Journal of World Economy
ISSN 2709-3999
www.paradigmpress.org/JWE
Volume 4 Number 6 December 2025

Application of Functional Regression Model on OADR-YADR Relation: The Case of Greece

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doi:10.63593/JWE.2025.12.01

Abstract

In the social security system and healthcare system, the process of demographic aging is of major interest. The current research work provides a statistical method based on functional time series regression analysis to improve old-age dependency ratio modeling for the Greek population. The functional time series regression-based model was applied to the old-age dependency ratio and young-age dependency ratio of the Greek population over the years from 1980 to 2023. The estimation of the functional regression model was used to model the relationship between the two age dependency ratios. Therefore, the functional regression model was used to measure the impact of the functional coefficient on young–age dependency ratio and old-age dependency ratio differences. The research findings revealed a varying functional-coefficient with a strong negative function of young-age dependency of the Greek population over the last years. The results confirm a broader usage of the functional regression models to provide more accurate estimates in demography, public health, and age-related policy studies.

Keywords: functional time series regression analysis, old-age dependency ratio, young-age dependency ratio, population aging, Greece

1. Introduction

As many countries face the phenomenon of demographic aging, the budgetary impact of aging has become an important topic in contemporary economic literature. Increased life expectancy and falling birth rates have led to an increase in the dependency ratio, meaning fewer workers are supporting a growing number of retirees (Prohnitchi, 2024; Agnihotri, 2023). Old age is going through significant demographic changes; potentially exceeding the working-age group and having an impact on labor markets; financial systems; and the pressure for major services, including healthcare, social security, housing, and technologies (Rashmi & Paul, 2024). There are rising concerns about the adverse effect of population aging on economic growth. These concerns are particularly very marked in advanced economies and in some of the Asian economies that are facing fast aging (Park & Shin, 2023). An aging society has the potential to develop unfavorable socio-economic effects. The phenomenon of the aging population places pressure on society with large healthcare costs and other age-related expenses, especially through the pension system, which can significantly damage Gross Domestic Product (GDP) growth (Jayawardhana et al., 2023). The interconnection of aging and economic well-being is a key point in this debate (Agnihotri, 2023). Thus, governments and global research worldwide are interested in the connection between the aging population and economic growth since the impact of different age groups has varying degrees of productivity and financial needs.

Using probabilistic population projections for the whole world, Gerland et al. (2014), indicated that the ratio of working-age people to older people will almost certainly decline considerably in all of the countries. Population aging is not a challenge only to those within the age of 65+ but to the younger generations as well, who are supposed to invest time and resources in care for the elderly population (Thobekile et al., 2023). The old-age dependency ratio defined as the proportion of the population aged 65+ to the proportion of the population aged 15–64 in the EU almost doubled from 15.2% in 1960 to 29.9% in 2016, therefore, maintaining fiscal sustainability will become extremely difficult in front of such a serious demographic change (Jayawardhana et al., 2023). One in every six people in the world will be over 65 years old in 2050, and the proportion will rise to one in four by 2100, compared to one in 11 in 2019 (Abio et al., 2023). Among the most affected by this change in the age structure of the population are Europe, and especially the countries of Southern Europe. Thus, one in five Europeans was over 65 in 2019, and it is expected that this will be the case for one in four by 2050, and one in three by 2100 (Abio et al., 2023). On the other side, the young-age dependency ratio is defined by Eurostat (2025) as a proportion of young people at an age when they are generally considered economically inactive, (i.e. under 15 years), compared to the proportion of people of working age (i.e. 15-64).

From the perspective of this paper, an increasing dependency ratio is thus far carrying out substantial influence and causing policy challenges to arrange and maintain public financing of healthcare, pensions, and social protection for the older population (Sheraz et al., 2023). The division of the total dependency ratio into the young and old populations is marked by a good reason, to be specific; the trend of the old population has been rising since the 1990s whereas the young population has been found to reduce in the time of the same period. Therefore, the old-age dependency ratio presents the number of older people 65+ relative to the working age population (commonly defined as aged 20 to 64); the total age dependency ratio takes into account the total number of economically dependent persons (those persons below age 15 plus persons 65+) relative to the working age persons (defined as aged 15 to 64), (Kelin et al., 2023).

