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ANALYZING EMPLOYMENT BY OCCUPATION ACROSS SECTORS IN GREEK LABOR MARKET

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ABSTRACT. In this paper we investigate the trends in the number of employees by occupational category across the economy's main sectors. For the purpose of our study we use mixed-fixed and random coefficient modeling, taking unemployment, gross value added, employee compensation, and proxies for labor force participation rate as the determining factors. Using annual data from 2000 to 2018, we examine the effects of the determining factors on the share of workers by sector and occupation. Our econometric research shows that the regression coefficients vary between sectors and categories of occupation and the proposed model correctly estimates the dependent variable and the heterogeneous variation of the random effects. Our model can be used to identify occupations with current and future shortages across sectors as well as for assessment and anticipation of employment needs. This study's main contribution is the provision of a flexible and innovative econometric tool, with minimal data requirements, for investigating and assessing employment across economic activities over time. Moreover, in conjunction with other forecasting macroeconomic models, it can offer accurate forecasts for future levels and trends in employment.

JEL Classification: C53, J01, J11

Keywords: occupation, employment, employment behavior, mixed fixed and random coefficient modeling

Introduction

The Greek sovereign debt crisis exposed the Greek economy's structural weaknesses and led to significant employment disruptions at the sector level and in the occupational categories within the sectors. Cedefop (2020) forecast that employment in Greece would record an increase of 2.5% shortly (2018-22), 3% in the medium-term (2022-26), and 2.7% in the long term (2026-30). From 2000 onwards, the labor force size has recorded a downfall by 6%, expected to last until 2030. Except for the business and other services sectors, as well as primary sector and utilities, all the rest were expected to experience employment growth over the short term (2018-22) and the long term (2022-30). The factors that may affect Greece's future employment include overall trends of the economy, shifts of employment between sectors, and changes in the occupational structure within sectors (Cedefop, 2020). Therefore, the influence of the determinants of employment may not be homogeneous between sectors and occupations.

Labor market participants require the development of employment forecasting models that would enable them to design their policies. These models can provide information to the main social partners and stakeholders in the labor market (employers, employees, trade unions, and policymakers) to reduce the social and economic problems arising from market deficiencies, reduce adjustment costs and ultimately increase the labor market's productivity and efficiency. In particular, in terms of productivity and efficiency, forecasting models ensure that employees are employed in jobs that correspond to their skill level, resulting in a significant improvement of these features. For forecasting, simple extrapolative approaches or shift-share techniques are used in most studies (Briscoe & Wilson, 2003). However, recently the increasing availability of data on the occupational categories within sectors in many countries allows for the development of longitudinal and panel data econometric techniques for modeling and analyzing employment in these groups (Briscoe & Wilson, 2003; Cörvers & Dupuy, 2010; Weber & Zika, 2016). Longitudinal or panel data methods, having both cross-sectional and time-series characteristics, use information in both dimensions to provide projections and forecasts that are superior to traditional methods that use only one dimension (Frees & Miller, 2004).

In this paper, we use annual data for employment over the period from 2000 to 2018 for six main sectors and ten occupational categories of the Greek labor market. We apply mixed fixed and random coefficient techniques to analyze the impact of certain variables on the employment by occupational category across the main sectors of the economy (Goldstein, 1995; Rabe-Hesketh and Skrondal, 2008; Im et.al. 2003; Hsiao, 2014; Bresson et al., 2006; Frees and Miller, 2004; Alvarez-Cuadrado and Poschke, 2011). Linear mixed models containing both fixed and random effects allow for the inclusion of random deviations (effects) other than those associated with the overall error term. The econometric modeling considers six explanatory variables; unemployment, gross value added, employee compensation; two variables, one for the total population size of citizens aged between 15 and 19 years old and another for the number of people aged 65 and above; and the time trend. Econometric literature identifies many difficulties in applying regression models for forecasting, though the proposed model may be acceptable for this purpose under certain conditions. Hence, we proceed for future forecasts of the number of employees per occupational category per industry sector. Having the estimates of the model parameters and using forecasts of the exogenous variables, we derive forecasts in a specific period in the future employment series by occupations and sectors.

The paper's structure is as follows: Section two presents a literature review, while section three provides a discussion of the data and their sources. Section four outlines the methodology of the research and summarizes the results. The last section concludes.

1. Literature review

Employment forecasts are a focal point of all economic forecasts. Internationally, early works for forecasting labor demand can be found in the mid-1950s (Hughes, 1993). Long-term labor market projections become a widespread tool for policy consulting (Wilson 2001), and long-term labor market projection frameworks are frequently used to assess future skill needs (Maier et al., 2017). Several factors affect the supply and demand of labor in an economy. These factors may be cyclical, associated with short-term fluctuations in aggregate demand. There are also structural features, including technological advances, globalized competition, and changes in the population's demographic structure that reflect long-term trends and developments in the economy and society, regardless of the short-term fluctuations (Maier et al., 2017).

In many countries today, such applications for forecasting and projection purposes are employed. In the US, the Bureau of Labor Statistics estimates models for hundreds of detailed industries aggregated into subsectors and sectors. Macroeconomic factors like labor force, GDP, and labor productivity influence total employment. The behavior of these macro-variables and projection models for each sector determine the final projections of employment and production in the industry (Lacey et al., 2017). In Canada, The Canadian Occupational Projection System (COPS) for nearly 30 years has produced analytical outputs and Labour Market Information. Using a system of models, provide, among others, projections of occupational trends for policy analysts and labor market information users (Ignaczak, 2017). Davis, et.al. (2006) argue that labor market flows vary considerably between industrial sectors, although industrial groups are broadly defined. Weber and Zika (2016) state that the use of disaggregated data produces more accurate employment forecasts.

