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ORIGINAL PAPER

Can Romania's labour market thrive in the age of population ageing? A Bayesian VAR approach

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Abstract
After the fall of communism and the transition to a democratic and open society, Romania has been making significant progress adapting its economy to rising demands from internal and external forces with the goal of becoming an integral part of a much larger system of trade and commerce within the European Union. As many Member States, Romania is undergoing a severe demographic transformation, defined by decreasing birth rates, a higher life expectancy known as population ageing. Similarly, due to harsh economic conditions and social factors, a large number of capable young adults have migrated to other Member States in search of higher wages and better conditions resulting in challenges for labour market efficiency. Romania's current labour market requirements for employees are covered by a slowly shrinking group of adults, leading to shortages of labour resources, with significant consequences for economic growth. This paper aims to evaluate future employment trends under current economic and demographic conditions. To these ends, a VAR model will be employed to assess the effects that economic and demographic factors have on the employment rate. The expected results are of a slowing down of economic growth due to the expected decline in labour resources.

Keywords: *Bayesian VAR; Employment; Population Ageing; Productivity; Wages.*

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Introduction

In the last few decades, a series of phenomena have transformed the demographic landscape in Romania, where due to the decline in birth rates and the increase in life expectancy, the population started getting older. *Demographic ageing* is a complex phenomenon, which results in changes in the working segment of the population (ages 15 to 64 years old), affecting economic growth and development in key areas due to capital transfer to social programs.

The decline in the active share of the population on the labour market will lead to a reduction of the tax base, where the public revenues collected for state and local budgets (especially for social insurance schemes) will be lower. Thus, governments will be forced to increase taxes and duties to cover the rise in expenditures or contract funds from external sources to cover payments for social protection and retirement schemes.

Concerning the labour market, demographic ageing tends to result in an acute shortage of active qualified personnel, due in part to lower numbers of young employees and high retirement rates causing an imbalance between inflows and outflows of human capital. Similarly, this results in a skill disruption where experienced employees leave the labour market failing to pass valuable knowledge to younger generations taking their place thus contributing to the knowledge gap.

Ageing populations tend to have different preferences regarding consumption and saving, causing shifts from in capital from one sector of the economy to another. For instance, elderly individuals in western nations hold accumulated capital in financial assets (stocks, bonds, indices) thus pushing valuations higher and out of reach for younger generations. Elderly individuals are less prone to travel, to buy new clothes and electronics thus lower consumption needs, in favour of healthcare and medical expenditures. This in effect creates an environment of hostility between generations where the possibilities for younger individuals to invest in financial assets decrease due to high valuations. A similar concern has been expressed by several authors when due to the retirement of older generation and the decline in income where most are forced to liquidate assets in order to cover current living expenses, thus collapsing asset prices across the board (Cristea and Mitrica, 2016; Hsu, 2017).

The focus of this paper is the analysis of the effects of population ageing on labour market indicator of growth, through the implementation of vector autoregressive models or VAR. The current paper introduces an element of originality, providing a window into how the rising share of elderly might influence the labour market trends. The main aim of implementing a VAR model is to assess how a sudden innovation to the share of the population age 65 years and older might impact nominal wages, the employment and unemployment rates over an 8 year period. For this purpose, we employ impulse response functions where the main causal variable is the share of the population age 65 years and older. The model is assessed for autocorrelation and normality of residuals. Similarly, the model is evaluated for stability using Eigenvalue stability test.

Theoretical framework

A generally accepted consensus is emerging among demographers and economists regarding population, due to its potential to become a fundamental factor determining the development of societies in current times and the decades to follow

(Rios and Patuelli, 2017). The ageing process can be observed at a regional level, with estimates published by the OECD that show an increase in the share of elderly individuals (65 years and older), a rise in life expectancy and a decline in birth rates leading to a shift in population trends, transfers of wealth and technology and changes in how human capital is allocated (OECD, 2015, 2019).

In a study publish by the United Nations, estimates show that by 2030 older individuals are expected to outnumber children under 10 years old and by 2050 the share of the population age 60 years and older will overtake generation between 10 and 24 years old (United Nations, 2019). The European Union member states are also following along the same lines, mirroring trends that are taking place in industrialised nations around the globe. Between 2017 and 2070 it is estimated that the EU28 population will increase slightly from 511 million to 520 million but with a severe decline in the age group between 15 to 64 years old from (European Commission, 2017).

Demographic trends in Romania

In Romania the demographic landscape is projected to take a negative turn, with the total population expected to decline from 19.3 million in 2015 to an estimated 18 million in 2030 (Figure 1.), with the main indicators of population growth, most notably fertility, holding a steady level of 1.81 children per woman (European Commission, 2018).

The decline in the overall size of the population will continue to shift downward reaching an estimated level of 17 million by 2040 with a slight increase in fertility to 1.85 children per woman, being lower then the general replacement level of 2.1 children per couple, as it is stipulated in the literature (Parr and Guest, 2014). Toward the end of the projected period, it is estimated the population in Romania will hit an all-time low of around 15.7 million by 2060, with fertility rates hovering at 1.88, well below an adequate population replacement level (European Commission, 2018).

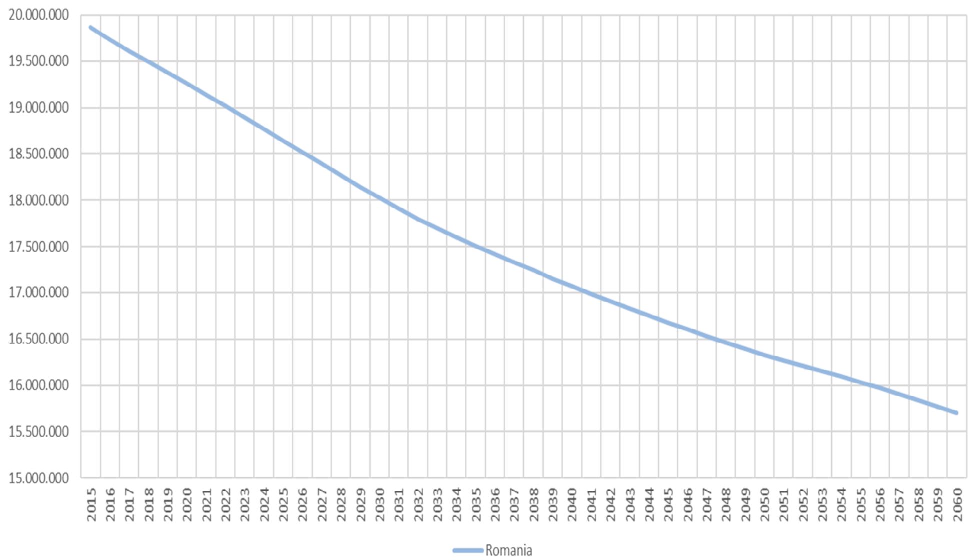


Figure 1. Population projection in Romania (2015-2060)

Source: Authors own creation based on Eurostat data

Between 2016 and 2020, the population structure in Romania will change in a gradual manner, declining primarily within the age groups between 0 to 14 years old and 15 to 64 years old, and expand in the age groups where individuals are older than 65 years as can be observed in Figure 2. In 2020, the age group of 0 to 14-year-old is estimated to represent 15.5% of the total population while individuals between the ages of 15 and 64 represent 67.1%.

