Nierówności Społeczne a Wzrost Gospodarczy, nr 72 (4/2022)
Social Inequalities and Economic Growth, no. 72 (4/2022)
DOI: 10.15584/nsawg.2022.4.1 ISSN 1898-5084, eISSN 2658-0780

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Employee compensation as a function of the sectoral structure of the economy

Introduction

In the economy, a high level of employee compensation and productivity is a desirable phenomenon. Therefore, it is widely believed that in countries where employee compensation and productivity are relatively high, the economy is

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developing well. Work productivity influences the standard of living, determines real compensation, and also reduces disproportions between regions, especially in the long run (Filippetti, Peyrache, 2013; Krugman, 1994). Productivity is also considered to be one of the key measures that describe the competitiveness of countries (Porter, 1990). Therefore, it is worth noting which factors determine a certain level of compensation and productivity. No wonder that over the past twenty years, this subject has been of interest and research by scientists (Ahmad et al., 2019). Nowadays, more and more is said about the importance of artificial intelligence (AI) for the labour market. According to Hui and Jiang (2020), if AI develops an alternative relationship with the labour force, and when the degree of substitution of AI for the labour force is higher and higher, the compensation for employment will increase at first and then will decrease.

Typically, the literature uses the gross domestic product (GDP) per capita to measure the relationship with productivity. However, there are many other indices that have been used in research. For instance, some research has found relationships between labour productivity and variables such as: inflation (Fortune, 1987), unemployment (Weisskopf, 1987), foreign direct investment (Egger, Pfaffermayr, 2001), vocational training of employees (Sala, Silva, 2011), gross national income (Fuentes-Castro, 2012), labour flexibility (Ingason, 2013), human capital (Azorin, del Mar Sanchez de la Vega, 2015), technology development (Filippetti, Peyrache, 2015), resource productivity (Stocker et al., 2015), expenses, savings, reforms in the labour market (Choudhry et al., 2016), information and communication technology (Hagsten, 2016), exports of goods (Csordas, 2017), compensation, employment (Conti et al., 2019), production innovations (Woltjer et al., 2019), age of the active population (Milanez, 2020), customer life cycle (Lew, 2017; Lew et al., 2017a) and even high air temperature and physiological stress of employees (Ioannou et al., 2021). Today, modern technology plays an important role in employment opportunities and compensation levels. Employees need to adapt to the prevailing conditions and develop their knowledge of modern technologies (Asonitou, Kavoura, 2019). The use of new variables in research means that one knows more and more about what causes changes in labour productivity and employee compensation. This knowledge is very important as it is relevant to productivity. One of the factors related to productivity is the level of employee compensation. Therefore, the aim of the study was to find how the structure of the economy influences employee compensation.

The result variable in the performed models is compensation of employees. It is a variable of the level type. Compensation of employees is shown in the euro, thanks to which it was possible to include in one model also the countries where the currency is different from the euro.

The explanatory variable is the sectoral structure of the economy.

The data concern the period 2013–2020 and include all countries belonging to the European Union. They constitute a panel with two levels: the year level and the country level; therefore, multi-level modelling was chosen as the method of data analysis. The two-level structure for the problem under study is presented in Figure 1. The observations regarding the relationship between the outcome variable and the predictor are related (correlated), so adjustments must be made with respect to countries. It can be said that the information on the shaping of the values in subsequent years is concentrated or belongs to a given country. Therefore, the lower level is the *Year*, and the higher level is the *Country*.

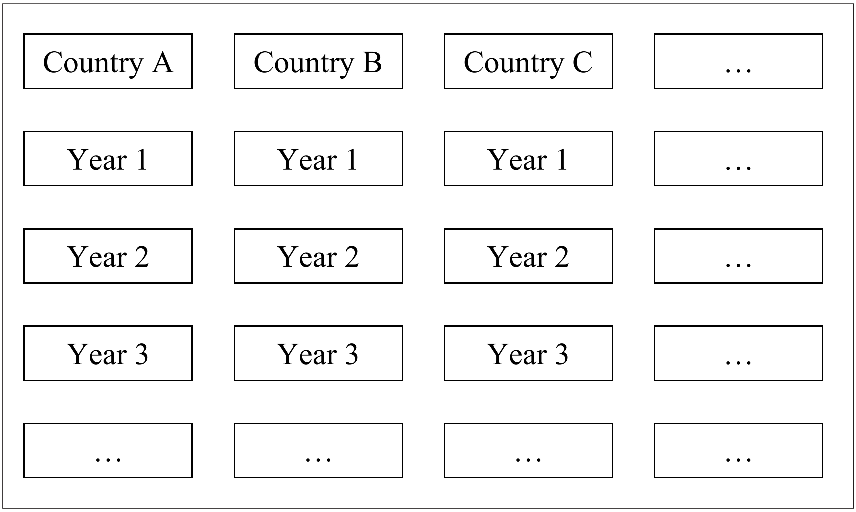


Figure 1. Two-level structure: years are concentrated around countries

Source: own study.