Implications of aging can increase the economic burden brought by the proportion of people aged 65+ to the total population or working-age population (Friedlander & Klinov-Malul, 1980). This process of aging population is led by two key factors: increasing life expectancy and low fertility (Kelin et al., 2023). In this case, an economic burden is increased when there is a substantial decline in the proportion of young and an increase in the proportion of old as well as a decrease in the share of the working-age population (Friedlander & Klinov-Malul, 1980). The recipients of services such as healthcare, pensions and long-term care are children and the elderly, who are a dependent part of the population and financed mainly by the working-age population (Kelin et al., 2023). Lee and Shin (2019) employed a panel model from 142 nations between 1960 and 2014, to explore the impact of population aging on economy growth. These scholars found that the population aging rate, reflected by the old-age dependence ratio, harms economic development when it crosses a particular threshold, while the negative effects become larger as population aging moves forward. Additionally, Lee and Shin (2019) discovered how population aging has hindered growth in economies in the last few decades, especially in older industrialized nations.

Mortality and its transition in Greece are well-studied phenomena and some subsequent analyses showed the almost constant increase in average longevity in a few ages. These developments follow the decline in infant and child mortality, the temporal changes in the age of prominence of the accident, and the development of mortality among middle-aged and older adults (Zafeiris, 2023). As a result, compared to other countries in Southeastern Europe, mortality and health transition have progressed in Greece (Zafeiris, 2023), on the contrary, the mortality pattern prevailing in Greece has more similarities with Western and Southern Europe. From 2008 on, Greece experienced a very great financial and socio-economic crisis that required an examination of the crisis' effects on mortality. Some researchers pointed out a "crude mortality" increase in 2009–2015 that did not only arise from the economic crisis but also from population aging (Zafeiris, 2023). In countries like Italy, Greece, and France, the impact of the aging population is fairly low compared to other European countries (Jayawardhana et al., 2023). This is because these nations place a strong emphasis on the engagement after retirement of the elderly population, thus a lot of the aged population serves in hotels and restaurants and such kinds of opportunities enable the elderly population to be economically active. Together with this mortality transition, the country has also experienced a continuous decline in fertility rates, so that the proportion of the population under 15 has decreased with a proportional increase in the adult and elderly population. As a consequence, the old-age dependency ratio in Greece increased substantially reaching 37.3 in 2023, and the young-age dependency ratio decreased to 21.6 in 2023 (World Bank, 2025). This means that for every 100 working-age Greeks (considering the interval between 15 and 64 years old), there are 37.3 seniors aged 65+.

The principal contribution of this study is to examine the relationship between old-age dependency ratios with young-age dependency ratios about the population aging process in Greece. This work aims to adapt the functional-coefficient modeling technique concerning actual demographic time series. Therefore, the study adapts the local linear regression techniques to estimate the coefficient functions analyzing the changes in the contributions of young-age dependency on the old-age dependency trend in Greece from 1980-2023. The functional coefficient modeling perspective is shown to be a more informative approach with outstanding advantages. It is especially relevant in modeling time series data where it is practical to presume that the coefficients change over time *t* and also this model is important for modeling the population dynamics where it is reasonable to expect different behaviors based on the population size (Cai, Fan & Yao, 2000). The rest of the paper is organized as follows. After the Background, Section 2 provides an overview of the methodology and data. The results of the estimation of the functional regression model are provided in Section 3. The discussion is presented in Section 4. Section 5 provides the conclusion.

2. Data and Methods

The data for the old-age dependency and youth dependency ratios for Greece were retrieved from the World Bank's World Development Indicators (https://data.worldbank.org/indicator), (World Bank, 2025). These are annual time series data for the period from 1980-2023 for the population of Greece. Data are presented as the proportion of dependents/seniors per 100 working-age population. World Bank estimates are based on age distributions of the United Nations Population Division's World Population Prospects. It is important to emphasize that dependency ratio data show only the age composition of a population, but not economic dependency.

In this research study, a functional coefficients regression model was estimated. Functional coefficient regression is a kind of semi-parametric approach that extends the standard regression framework allowing for non-linear, dynamic coefficients in regression estimation as well as β_j to be functions of the variable Z_t (Fan & Gijbels, 1996; Cai, Fan, & Yao, 2000). In the standard linear regression assumptions, the relationship between a dependent variable and explanatory variables is shown in eq. (1).

$$Y_t = \beta_0 + \sum_{i=1}^{k} \beta_i X_{it} + \epsilon_t \qquad (1)$$

For most applications, this framework is usually enough, but the condition that coefficients are the same for all observations is quite restrictive and in practice is broken many times. Otherwise, nonparametric modeling is skeptical as to the nature of the relationship between variables, presuming a basic functional relationship between the dependent and explanatory variables as presented in eq. (2).

