu and Melenberg found that they are not useful at interpreting the results, but just at summarizing and extrapolating past performance (Niu & Melenberg, 2013). Thus, they extended this model by incorporating the presence of the GDP per capita variable as it is a good indicator of a country's economic growth. Niu and Melenberg study the presence of GDP growth in the Lee-Carter model for six OECD countries (USA, The Netherlands, Japan, UK, Australia and Canada), compared to this paper that will focus on the Austrian population. Lee-Carter model is selected for the study as the model itself and its variants are widely accepted extrapolative methods for forecasting mortality due to their simplicity and availability of high quality long time series data (Rabbi & Mazzuco, 2018).

Many studies show evidence of the negative relationship between mortality and GDP per capita, with causality usually going both directions (Niu & Melenberg, 2013). This double causality, even though lacking from a clear explanation (D. E. Bloom et al., 2009), may be due to technological progress that tends to increase per capita income and lead to improvements in health or because increased health leads to more productivity in the workplace and thus resulting in economic growth. Therefore, our main hypothesis in this paper, that will be later explored, is that mortality for Austria is negatively related to GDP per capita.

There exist some studies that agree with the fact that upward cycles of the economy relate to increases in mortality, while downward cycles relate to decreases in mortality. There are some explanations that state that this may be due to the stress increase at work, more possible traffic accidents, more pollution in upward cycles or even more suicides. This association still remains unknown, which undermines the reliability of the conclusions. These studies go further into explaining that because long term cycles of the economy are used in the research, an explanation to this phenomenon would be that economic expansions decrease mortality due to lagged effects, or in other words with a delay (Rolden et al., 2014). The latter explanation, which is in line with our hypothesis, may explain why there are differences in the takeaways of similar studies. Hence, this explanation highlights the importance of economic studies related to mortality that try to give an explanation to this phenomenon.

Therefore, by achieving an accurate common explanation, all the parties involved in the economy will be able to understand the trend and thus, anticipate future results. For individuals, it is of interest given that they have to plan future savings and insurances. For policymakers and governments, it is relevant to know until what extend these variables are correlated in order to know how they can influence economic outcomes by applying education and environmental policies or increasing health expenses. Pensions and insurances that also want to reduce the longevity risk uncertainty.

3. EMPIRICAL STRATEGY

3.1. Lee-Carter model and parameter estimation

The Lee-Carter model (1992) has been extensively used in many researches and articles for fitting and forecasting human mortality. It is a model that can be used for forecasting mortality and life expectancies. It uses time and age data for different genders displayed in matrix form. This model was the first stochastic mortality model for human mortality introduced and has been widely accepted since then as it reflects the reduction of the annual log age-specific death rates through a time-dependent index (Seklecka *et al*).

This model is given by:

$$\ln (m_{x,t}) = \hat{a}_x + b_x k_t + \varepsilon_{x,t} \quad (1)$$

where,

x denotes age

t denotes year

$m_{x,t}$ defines the central rate of mortality for person of age x at time t

$\hat{a}_x$ denotes the coefficient that describes average age-specific mortality

b_x represents the decline in mortality at age x

k_t indicates changes in mortality level

$\varepsilon_{x,t}$ is the error term

The explanations of how these terms are obtained are hereunder discussed. First of all, the term $\hat{a}_x$, which as mentioned previously indicates the average of age-specific mortality at year t. is extracted from the following:

$$\hat{a}_x = [\textstyle\sum_t \ln (m_{x,t})] / t \quad (2)$$

The term $m_{x,t}$, which indicates central death rates, is calculated as follows:

$$m_{x,t} = M_{x,t} / P_{x,t} \quad (3)$$

where,

$M_{x,t}$ stands for number of deaths (mortality) of age x at time t

$P_{x,t}$ denotes population number of age x at time t

This model uses the SVD (singular value decomposition)[1] parametrization in order to find univariate time series that capture most of the mortality trend (i.e. parameters b_x and k_t). The model cannot be fit using Ordinary Least Squares (OLS) because there are no given regressors.

In order to find these parameters, SVD is applied to the matrix $A = \ln(m_{x,t}) - \hat{a}_x$ of size x x t, where,

$$A = \begin{pmatrix} \ln(m_{x,t}) - \hat{a}_x & \ln(m_{x,t+1}) - \hat{a}_x & \cdots \\ \ln(m_{x+1,t}) - \hat{a}_{x+1} & \ddots & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

This method decomposes the matrix A as $A = UDV^T$, where:

U = unitary matrix of size x x t

V = unitary matrix of size t x t

D = diagonal matrix of size t x t that captures the correlation variation

The decomposition can be written as follows;

$$SVD(A) = \lambda_1 U_{x,1} V^T_{t,1} + \lambda_2 U_{x,2} V^T_{t,2} + \ldots + \lambda_k U_{x,k} V^T_{t,k} \;;$$

$$SVD(A) = \sum \lambda_i U_{x,i} V^T_{t,i} \qquad (4)$$

Once the results of the decomposition are obtained (see Equation 4), it is time to find the parameters b_x and k_t, that as the Lee-Carter model explains, they are obtained from the first column of the U matrix (b_x), the first column of the transposed V matrix and the first term (λ_1) of the diagonal matrix, which captures the largest correlation variation. Thus,

$b_x = U_{x,1}$ for all ages x

$k_t = \lambda_1 V^T_{t,1}$ for all years t

[1] Decomposition method used for reducing matrices into smaller parts in order to make easier and simpler calculations afterwards.