Bishop and Carter (1991) and Bishop (1997) analyzed occupational employment trends for 13 general occupational categories in the US. They state that the evolution in occupational employment shares follows a logistic growth path. In their model, the dependent variable is the log of the ratio of the occupation's share of employment by category each year divided by the difference of 0.2 minus, that same occupational share in the same year. The responding variable is assumed to depend on time, the unemployment rate, and a vector of structural variables.

Spalletti (2008) states that workforce forecasting is a critical issue for two main reasons. First, demographic change is reducing the workforce in the long run, and second, more and more sectors of the economy rely on innovation, high-tech products, and increasing productivity to maintain international competitiveness. Both factors create the need for a more comprehensive approach to the problem of workforce planning.

Toossi (2011) states that according to the Bureau of Labor Statistics model, the job supply is a product of many demographic features, such as the size and growth of the population, by age, sex, race, nationality. Lacey et al., 2017 estimate that during the decade 2016–2026, population change will have far-reaching implications for the workforce, economy, and employment. Briscoe and Wilson (2003) use annual data from UK Labor Force Surveys to model occupational trends from 1981 to 1999. In particular, they use data for 17 standard industries for nine occupations. Using panel data models, they analyze the trends in occupational employment shares across industries and occupational categories over the above period. Foster-McGregor & Pöschl (2009) evaluate labor mobility's importance at the cross-sectional level for employment flows and reveal that labor mobility has beneficial effects on industry productivity.

Maier et al. (2017) argue that employers respond to job shortages by raising wages to attract employees who can, to some extent, adapt their behavior to mobility. Cörvers and Dupuy (2010) present several examples suggesting the importance of employment dynamics across occupations and sectors. They investigate these dynamics by estimating labor demand equations by sector and occupation using multiple cointegrating models (Stock and Watson, 1993; Mark et al., 2005). This system dynamic OLS techniques relate long-run employment to variables as sector capital stock, R&D stock, and value-added. The data used is from the Labor Force Survey of the Netherlands during 1988–2003, distinguishing between 13 sectors of industry and 43 occupations.

In econometric models, where macroeconomic variables are used as regressors, their future values are unknown. Hence, they need to be forecasted and the forecasts fed into the model to attain the dependent variable's future values. These forecasts may be obtained either by developing separate forecasting models or by specialist bureaus or government organizations (Makridakis et al., 1998; European Commission, 2020).

Regardless of the mathematical or statistical complexity of the model is used, prediction can never be entirely accurate. Any types of statistical forecasts are merely extensions of established prior patterns and existing relationships. These forecasts are accurate when the conditions that prevailed in the past did not produce significant changes. Even in the case of labor employment programs, like the Employment Projections (EP) program developed by the US Bureau of Labor Statistics (BLS), several assumptions are made governing the development process, these are: a) major social and demographic trends will continue, b) there will be no significant natural disaster or major armed conflict, c) the projected US economy will be close to full employment / potential output, d) existing laws and policies having a significant impact on economic trends are considered to be applicable throughout the projection period (US Bureau of Labor Statistics, 2020).

2. Data analysis and model specification

2.1. Data analysis

For the study's purposes, we use employment data for six industry sectors and ten occupations. Table 1 presents the Greek economy's main sectors, while Table 2 shows the occupation by category analyzed in this study.

Table 1. Sectors Classification

#	**Sectors**
1	Agriculture, forestry, and fishing
2	Industry including energy
3	Construction
4	Trade, hotels and restaurants, transport and communication
5	Financial, real estate, renting, and business activities
6	Other service activities

Table 2. Occupational classification

#	**Occupational categories**
1	Managers
2	Professionals
2	Technicians and associate professionals
4	Clerical support workers
5	Service and sales workers
6	Skilled agricultural, forestry, and fishery workers
7	Craft and related trades workers
8	Plant and machine operators and assemblers
9	Elementary occupations
10	Occupations not possible to classify

As shown in Table 3 and Figure 1, the evolution of the percentage of employees per sector of activity as a percentage of the total number of employees in the economy displays mixed trends. The employees' percentage in the sector "Agriculture, forestry, fisheries" decreased from 17.28% of the total number of employees in 2000 to 12.27% in 2018. The "Industry, energy" sector also decreased by almost four percentage points, from 15.42% in 2000 to 11.29% in 2018. The "Construction" sector also recorded a similar decrease of four percentage points from 7.34 % in 2000 to 3.96% in 2018. On the contrary, an increase in the percentage of employees presented in the sectors of economic activity "Trade, hotels, catering, transport, and communications", "Financial, business activities" and "Other services". The "Other services" sector recorded the largest increase from 22.60% in 2000 to 27.37% in 2018.

The "Trade, hotels, catering, transport and communications" sector increased about four percentage points, from 29.82% in 2000 to 33.92% in 2018. The sector "Financial, business activities" followed the same rising trend in which the percentage of employees increased from 7.55% in 2000 to 11.20% in 2018.

Table 3. Time series of employment share by sectors

year	Agriculture, forestry, and fishing	Industry including energy	Construction	Trade, hotels and restaurants, transport and communication	Financial, real estate, renting, and business activities	Other service activities
2000	17.28%	15.42%	7.34%	29.82%	7.55%	22.60%
2001	15.86%	15.54%	7.50%	30.22%	8.08%	22.80%
2002	15.31%	15.20%	7.65%	30.07%	8.38%	23.40%
2003	15.09%	14.53%	8.10%	30.38%	8.42%	23.48%
2004	12.38%	14.26%	8.14%	30.25%	9.23%	25.74%
2005	12.16%	14.12%	8.27%	30.98%	9.25%	25.22%
2006	11.72%	13.91%	8.11%	30.95%	9.18%	26.13%
2007	11.33%	13.73%	8.72%	30.72%	9.21%	26.29%
2008	11.14%	13.60%	8.62%	31.11%	10.11%	25.43%
2009	11.69%	13.00%	8.13%	31.36%	10.04%	25.77%
2010	12.40%	12.31%	7.28%	31.44%	9.97%	26.60%
2011	12.35%	11.63%	6.07%	32.02%	10.66%	27.28%
2012	13.01%	11.10%	5.44%	31.48%	11.50%	27.47%
2013	13.69%	10.94%	4.62%	31.72%	11.22%	27.81%
2014	13.57%	10.69%	4.28%	32.43%	11.32%	27.71%
2015	12.90%	10.91%	4.02%	33.41%	11.35%	27.41%
2016	12.37%	11.24%	4.00%	33.72%	11.32%	27.34%
2017	12.08%	11.43%	3.98%	33.99%	11.23%	27.30%
2018	12.27%	11.29%	3.96%	33.92%	11.20%	27.37%

Source: *Hellenic Statistical Authority, own compilation*

Figure 2 displays the evolution of the professions' categories from 2000 to 2018 in percentages of total workers, and records no significant fluctuations during the decade 2000 - 2010. Figure 2 presents the time trends by profession category.