$$Y_t = f(X_{1t}, \dots X_{kt}) \qquad (2)$$

The flexibility of this specification is challenging as it can be tough to explain nonparametric estimates, for instance, discussing the marginal effects of a given variable upon Y_t can be difficult. A more flexible, area of compromise between these two extremes is the functional coefficients model in eq. (3).

$$Y_t = \beta_0(Z_t) + \sum_{i=1}^{k} \beta_i(Z_t) X_{it} + \epsilon_t \qquad (3)$$

In eq. (3), β_0 are no longer simple coefficients, but they are functions of the variable Z_t (IHS, 2024). Accordingly, the relationship is linear in variables, but non-linear in parameters. Compared to the specification of linear regression in eq. (1), the coefficients are no longer constant but rather vary over observations. Thus, non-linear occurrences easily fit in with this framework, coefficient relationships are dynamic, and the explanation of coefficient relationships is still intuitional, i.e. unlearned. The estimation of functional-coefficient models is based on local polynomial regression which incorporates two different techniques: the non-linear functions are approximated $\beta_j(z)$ using Taylor's Theorem and local regressions are estimated with penalizing of observations using a kernel function. The basic idea is that for each z of interest, a local regression is estimated with kernel-weighted squared residuals. Then, estimating this regression for a corresponding set of points z discovers the functional coefficients relationship. However, there are some major points to highlight: functional coefficient estimation is a set of coefficients estimated at a corresponding set of points z and the objective function depends on the kernel bandwidth (IHS, 2024).

The most important step in estimating functional-coefficient regressions is the optimal selection of the bandwidth parameter. The bandwidth is selected between two extremes that balance bias and variance, i.e. when, the functional coefficient estimator reduces to interpolating the data points in (small bias, large variance) and when, the functional coefficient estimator reduces to the mean of (large bias, small variance). The data-driven method, Akaike Information Criterion (AIC) calculates the optimal bandwidth using non-parametric AIC with non-parametric degrees of freedom. The idea comes from Hastie and Tibshirani's (1990) degrees of freedom smoothing literature, and the actual bandwidth methodology proposed in Cai, Fan, and Yao (2000) and Cai (2003). Thus, for each estimation point and a given bandwidth, the functional coefficients are estimated and then used to calculate the standard error of the local polynomial regression residuals. The standard error and the estimated nonparametric degrees of freedom are then used to obtain a functional AIC value. The optimal bandwidth is obtained as the one that minimizes the AIC summed over z. The optimal estimation bandwidth estimators themselves seek preliminary-functional coefficient estimates to obtain standard errors, covariance matrix, and bias estimates. These preliminary estimates seek their pilot bandwidth, which is mostly determined using one of the following methods which do not depend on other bandwidths: Modified Multi-Cross-Validation (MMCV) and Auxiliary Polynomial Degree (Cai, Fan, & Yao, 2000; Fan & Gijbels, 1995a; Fan & Gijbels, 1996). The optimal predictor is given by the well-known conditional expectation of the forecast value conditional on the observable information up to time. This predictor may be evaluated in one of the following ways: Plug-in Method, Monte Carlo (asymptotic), Monte Carlo (bootstrap), and Full bootstrap methods (Fan & Yao, 2003; Davison & Hinkley, 1997).

3. Results

The dependent variable is followed by functional-coefficient regressors. The LOGOADR (-1) is the dependent variable, and the lag variable LOGYADR (-2) has functional coefficients. Therefore, the variable upon which the functional coefficients depend and will vary is LOGLYNX (-2). The settings of bandwidth selection methods are associated with the data-driven method such as Multi Cross-validation and the Epanechnikov is the type of kernel used in the estimation. Figure 1 shows the functional coefficient relationships for the regressor.