Because the parametrization of the model is invariant to transformations, for unique solution, according to Lee and Carter, these constraints must be followed: $\Sigma_t k_t = 0$ and $\Sigma_x b^2_x = 1$ (Chavhan & Shinde, 2016).

3.2. Fitting mortality and economic data

In order to analyze the effects of the mortality on the economic growth, Niu and Melenberg incorporated a new factor to the LC model by adding a parameter d_x denoting the natural logarithm of real GDP per capita in US$ (included as an observable factor), this new model was named LC-GDP model (see equation 5);

$$\ln (m_{x,t}) = a_x + b_x k_t + d_x g_t + \varepsilon_{x,t} \tag{5}$$

Furthermore, in order to study the correlations between the mortality index and GDP per capita fluctuations, the three different coefficients that are going to be analyzed are (as proposed by *Secklecka et al*): Pearson, Kendall and Spearman. Pearson correlation coefficient measures the degree of the relationship between linearly related variables, Kendall rank correlation is a non-parametric test that measures the strength of dependence between two variables and Spearman rank correlation is a non-parametric test that is used to measure the degree of association between two variables.

The relationship between economic growth and health or mortality has been studied for several decades. It is generally accepted that the two variables are closely linked, with causation often going in both directions, which is argued to be mainly due to health-care technology (D. Bloom et al., 2001). The majority of the related studies show that the improvements in mortality have been accompanied by growth in GDP, and so found a negative relationship between variables. This leads to our hypothesis where it is expected that the correlations between economic growth fluctuations and human mortality for both genders are negative.

3.3. Forecasting

One of the main purposes of studying these models is being able to identify future trends in order to help understand patterns and help public policies of possible future behaviors.

Lee and Carter used ARIMA[2] (Autoregressive Integrated Moving Average) models for forecasting mortality data. They are non-seasonal[3] models denoted as ARIMA (p,d,q) where its parameters are non-negative and can be described as: *p*, the order (number of autoregressive terms) of the model; *d*, the degree of differencing or in other words, the non-seasonal differences (the number of times the data have had past values subtracted); and *q*, the order of the moving average model.

ARIMA model can be explained by the following decomposition: ARMA that stands for Autoregressive Moving Average and I (Integrated), which determines that the values have been replaced with the difference between their values and the previous ones. The purpose is to fit and forecast the data of the model as well as possible. The decomposition of the ARIMA process in order to better understand the method can be explained as follows:

AR: evolving variable of interest is regressed on its own lagged values.

$$y_t = py_{t-1} + u_t \quad (AR_1)$$

$$y_t = p_1y_{t-1} + p_2y_{t-2} + u_t \ (AR_2)$$

MA: this part indicates that the regression error is a linear combination of error terms whose values occurred contemporaneously and at various times in the past.

$$y_t = u_t + \varnothing u_{t-1} \quad MA\ (1)$$

$$y_t = u_t + \varnothing u_{t-1} + \varnothing u_{t-2} \quad MA\ (2)$$

ARMA (p, q): representation of both the auto regression term and the moving average term, in order to predict future values of the data.

$$y_t = p_1y_{t-1} + ... + p_py_{t-p} + u_t + \varnothing_1u_{t-1} + ... + \varnothing_qu_{t-q}$$

$$(AR_2) \qquad\qquad\qquad MA\ (2)$$

[2] Autoregressive Integrated Moving Average (ARIMA) is used for interpreting, forecasting and projecting future values of a time series data using historical data points.
[3] ARIMA models reduce seasonality, which is a term that refers to the patterns that data repeat during a year, in order to increase efficiency of the calculations.

ARIMA (p,d,q): final representation of the model where "I" is added in order to remove stationarity.

$$Z_t \simeq \text{ARIMA}\ (p, q, \delta)$$

Depending on whether the data is stationary, auto correlated, with or without constant, there exist different models of ARIMA. For instance, a random walk ARIMA (0,1,0), one of the simplest and most important models, happens when z is not stationary. And can be interpreted as:

$$\text{ARIMA}\ (p, q, 1) \quad \rightarrow \quad y_t = z_t - z_{t-1}$$

Therefore, meaning that the future values forecasted will be equal to the last observed values.

Lee and Carter used an ARIMA model with a random walk of (0,1,0) due to its linearity in order to forecast the future mortality of index k_t for future time points. Therefore, as this study used Lee Carter model, this approach will be the one used. Thus, as mentioned before, the mortality estimates will be forecasted as follows:

$$k_t = \theta + k_{t-1} + \delta_t$$

4. DATA

In order to evaluate the relationship between Austrian mortality and economic growth, public data from the Human Mortality Database has been obtained. This database contains data for 41 different countries with sex-specific mortality and population information for years 1960 to 2017. This data is used as suggestion from previous research articles. This information is collected from the work of two research teams from USA and Germany; the Department of demography at Berkeley, and the Max Planck institute for demographic research in Germany. Therefore, the dataset is expected to represent accurately all mortality and population information for the selected country and period of time.

This data will be together analyzed with public data obtained from The World Bank Group. The database contains yearly GDP per capita[4] in current US$. The quality of the data can be considered reliable as it relies on official sources and because it has also been used in similar research projects such as the "Mortality effects of economic fluctuations in selected Eurozone countries" (Seklecka et al.).