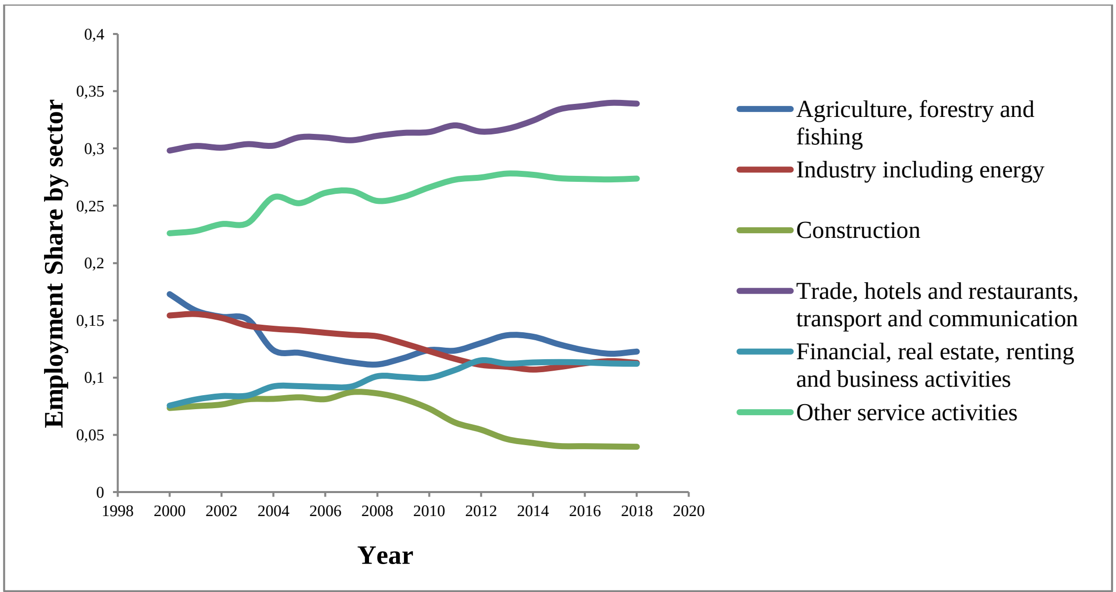

Figure 1. Share of employees by sector over the period 2000-2018
Source: *Hellenic Statistical Authority, own compilation*

There is a clear upward trend for the categories "Professionals" and "Service and sales workers". In particular, "Professionals" increased by about eight percentage points, from 11.82% in 2000 to 19.26% in 2018. The largest increase recorded in the profession category "Technicians and associate professionals" reaching 23.38% in 2018, from 12.96% in 2000. The category "Craft and related trades workers" had a marginal increase from 6.63% in 2000 to 7.96% in 2018, while the category "Elementary occupations" from 5.70% in 2000 to 6.84% in 2018. On the contrary, a downward trend for the same period over seven percentage points was presented by the category "Managers", especially, from 9.93% in 2000 on the total number of employees reached 2.83% in 2018. The profession category" Craft and related trades workers" had a similar decrease, reaching in 2018 at a rate of 9.25% from 16.12% in 2000.

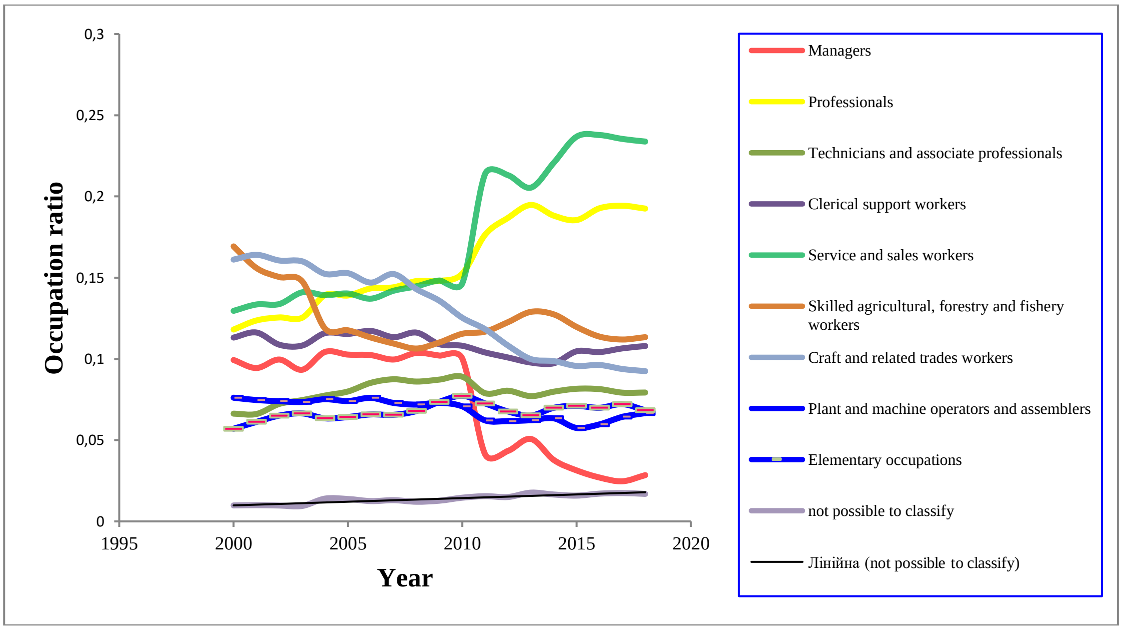

Figure 2. Share of employees per occupation category over the period 2000-2018
Source: *Hellenic Statistical Authority, own compilation*