The share of individuals ages 0 to 14-year-old will continue to decline reaching by 2060 a level of 15.2% within the total population and for individuals in the 15 to 64 years old group will reach 54.1%. The decline is more significant in the case of individuals with an age between 15 and 64 years old.

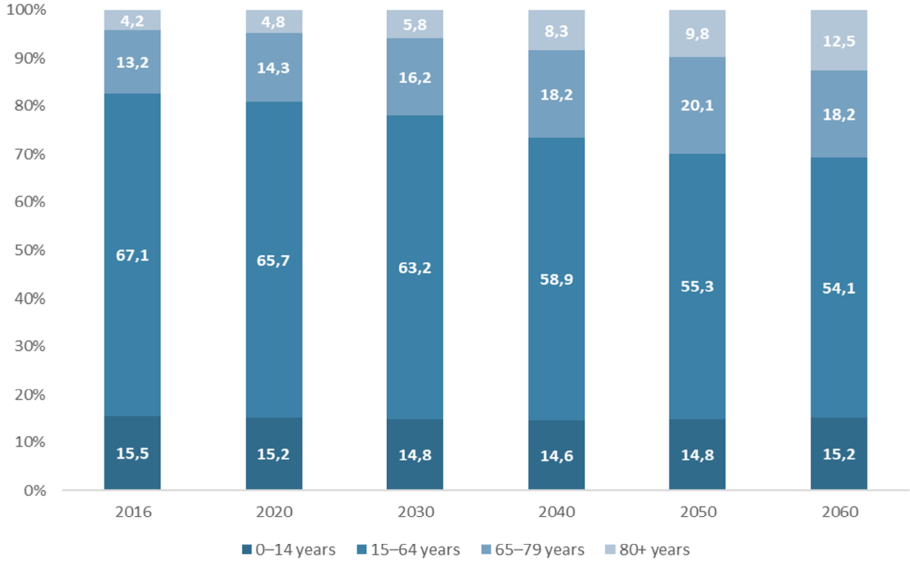


Figure 2. Population structure changes by age in Romania (2015-2060)
Source: Authors own creation based on Eurostat data

For the groups of elderly individuals ages 65 to 79 years old and 80 years and more, the increases can be observed for the entirety of the projected period rising from 13.2% for individuals ages 65 to 79 years old to 18.2% and for individuals that are older than 80 years it is estimated to climb from 4.2% in 2016 to 12.5% in 2060.

Regional demographic trends analysis

To help get a clearer picture of how *population* as a whole evolved at a regional level between 2000 and 2017 we can observe the changes as highlighted in Figure 3. In 2000, based on the colour coding utilised to group respective counties, we can observe that the counties with the lowest population figures between 233 and 356 thousand inhabitants are coloured with red and are comprised of the Caraș-Severin, Mehedinți, Giurgiu, Călărași, Ilfov, Ialomița, Tulcea, Sălaj, Bistrița Năsăud, Harghita and Covasna.

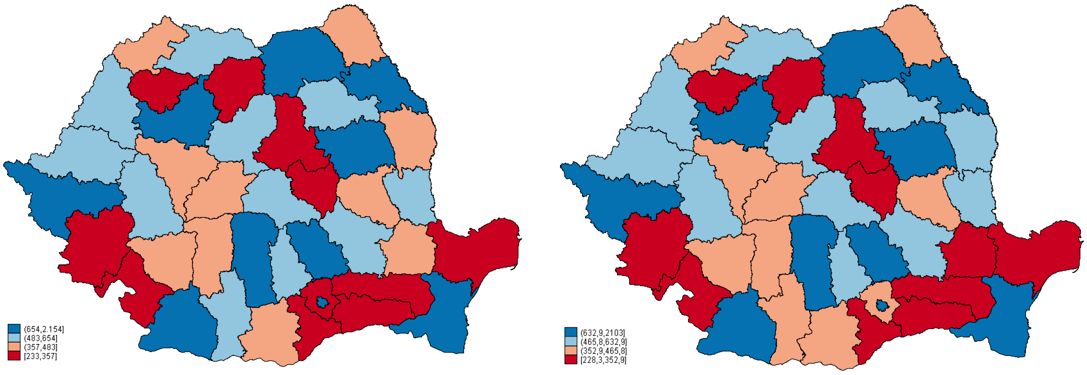


Figure 3. Total population changes by region in Romania between 2000 (left) and 2017 (right), thousands

Source*:* Own creation based on National Institute of Statistics data

The next group is colour coded orange and contains counties that have a population between 357 and 483 thousand inhabitants and is comprised of Gorj, Vîlcea, Sibiu, Alba, Sibiu, Teleorman, Satu Mare, Botoșai, Brăila, Vrancea and Vaslui. The group coloured light blue contains populations between 483 and 654 thousand and is comprised of Olt, Dâmbovița, Buzău, Galați, Braov, Mureș, Neamț, Maramureș, Bihor and Hunedoara. The group that contains the counties with the largest populations with values between 654 and 2154 thousand people are Timiș, Dolj, Argeș, Prahova, Bucharest, Constanța, Bacău, Iași, Suceava and Cluj.

In 2017 when compared to groups in 2000, the only counties that registered an increase in population numbers are Suceva, Iași, Vaslui, Sibiu, Timiș, Brașov, Constanța and Ilfov. Thus, out of the 42 counties, only 8 registered population growth mainly due to internal migration patterns and 34 have seen declines in the number of residents.

The *birth rates* in Romania between 2000 and 2017 at a regional level have decrease in all counties. In 2000, the lowest birth rates, regions colour coded red, with values between 7.2 and 9.7 births per 1000 individuals have been recorded in Teleorman, Brăila, Cluj, Brașov, Timis, Arad, Caraș-Severin, Hunedoara and Cluj. Values between 9.7 and 10.2 births per 1000 individuals, have been recorded in Olt, Mehedinți, Vâlcea, Argeș, Giurgiu, Buzău, Bihor, Sibiu, Giurgiu, Ilfov, București, Prahova, Constanța and Tulcea. Values between 10.2 and 11.1 births per 1000 individuals, colour coded light blue, have been recorded in the year 2000 in Dolj, Gorj, Dâmbovița, Călărași, Ialomița, Galați, Vrancea, Harghita, Mureș, Bihor and Satu Mare (Figure 4).