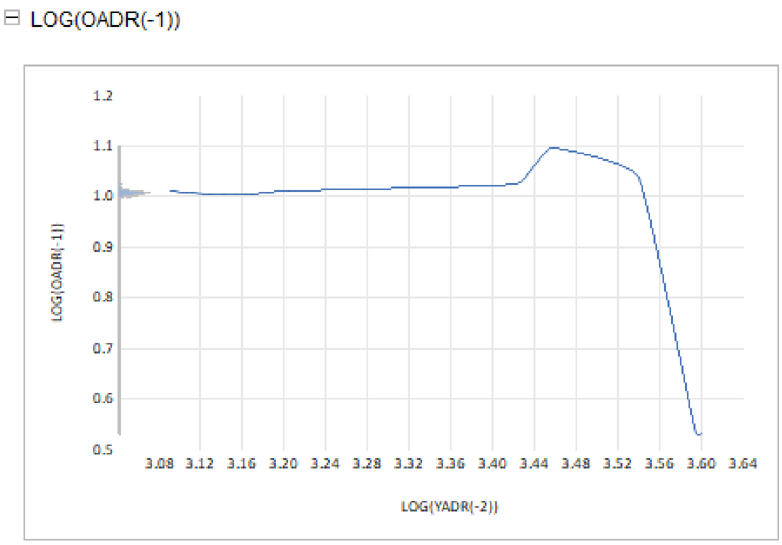

Figure 1. Functional coefficients relationships

Source: Author's design.

The coefficient function YADR (-2) is negative and strongly decreasing during the decrease phase. Given the necessary time, the coefficient function varies concerning the young-age dependency time series. Thus, at the first period of the time series, the coefficient corresponds roughly to the young-age dependency increase phase, and in the later period of the time series, the coefficient corresponds to the young-age dependency decrease phase. This means that both the old-age dependency ratio and the young-age dependency ratio behave differently when the youth population increases or decreases. This further means that both the old-age dependency ratio and the young-age dependency ratio behave differently when the youth population increases or decreases. The young-age dependency ratio implies that the increase and decrease rate of the old-age dependency ratio or the proportion of the older population as well as their trend depends on the abundance of the young population. This pictures a gradual change in old-age dependency corresponding to the changes in the coefficient function of the young-age dependency ratio. The different signs of the coefficient reflect that old-age dependency and young-age dependency are related to each other and the model presents the interaction between these two ratios in a manner that is one-step further closer to reality.

Figure 2 shows the graph of the Functional Residuals of the residuals, actuals, and fitted values from the fitted model.

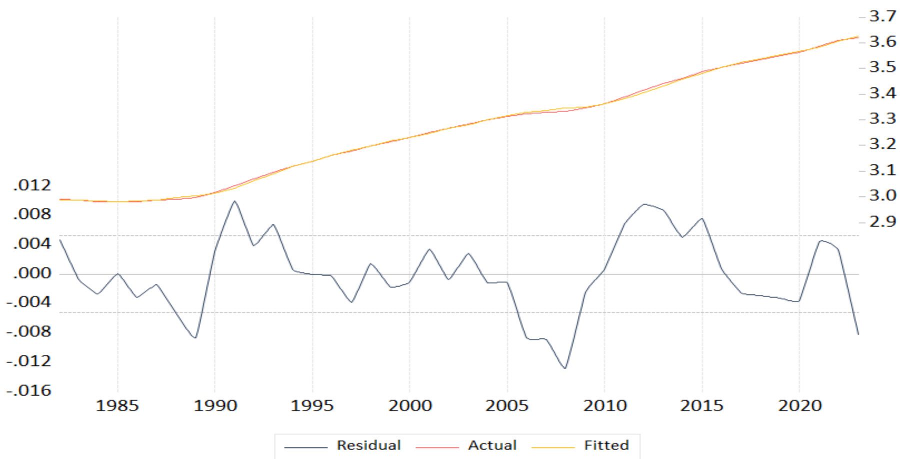

Figure 2. Functional Residuals

Source: Author's design.

The Functional bias and Functional covariance curves (Figure 3-4) were estimated using local pilot bandwidth computation. The optimal selection of bandwidth is the one that minimizes the estimation of our bias and covariance. A pilot bandwidth may be costly to compute, and therefore a local pilot bandwidth can be computed once and then made available for use in all subsequent procedures. The local pilot bandwidth may be set automatically when an estimation final stage bandwidth procedure or non-parametric AIC is employed and the local pilot bandwidth will be initialized to the pilot bandwidth obtained in that procedure.