In order to analyze the data, female and male mortality as well as the total population, together with GDP per capita are going to be considered. Lee-Carter model decomposes age-specific mortality for both genders as they show different trend patterns. As mortality data at very old ages is not very reliable, the maximum age set in our sample will be 89 years old (from 0 to 89 years old). To sum up, we will account for 58 years of sample and 90 different age groups, therefore having a matrix of size 90 x 58 in the SVD parametrization from where the results will be extracted (see Table 2&3, in the Appendix).

GDP per capita is included as an observable factor which captures the correlation between long term trends in mortality dynamics and economic growth (Niu & Melenberg, 2013). As the Lee-Carter model indicates, natural logarithm of the GDP per capita will have to be considered in order to analyze accurately the economic growth trend (see figure 6 in the Appendix).

[4] GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Source: World Bank national accounts data, and OECD National Accounts data files.

5. RESULTS AND DISCUSSION

As discussed in the literature above, the Lee-Carter model is going to be used in our dataset with the natural logarithm of real GDP per capita factor included as proposed by Niu and Melenberg.

In figure 1 and 2, the age specific central death rate for females and males are plotted to show the decrease of mortality through years (difference for every 10 years gap) as analyzed in previous studies (Chavhan & Shinde, 2016).

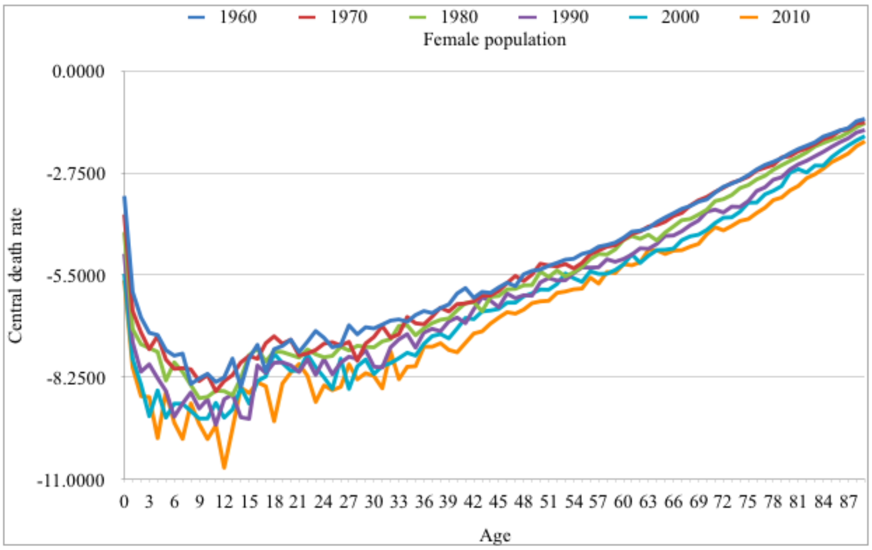

Figure 1. Pattern of age specific female central death rates for Austria 1960-2017

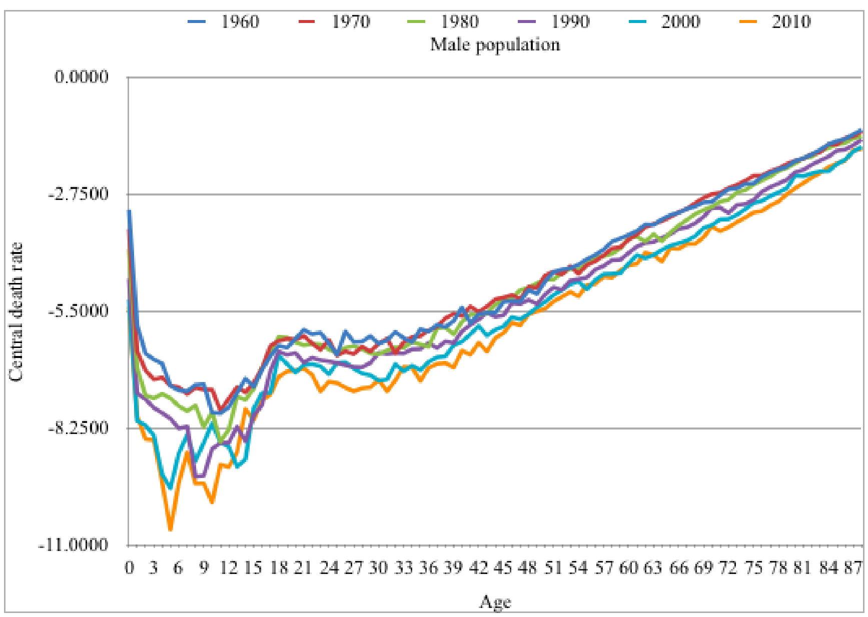

Figure 2. Pattern of age specific male central death rates for Austria 1960-2017

These graphs are going to be useful in order to understand the steady decline of parameter k_t, which is going to be analyzed continuously. The pattern shows and immense mortality for newborns, that immediately decreases and starts increasing again as age increases. Central death rates for females and males, even though showing the same pattern through years for all ages, it can be concluded that as years go by, mortality decreases for all age groups.

The previously discussed methods for mortality fitting and forecasting are applied to the selected data. Firstly, the Lee-Carter model is used in order to find the changes in mortality level parameter (k_t), which as seen in Figure 1 and 2 has been found to be negative for both genders (see Figure 3) by applying the SVD analysis (with a matrix of size 90 x 58).