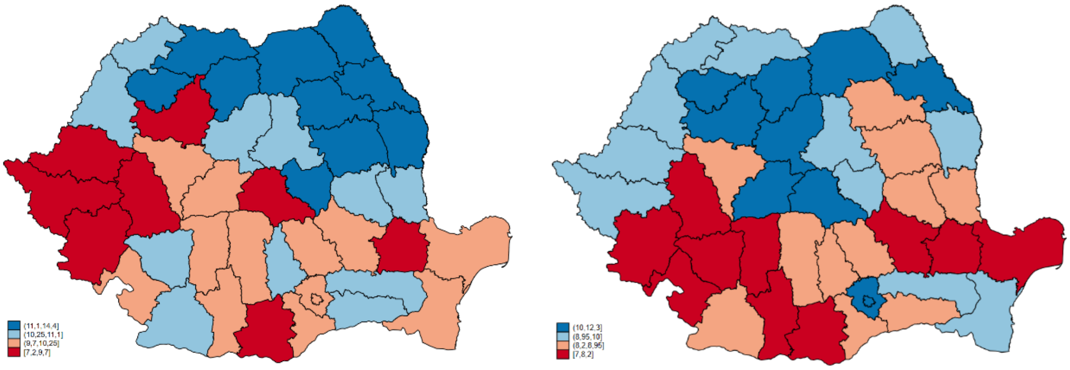


Figure 4. Crude birth rates changes by county in Romania between 2000 (left) and 2017 (right)

Source*:* Authors own processing in Stata 16

The highest birth rates with values between 11.1 and 14.4 births per 1000 individuals, colour coded blue, have been recorded in 2000 in Covasna, Vaslui, Bacău, Iași, Neamț, Suceava, Botoșani, Sălaj, Maramureș and Bistrița-Năsăud. In 2017, the birth rates, have decreased to a higher extent in Botoșani, Vaslui, Bacău, Vâlcea, Gorj with values between 7.1 and 7.7 births per 1000 individuals, marking a drop of close to 50%. The lowest drops in birth rates have been recorded in 2017 in Brașov, Timiș, Ilfov, Sibiu and Arad with between 0.5 and 2.3 births per 1000 individuals.

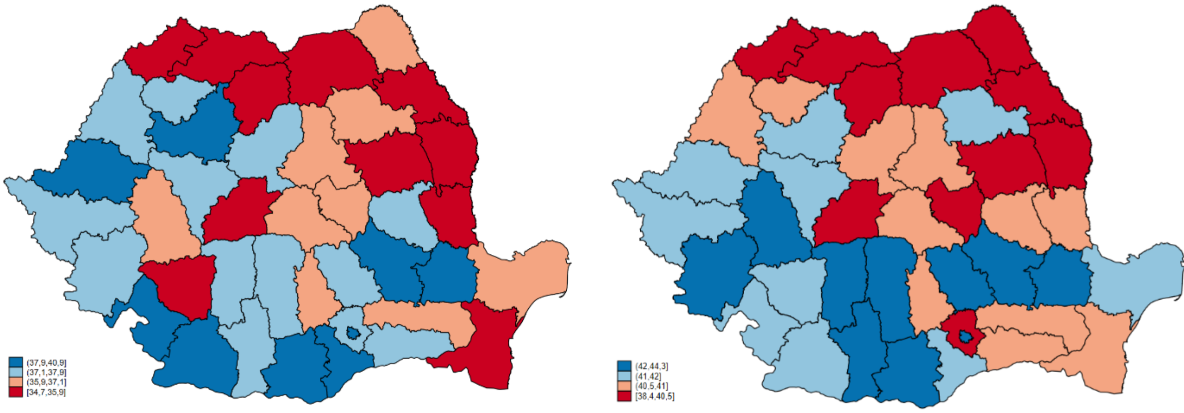


Figure 5. Median age by county in Romania between 2000 (left) and 2017 (right), years

Source: Authors own processing in Stata 16

The *median age* has seen gains between 2000 and 2017 in all 41 counties in Romania for both men and women (Figure 5). In 2000 the counties that recorded the lowest median age with values between 34.7 and 35.9 years, colour coded in red, were Gorj, Sibiu, Constanța, Galați, Vaslui, Bacău, Iași, Suceava, Bistrița-Năsăud, Mureș and Satu Mare. Values between 35.9 and 37.1 years, were recorded in Tulcea, Ialomița, Dâmbovița, Hunedoara, Brașov, Covasna, Hargita, Neamț and Botoșani. Values between 37.1 and 37.9 years, colour coded light blue, were recorded in Olt, Vîlcea, Arges, Prahova, Ilfov, Călărași, Vrancea, Timiș, Craș-Severin, Alba, Bihor and Sălaj. Finally, the counties with the highest median age, with values between 37.9 and 40.9 years, colour coded blue, have been recorded in Buzău, Cluj, București, Călărași, Giurgiu, Teleorman, Olt, Dolj, Mehedinți and Arad. When comparing on a county by county level, between 2000 and 2017, the highest gains in terms of median age, were recorded in Constanța, București-Ilfov, Tulcea, Gorj, Vâlcea, Brăila, Galați, Brașov, Sibiu and Hunedoara with net gains between 3.6 and 5.8 years on average. The lowest gains to the median age were recorded in Ilfov with 0.9 years and Giurgiu with 2.2 years.

The *share of the population between the ages of 0 and 19 years old* represent younger generations that will replace working-age adults and take an active role in Romania's economic development at a regional and national level. Between 2000 and 2017, noticeable shifts at a regional level can be observed in Figure 7, that will lead to structural imbalances in the labour market over a longer period of time. In 2000, the share of the population between 0 and 19 years old had the lowest values between 22.5% and 25.1% of the population in Dolj, Teleorman, Giurgiu, București-Ilfov, Prahova, Buzău, Brăila, Timiș, Arad and Cluj. The regions where the population age 0 to 19 years old are between 25.1% and 26.5% were Olt, Vîlcea, Arges, Brașov, Mureș, Alba, Hunedoara, Caraș-Severin, Mehedinți and Bihor. The third group, colour coded light blue, where the share of the population age 0 to 19 years old registered values between 26.5% and 27.5% were Sibiu, Sălaj, Harghita, Neamț, Vrancea, Galați, Dâmbovița, Ialomița, Călărași, Constanța, and Tulcea. The regions that presented the highest share of individuals between the ages of 0 and 19 years, colour coded blue, were Gorj, Covasna, Bacău, Vaslui, Iași, Botoșani, Suceava, Bistrița-Năsăud, Maramureș and Satu Mare.

In 2017, however, the share of individual between 0 and 19 years shifted lower in all regions with varying speeds. The highest declines registered in the population age 0 to 19 years old, occurred in Gorj with a decline of 9.9%, Galați with a deline of 8.7% and Olt with 8.3%. Declines between 8% and 7% occured in Mehedinti, Dambovita, Brăila, Alba, Caraș-Severin, Satu Mare, Bistrița-Năsăud, Iași, Tulcea, Neamț and Bacau. More moderate declines between 5% and 6% occurred in Giurgiu, Arad, Cluj, Ialomița, București, Bihor, Teleorman, Dolj, Buzău, Sălaj, Călărași, Brașov, Prahova, Vrancea, Timiș, Covasna, Suceava, Harghita, Sibiu, Constanța, Argeș, Botoșani. Lastly the regions with the smallest declines are Ilfov with a decline of 3% of individuals ages 0 and 19 years old, and Mureș with a decline of 4.9%.