Multi-level modelling was originally used to analyze the educational process (Goldstein, Cuttance, 1988; Nutall et al., 1989), but is now more widely applied. The essence of multi-level modelling is data hierarchy. In this problem – determining the factors influencing the compensation of employees, one deals with a hierarchical structure. First, the behaviour of the outcome variables in the subsequent years of the analysis and by country can be assessed. If we assume that the year is level 1 and the country is level 2, then, in the case of the standard regression model, all countries should be included as independent variables. Meanwhile, when the multi-level analysis is used, not all intercepts and regression coefficients for each country are estimated, but only one intercept and one regression coefficient and their variances, as well as the variance between intercepts and regression coefficients.

The analyses were performed in the MlwiN 3.05 module.

Literature review

Employee compensation and productivity differ depending on the region or industry (Bernard, Jones, 1996). Researchers also found that increases in employee compensation, labour productivity and productivity levels were inversely proportional to different industries and regions (Abramovitz, 1986). It happened that when examining the dependence of variables at the level of the region, individual countries in the region, or dividing the region by industry, the results were different (Rodrik, 2012). Because of this, researchers often focus on factors that influence labour productivity in a given region, such as the EU, and then divide that area into sub-regions, such as the EU Member States. There is no shortage of research on labour productivity in EU countries. The subject of the research was the aspect of the level (an increase or a decrease) of productivity in the EU (Mitchell et al., 2006; Turner, Boulhol, 2011). Arnold and Wörgötter (2011) proposed a model that measured potential benefits of additional reforms and increased integration of EU service markets. In such a case, average employee compensation and labour productivity in the EU would increase by almost 10% in 10 years. The ageing of the EU population is also an important problem. Productivity was found to decline with increasing age of the economically active population (Calvo-Sotomayor et al., 2019). These results were confirmed in other studies (Cristea et al., 2020; Feyrer, 2007; Kelley, Schmidt, 2005; Sarel, 1995). Research on the impact of human capital on labour productivity in the EU showed that labour, allocation, diffusion and research effects of human capital increased the level of employee compensation and productivity (Cörvers, 1997).

Researchers also explored the employee compensation and productivity of the EU not as a whole, but for individual countries (Mihai, 2014; Piscitello, Rabbiosi, 2005; Polyzos, Arabatzis, 2006; Roberts, Thompson, 2009). Researchers from OECD (2001) showed that there were characteristics of individual EU Member States that prevented them from catching up with other countries in terms of labour productivity and, therefore, also in employee compensation. Focusing on advanced economies, Berg, Buffie and Zanna (2018) found that the more easily robots substitute for workers, the higher the increase in GDP per capita and the greater the decrease in labour share, leading to a richer economy, but with more inequality. During a long transition, real wages may fall. On the other hand, some argue that although technology indeed displaces some workers, there are countervailing forces which compensate for the displacements, notably increasing product demand, local demand spillovers, increasing demand for new complementary skills, or even new jobs required for new products and services (Acemoglu, Restrepo, 2018a). Moreover, that will increase compensation in modern economies.

The relationship between labour compensation and labour productivity is at the heart of macroeconomic analysis (Atkinson, 2009). According to the theory of economics, the dynamics of compensation should reflect changes in productivity, so both of these figures should grow together. The claim that compensation growth should reflect increase in labour productivity means that nominal unit labour costs should only be driven by the rate of inflation, so real unit labour costs should remain constant (Pasimeni, 2018). Compensation is a component of labour costs. Therefore, labour costs are a broader concept and include all costs related to the performance of work by employees. In addition to wages and salaries, they may include, for example, costs of employee training.

Researchers confirmed that increase in labour compensation is accompanied by a growth in labour productivity, while labour productivity is growing at a faster pace than labour compensation (Bivens, Mishel, 2015). Additionally, it was found that there was a significant and positive association between compensation and productivity, but not all productivity gain drove increases in compensation, so there was, in fact, a significant difference between labour productivity and labour compensation (Pasimeni, 2018). AI is important for compensation in modern economies. Regarding employment income, AI suggestively improves the labour income share of enterprises (Chen, Hu, 2020), as well as aggravates the income gap between high-skilled and low-skilled labour (Pan, 2019).