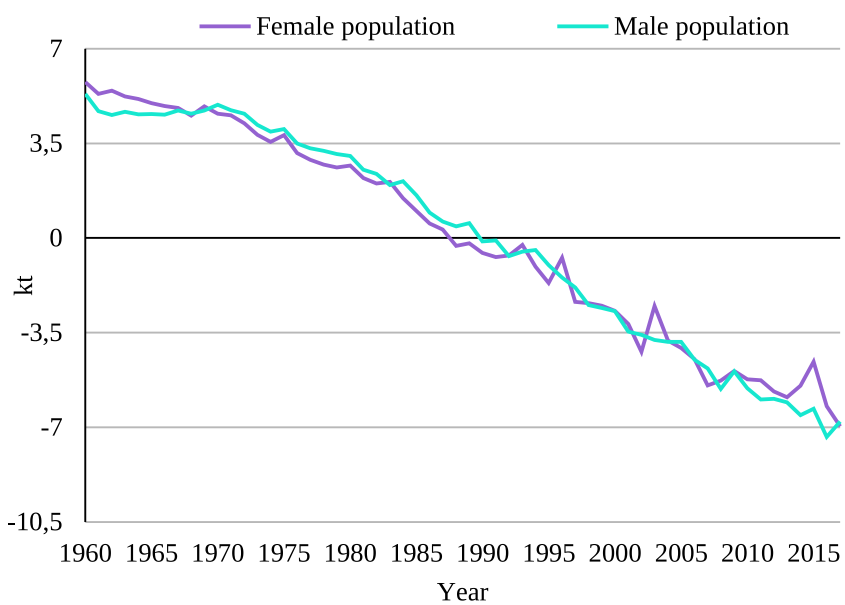

Figure 3. Time-dependent factor k_t plot 1960-2017

Once the SVD analysis has been applied and the parameters of interest have been found, the GDP per capita variable is added. In order to compare the accuracy between the Lee-Carter model and its later extension by Niu and Melenberg, it is compared the variation (R-squared) that can be explained by each model for males and for females.

The results show that for females a 98.96% of the variation can be explained by the LC (Lee-Carter) model, and when adding the GDP variable the R-squared increases to 99.36%. For males, the same phenomenon can be observed as for the first model the R-squared is 97.89%, and with the model's extension increases up to 98.69%. By knowing that the accuracy is increased with Niu and Melenberg's model, the correlation coefficients between mortality index and GDP per capita can be determined with high reliability (see Table 1).

	Female	**Male**	**Gender-neutral**
Pearson	-0.97069891	-0.97829381	-0.9768
Kendall's tau	-0.89594676	-0.85722928	-0.90199637
Spearman's rho	-0.98037467	-0.97016211	-0.98178966

Table 1. Austria's correlation coefficients of LC-GDP model for all gender categories

The table above shows that the general correlation pattern of the panel data for females, males and gender-neutral[5] is negative (see Figure 7, Appendix). Therefore, it can be concluded that mortality rates and macroeconomic data are highly negatively correlated regardless of gender. Additionally, Spearman's test provided the highest correlations for female and gender-neutral categories. These findings compare well with other similar studies (Secklecka et al., 2018). Not only we can now answer to the question of whether these two variables are correlated or not but also conclude that our results are in line with the hypothesis of negative correlation.

Finally, ARIMA procedure is applied in order to forecast the next 10 years of mortality rates for females and males. As Lee and Carter (1992), a random walk drift was used in this study (0,1,0) due to its linearity for modeling the mortality index, and the results were obtained with 95% confidence intervals (see Table 4&5, Appendix) of the forecasted mortality values. The study concludes with the idea that mortality will decline substantially for both genders for the following 10 years, 2018-2027 (see Figure 4&5). Even though there is more variance in the confidence intervals for females than for males, the expected mortality improvement in females is expected to be higher than for males.

[5] Applicable to both females and males.

While females mortality decreases a 43%, for males it will only decrease a 18.9%. To sum up, *ceteris paribus* it is expected that all population will show a decreasing trend for the next decade for all ages, these results are in line with the previously discussed studies that concluded the same.

Given that the findings of this study showed a highly negative correlation between GDP per capita and mortality rates, and that mortality is going to continue decreasing for both genders for the next decade, it can be concluded that economic growth will increase during these years as long as no other variables change the outcome. Thus, given that reduced mortality helps boost the economy, it should be noticed by policymakers that by improving further the health system and applying or changing more policies concerning human health (climate change issues, for instance), they can change the economic outcome in the future, which is everyone's main concern.

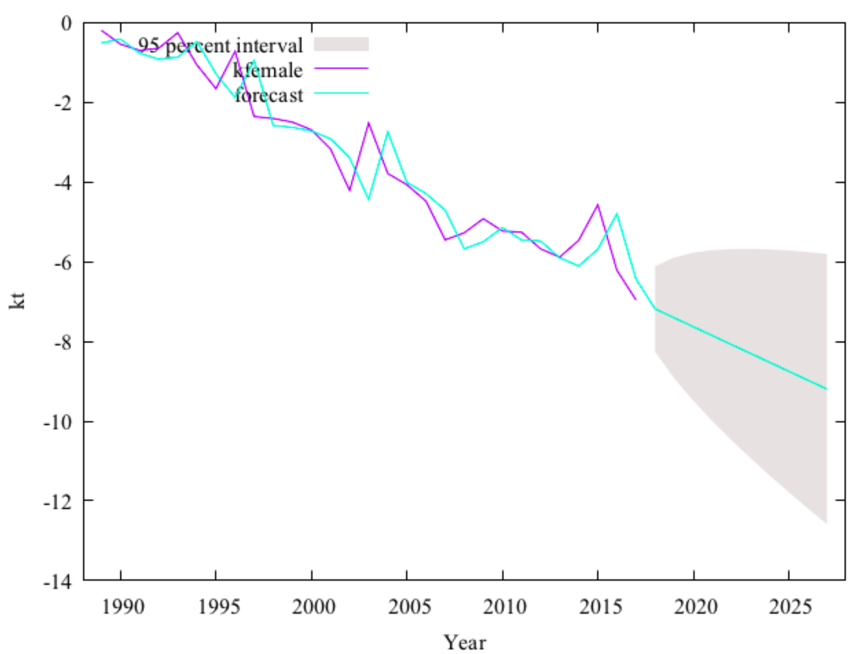

Figure 4. Actual and fitted male's mortality data and its forecast 1989-2027 (ARIMA)