⊟ LOG(OADR(-1))

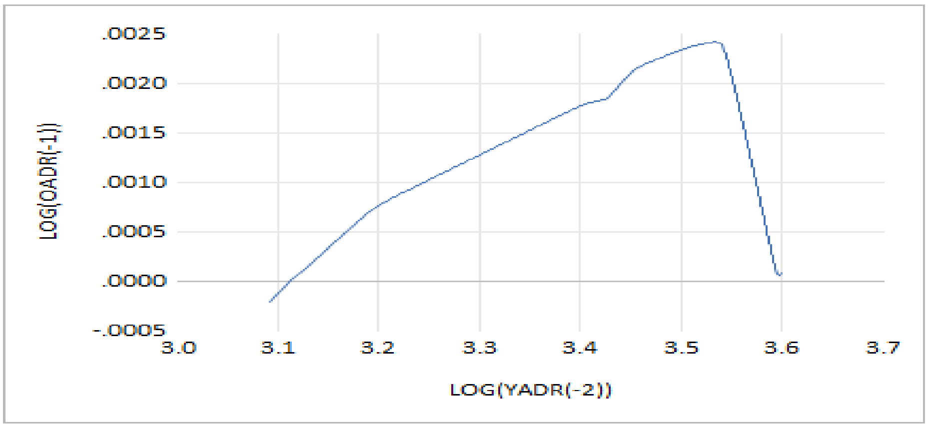

Figure 3. Functional bias

Source: Author's design.

⊟ LOG(OADR(-1))

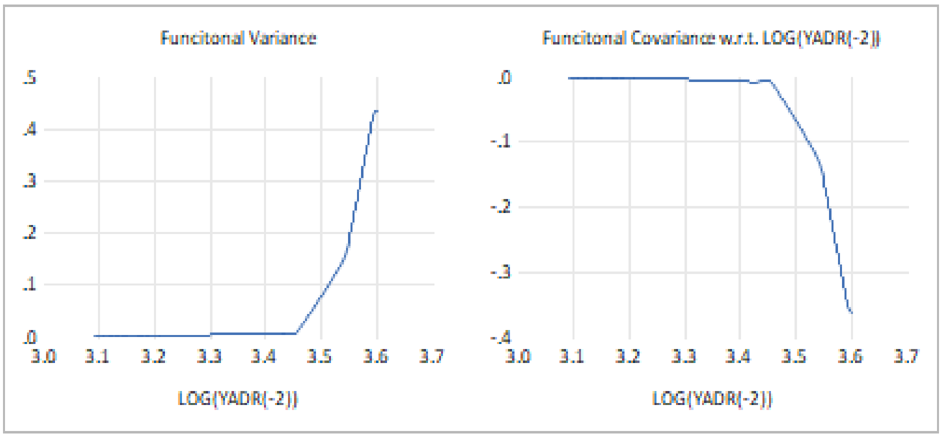

Figure 4. Functional covariance

Source: Author's design.

Bandwidth selection is a crucial part of functional-coefficient estimation. Figure 5 shows how the estimation objective function changes throughout the length of the bandwidth search grid, i.e. the graph in Figure 5 shows the relationship between the final bandwidth and the value of the objective function.

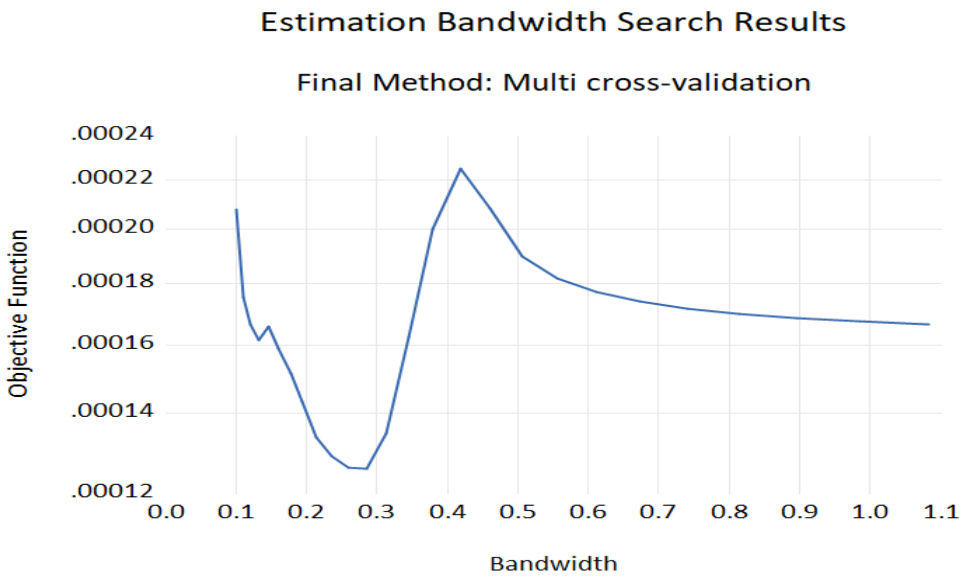

Figure 5. Estimation Bandwidth

Source: Author's design.