According to the authors, fewer people can produce more and more goods and services. During the last 150 years, labour productivity has grown more than 50 times. Nowadays, we can refer to the phenomenon of "growth without jobs" (Grishnova, Cherkasov, Brintseva, 2019). It is undoubtedly a result of several industrial revolutions, starting from the First Industrial Revolution, which brought mechanical innovations, like the steam engine and railroads. The Second Industrial Revolution brought the concept of mass production, while the Third Industrial Revolution brought computers and the internet. Now, we are witnessing the Fourth Industrial Revolution combining many different forces such as computing, wireless networks, Internet of Things (IoT), and artificial intelligence (AI) on the one hand, and smart materials, nanotechnology and 3D printing on the other hand (Kumar, 2018). In addition, new technologies and innovations can guarantee the viability of companies and organisations, indirectly affecting society as a whole (Makarona, Kavoura, 2019). The increasing presence of industrial robots and high-tech machines in industrial production has caused changes in compensation structures as well as skill changes. This phenomenon, referred to in the literature as wage polarisation, has created opportunities for highly skilled workers. The highest increase in average wages is seen in high-skilled job groups, while the lowest increase is seen in medium-skilled workers. This situation can also be explained as a natural consequence of the changes in demand for skills as a result of job polarisation (Dagli, Ozbay, 2021).

The simulation results reveal a refined interplay of effects of robotics in case of emergence of sectors and mobility of labour, inherent mechanisms of the labour market driving a wage-price spiral, and policy interventions to manipulate robotisation or consumption (Vermeulen, Pyka, Saviotti, 2020). Robotisation results in lower unit production costs and lower product prices, softens wage competition across sectors, and thus causes stagnation of wages and possibly an income gap between low- and high-skilled occupations. However, it is also found that the emergence of new sectors results in (sectoral) labour shortages and thus induces renewed price-wage spirals, effectively breaking away from wage stagnation, drawing in (un)employed workers across "vacancy chains" in which workers migrate stepwise to more advanced occupations/sectors. This is the case even if firms have strict requirements regarding skill distances or if workers' labour mobility across occupations/ sectors is limited. In general, the (desirability of) effects of robotisation and the effects of policy interventions are to be differentiated between economies with labour surplus and economies with (nearly) full employment. Whenever employment levels are low, robotisation will exacerbate unemployment and cause wage stagnation, such that it is commended to have robot taxation to prevent robotization, a universal basic income (to stimulate product and labour demand), and to stimulate innovation to create new sectors. However, whenever employment levels are (again) high, robotisation will "free up" labour, resolve labour shortages, reduce vacancies in new sectors, and relieve firms from (fierce) wage competition. In this case, a universal basic income would exacerbate shortages, a robot tax would sustain fierce wage competition, while the creation of new sectors would increase labour demand, such that these interventions are discommended. From this, it may be conjectured that there is a basin of attraction of Schumpeterian creative destruction in which, on the one hand, high, escalating wages under labour scarcity (i) invites technological substitution and (ii) slows down sector emergence, both reducing wage competition and labour utilisation. On the other hand, labour surplus (i) invites a reduction of wages, which (ii) drives entrepreneurial activities and, thereby, the creation of (labour-intensive) opportunities, both restoring labour utilisation and, hence, wage competition.

Acemoglu and Restrepo (2020) demonstrated high and robust negative effects of robotisation on employment and wages, and Compagnucci *et al.* (2019) used IFR data to demonstrate that the introduction of robots plays a key role in slowing down human labour and compensation growth, while Cho and Kim (2018) used IFR data for the multiple regression considering the triangular relationship of employment-working-hours-wages, to show that job destruction due to robotisation is not yet very remarkable. In contrast, Cséfalvay (2020) claims that "recent studies clearly show that robotisation is associated with economic growth and productivity gains."