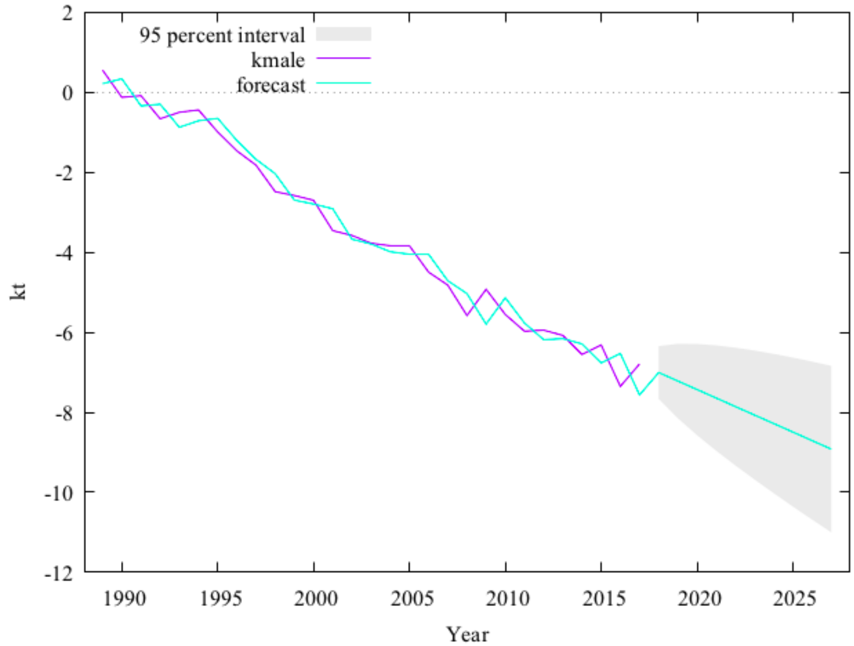

Figure 5. Actual and fitted female's mortality data and its forecast 1989-2027 (ARIMA)

6. CONCLUSIONS

As in most countries, there has been an important decrease in mortality in Austria for the past decades. The purpose of this research is to study the effects of human mortality due to economic growth fluctuations in order to help governments and policymakers with decision-making policies.

It is fundamental that resources are allocated efficiently, but sometimes governments underestimate the implications that a proper health system have on the economy, ending in poor resource allocation outcomes. In this research paper the relationship and causality of these two variables has been analyzed and examined. The interpretations, results and takeaways of different authors have been discussed and compared. This project highlights the importance of mortality studies, not only to fit and understand data but also to forecast and anticipate future behaviors. Also, when the principle objective is the study and prediction of mortality estimates, it is illustrated the importance of the Lee Carter model performance for its approach.

The relevance of this paper is that given the increasing number of experts that have begun to express concern on this topic, the information can be useful for the principal actors whose main concern is to whether plan one's future, price financial instruments properly or reduce uncertainty.

Firstly, mortality age and gender specific data has been fitted and forecasted by applying the Lee-Carter model. Secondly, with the added variable of GDP per capita as proposed by Niu and Melenberg, we have been able to interpret the correlation between human mortality and macroeconomic data. Based on the findings, we have been able to demonstrate that increases in economic growth result in decreases of mortality and otherwise. In summary, the results showed a negative relationship between the variables. Given that the results of the data, which is available for 57 years, demonstrates a very good fit with the model, the main question of the paper could be finally answered rigorously.

The structure of the project has been organized by the different key points of the work. Discussing the conclusions of different authors and constructing the hypothesis that lead to the corroboration of its certainty, which asserted that economy and mortality are negatively related. Therefore, when positive economic growth exists, low levels of mortality can be experienced. Even though the existence of some contradictory opinions, the results were shown to be in line with most of the authors.

Based on the findings of this research paper, the results based on mortality rates and economic fluctuations in Austria for years 1960-2017 can be linked to the results obtained in other similar researches. The general mortality pattern is similar for both genders with high newborn's mortality followed by a sudden bump decrease in infant's mortality reaching the minimum point, and later increasing as age does so too. Finally, female mortality improvements for the next 10 years have been expected to be larger than that for males, even though females showed wider confidence intervals.

The main conclusions that can be deducted from the study are that the trend for both females and males was forecasted to be decreasing for the next decade, which indicates that given the correlation with the GDP per capita factor, the economic growth will increase. As previously discussed, this can be due to causality going both ways. Yet, even if the regressions show strong correlation it cannot be answered with enough statistical evidence the question of to what extend does each variable cause an effect on the other.