If the estimation considers the computation of a pilot bandwidth, the graph will also show the relationship between both the final and the pilot bandwidths and the objective function. In this case, Figure 6 presents how the estimation objective function changes throughout the length of the pilot search grid.

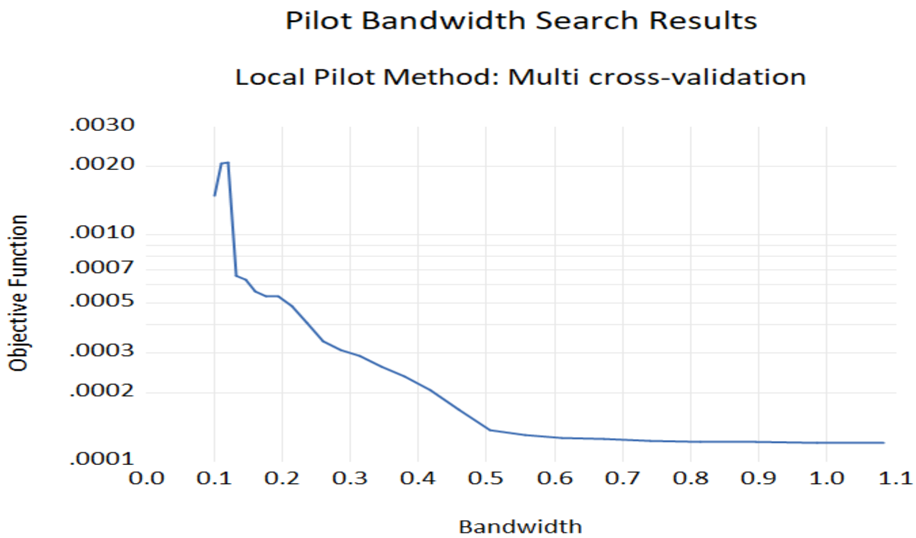

Figure 6. Estimation pilot bandwidth

Source: Author's design.

Figure 7 presents the confidence interval with a confidence level of 0.95 and the pilot bandwidth.

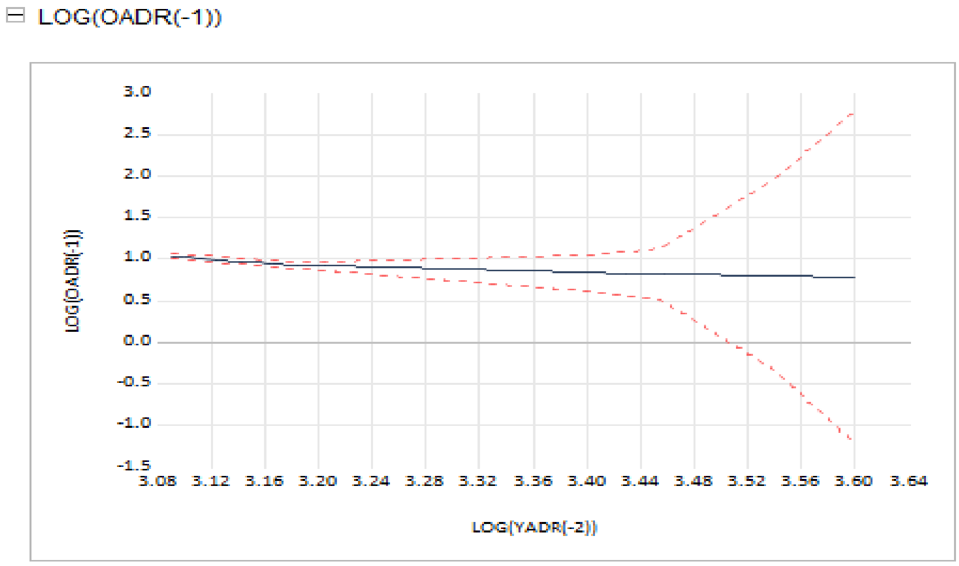

Figure 7. Confidence interval estimation

Source: Author's design.

Table 1 specifies the Functional coefficient equality significance hypothesis tests and options connected with the pilot phase estimation.