One important area of research is the impact of structural changes in the economy on productivity and wages. A few studies seek to identify the role of entrepreneurship in inducing structural changes in economy (Neffke et al., 2017). Gajewski and Kutan (2018) argue that the emergence of new firms is determined by the specific conditions of the economic sector. Structural change is expressed in "the reallocation of labour and value added across sectors" (Ciarli, Valente, 2016, p. 40). This implies a continuous shift from sectors with lower productivity to those with higher productivity (Vu, 2017). Such a shift from agriculture to manufacturing is observed, followed by the predominance of the service sector (Gries, Naudé, 2008). This is supported by a subsequent increase in industrial productivity (Gurgul, Lach, 2015) and a decline in the share of agricultural labour (Cai, 2015). Projections show that we can expect a growth in the number of better-educated employees in the manufacturing sector, and a growth of labour productivity in the U.S. manufacturing sector (Rojko et al., 2020). Changes in the structure of the economy can therefore be expected to manifest themselves in a reduction in the importance of agriculture, an increase in productivity in industry and an increase in the importance of services. However, Acemoglu and Restrepo (2020) find that the increase in industrial robots in U.S. manufacturing had extensive negative effects on compensation and employment across commuting zones with the strongest wage effects on workers with high school education or less. The second perspective is more novel and relevant to current debates about automation reducing employment and its policy implications. Even though automation expands productivity, a force which always raises welfare, it also reduces employment, but compensation is higher (Acemoglu, Restrepo, 2018b).

Methods of multi-level analysis

The multi-level modeling approach was used to describe the relationships between the result and explanatory variables. This is a two-level modeling as the data is observed at the country level and in time. Appropriate types of multi-level models are used depending on the specific situation and the specificity of the relationship in the data. The details concern the number of levels and type of design (here these are a random intercept, random slopes and random coefficients regression model). In the paper, the random coefficients regression model was applied. The models of multi-level analysis also differ in the scale of the outcome variable and number of outcomes. There are univariate and continuous outcome variables.

There exist many procedures to estimate the parameters of multi-level models (Searle et al., 1992; Rao, 1971; Hox, 2002; Bryk, Raudenbush, 1992; Mass, Hox, 2003). The most popular are the minimum standards quadratic estimation (MINQUE), maximum likelihood method (ML and REML), expectation maximization (EM) and the iterative generalized least squares (IGLS), as well as its derivatives (RIGLS).

In the IGLS method applied in the paper, the model parameters estimation procedure is two-stage and includes the usual estimation of constant parameters using the least squares method (OLS), which is used to estimate the random part of the model (model covariance matrix). The resulting estimate of the random part of the model is applied to make an improved estimate of the part fixed, which is, in turn, used again to improve the estimate of the random part of the model. Thus, the constant and random parts of the model, until convergence is reached, are alternately estimated (Goldstein, 1986). The parameter estimates resulting from IGLS procedure are maximum likelihood estimates (Goldstein, 1995).

The procedure for estimating the parameters of multi-level models presented below comes from the work by El-Horbaty and Hanafy (2018).

Suppose the data set is divided into m groups, with a different number of n_j responses (j = 1,2, ..., m) in each group. The data includes the vector of the result variable Y_j, a set of explanatory variables W_j and another set of explanatory variables from the level of the Z_j group. To model this data, separate regression models are considered for each level. So the model at the general level is:

$$Y_j = W_j \alpha_j + \varepsilon_j \tag{1}$$

where:
Y_j – length vector n_j representing the response of group j;
W_j – matrix of size n_j x q independent variables;
$\varepsilon_j : N\left(0; \sigma_e^2 I_{n_j}\right)$ – vector of length n_j representing residues on the same level.

And the model on the group level is given by:

$$\alpha_j = Z_j \beta + \delta_j \tag{2}$$

where:
Z_j – matrix of size q x p second-level independent variables;
β – vector of size p x 1 representing the fixed effects;
$\delta_j : N\left(1; \Omega_g\right)$ – vector of size q x 1 representing random effects; where Ω_g is a symmetric covariance matrix:

$$\Omega_g = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1q} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2q} \\ \vdots & \vdots & \dots & \vdots \\ \sigma_{q1} & \sigma_{q2} & \dots & \sigma_{qq} \end{bmatrix}. \tag{3}$$

The combined model for group j is expressed by the equation:

$$Y_j = X_j\beta + W_j\delta_j + \varepsilon_j. \tag{4}$$

By combining the data for all groups, we get:

$$Y = X\beta + W\delta + \varepsilon, \tag{5}$$

where:

$$Y = \left(Y_1^T, \dots, Y_m^T\right)^T;\ X = \left(X_1^T, \dots, X_m^T\right)^T;\ \varepsilon = \left(\varepsilon_1^T, \dots, \varepsilon_m^T\right)^T \sim N\left(0; \sigma_e^2 I\right);$$

W – matrix of a single block level with W_j in the corresponding block,
$\delta \sim N\left(0;\Omega\right)$; $\Omega = diag\left(\Omega_g\right)$; with Ω_g of a covariance matrix at the group level.