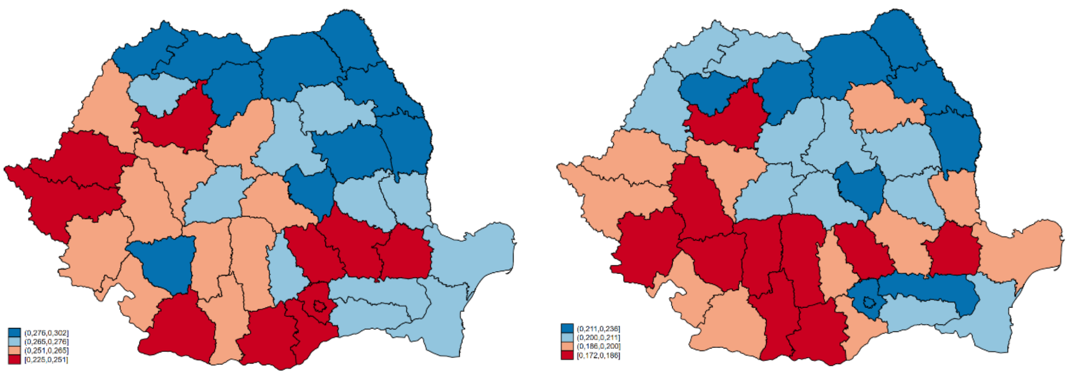


Figure 7. Share of population age 0 to 19 years old, by county in Romania between 2000 (left) and 2017 (right)

Source*:* Authors own processing in Stata 16

The elderly segment of the population that have exited the labour market consists of *individuals age 65 years and old*, they rely to a great extent on financial services accrued through pensions and on social security services and health-related services. At a regional level the share of people age 65 years and older, as can be observed in Figure 8, was the lowest with values between 14.6% and 16.9%, colour coded red, in Satu Mare, Maramureş, Bistriţa-Năsăud, Iași, Sibiu, Brașov, Covasna, Galaţi, Tulcea and Constanţa. The second category of regions, colour coded light red, with values between 16.9% and 18.7% were Timiş, Hunedoara, Gorj, Bihor, Suceava, Neamţ, Bacău, Harghita, Vaslui and Arges. The third group of regions with values between 18.7% and 20.1%, representing the share of individuals older than 65 years, colour coded light blue, were Caraș-Severin, Zalău, Cluj, Alba, Dâmboviţa, Prahova, Vrancea, Brăila and Ialomiţa. Finally, the regions with the highest share of elderly, colour coded blue, were Arad, Mehedinţi, Dolj, Olt, Teleorman, Vîlcea, Giurgiu, București-Ilfov, Călărași, Buzău and Botoșani.

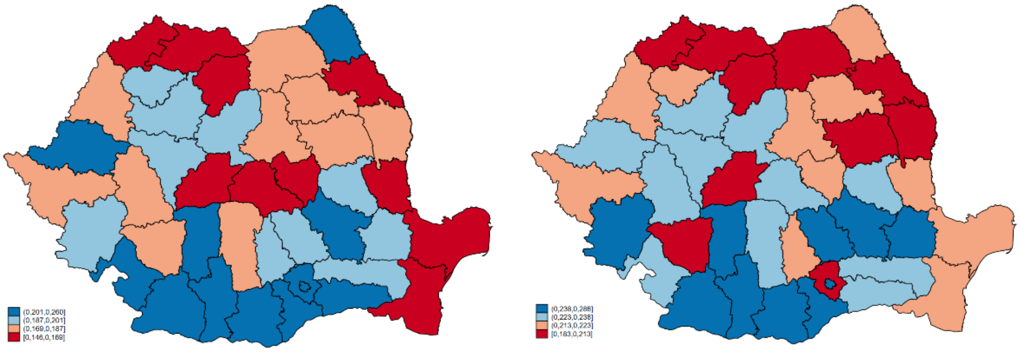


Figure 8. Share of population age 65 and older, by county in Romania between 2000 (left) and 2017 (right)

Source: Authors own processing in Stata 16

When comparing how the share of elderly evolved at a regional level in 2017 (Figure 8), an increase in all regions occurrent in the share of elderly ages 65 years and older, with increases of 7% in three regions (Hunedoara, Brasov, Constanta), 6% in four regions (Maramures, Galati, Tulcea, Bucuresti), increases of 5% in 9 regions (Cluj, Alba, Valcea, Braila, Sibiu, Harghita, Covasna, Arges, Caras-Severin), increase between 4% and 2% in 22 regions (Suceava, Calarasi, Iasi, Dolj, Vrancea, Teleorman, Mehedinti, Arad, Ialomita, Salaj, Buzau, Dambovita, Bihor, Gorj, Bacau, Olt, Bistrita-Nasaud, Mures, Satu Mare, Neamt, Prahovam and Timis), Vaslui and Botoșani registered a small increase of 1% and Ilfov was the onlz region that recorded a decreased from 20% to 18%.

Methodology and data

Vector autoregressive models or VAR are considered one of the most accurate, flexible, and easy to use models, being applied mainly in multivariate time series analyses. The VAR model is a natural extension from a univariate to multivariate autoregressive model in dynamic time-series analyses (Stock and Watson, 2001; Rubio-Ramirez, Waggoner and Zha, 2010).

Vector autoregressive models have proven to be particularly useful for describing the dynamic performance of time series and for forecasts in time-series driven fields. The high degree of utilisation resulting from the high predictive power, when comparing results to traditional univariate models (ARMA, ARIMA), even when using small data sets (Sims, 1980; Lütkepohl and Saikkonon, 1994; Rubio-Ramirez, Waggoner and Zha, 2010). The VAR model is very popular among researchers, as well as decision-makers from banking and financial institutions to demographic research centres and medical institutions, due to the possibility of involving structural inferences and policy analysis. Within the structural analysis, certain hypotheses regarding the causal nature of the data are the subject of an investigation where the evolution is tracked under the impact of unexpected shocks or innovations on the variables included in the VAR model. The vector autoregressive model (VAR) can be written as the following equation (1.1) (Phillips and Loretan, 1989; Hansen and Phillips, 1990; Rios and Patuelli, 2017):

$$v_t - c + \sum_{i=0}^{N} \beta_i v_{t-i} + e_t \tag{1.1}$$

where:

v_t – represents an $M \times 1$ vector comprised of exogenous variables;

c – represents an $M \times 1$ vector comprised of constrains;

β_i – represents a variable that is comprised out of an $M \times M$ matrix of coefficients,

that take values from $i = 1$ to N;

e_t – where $e_t \sim (0, \Sigma)$, Σ is a $M \times M$ matrix of covariations.

The reduced form VAR presented in Equation 1.1 does not serve as a starting point for structural analysis, because the cross-correlations between the reduced error forms suggest that the interpretation of the influence of a change in one variable on another variable, when the other variables remain constant is no longer valid (Hand, 1999; Fernandez-Villaverde et al., 2007). Thus, we can employ a reduced structural form of the VAR model as an autoregressive structural vector (SVAR), as shown in equation (1.2) (Gottschalk, 2001):

$$A_0 z_t = A_0 \sigma + \sum_{i=0}^{N} A_0 \beta_i v_{t-i} + \varepsilon_t \tag{1.2}$$

where:

A_0 – represents a matrix where the diagonal values are one;

σ – represents a vector of constraints;

β_i – represents a k x k matrix (where $i=0....p$)

ε_t – represents shocks with a null mean that signifies the lack of serial correlations between shocks or innovations.