Table 1. Functional coefficient equality significance hypothesis tests

Functional Coefficient Equality Hypothesis Tests

Restriction	Statistic	p-value
C(1) = @CONST	8.070581	< .01
C(2) = @CONST	6.959066	< .01
Critical values:		
Level	Value	
1%	5.29	
5%	3.66	
10%	2.94	

Reject null when absolute value of statistic exceeds critical value

Source: Author's calculation.

A forecast was performed using the estimated functional coefficient model. There are a few choices of forecast stochastic methods: Plug-in, Monte Carlo (asymptotic), Monte Carlo (bootstrap), and Full bootstrap methods. In our case, the Monte Carlo methods were employed, thus the forecast confidence levels were derived from the distribution of the simulation results and the specification of the confidence interval level of 0.95 was chosen (Figure 8-9).

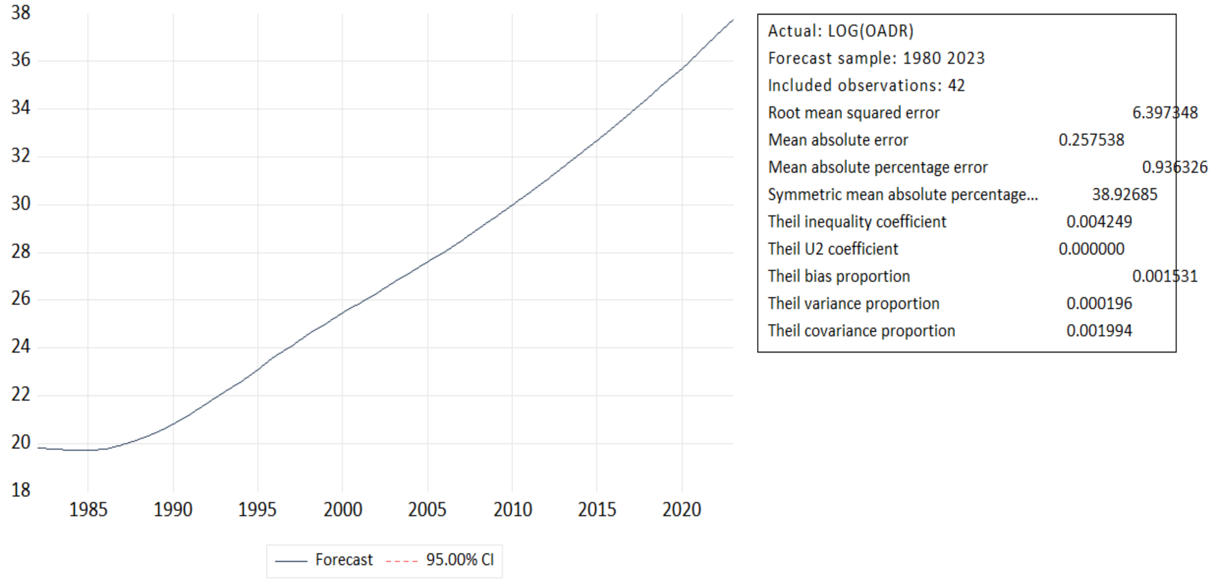

Figure 8. Forecast estimation: Monte Carlo (asymptotic) method

Source: Author's design.