The IGLS method estimates regression coefficients, variances and their random effects. Assuming that the residuals have a multivariate normal distribution, the method constructs an additional linear model whose unknown parameters are the intergroup covariances σ_{jk}, which represent the covariance between the j-th and k-th elements α (i.e. correlations between first-level parameter estimates); j, $k = 1, .., q$ and within-group variance. The IGLS procedure is an iterative procedure and lasts until the model converges, as detailed in the literature on the subject (Lindquist et al., 2012). In practice, it happens that the models do not converge (negative variances), which may be caused by the use of e.g. small samples. This is especially true for estimating random regression coefficients, less frequently for intercepts.

All the models estimated are presented in Table 2. Each row of the table refers to one model. For each row there is the following:

1. The first line contains information about the intercept, and the second line contains the regression coefficient. For each model, the values of structural parameters were given along with their standard errors.
2. Then the confidence intervals for these parameters, the z-ratio statistic and the *p*-value significance level; *p*-values less than 0.05 were taken as indicative of the existence of a given structural parameter.
3. The next column contains the VIF values. In some models, they are very high, which is not preferred as described above. On the other hand, even at high

VIF values, the directions of the regression coefficients are consistent with the theory of economics.

4. Next columns concern the values of the variance of random structural parameters and their standard errors (according to the Ω_u matrix) as well as the covariance of the random intercept and the random regression coefficient. Some models failed to converge, therefore the random regression coefficient was turned off (this is shown by the ”-“ sign).
5. The last two columns are the residual variance (including standard error) and the IGLS statistics respectively.

It should be noted that correct models were obtained in the vast majority of cases, whereas problematic cases were in the minority. Due to the transparency of the assessment, the tables also include problematic models. This does not prevent one from drawing general conclusions, as each of the models can be interpreted individually.

Empirical results

Depending on the production resources available or the degree of modernity, economies differ in the shares of individual sectors in the gross domestic product. Frequently, economies are divided due to the participation of traditional manufacturing sectors such as agriculture, construction or industry, and modern manufacturing sectors such as trade, services, the financial and IT sectors. As a rule, traditional sectors are considered to have low requirements in terms of employee competences, and thus low compensation. The situation is different in the case of modern sectors where requirements for employee competences are much higher, and therefore salary expectations of employees are higher.

For compensation of employees, the following variables are operative, which have a significantly positive impact (Table 2):

- Information and communication/GDP (β_0=19986.2; β_1=2060.1);
- Prof., scientific, techn.; admin., support serv. activities/GDP (β_0=-6949.6; β_1=3903.4);
- Public admin.; compulsory s.s.; education; human health/GDP (β_0=19667.6; β_1=715.9).

Among these variables, the strongest positive influence on *Compensation of employees* has *Prof., scientific, techn.; admin., support serv. activities/GDP* (regression coefficient 3903.4) and *Information and communication/GDP* (regression coefficient 2060.1). Each increase in these activities causes an increase of employee compensation in the economy. The regression coefficient shows that a 1% higher share of a given activity allows for a higher salary per employee by the value of the regression coefficient.

The variables that have a significantly negative impact are the following:
- Agriculture, forestry and fishing/GDP (β_0=39366.0; β_1=-4614.3);
- Industry, including energy/GDP (β_0=56790.9; β_1=-1367.9);
- Distributive trade, repairs; transport; accommod., food serv./GDP (β_0=76808.4; β_1=-2215.0);
- Financial and insurance activities/GDP (β_0=37625.1; β_1=-1493.9);
- Other service activities/GDP (β_0=35160.7; β_1=-1349.0).

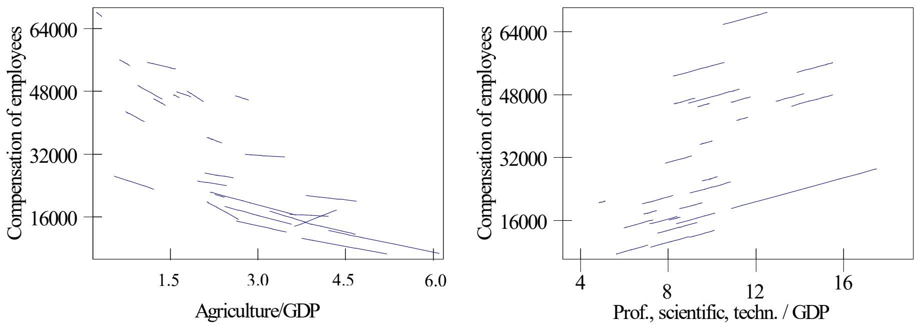
Agriculture, forestry and fishing/GDP had the strongest negative impact (regression coefficient -4614.3). Any limitation of the above-mentioned activities is beneficial for employee compensation. The regression coefficient shows how much employee compensation will decrease if the share of a given activity increases. But also the other way around, limiting the share of the above-mentioned activities is beneficial for employees' compensation.