When comparing equations 1.1 and 1.2, we can observe that $e_t = A_0^{-1}\varepsilon_t$ și $E[\varepsilon_t', \varepsilon_t] = \sum = (A_0' A_0)^{-1}$. Thus, matrix A_0 allows us to find structural shocks that our research is focused on (Rubio-Ramirez, Waggoner and Zha, 2010). Hence, dynamic models can be seen as stochastic process restriction, that allows for the mapping of structural shocks like ε_t and y_t, written as $y_t = C\varepsilon_t$, where ε_t represents the dynamic evolution of shocks or innovation until time t. The construction of the mapping variables can be interpreted as a structural reply to shocks in period t. A basic representation of an impulse response function (IRF) can be written as follows (1.3) (Gottschalk, 2001; Ronayne, 2011):

$$y_t \quad C_0\varepsilon_t + C_1\varepsilon_{t-1} + \ldots + C_n\varepsilon_{t-n} \tag{1.3}$$

where C_n – represents the *n*th response to an impulse that can be written as y_{t+n} to ε_t in such a manner that $C_n = D_n A_0^{-1} = D_n C_0$, where $C0 = A_0^{-1}$ and D_n are the *n*th response to a y_{t+n} impulse, to a change of one unit in e_t ($D_0 = I_n$) (Ouliaris, Pagan and Restrepo, 2018).

Evaluating the stationarity of time-series data sets

The order of integration within time series falls into the category of descriptive statistics and specifies the minimum number of differences or lags to convert a time series into a stationary form (Adhikari and Agrawal, 2013). In statistical and econometric analysis, stationary time series are ideal, because the changes brought about by variations over time of the variables do not alter the form of the distribution (Etuk and Mohamed, 2014).

The order of integration in the case of time series is denoted by *I(d)* and represents the state of the time series that can be either (Etuk and Mohamed, 2014; Zhang et al., 2014):

- stationary, being represented by a process denoted by *I (0),* and
- non-stationary being represented by a process that is denoted by *I (1).*

In the case of non-stationary time series, the standard procedure is to transform the series with successive differences of order *d* to bring it into a stationary form. Transforming the time series by means of logarithms helps to stabilize the variation, and by means of differentiations helps to stabilize the average of the series, leading to the reduction of the trend or seasonality (Zi-Yi, 2017, p.). The unit root test is a very common procedure used to determine whether a time series has the characteristics of a random walk (Saikkonen & Lütkepohl, 1999; Zi-Yi, 2017). The most common form of unit root test is the Augment Dicky Fuller test, that can be written including a trend and constant element, as the following equation (1.4) (Dickey and A. Fuller, 1979; Dickey and Fuller, 1981):

$$\Delta y_t = (\theta_1 - 1)y_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{1.4}$$

where:

y – represents the autoregressive process;

θ_1 – represents the autoregressive parameter;

ε_t – represents the non-systematic component of the model, that equates to a white noise process;

τ_0 – represents the constant;

$\tau_0 t$ – represents the trend.

Determining the optimal number of lags

In determining the optimal lag length, the most used approach is to apply the information criterion (IC) tests. The most reliable IC tests are the Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC) and the Schwarz Information Criterion (SIC). An important issue in the use of a group of informational criteria is related to the decision of choosing a viable result, where each informational criterion may suggest a different lag length.

A similar scenario was presented by Lütkepohl (1990), where he was forced to choose an outcome, although he was faced with different suggestions for an optimal lag length as a result of using three informational criteria (Lütkepohl, 1990). Thus, it is possible to speak of a predisposition on the part of the researchers to favour the results offered by a criterion to the detriment of others. In an autoregressive process of dimension *Z* and order p_0, which may represent a VAR model, the informational criteria used to determine the order of the lags can be calculated using equations (1.5) - (1.7) (Dickey and Fuller, 1981; Arltová and Fedorová, 2016):

Schwarz Information Criterion (SIC):

$$\mathrm{SIC(p)} = \ln\left|\vec{\Sigma}(\mathrm{p})\right| + \frac{\ln \mathrm{N}}{\mathrm{N}}(Z^2\mathrm{p}) \qquad (1.5)$$

Hannan-Quinn Information Criterion (HQIC):

$$\mathrm{HQIC(p)} = \ln\left|\vec{\Sigma}(\mathrm{p})\right| + \frac{2\ln\ln \mathrm{N}}{\mathrm{N}}(Z^2\mathrm{p}) \qquad (1.6)$$

Akaike Information Criterion (AIC):

$$\mathrm{AIC(p)} = \ln\left|\vec{\Sigma}(\mathrm{p})\right| + \frac{2}{\mathrm{T}}(Z^2\mathrm{p}) \qquad (1.7)$$

where:

N - represents the data set dimension;

$\vec{\Sigma}$ - represents the quasi-maximum probability to estimate the covariation matrix of innovations Σ (Leon-Gonzalez, 2003; Pearson and Samushia, 2016);

$\hat{p}$ – is utilised to estimate the lag value, by minimising the output of the informational criterion $\{p:1\leq p\leq\bar{p}\}$, where $\bar{p} \geq p_0$ (Tjøstheim and Paulsen, 1985; Ventzislav and Kilian, 2005).

The data utilised in the econometric analysis have been collected from official sources (Eurostat and the National Institute of Statistics) for the period from 1998 to 2018, depending on their availability. The data sets present no gaps, with small adjustments for nominal net wage in accordance with guidelines approved by the National Bank of Romania(BNR, 2018). The data were collected at the national level, according to the information presented in Table 1.

Table 1. Variables utilised in the econometric model

Abbreviation	Description	Unit of measure	Source
empl	Employment rate	% of the active population	Eurostat
wages	Nominal wages	RON	National Institute of Statistic
unempl	Unemployment rate	% of the employed population	Eurostat
pop65	Share of population 65 years and older	% of the total population	Eurostat

Source: own creation based on collected data

The collected data can be group into two categories, namely demographic indicator (Share of population 65 years and older) and labour market indicators (Nominal wages, Unemployment rate, Employment rate). The main goal is to assess by way of econometric analysis how a sudden shift in the demographic indicator might influence the labour market indicators. The employed analysis revolves around vector autoregressive models that will allow us to observe the changes in the selected labour market indicators (Nominal wages, Unemployment rate, Employment rate), to an impulse or an innovation within the demographic indicator (Share of population 65 years and older).

Results and discussion

The descriptive statistics for the variables used in the VAR model contain the number of observations, the mean, the standard deviation, minimum and maximum values for all variables (Table 2). From the descriptive statistics, we can infer a normal distribution of the data, with a significant deviation from the mean on behalf of salaries due to economic policy.