Unfortunately this research has some limitations. The data set only accounts for mortality data, and therefore the sample might not be perfectly representative. Future researches could add morbidity data in order to account for all the illnesses, impairments and health degradation problems that may also affect the life expectancy of individuals. What is more, the effects of this relationship might not only come from their correlation but some other factors (possible omitted variable bias) such as technological progress, which has not been considered in this research. Therefore, suggesting the addition of more variables and cohort effects in further studies.

Furthermore, causality could not be answered. This can probably be explained by the limitations of the procedures, which consequently leads to suggest further developments of mathematical, statistical or econometric approaches in order to assess this issue more accurately.

Further studies, could perhaps find more evidence and data collection in other countries in order to compare them to each other, which is beyond the scope of this study and thus, study the differences between rich and poor countries, for instance.

To conclude, mortality studies are very relevant for different actors of the economy, and even though having obtained accurate results, this research leaves room for further similar studies in order to manage these issues in a more complex and accurate way. Because, is there anything that the economy does not affect?

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APPENDIX

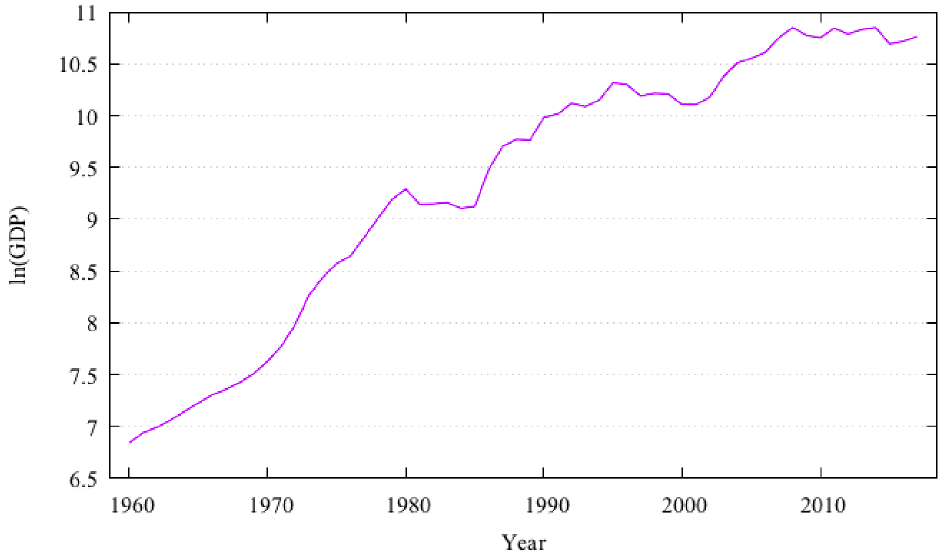

Figure 6. Austria's economic growth from 1960-2017

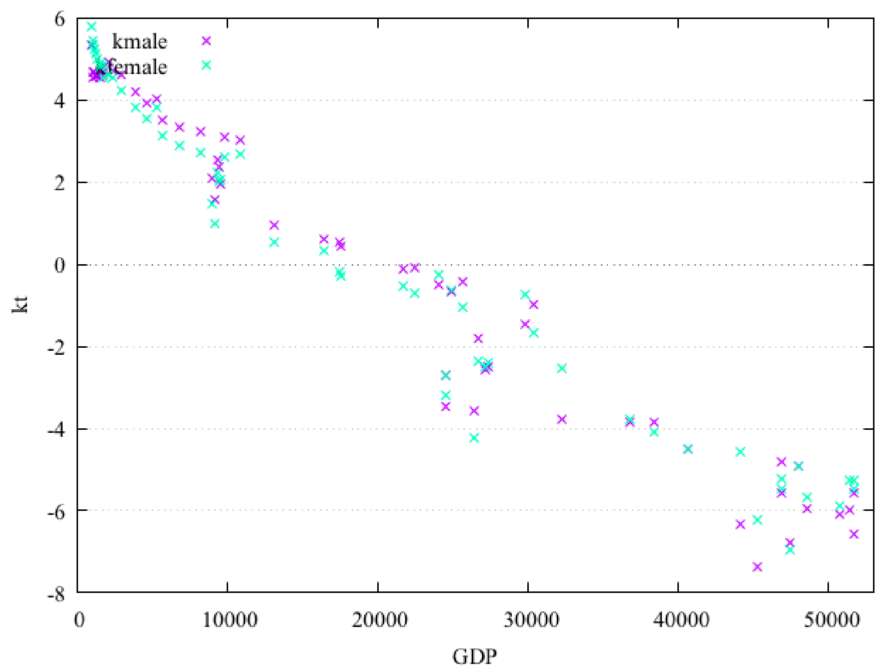

Figure 7. Correlation between mortality index k_t and GDP per capita (in current US$)