Occupation category "Skilled agricultural, forestry and fishery workers "decreased by about 5%, from 16.93% in 2000 to 11.34% in 2018. This percentage reveals a marginal decrease in the categories of occupations "Clerical support workers" and "Plant and machine operators and assemblers", for less than one percent for "Clerical support workers ", from 11.32% in 2000 to 10.80% in 2018 and for "Plant and machine operators and assemblers ", from 7.62 in 2000 to 6.67% in 2018.

Table 4 (Annex 1) presents descriptive statistics of the variables of interesting determined by the discussion in the literature review section.

Table 5 shows the Spearman's correlation matrix between the variables that represent the employment per sector.

Table 4. Correlations of employment share between sectors

1	Agriculture, forestry and fishing	1					
2	Industry including energy	0.160	1				
3	Construction	-0.333	0.673	1			
4	Trade, hotels and restaurants, transport and communication	-0.306	-0.883	-0.739	1		
5	Financial, real estate, renting and business activities	-0.206	-0.961	-0.669	0.890	1	
6	Other service activities	-0.140	-0.962	-0.656	0.836	0.908	1

Source: *own compilation*

A preliminary conclusion drawn from the correlation table concerns the Construction and Industry sector. Both sectors show a high and statistically significant negative correlation with the sectors of *Trade, hotels and restaurants, transport and communication (4) , Financial, real estate, renting and business activities* (5), and *Other service activities (6)*. The lowest degree of correlation with other sectors of the economy is presented for the employment in the *Agriculture, forestry, and fishing* sector.

2.2. Model specification

After investigating and presenting the relationships between the share of employees in the main sectors of the economy, we will present the econometric model development that will be used to predict the number of employees per category per industry. In particular, the process is integrated into two stages: The first specifies the econometric model is used to estimate the relationship's parameters between the dependent variable and the variables that potentially affect the employment behavior per occupational category in each economic sector. The second includes the forecast of the explanatory variables' values in the period under consideration, i.e., from 2017 to 2025. Although the available data are until the year 2018, data up to 2015 used to estimate model parameters, while the period 2016-2018 constitutes the validation period to testing the model on actual data. Using the estimates of the explanatory variables and having available the estimates of the model's parameters, the forecasts for the number of employees for the period 2017-2025 are generated. According to the preceded analysis, Table 6 includes the variables affecting the number of employees by occupational category in each sector.

Table 6. Variable definition

Variables	**Description**	**Variable name**
1	Number of persons employed by occupation by industry	*logpro*
2	Compensation of employees by industry	*logcoben*
3	Gross value added by industry	*logaddedvalue*
4	Unemployment rate by Industry	*logunempl*
5	Population aged between 15 and 19 years	*logunder*
6	Population aged 65 years or over	*logabove*
7	Time trend	*year*

Source*: own data*

For the study's purposes, the following model is used :

$$y_{ijt} = b_0 + h_i + \delta t + x'_{kit}\beta_i + \varepsilon_{it} \qquad (3)$$

We define the dependent variable $\boldsymbol{logpro_{ijt}}$ as the *log* of the number of persons employed in occupation *i* in sector *j* at time *t*.

Where $\boldsymbol{i}$=*(1,2,..,10)* the categories of professions, $\boldsymbol{j}$=*(1,2,..,6)* the main sectors of the economy, $\boldsymbol{k}$=*(1,2,3)* the explanatory variables, $\boldsymbol{t}$ =(2000, 2001,…,2017) the time period of the data. Therefore, occupation-sector combinations are 60.

The error term (disturbances) ε_{it} covers the effect of random factors that change both over time and from category to category of a profession.

We assume the presence of unobserved effects at the occupational category across sectors level and, allowing for the inclusion of random deviations (effects) other than those associated with the overall error, we estimate these parameters (the coefficients of the variables), treating them as random variables different for each occupational category. The first step is to determine the model that best fits the data. Our work aims to take advantage of each of the explanatory variables' contribution in determining employment for each category of occupation in each economic sector. This contribution is represented by the coefficients, b_{ki}'s, in the model. However, the variables included in the model representing the conditional effects, together with the error terms, cannot fully describe the systematic differences between employment levels in each occupational category across sectors. The possibility of including additional variables is not an option since our goal is to keep the model as simple as possible, given the difficulty of finding relevant data. There were a few alternatives for deriving the coefficients' estimates; mixed fixed and random coefficient modeling was considered the best practice. Another alternative could be to consider the b_{ki}'s as fixed and different for each occupation category by sector. In this case, the pattern coincides with that of Zellner's seemingly unrelated regression framework (Zellner, 1962). However, to conclude about the characteristics of the number of occupation categories and sectors, we consider each category's different coefficients to represent a random effect for the specific population. The coefficients (as random variables) are unrelated to the explanatory variables. Therefore, the mixed fixed and random coefficient model is the most appropriate for the study's purposes.

Conclusively, we allow the coefficients b_{ki}'s to vary between occupational categories by treating them as random variables consisting of two parts. The first part is the common mean of the specific category's coefficients, while the second part is represented by random factors with constant variation and an expected value of zero.

Therefore the coefficients b_{ki} will have the following form:

$$\beta_{ki} = b_k + \alpha_{ki} \tag{4}$$

Where $\boldsymbol{b_k}$: the coefficient of the $\boldsymbol{k}$ explanatory variable common within sectors and occupations.