Table 2. Descriptive statistics of selected variables

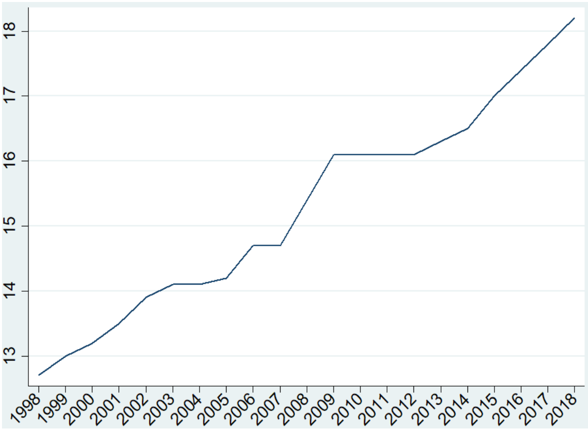
Variable	Obs	Mean	Std.Dev.	Min	Max
empl	21	65.129	2.179	62.2	68.9
wages	21	1145.524	743.556	104	2642
pop65	21	15.29	1.635	12.7	18.2
unempl	21	6.757	.98	4.2	8.3

Source: Authors own processing in Stata 16

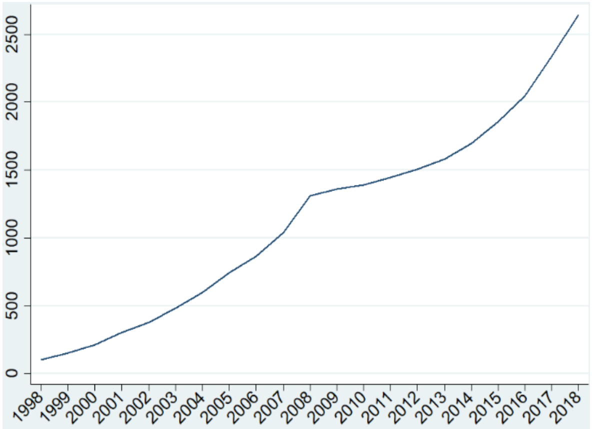
The demographic trend between 1998 and 2018, is represented by the *share of the population age 65 years and older*, that presents an increase in the number of elderly individuals in the total population from 12.7% to 18.2%, signalling an accelerating trend in the population ageing phenomenon (Figure 9 (a)). This trend is significant due to the changes it has on the structure of the population where elderly individuals are on track to overtaking young adults within the next decades (European Commission, 2017).

Nominal wages have had an upward trajectory during the timeframe in question, from 104 lei in 1998 to 2642 lei in 2018, as a result of economic expansion, but also due to monetary policies adopted at a national level (Figure 9 (b)). This trend reflects the rise in the standard of living and the rise in the specialisation of labour that has taken place over the past few decades since Romania has transitioned to open market economy.

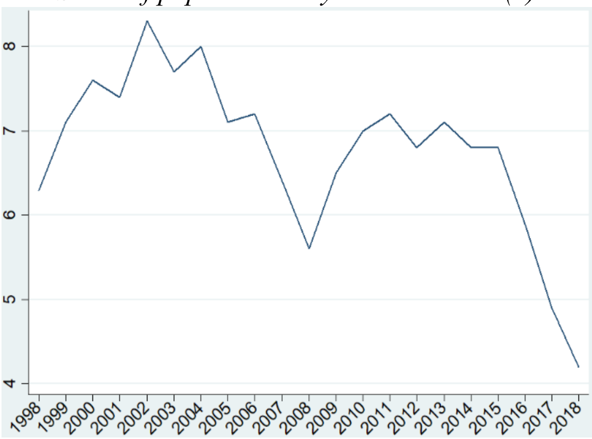
The *unemployment rate* showed a rising trend between 1998 and 2002, from 6.3% to 8.3%, but, starting with 2003, gradually decreased to a value of 4.2% recorded in 2018 (Figure 9 (c)). It's important to note the effects of the economic crisis that culminated in 2008 where a reversal of the previous trend moved the unemployment rate from 5.6% in 2008 to 7.1% in 2011.



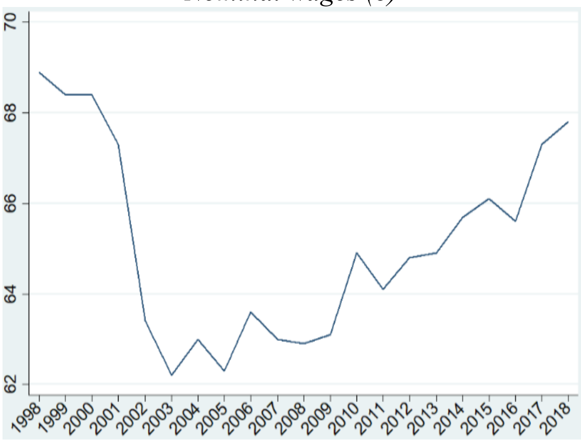
Share of population 65 years and older (a)



Nominal wages (b)



Unemployment rate (c)



Employment rate, 15-64 years old (b)

Figure 9. Changes between 1998 and 2018 in demographic and economic variables
Source: Authors own processing in Stata 16

The *employment rate* for individuals between the ages of 15 and 64 years old in the period from 1998 to 2003 decreased by about 6.7%, from 68.9% to 62.2%. Similarly, the effects of the decline in growth due to the economic crisis of '08 resulted in a period of consolidation between 2008 and 2009, followed by a sharp increase to 64.9% in 2010. Between 2003 and 2018, the employment rate gradually increased to 67.8% (Figure 9 (d)).

The next step is to evaluate the time series employed in the VAR model for stationarity, by applying the Dickey-Fuller Augmented test, using the Stata 16 econometric package. Following the initial evaluation for stationarity, by applying the

ADF test at level, the time series is determined to not be stationary. Thus, a new series will be generated, by logarithmic and first differential transformations, where appropriate.

Table 3. Augmented Dicky-Fuller test for log_wages

	Interpolated Dicky-Fuller		
Test statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
-8.339	-3.750	-3.000	-2.630
MacKinnon approximate p-value for Z(t) = 0.0000			

Source: Authors own processing in Stata 16

For the *nominal wages*, we proceeded by transforming the series using a logarithm function and running the Augmented Dicky-Fuller unit root test with the option of trend (Table 3). The value of the test statistic is of -8,339, being higher in absolute terms than the critical values for the intervals of 1%, 5% and 10%. Thus, the null hypothesis is rejected (H_0: $\theta_1 = 1$). The P-value indicator is less than 0.05 (5%), so we can talk about the alternative hypothesis of the form H_1: $| \theta_1 | <1$, which is a process that does not contain a unit root and is stationary I (0).

Table 4. Augmented Dicky-Fuller test for dlog_pop65

	Interpolated Dicky-Fuller		
Test statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
-8.339	-3.781	-2.567	-1.333
MacKinnon approximate p-value for Z(t) = 0.0007			

Source: Authors own processing in Stata 16

For the transformation of the time series, which includes *the share of the population aged 65 years and older*, in a stationary form, we proceeded to testing in a successive manner for stationarity, using the ADF test with the option of drift, after transforming the series by logarithm and by applying the first differential. The null hypothesis (H_0: $\theta_1 = 1$) was rejected by obtaining a value of -8,339, which is, in absolute terms, higher than the critical values of 1%, 5% and 10%. The p-value of the test is less than 0,05 or 0,5% so the series meets the stationary conditions (H_1: $| \theta_1 | <1$) or the lack of unit root (Table 4)

Table 5. Augmented Dicky-Fuller test for dlog_unempl

	Interpolated Dicky-Fuller		
Test statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
-3.376	-2.567	-1.740	-1.333
MacKinnon approximate p-value for Z(t) = 0.0018			

Source: Authors own processing in Stata 16

The time series for the *unemployment rate* was transformed by the application of the logarithmic function and by the first differential, where, after each transformation, the null hypothesis was tested (H_0: $\theta_1 = 1$), namely, the existence of a unit root with the ADF test.