The variables that have a non-significantly impact are the following:
- Construction/GDP (β_0=36536.7; β_1=-1047.7);
- Real estate activities/GDP (β_0=28146.4; β_1=323.9).

In all models, the covariance between the intercept and the regression coefficient is negative, so the higher the intercept, the weaker the compensation of employees' response to changes in predictors.

In addition, it is worth paying attention to the value of intercepts as they show what theoretically would happen in an economy that would give up a given branch of the economy. Thus, the highest value of the intercept 76.808,405 was obtained for *Distributive trade, repairs; transport; accommod., food serv./GDP* = 0. On the other hand, the lowest value of the intercept -6.949,636 was obtained for *Prof., scientific, techn.; admin., support serv. activities/GDP* = 0. Therefore, the comparison of the value of intercepts with regression coefficients allows to answer the question of what type of economy should be promoted. The lower the β_0 value, the more significant the activity, and the higher the β_0 value, the less significant the activity. The activities of the first group have low β_0 values, while the activities of the second group have high β_0 values. High β_0 values mean that giving up such an activity is beneficial for productivity and negative regression coefficients, which means that any restriction of such an activity is beneficial for productivity. Obviously, the question of resignation from a given activity should be considered only in purely theoretical matters.

Examples of a negative impact of *Agriculture/GDP* on *Compensation of employees* and a *Positive impact of prof., scientific, techn.; admin., support serv. activities/GDP* on *Compensation of employees* are shown in Figure 2. These are only selected variables concerning the structure of the economy among those described above, which have the strongest influence on compensation of employees.



Explanations: each linear function represents a different EU country

Figure 2. Examples of negative and positive impact of the economy structure on *Compensation of employees*

Source: own calculation.

The impact of two selected sections of the economy: negative impact of *Agriculture/GDP* and a positive impact of *Prof., scientific, techn.; admin., support serv. activities/GDP* on *Compensation of employees*, is shown by country (Table 1). It should be noted that the conclusions drawn from the country-by-country approach are subject to high uncertainty compared to the multi-level analysis presented above. The uncertainty results from short time series and hence from a small number of degrees of freedom.

Out of 27 analyzed countries, 19 had a negative impact of *Agriculture/GDP* on *Compensation of employees*, of which for 10 countries this impact turned out to be statistically significant at $p<0.05$ (Bulgaria, Czechia, Germany, Estonia, Hungary, Malta, the Netherlands, Portugal, Romania, Slovakia); for the remaining 9 countries, the impact is negative but statistically insignificant (Belgium, Ireland, Greece, Italy, Cyprus, Lithuania, Luxembourg, Austria, Poland). Meanwhile, for 8 countries, the impact of *Agriculture/GDP* on *Compensation of employees* is positive (Denmark, Spain, France, Croatia, Latvia, Slovenia, Finland, Sweden), but only for Latvia it turns out to be significant. Therefore, taking into account all countries, the result is consistent with the multi-level analysis and shows the negative impact of *Agriculture/GDP* on *Compensation of employees*.

Impact study of *Prof., scientific, techn.; admin., support serv. activities/GDP* on *Compensation of employees* allows for the conclusion that for 23 out of 27 countries this impact is positive. For 17 countries, a positive, statistically significant impact was found at $p<0.05$ (Belgium, Bulgaria, Denmark, Estonia, Spain, France, Italy, Latvia, Lithuania, Luxembourg, Hungary, Malta, the Netherlands, Poland, Portugal, Romania, Finland) and for 6 countries, the impact turned out to be positive but statistically insignificant (Czechia, Germany, Greece, Austria, Slovenia, Slovakia). Only in 4 cases a negative link was obtained (Ireland, Croatia, Cyprus, Sweden), and only for Croatia it was statistically significant. Therefore, as for the influence of *Prof., scientific, techn.; admin., support serv. activities/GDP* on *Compensation of employees*, it can be considered that the results are consistent with the above-obtained results for the multi-level analysis.