$\boldsymbol{\alpha_{ki}}$: the variable part of the coefficient as a random variable with zero mean, constant variance, and covariance unrelated to the explanatory variables.

The model should have the following form (model 5):

$$logpro_{ijt} = b_0 + \delta t + (b_1 logcoben_{it} + b_2 logaddedvalue_{it} + b_3 logunempl_{it} + b_4 logaddedvalue_{it} + b_5 logunempl_{it}) + (h_i + \alpha_{1,\iota} logcoben_{it} + \alpha_{2,\iota} logaddedvalue_{it} + \alpha_{3,\iota} logunempl_{it} + \alpha_{4,\iota} logaddedvalue_{it} + \alpha_{5,\iota} logunempl_{it} + u_{sit}) \tag{5}$$

Along with the estimation of model 5, we will estimate the corresponding simpler model that does not allow heterogeneity in the effects of explanatory variables using the maximum likelihood estimation method. Then we apply the appropriate test for heterogeneity in the effects:

$$logpro_{ijt} = b_0 + \delta t + b_1 logcoben_{it} + b_2 logaddedvalue_{it} + b_3 logunempl_{it} + b_4 logaddedvalue_{it} + b_5 logunempl_{it} + u_{sit} \tag{6}$$

As mentioned above, the estimation period was initially for the years 2000-2016. The period 2017-2018 will be the period of testing the model's forecast performance. We notice that the limited availability of data does not allow for further increases in the validation period. Then we will get the estimates of independent variables with the methods that we will describe in the next section. Having these estimates available, we will then proceed to the last stage of our work regarding the forecast (out of sample) of employment per occupation category per sector of activity.

3. Conducting research and results

3.1. Models estimations

Out of the total econometric models arise a series of useful conclusions. Table 7 presents the estimates of models 5 and 6. From the two models comparison based on the Loglikelihood statistic's value, we found that model 5 is appropriate for testing our hypotheses.

Table 7. Estimations of model 5 and 6

Depented variable: $\mathbf{logpro_{ijt}}$,the natural logarithm of the number of employees in occupation **i** in sector **j** at time **t**.

	Model 5				**Model 6**			
Panel A	**Coef.**	**Std.Err.**	**z**	**P>|z|**	**Coef.**	**Std.Err.**	**z**	**P>|z|**
logcoben	0.388	0.129	3.000	0.003	0.361	0.092	3.910	0.000
logaddval	0.266	0.111	2.400	0.017	0.357	0.055	6.510	0.000
logunempl	0.334	0.101	3.320	0.001	0.366	0.059	6.260	0.000
logunder	-1.421	0.718	-1.980	0.048	-1.454	1.158	-1.260	0.209
logabove	-0.603	0.569	-1.060	0.290	-0.330	0.928	-0.360	0.722
year	-0.006	0.008	-0.780	0.437	-0.003	0.013	-0.200	0.838
constant	46.628	22.587	2.060	0.039	35.286	37.256	0.950	0.344
Panel B Random-effects Parameters	**Estimate**	**Std. Err**			**Estimate**	**Std. Err**		
var (logcoben)	0.460	0.136						
var (logaddval)	0.288	0.110						
var (logunempl)	0.183	0.075						
var (logunder)	1.400	0.364						
var (logabove)	1.015	0.278						
var(year)	0.000	0.000						
var(Residual)	0.034	0.002			0.325	0.008		
Loglikelihood :	-237.24				-363.03			
AIC	443.62				742.01			
BIC	508.89				783.97			

Notes: Panel A presents estimations of the fixed part of the model while Panel B estimations of the random parameters.
Source: own compilation

More specifically, the difference *-2Loglikelihood (6) -2Loglikelihood (5) = -2 (-363.03) - 2(- 237.24) = 251.26* that follows a χ^2 distribution with 6 degrees of freedom, which are the additional parameters for the model (5), i.e., variances of the coefficients, is statistically significant that leads us to the conclusion that model (5) fits better our data. The proportion of variance between occupation and sector specific depended variable explained by the variability in coefficients can be computed by comparing the two models' residual variances. The residual variance for models (6) and (5) is 0.325 and 0.034, respectively. The residual variance explained by introducing random effects in slopes at the firm level is *89.5% (= (0.325-0.034)/0.325).*

Based on the estimates of the fixed part of the model, we conclude that the coefficient of the variables *logcoben*, *logaddval*, *logunempl* and *logunder* are found statistically significant at CI 95%. The *trend*, as well as the *logabove* coefficients, are found statistically insignificant. When we refit the model excluding the two variables with insignificant z-statistic, we did not receive substantially better performance in terms of overall model fit statistics, e.g., BIC and AIC.

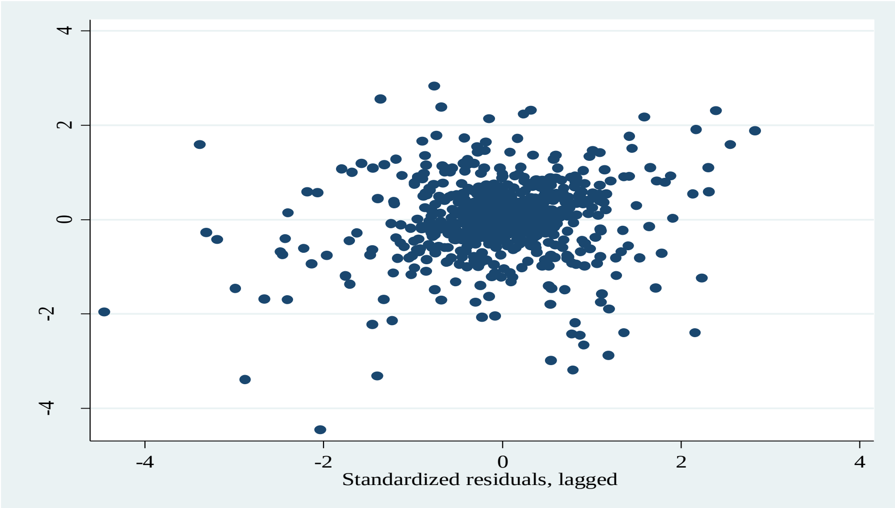

Figure 3. Scatter plot of residuals versus lagged residuals
Source: *own data*

To ensure reliable results, we examine the behaviour of the error terms plotting current versus lagged residuals (Figure 3). The plot did not display correlation patterns. Hence, we do not consider the autocorrelation structure of the error terms.