Stationary (H_1: $|\theta_1| <1$) or lack of unit root was obtained after applying the first difference and testing with the inclusion of the drift option in the ADF test. The null hypothesis was rejected, by obtaining a value of -3,376, which is in absolute terms higher than the critical values of 1%, 5% and 10%. The p-value for the test is less than 0,05 or 0,5% so the series meets the stationary conditions (H_1: $|\theta_1|$ <1) and lacks a unit root (Table 5).

Table 6. Augmented Dicky-Fuller test for dlog_empl

	Interpolated Dicky-Fuller		
Test statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
-3.585	-2.567	-1.740	-1.333
MacKinnon approximate p-value for Z(t) = 0.0011			

Source: Authors own processing in Stata 16

For the *employment rate*, we proceeded correspondingly, by testing the time series at level for the existence of a unit root and subsequently transforming the series by logarithm and by applying the first differential. The lack of unit root or the stationary state (H_1: $|\theta_1|$ <1) resulted from the final transformation of the series. The ADF test was used with the trend and drift options, and the value obtained (Statistical test: -3,585) was higher in absolute terms than the critical values of 1%, 5% and 10%. The or p-value of the test is 0.0011, being less than 0.05 or 0.5%, thus, the series meets the conditions of stationarity (H_1: $|\theta_1|$ <1) or the lack of a unit root (Table 6).

Table 7. Optimal lag selection criteria

Selection-order criteria (lutstats)
Sample: 1998-2018 Number of observations = 21

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-155.212	-	-	-	1603.39	6.90875	6.90875	6.90875
1	-94.4969	121.43	16	0.0000	8.93805	1.64813	1.72608	2.43233
2	-71.321	46.352	16	0.0000	5.77664	**-213.19***	**-212.878***	**-210.053***
3	17.4174	177.48	16	0.0000	0.004791*	-7.75356	-7.51971	-5.40096
4	1779.63	3524.4*	16	0.0000	-	0.803909	0.959811	2.37231

Endogenous: log_wages dlog_empl dlog_pop65 dlog_unempl
Exogenous: _cons
Source: Authors own processing in Stata 16

Assessing the appropriate number of lags for the VAR model is done by applying the *varsoc* function in the State. The *varsoc* function reports for the Final Projection Error (FPE), the Akaike Informational Criterion (AIC), the Hannan-Quinn Informational Criterion (HQIC) and the Schwarz Bayesian Informational Criterion (SBIC). The resulting test statistics used in estimating the order of the "true" lag for an autoregressive vector of size *n*. In Table 7, the optimal lag length of two lags is marked with an asterisk for three of the four tests.

After determining the optimal lag length for the VAR model, the next step in to estimate the VAR model for the selected variables followed by the construction of the impulse response function (IRF). The order of the variables within the VAR model is important and will start with the representative variable of demography (dlog_pop65), to assess the effects of population ageing on the labour market variables (log_wages, dlog_empl, dlog_unempl), as can be seen in Figure 10.

```
Vector autoregression

Sample:  2001 - 2018                          Number of obs     =        18
Log likelihood =   195.0685                   AIC               = -17.67428
FPE            =   3.68e-13                   HQIC              = -17.42874
Det(Sigma_ml)  =   4.54e-15                   SBIC              = -15.89354

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlog_pop65           9     .010229   0.7623   57.72106   0.0000
log_wages            9     .054723   0.9960    4453.08   0.0000
dlog_empl            9     .019708   0.5023   18.16633   0.0200
dlog_unempl          9     .109828   0.3277   8.774614   0.3617
----------------------------------------------------------------
```

Figure 10. Estimated VAR model results
Source: Authors own processing in Stata 16

The impulse response functions estimated in Figure 11, are used to observe how a 1% shock in the share of the elderly population (dlog_pop65) will cause fluctuations within the selected labour market indicators, including the direction and the intensity of the responses. The time interval on which the analysis is performed is equal to 8 periods or the equivalent of 8 years, starting in 2018.

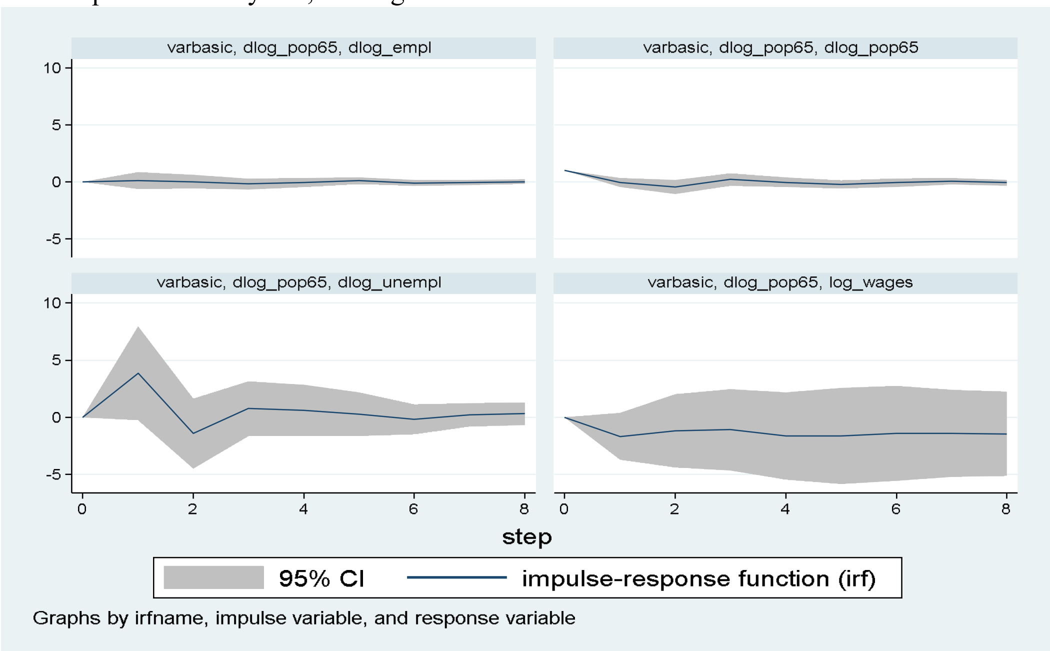


Figure 11. Estimating the effects of a shock in dlog_pop65 on dlog_empl, log_wages and dlog_unempl (IRF), for an 8-period timeframe
Source: Authors own processing in Stata 16

The effects of a 1% increase in the share of elderly individuals age 65 years and older (dlog_pop65) will generally tend to have a negative impact on the unemployment rate (dlog_unempl) during the proposed timeframe. A gradual short-term decrease can be observed, followed by a period of consolidation and a continuation of the previous trend, defined by a slow but steady rise in unemployment due to demographic ageing. The long-term influence of increasing the share of the population age 65 years and over is perceived as negative, due to a myriad of causes from economic and financial to social (Pissarides, 1989; Biagi and Lucifora, 2008; Akanni and Čepar, 2015; Axelrad, Malul and Luski, 2018).