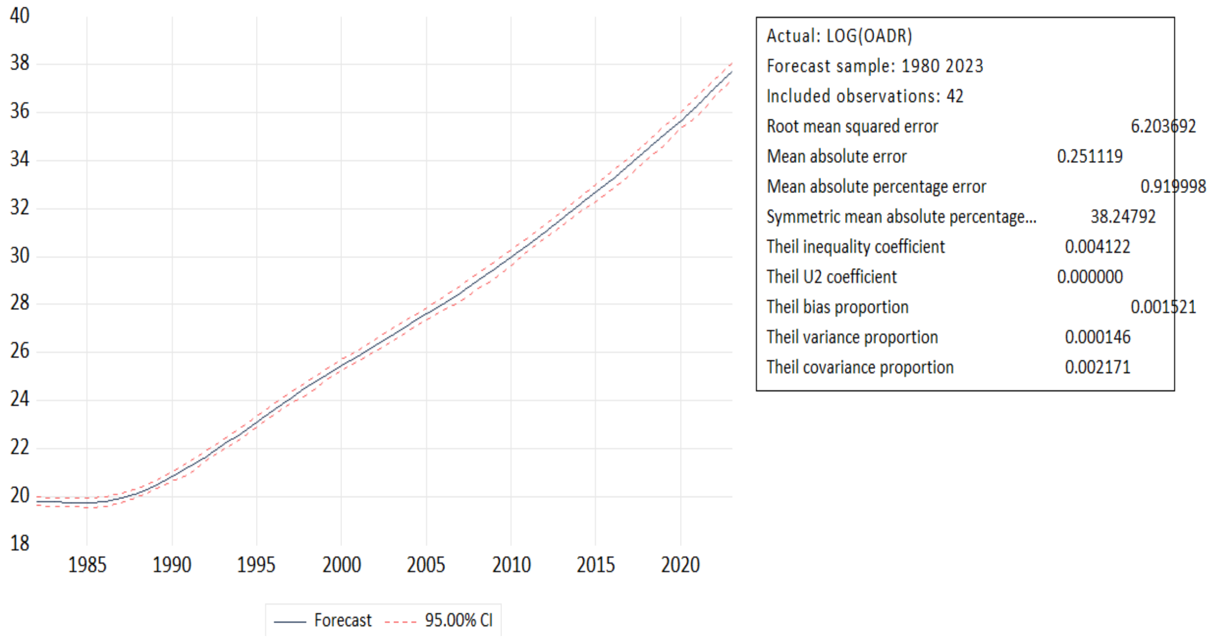

Figure 9. Forecast estimation: Monte Carlo (bootstrap) method

Source: Author's design.

4. Discussion

Our findings provide new insights into the evolving dynamics of the Greek population in terms of the differences in the young-age dependency ratio to the changes in the old-age dependency ratio and the overall population aging. Some evidence that was found has not been highlighted in the demographic literature. The research study introduces an applied approach to modeling the old-age dependency ratio series using the functional-coefficient time series analysis technique. In general, this approach performs solid modeling results compared to standard regression approaches. This method was demonstrated on the Greek annual old-age dependency ratio. The functional regression method was used to identify increased or decreased coefficient function concerning the young-age dependency ratio and the changes to the old-age dependency ratio over time across different age groups for the Greek population. Thus, it was also shown how the functional-coefficient estimation can model and examine the effects of differences in the young-age dependency ratio on the old-age dependency ratio. The coefficient function varied concerning the young-age dependency time series. Hence, at the first period of the time series, the coefficient corresponds roughly to the young-age dependency increase phase, and in the later period of the time series, the coefficient corresponds to the young-age dependency decrease phase. Therefore, the coefficient function YADR (-2) was negative and strongly decreasing during the decrease phase. The research findings revealed a varying functional coefficient with a strong negative function of young-age dependency of the Greek population over the years. Indeed, the findings confirm the strong negative function of the functional coefficient of the young-age dependency ratio series over the recent years in a Greek population. These findings showed that both the old-age dependency ratio and the young-age dependency ratio behave differently across time depending on whether the youth population increases or decreases. The different signs of the coefficient reflect that old-age dependency and young-age dependency are related to each other and the model presents the interaction between these two ratios in a manner that is one-step further closer to reality. Hence, our findings reveal that it is apparent that the increase and decrease in the young-age dependency ratio over time can lead to opposite changes in the old-age dependency ratio. The findings of the functional regression estimation reveal unique dynamic patterns of age dependency ratio series over time and age. This research contributed to considering a different and non-standard modeling technique that can be used to estimate some of the demographic components of population aging. Understanding the temporal trends of age-dependency series is very important in demography as well as the formulation of age-related policies. It is crucial that such patterns are based on the best accessible statistical modeling approaches and to keep at a minimum possible prediction errors. The functional time series analysis may reveal the temporal variability, the changes of specific age groups as well as the cause of age differences, providing additional understanding for forecasting age-related policies and the population age structure. In addition, the broader use of functional regression techniques to acquire more accurate estimates in demography, public health, and pension policy studies should be considered.

5. Conclusion

This paper highlights the functional differences between the old-age dependency ratio and the young-age dependency ratio. The functional-coefficient method has been proven successful in modeling the nonlinear features of our demographic time series data. The proposed procedure enhances the importance of considering differences in the functional coefficient related to different behavior over the time of the observed phenomenon. However, this study obtained additional knowledge on the existence of functional differences in curves and improved the classic functional-coefficient performance. Some other similar algorithms could be developed both graphical and analytical for the estimation of functional-coefficient models that are beyond the span of this article. Nonetheless, this research delivers solid findings that could drive further research works.

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