Table 1. The impact of selected sectors of the economy on *Compensation of employees*

Country	Agriculture, forestry and fishing/GDP		Prof., scientific, techn.; admin., support serv. activities/GDP	
	regression coefficient	*p*-value	regression coefficient	*p*-value
Belgium	-7317.92	0.5395	2253.32	0.0015
Bulgaria	-2448.03	0.0007	2616.05	0.0036
Czechia	-11107.61	0.0014	8745.87	0.0560
Denmark	1015.62	0.8069	2472.82	0.0000
Germany	-14961.26	0.0467	8625.53	0.0769
Estonia	-3985.56	0.0465	7262.40	0.0001
Ireland	-10484.08	0.1487	-1502.99	0.3513
Greece	-665.41	0.4184	2464.02	0.2004
Spain	1202.82	0.3018	1351.12	0.0052
France	6743.93	0.2504	2103.83	0.0042
Croatia	763.74	0.5175	-3460.81	0.0080
Italy	-5006.38	0.1050	3078.36	0.0018
Cyprus	-829.45	0.5204	-311.49	0.3544
Latvia	9852.02	0.0072	6046.88	0.0001
Lithuania	-4843.29	0.3090	4910.29	0.0036
Luxembourg	-67827.20	0.0598	4381.37	0.0000
Hungary	-2972.56	0.0002	1780.68	0.0026
Malta	-6556.89	0.0019	695.02	0.0000
Netherlands	-17046.60	0.0416	2356.78	0.0491
Austria	-21530.84	0.1151	6379.81	0.1389
Poland	-3188.50	0.0798	2571.98	0.0003
Portugal	-18657.91	0.0225	1738.93	0.0347
Romania	-2863.39	0.0384	3509.70	0.0039
Slovenia	557.78	0.9284	766.36	0.8336
Slovakia	-4055.18	0.0269	1002.06	0.4185
Finland	3501.35	0.3667	1536.58	0.0212
Sweden	5792.62	0.4571	-721.62	0.3838

Notes: regression coefficient estimated by LSM method, *p*-value < 0.05 – significant impact.

Source: own calculation.

Table 2. Outcome variable: compensation of employees

Independent variable		Coef.	S.E.	Conf Int 2.5%	Conf Int 97.5%	z-ratio	*p*-value	VIF	Var (βi)	S.E.	Covar (β_1/β_0)	S.E.	Var (residual)	S.E.	IGLS
Agriculture, forestry and fishing/GDP	β_0	39366.0	3894.7	31732.4	46999.5	10.107	0.000	2.859	3.52E+08	1.11E+08	-6.4E+07	2.63E+07	2.67E+06	2.90E+05	4001.747
	β_1	-4614.3	1033.8	-6640.6	-2588.1	-4.463	0.000		1.75E+07	7.27E+06					
Industry, including energy/GDP	β_0	56790.9	5201.6	46595.9	66985.9	10.918	0.000	3.419	5.08E+08	1.91E+08	-1.4E+07	7.33E+06	2.05E+06	2.23E+05	3959.292
	β_1	-1367.9	221.2	-1801.5	-934.3	-6.184	0.000		6.84E+05	3.26E+05					
Construction/GDP	β_0	36536.7	4415.9	27881.7	45191.7	8.274	0.000	15.785	0.000	0.000	0.000	0.000	2.67E+08	2.57E+07	4803.844
	β_1	-1047.7	785.9	-2588.1	492.7	-1.333	0.183		0.000	0.000					
Distributive trade, repairs; transport; accommod., food serv./GDP	β_0	76808.4	5008.4	66992.2	86624.6	15.336	0.000	28.282	0.000	0.000	0.000	0.000	1.92E+08	1.84E+07	4732.272
	β_1	-2215.0	237.0	-2679.5	-1750.4	-9.345	0.000		0.000	0.000					
Information and communication/GDP	β_0	19986.2	3247.8	13620.6	26351.7	6.154	0.000	8.962	0.000	0.000	0.000	0.000	2.54E+08	2.45E+07	4793.395
	β_1	2060.1	581.1	921.3	3199.0	3.545	0.000		0.000	0.000					
Financial and insurance activities/GDP	β_0	37625.1	4610.7	28588.2	46661.9	8.160	0.000	2.135	4.83E+08	1.55E+08	-4.9E+07	2.18E+07	2.31E+06	2.55E+05	4007.747
	β_1	-1493.9	746.9	-2957.9	-29.9	-2.000	0.045		1.09E+07	3.96E+06					
Real estate activities / GDP	β_0	28146.4	6424.0	15555.6	40737.2	4.381	0.000	4.633	8.81E+08	2.98E+08	-7.3E+07	2.74E+07	2.59E+06	2.86E+05	4024.348
	β_1	323.9	623.3	-897.8	1545.5	0.520	0.603		8.09E+06	2.81E+06					
Prof., scientific, techn.; admin., support serv. activities/GDP	β_0	-6949.6	3422.0	-13656.5	-242.7	-2.031	0.042	15.087	0.000	0.000	0.000	0.000	1.68E+08	1.61E+07	4703.462
	β_1	3903.4	341.6	3234.0	4572.9	11.428	0.000		0.000	0.000					
Public admin.; compulsory s.s.; education; human health/GDP	β_0	19667.6	7163.4	5627.6	33707.5	2.746	0.006	5.814	1.10E+09	3.70E+08	-4.1E+07	1.58E+07	2.26E+06	2.50E+05	3993.262
	β_1	715.9	320.5	87.9	1344.0	2.234	0.025		1.94E+06	7.36E+05					
Other service activities/ GDP	β_0	35160.7	3280.3	28731.4	41590.0	10.719	0.000	1.118	2.60E+08	7.07E+07	-	-	3.53E+06	3.64E+05	4041.912
	β_1	-1349.0	332.2	-2000.1	-698.0	-4.061	0.000		-	-					