Table 8. Averages of the estimations of employment elasticities across sectors

sector	Coefficients				
	logunempl	**logaddval**	**logcoben**	**logunder**	**logabove**
Agriculture, forestry and fishing	55.6%	-13.3%	47.5%	-147.5%	-35.6%
Industry including energy	19.1%	58.6%	16.3%	-165.2%	-49.1%
Construction	36.6%	38.8%	52.0%	-157.3%	-61.1%
Trade, hotels and restaurants, transport and communication	33.3%	37.1%	40.6%	-143.5%	-62.4%
Financial, real estate, renting and business activities	37.2%	9.1%	25.0%	-79.4%	-111.7%
Other service activities	28.8%	17.9%	52.9%	-159.3%	-38.0%

Source: *own compilation*

Table 8 includes the averages of the empirical Bayes[1] estimations by sector of $\boldsymbol{b_{kj}}$, coefficients as denoted in the previous section. The elasticities concerning unemployment are bounded by 19.1% (*Industry including energy*) and 55.6% (*Agriculture, forestry and fishing*). The elasticities concerning *compensation* are bounded by 52.0% (*construction sector*) and

[1] The Bayes predictor of sector and category -specific slopes is a weighted average between the least square estimators of $b_{k,s}$ and the overall mean b_k (k=1,…,5) and are different from the classical sampling approach predictors (least square estimators). Moreover, in the Bayesian approach prior probability distributions are introduced for the parameters as a part of the model (see, Hsiao and Pesaran (2004).

16.3% (*Industry including energy sector*). The elasticities for *value added* are bounded by -13.3% (*Agriculture, forestry, and fishing*) and 58.6% (*Industry including energy).*

Table 9. Averages of the estimations of employment elasticities across occupation categories

occupation	Coefficients				
	logunempl	**logaddvalue**	**logcoben**	**logunder**	**logabove**
Managers	33.3%	82.0%	112.0%	-314.0%	58.4%
Professionals	49.2%	17.8%	2.1%	-56.7%	-134.0%
Technicians and associate professionals	39.6%	37.9%	53.4%	-150.4%	-66.5%
Clerical support workers	29.6%	40.3%	25.7%	-151.3%	-51.5%
Service and sales workers	47.6%	-6.0%	-28.0%	-21.4%	-147.3%
Skilled agricultural, forestry and fishery workers	6.7%	5.9%	110.5%	-222.6%	25.0%
Craft and related trades workers	21.8%	26.6%	35.8%	-164.2%	-31.6%
Plant and machine operators and assemblers	23.7%	0.4%	25.8%	-136.4%	-46.9%
Elementary occupations	33.0%	18.0%	47.6%	-96.4%	-105.3%
Occupations not possible to classify	45.1%	23.9%	7.1%	-89.7%	-105.4%

Source: *own compilation*

Table 9 presents the averages by occupation category of $\boldsymbol{b_{k,i}}$, coefficients. The highest elasticity concerning *logunder* (-21.4%) is estimated for *Service and sales workers* while the lowest for *Managers* (-314.0%). However, in the *Managers* profession, the elasticity of occupation concerning *logabove* shows the highest value (58.4%), while in *Service and sales workers,* the lowest value is estimated (-147.3%). The elasticities of occupation concerning *logaddvalue* are positive in all occupation categories though in *Service and sales workers* category negative (-6.0%).

The results suggest a positive effect of the unemployment rate on the number of people employed in all sectors of the economy. Using the term "Greek paradox", this study provides the following explanation. The undeclared economy includes unregistered employees without a contract who work for a business, for a household, as family members, private tutors, or as farm workers. They may be Greek citizens, legal immigrants, or immigrants with irregular status, and the movement from undeclared to registered employment is a "gray area" that influences statistical analysis. Moreover, according to the Diagnostic report on undeclared work in Greece (ILO, 2016) there are problems with the estimates of the undeclared economy in Greece; there are very few data sources, leading to inconsistent estimates about the undeclared work rates. Hence, the shift from undeclared to registered employment along with the inconsistency of the estimates about real undeclared employment, add bias to statistical inference.

According to the study's analysis, and in line with Cedefop (2020), employment in the Greek agricultural sector is expected to decline significantly in recent years. Moreover, our results indicate a negative correlation between value-added and the number of employees in the agricultural sector. The relationship can be interpreted as follows: The family nature of the agricultural sector in Greece also determines the employment structure for the self-employed and employees. Besides, employment in the Greek agricultural sector remains directly linked to the population's retention in rural areas, especially in mountainous and disadvantaged areas. Also, increasing industrial wages attract low-paid or underemployed labor from agriculture into manufacturing while non-agricultural productivity increases played a larger role than agricultural productivity in overall reallocations of labor out of agriculture (Alvarez-Cuadrado and Poschke, 2011). Internal migration to urban centers in search of employment in combination with the predominance of only large agricultural firms may lead on the one hand to higher value-added due to intensification and modernization of agricultural production and, on the other hand, to a reduction of self-employed and employees.