As the share of elderly increases, the perceived costs associated with social security and pensions systems will increase causing more pressure on working individuals that are confronted with an increase in the dependency ratio. Thus, a rise in taxes from business will take place to offset the rising expenditures experienced by social security schemes. This will have the undesired effect of taking vital resources form medium and small enterprises, leading to bankruptcies and higher unemployment. In financial terms, as individuals approach the retirement age and retire, they tend to liquidate holdings of assets (stocks, bonds, real estate) to cover for the decline in living expenses resulting from retirement. This will drive asset prices down, resulting in a loss of funds for many businesses, slow economic growth, and a decline in the rotation of capital. This sudden drop in asset prices will have the effect of increasing the cost of capital over the short term, resulting in higher costs for struggling business and in layoffs of reduces work hours. On a social level, it can be argued that the rising share of elderly individuals tends to create tensions between generations due to the flow of resources and the social responsibilities that come with caring for elderly individuals as opposed to focusing on raising children.

The effects of a one percent rise in the share of elderly individuals above the age of 65 years old (dlog_pop65) on the employment rate tends to produce low fluctuations in the first part of timeframe, followed by a stabilization due to demographic constraints (Serban, 2012; Radović-Marković, 2013; Kühn, Milasi and Yoon, 2018). In this scenario, a jump in elderly individuals may be linked to a huge jump in retirement claims that will cause the employment rate to rise in the short run, but as the need for employees rises, employers will be forced to take action by rising wages and attracting back into the workforce recent retired individuals. Thus, due to monetary stimulus, the effect of this shock would be short and of low intensity.

Nominal wages (log_wages), tend to respond along similar lines to an increase of 1% to the share of elderly individuals (dlog_pop65), but with a slight decrease in the first periods, after which a steady but stable rise will follow, returning nominal wages to equilibrium. The first drop may be attributed to the desire of employers to attract younger talent for less capital, but as the supply is smaller, wages will have to climb to at least to previous levels. Higher increases in income will motivate greater employability on the part of the elderly and will motivate a delay in retirement, thus reducing the unemployment rate and maintaining a stable level of employment rate (Papadopoulos, Patria and Triest, 2017).

Table 8. Lagrange-multiplier autocorrelation test results

lag	chi2	df	Prob>chi2
1	48.8777	16	0.00003
2	28.9574	16	0.02422

H0: no autocorrelation at lag order

Source*:* Authors own processing in Stata 16

The final part of the VAR analysis consists of evaluating the model for autocorrelation, normality, and stability. To evaluate for the autocorrelation of residuals (Table 8), we used the *varlmar* test with two lags, similar to the number of lags used in the VAR model. The *varlmar* test refers to the Lagrange-multiplier (LM) test for autocorrelation in the residue of the VAR model. For our particular model, we can confirm that we have no autocorrelation of residuals, confirmed the null hypothesis (H_0: no autocorrelation at lag order) for the model, as can be observed in Table 8 (Johansen, 1995).

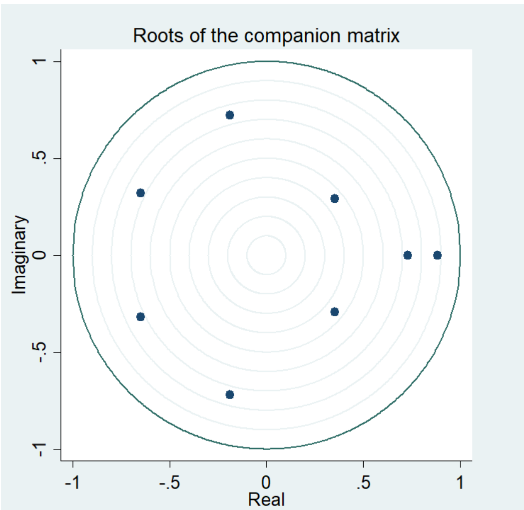
Table 9. Jarque-Bera normality test

Equation	chi2	df	Prob>chi2
dlog_empl	0.995	2	0.60812
dlog_wages	1.101	2	0.57672
dlog_pop65	0.103	2	0.95004
dlog_unempl	0.742	2	0.57672
ALL	2.940	8	0.93807

Source: Authors own processing in Stata 16

The Jarque-Bera test is computed individually for each equation, but also for the compound equation, being built on the basis of kurtosis and skewness indicators (Table 9). In our case, for the VAR model, the value of the Jarque-Bera test at the compound equation level is 0.93897, which is higher than the critical value of *p* for 0.05, so that the null hypothesis (H_0: the error term is distributed normally) cannot be rejected (Lütkepohl, 2005).

The last test applied to the VAR model is the stability test, that verifies the stability condition of the eigenvalues following the estimation of the parameters of the autoregressive vector model (Hamilton, 1994; Lütkepohl, 2005).



(a)

Eigenvalue stability condition

Eigenvalue	Modulus
.8826484	.882648
-.1889906 + .7217161*i*	.746051
-.1889906 - .7217161*i*	.746051
.7275113	.727511
-.6487734 + .3189194*i*	.722922
-.6487734 - .3189194*i*	.722922
.3526529 + .2920939*i*	.457911
.3526529 - .2920939*i*	.457911

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

(b)

Figure 12. Eigenvalue stability test

Source: Authors own processing in Stata 16

The test results are presented in a visual form using the Roots of the companion matrix and in a tabular form where the Eigenvalue stability condition is verified. Following its application, the results in the Modulus column are lower than the critical level of 1, so the VAR model satisfies the stability conditions (Figure 12 (b)). Similarly, in the graph in Figure 12 (a), the points are inside the circle, so the VAR model is considered stable.

Conclusions

The study of demography is a complex topic, which takes place over long periods, and aims to assess the natural transformations that take place within a group of individuals, to provide solutions that can reduce undesired social and economic consequences. A population, by its nature, is subject to universal laws that govern its transition over time, resulting in fluctuations in its size, in the median age and in the age composition for different groups of individuals.

Demographic changes tend to take place in a similar manner where there are homogeneous groups of regions, due to socio-economic, cultural and political trends, that have a tendency to spread from one group to another. The demographic changes, that are taking place in Romania are referred to as population ageing. This phenomenon is intensively studied in the scientific literature and in academic circles, but also in government decision-making groups. The interest stems from the need to develop approaches aimed at remedying the social and economic effects produced by the phenomenon of population ageing.

The effects of population ageing are represented by declining birth rates and increasing life expectancy, which have led to the erosion of the share of individuals ages 0-19 years old and the growth of the elderly individuals age 65 years and over. These changes put pressure on social security schemes, which are designed to serve a population with a relatively balanced demography, where the number of youths outweighs the number of the elderly. In an equal manner, the number of active individuals that work and that are counted in the labour force is declining. Thus, the labour market will be faced with a declining number of young individuals that will join a productive life and an increasing share of elderly individuals approaching individuals approaching age that will exit the labour market. Population ageing trends through the rise in the share of individuals of age 65 years and older will inadvertently result in a labour market friction with the possibility of slowing down economic growth in key sectors of the economy. Thus, careful action must be taken by governing bodies to prepare and to transition to an economy where the elderly are still active and involved in labour market in a direct or indirect manner.

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