	Females		Males	
Age	a_x	b_x	a_x	b_x
0	-4.8033	0.20239	-4.567411	0.19571
1	-7.3779	0.18611	-7.179881	0.17678
2	-7.949	0.19884	-7.673269	0.17656
3	-8.2601	0.20822	-7.9418	0.15871
4	-8.5007	0.18187	-8.098031	0.18718
5	-8.6021	0.18277	-8.296792	0.20042
6	-8.6967	0.18285	-8.366754	0.18503
7	-8.6316	0.11003	-8.458392	0.17886
8	-8.5095	0.074194	-8.478519	0.17339
9	-8.8158	0.12305	-8.523386	0.17133
10	-8.9183	0.16127	-8.518743	0.13619
11	-8.9296	0.14854	-8.568536	0.15327
12	-8.6576	0.11631	-8.468526	0.17585
13	-8.7634	0.098736	-8.30996	0.12732
14	-8.5276	0.10068	-8.168195	0.1419
15	-8.3047	0.11238	-7.742515	0.11886
16	-7.9358	0.084016	-7.187258	0.12423
17	-7.9492	0.085844	-6.993293	0.11606
18	-7.8775	0.094918	-6.62425	0.097614
19	-7.8153	0.094777	-6.564277	0.099689
20	-7.8411	0.079401	-6.625224	0.10108
21	-7.8855	0.091522	-6.602851	0.097809
22	-7.8965	0.084892	-6.665742	0.098081
23	-7.9476	0.10656	-6.688504	0.091825
24	-7.8968	0.10967	-6.734357	0.086347
25	-7.9134	0.098869	-6.760017	0.099629
26	-7.8228	0.083857	-6.750289	0.089217
27	-7.8265	0.11021	-6.775309	0.10034
28	-7.6951	0.1033	-6.743366	0.095184
29	-7.6915	0.10162	-6.738695	0.10202
30	-7.6343	0.10664	-6.73614	0.096562
31	-7.5667	0.1234	-6.673486	0.10103
32	-7.4749	0.10494	-6.632896	0.10552
33	-7.3487	0.10626	-6.571998	0.10226
34	-7.2768	0.10427	-6.530479	0.093055
35	-7.2439	0.10793	-6.453762	0.10613
36	-7.0991	0.09645	-6.417928	0.10245
37	-7.0113	0.10592	-6.313704	0.1044
38	-6.959	0.10587	-6.243226	0.097372
39	-6.8419	0.10929	-6.143396	0.098333
40	-6.7696	0.10472	-6.071603	0.10093
41	-6.6546	0.099907	-5.965722	0.098753
42	-6.5505	0.093447	-5.881328	0.093422
43	-6.451	0.090213	-5.794542	0.095801
44	-6.3384	0.088507	-5.708393	0.09309
45	-6.2514	0.087887	-5.605902	0.08619
46	-6.1655	0.089752	-5.501362	0.079243
47	-6.0796	0.084989	-5.41996	0.08313
48	-5.975	0.078687	-5.320944	0.079347
49	-5.8843	0.079144	-5.216829	0.077121
50	-5.7918	0.077127	-5.132027	0.078269
51	-5.7182	0.076394	-5.030896	0.073077
52	-5.6296	0.075374	-4.939932	0.071521
53	-5.5442	0.072765	-4.840457	0.071955
54	-5.4759	0.072536	-4.718933	0.06774
55	-5.3821	0.073905	-4.651242	0.071938
56	-5.2952	0.072487	-4.557071	0.072306
57	-5.2203	0.07252	-4.448306	0.071701
58	-5.1033	0.074485	-4.363609	0.072278
59	-5.0441	0.075344	-4.281265	0.077683
60	-4.9327	0.074811	-4.172955	0.073062
61	-4.8431	0.076702	-4.071498	0.076337
62	-4.7618	0.079902	-3.990019	0.076855
63	-4.6545	0.079955	-3.902795	0.078515
64	-4.5531	0.084391	-3.81554	0.082801
65	-4.4641	0.084752	-3.718386	0.081939
66	-4.3584	0.088623	-3.623913	0.081582
67	-4.2548	0.090211	-3.537187	0.084944
68	-4.1485	0.091749	-3.446812	0.084981
69	-4.0414	0.094893	-3.359555	0.088939
70	-3.933	0.096701	-3.271597	0.087069
71	-3.8132	0.103	-3.178433	0.089707
72	-3.6995	0.10443	-3.096074	0.090944
73	-3.5897	0.10421	-2.993971	0.088686
74	-3.4619	0.10433	-2.90539	0.086377
75	-3.3461	0.10471	-2.806269	0.08364
76	-3.2098	0.1032	-2.710355	0.081063
77	-3.0871	0.10028	-2.604306	0.081568
78	-2.9659	0.10057	-2.510856	0.07925
79	-2.8455	0.099051	-2.421385	0.077817
80	-2.6958	0.095666	-2.303055	0.073736
81	-2.5733	0.09233	-2.208561	0.070438
82	-2.4466	0.086377	-2.100218	0.066177
83	-2.3205	0.08403	-2.003342	0.064223
84	-2.1939	0.080425	-1.905706	0.059882
85	-2.0679	0.072989	-1.808104	0.056792
86	-1.9468	0.06874	-1.707499	0.052441
87	-1.8369	0.063646	-1.603365	0.047829
88	-1.7182	0.060975	-1.518628	0.042418
89	-1.6162	0.055532	-1.424765	0.066771

Table 2. Fitted values of a_x and b_x, for 1960-2017 (SVD)