3.2. Out of sample forecasting

Since the purpose is to make future predictions for the dependent variable, estimates for the five dependent variables' future values for the six sectors should be provided. These values are then used in the estimated regression model, and the predicted values of the dependent variable are obtained. The model to forecast the explanatory variables' future values is the following (Holt's linear exponential smoothing method, see e.g., Gardner, 2006; Hyndman & Athanasopoulos, 2018). This method assumes two smoothing constants a and b (lie in the interval 0 and 1), and three equations:

$$\hat{y}_{it} = L_{i,t-1} + T_{i,t-1}$$
$$L_{i,t} = \alpha . y_{it} + (1 - a).\left(L_{i,t-1} + T_{i,t-1}\right)$$
$$T_{i,t} = \beta .\left(L_{it} - L_{i,t-1)}\right) + (1 - \beta).T_{i,t-1}$$

Where L_t denotes the estimate of the level of the series at time t and T_t denotes an estimate of the slope of the series at time t. $\hat{y}_{it}$ is the forecast value at time t and is point forecast of the explanatory variables. Holt's linear method does not permit the calculation of prediction intervals. However, prediction intervals can be obtained from the equivalent ARIMA (0,2,2) method (Makridakis et al., 1998). An iterative process chooses the values of α and β constants to minimize the in-sample sum-of-squared prediction errors. As mentioned above, values for the last two years of the data held out for validation, while the data used to estimate the model's parameters are for 15 years. To evaluate the model's forecasting performance, we compare the mean absolute error (MAE) of the forecast errors in the validation period with those in the estimation period. The formula of MAE and the results are :

$$MAE = \frac{1}{jn}\sum_{1}^{j}\sum_{1}^{n}\left|\widehat{logpro}_{jn} - logpro_{jn}\right|$$

Where *n* denotes the years within the validation and estimation period.

Table 10. Comparison of the mean absolute error (MAE) for the validation and estimation period

Period	***MAE***
Estimation period	0.1160
Validation period	0.1483

Source: *own compilation*

According to the results presented in Table 10, MAE for the validation period, although higher, is not alarming. Hence, our model provides a satisfactory fit to the data. However, as we already noticed, running separate models to obtain a more accurate forecast for independent variables will improve model performance.

Figures 4 to 9 below depict plots of the number of employees by sector over the estimation period (2000-2015). For comparison, at the same figures, the forecasts of the number of employees by sector are plotted.

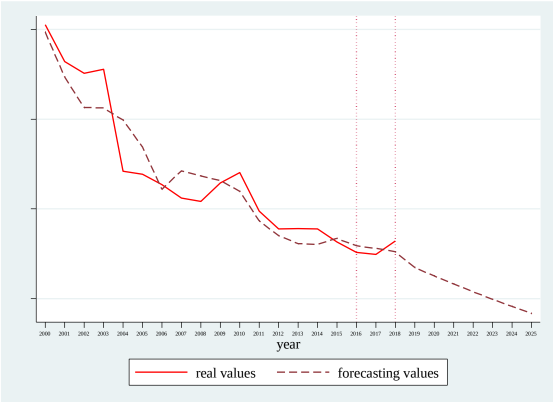

Figure 3. Agriculture, forestry and fishing

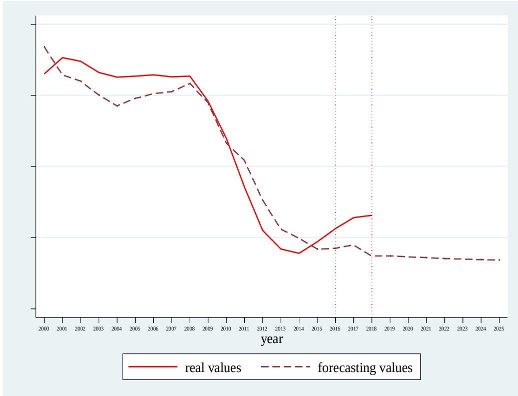

Figure 5. Industry including energy

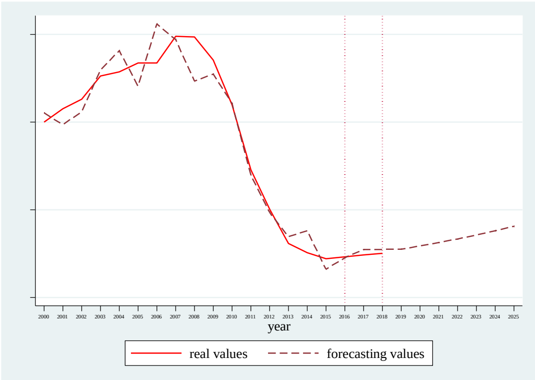

Figure 6. Construction

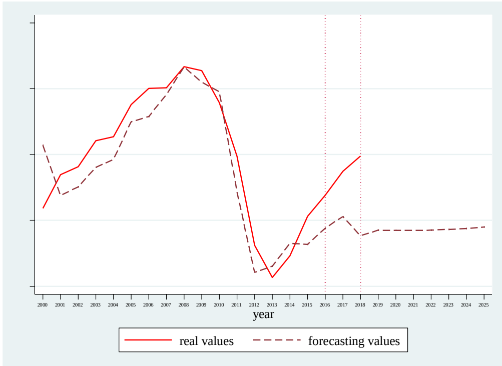

Figure 7. Trade, hotels and restaurants, transport and communication

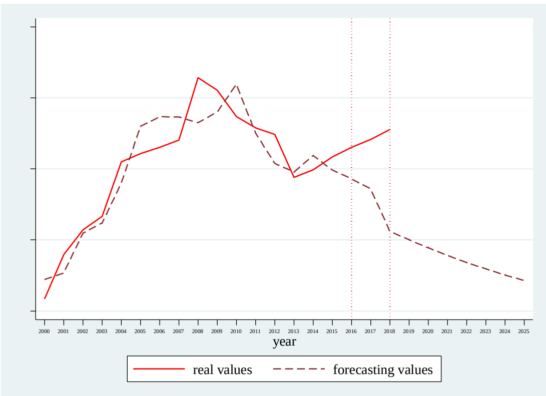

Figure 8. Financial, real estate, renting and business activities

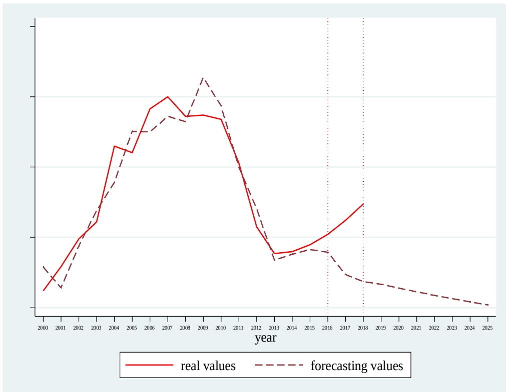

Figure 9. Other service activities

Conclusion

In this paper, we use a mixed fixed and random coefficient modeling to investigate the behavior of the number of employees by occupational category across the economy's main sectors. The determinants used to explain and predict the dependent variable are unemployment, gross value added, employee's compensation, two variables, one for the total population size aged from between 15 and 19 years old and another for the number of the people aged 65 years old and above, and time trend. Our results support the hypothesis that regression coefficients varying across sectors and occupation categories and the suggested model, correctly estimates the dependent variable and the heteroskedastic variances of the random effects.

Applying our model to the Greek labor market we confirm that the elasticity of the number of employees in the Greek economy's main sectors concerning unemployment, gross value added, compensation, and participation rate varies widely across sectors and occupational categories. Regarding the sign of the explanatory variables and especially of the unemployment variable, the following unexpected relationship was found: The impact of the unemployment rate on the number of employees in all sectors of the economy is positive. A possible explanation for this paradox may be the recorded shift of undeclared to registered employment in the Greek labor market, along with the inconsistency of competent authorities and bodies' estimates about real undeclared employment. Moreover, the results indicate a negative correlation between value-added and the number of employees in the agricultural sector. Thus, the share of employment in the primary sector is higher than its contribution to the sector's total value-added. This result is consistent with Alvarez-Cuadrado and Poschke (2011), who argue that the agricultural sector's labor share decreased more when the manufacturing productivity increased relative to agriculture.

Moreover, we use parameters' estimates to forecast future values of the number of employees by occupation within sectors. Testing the forecasting performance of the model, we perceive reasonable prediction accuracy. However, our model's forecasting ability may be improved if the exploratory variables' future values are derived using separate econometric models. Consequently, future research should be conducting by running separate models to obtain a more accurate forecast.

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Annex 1

Table 5. Descriptive statistics of the variables

Sector	Variable	Obs	Mean	Std. Dev.	Min	Max
Agriculture, forestry, and fishing	Number of persons employed by occupation by industry	95	106660.00	204424.40	900.00	688100.00
	Compensation of employees by industry	19	89.34	11.19	64.86	106.40
	Gross value added by industry	19	7067.25	897.90	5794.10	8944.86
	Unemployment rate by Industry	19	1.47	0.21	1.03	1.80
	Population aged between 15 and 19 years	19	599.29	60.51	525.50	720.54
	Population aged 65 years or over	19	2099.93	156.46	1793.88	2319.05
	year	19	2009	5.51	2000	2018
Industry including energy	Number of persons employed by occupation by industry	152	66712.50	69612.52	10500.00	328800.00
	Compensation of employees by industry	19	131.99	27.98	94.80	176.90
	Gross value added by industry	19	39556.07	3944.33	31049.00	47755.00
	Unemployment rate by Industry	19	11.06	1.04	8.60	12.97
	Population aged between 15 and 19 years	19	599.29	60.39	525.50	720.54
	Population aged 65 years or over	19	2099.93	156.14	1793.88	2319.05
	year	19	2009	5.50	2000	2018
Construction	Number of persons employed by occupation by industry	133	39222.56	74788.58	1800.00	310500.00
	Compensation of employees by industry	19	135.50	25.51	99.10	180.80
	Gross value added by industry	19	8905.59	4516.71	3313.80	18085.79
	Unemployment rate by Industry	19	6.06	2.88	2.87	10.75
	Population aged between 15 and 19 years	19	599.29	60.42	525.50	720.54
	Population aged 65 years or over	19	2099.93	156.22	1793.88	2319.05
	year	19	2009	5.50	2000	2018
Trade, hotels and restaurants, transport and communication	Number of persons employed by occupation by industry	152	161665.80	157523.60	24500.00	666100.00
	Compensation of employees by industry	19	108.64	10.44	86.50	126.00
	Gross value added by industry	19	48714.87	7530.40	39716.00	64978.00
	Unemployment rate by Industry	19	25.52	2.73	20.55	28.82
	Population aged between 15 and 19 years	19	599.29	60.39	525.50	720.54
	Population aged 65 years or over	19	2099.93	156.14	1793.88	2319.05
	year	19	2009	5.50	2000	2018

Financial, real estate, renting, and business activities	Number of persons employed by occupation by industry	152	50648.03	52184.69	1500.00	182400.00
	Compensation of employees by industry	19	136.83	26.13	105.20	182.30
	Gross value added by industry	19	7722.27	1410.97	5317.82	9774.65
	Unemployment rate by Industry	19	5.49	1.34	2.52	7.12
	Population aged between 15 and 19 years	19	599.29	60.39	525.50	720.54
	Population aged 65 years or over	19	2099.93	156.14	1793.88	2319.05
	year	19	2009	5.50	2000	2018
Other service activities	Number of persons employed by occupation by industry	190	106285.30	115110.70	1000.00	434800.00
	Compensation of employees by industry	19	118.54	20.85	87.05	148.90
	Gross value added by industry	19	75408.90	14074.50	46525.00	99591.00
	Unemployment rate by Industry	19	12.61	2.26	7.97	15.57
	Population aged between 15 and 19 years	19	599.29	60.35	525.50	720.54
	Population aged 65 years or over	19	2099.93	156.04	1793.88	2319.05
	year	19	2009	5.49	2000	2018

Source: *own compilation*