	k_t	
Year	Females	Males
1960	5.77089528	5.33027656
1961	5.33358512	4.69551628
1962	5.44964848	4.55323716
1963	5.24180032	4.66284704
1964	5.14439	4.57247232
1965	4.9859872	4.58071596
1966	4.87821408	4.55964888
1967	4.80626664	4.72085784
1968	4.52499064	4.59842452
1969	4.86873952	4.71169824
1970	4.5981224	4.9263382
1971	4.54068288	4.72207912
1972	4.23956952	4.59476068
1973	3.81114176	4.18624252
1974	3.55562472	3.93801736
1975	3.80107504	4.03236124
1976	3.13815192	3.49347144
1977	2.890362568	3.31852308
1978	2.719139504	3.22478984
1979	2.610182064	3.10632568
1980	2.674697896	3.032529836
1981	2.219445288	2.525393316
1982	2.01822932	2.376366624
1983	2.074454912	1.960093336
1984	1.477202336	2.100876388
1985	0.99986216	1.574504708
1986	0.533861848	0.939255916
1987	0.315117944	0.6060602
1988	-0.291396014	0.426012996
1989	-0.19596647	0.548140996
1990	-0.545616224	-0.130029682
1991	-0.700466064	-0.088051235
1992	-0.646697936	-0.664071
1993	-0.25710699	-0.501976612
1994	-1.063341712	-0.443080384
1995	-1.65923232	-0.99564852
1996	-0.725396	-1.467093132
1997	-2.36005368	-1.824470192
1998	-2.406419808	-2.486403952
1999	-2.499448144	-2.583648372
2000	-2.694535256	-2.701746148
2001	-3.1739776	-3.46171816
2002	-4.21410664	-3.58018232
2003	-2.518989424	-3.77589244
2004	-3.78952792	-3.83695644
2005	-4.07080392	-3.83909368
2006	-4.48235512	-4.49919552
2007	-5.45320144	-4.82283472
2008	-5.27732992	-5.58308152
2009	-4.92292216	-4.92603288
2010	-5.23143752	-5.55651868
2011	-5.25926904	-5.97450176
2012	-5.67851832	-5.94793892
2013	-5.88695864	-6.07953184
2014	-5.46445248	-6.55552572
2015	-4.57354776	-6.31737612
2016	-6.21501528	-7.3536322
2017	-6.96350552	-6.79428596

Table 3. Fitted values of k_t, for 1960-2017 (SVD)

Year	k_t male	Prediction	95% confidence interval		st. Error
1989	0.548141	0.213301			
1990	-0.13003	0.335429			
1991	-0.088051	-0.342742			
1992	-0.664071	-0.300763			
1993	-0.501977	-0.876783			
1994	-0.44308	-0.714689			
1995	-0.995649	-0.655792			
1996	-1.467093	-1.208361			
1997	-1.82447	-1.679805			
1998	-2.486404	-2.037182			
1999	-2.583648	-2.699116			
2000	-2.701746	-2.79636			
2001	-3.461718	-2.914458			
2002	-3.580182	-3.67443			
2003	-3.775892	-3.792894			
2004	-3.836956	-3.988604			
2005	-3.839094	-4.049668			
2006	-4.499196	-4.051806			
2007	-4.822835	-4.711908			
2008	-5.583082	-5.035547			
2009	-4.926033	-5.795794			
2010	-5.556519	-5.138745			
2011	-5.974502	-5.769231			
2012	-5.947939	-6.187214			
2013	-6.079532	-6.160651			
2014	-6.555526	-6.292244			
2015	-6.317376	-6.768238			
2016	-7.353632	-6.530088			
2017	-6.794286	-7.566344			
2018		-7.006998	-7.664644	-6.349351	0.33554
2019		-7.219709	-8.149762	-6.289657	0.474525
2020		-7.432421	-8.571498	-6.293344	0.581173
2021		-7.645133	-8.960426	-6.329839	0.67108
2022		-7.857844	-9.328386	-6.387302	0.75029
2023		-8.070556	-9.681454	-6.459657	0.821902
2024		-8.283267	-10.023237	-6.543298	0.887756
2025		-8.495979	-10.356084	-6.635874	0.949051
2026		-8.708691	-10.68163	-6.735751	1.00662
2027		-8.921402	-11.001063	-6.841741	1.061071

Table 4. Forecasted values with 95% confidence intervals of males (ARIMA)

Year	k_t female	Prediction	95% confidence interval		st. Error
1989	-0.195966	-0.514807			
1990	-0.545616	-0.419377			
1991	-0.700466	-0.769027			
1992	-0.646698	-0.923877			
1993	-0.257107	-0.870108			
1994	-1.063342	-0.480518			
1995	-1.659232	-1.286752			
1996	-0.725396	-1.882643			
1997	-2.360054	-0.948807			
1998	-2.40642	-2.583464			
1999	-2.499448	-2.62983			
2000	-2.694535	-2.722859			
2001	-3.173978	-2.917946			
2002	-4.214107	-3.397388			
2003	-2.518989	-4.437517			
2004	-3.789528	-2.7424			
2005	-4.070804	-4.012938			
2006	-4.482355	-4.294214			
2007	-5.453201	-4.705766			
2008	-5.27733	-5.676612			
2009	-4.922922	-5.50074			
2010	-5.231438	-5.146333			
2011	-5.259269	-5.454848			
2012	-5.678518	-5.48268			
2013	-5.886959	-5.901929			
2014	-5.464452	-6.110369			
2015	-4.573548	-5.687863			
2016	-6.215015	-4.796958			
2017	-6.963506	-6.438426			
2018		-7.186916	0.546737	-8.2585	-6.115332
2019		-7.410327	0.773202	-8.925775	-5.894878
2020		-7.633737	0.946976	-9.489775	-5.777699
2021		-7.857148	1.093473	-10.000316	-5.713979
2022		-8.080558	1.22254	-10.476693	-5.684423
2023		-8.303969	1.339226	-10.928803	-5.679134
2024		-8.527379	1.446529	-11.362525	-5.692234
2025		-8.75079	1.546405	-11.781688	-5.719892
2026		-8.9742	1.64021	-12.188953	-5.759448
2027		-9.197611	1.728933	-12.586258	-5.808964

Table 5. Forecasted values with 95% confidence intervals of females (ARIMA)