Notes: Coef. β_0, β_1 – structural parameters of the model, S.E. – standard error; Conf Int 2.5% – Conf Int 97.5% – confidence interval for structural parameters; z-ratio – test statistic of significance of structural parameters; *p*-value – significance level; VIF – variance inflation factor; Var (β_i) – variance of random structural parameters, S.E. – standard error; Covar (β_1/β_0) – covariance of random structural parameters, S.E. – standard error; Var (residual) – residual variation of the model, S.E. – standard error; IGLS-statistic – 2 * loglikelihood

Source: own calculation.

The conducted collective research (multi-level analysis) has a methodological advantage over individual conclusions for countries. First of all, the analyzed data set is larger, which is advantageous due to the number of degrees of freedom. Moreover, the method of multi-level analysis allows one to draw more general conclusions. Of course, the specificity of countries may cause deviations from general regularities, but the theory should be general in principle.

Conclusions

Research into factors influencing compensation and productivity is extremely important. It provides valuable information for shaping the fiscal policy of the state and sets directions for the development and transformation of the economy. Obviously, there is competition between entrepreneurs and employers for added value and a question may be asked whether growing salaries will reduce the profits of enterprises. Entrepreneurs will depend more on productivity. These two important groups must reach a compromise together, yet from a macroeconomic point of view, i.e. the economy as a whole and the strength of the state, these two things – compensation and productivity – come together.

The present research focused primarily on the construction of the economy, i.e. the impact of the output approach or economy structure on the *Compensation of employees*. Conclusions can be divided into two groups: those concerning methodology and the cognitive ones concerning directions and strength of influence of selected predictors on *Compensation of employees*.

The choice of the dependency description method fell on a multi-level analysis. The unquestionable advantage of this method is a possibility of including many groups of objects observed at different levels in one model. Whether multi-level modeling is an appropriate method depends on the goal of the development. Multi-level modeling allows one to observe the general regularities governing a given system, without delving into the issues of differences between individual objects. The scale of the differences is known, but it is not specified which objects it applies to. Naturally, there are no problems with the identification of individual objects and their mutual evaluation. Here, it was done for two variables: *Agriculture/ GDP* and *Prof., scientific, techn.; admin., support serv. activities/GDP*. In this individual approach, the LSM method was used, and the choice of a method depends only on the intention of the researcher. In this paper, thanks to the use of multi-level modeling, it was possible to determine the strength and direction of the impact of selected predictors on the outcome variable – employee compensation, but due to the fact that different countries were subject to the study, also the scale of differentiation of this impact was determined.

In the presented models, statistically significant regression coefficients were obtained, but they correlated with the intercept. In the case of standard modeling, the correlation of structural parameters is a problem, but in the case of multi-level modeling, on the contrary, it is of particular interest and is described and interpreted using appropriate parameters. This is of great practical importance.

The practical interpretation of the results clearly shows the significance of using multi-level modeling. Looking from the output approach of GDP, it was found that the increase in the share of information and communication and prof., scientific, techn.; admin., support serv. activities leads to the fastest growth of compensation of employees. This is a very important observation as some literature notes that modern forms of production reduce wages. On the other hand, the increase in agriculture, forestry and fishing has a negative effect on *Compensation of employees*. What became evident at this point in the application of multi-level modeling is the finding that the strength of the influence of a given predictor depends significantly on the share of a given GDP section in the entire economy; the smaller this share, the stronger the reactions to changes in the production structure. Thus, it can be concluded that a transition from traditional sectors of the economy to modern sectors leads to an increase in compensation and productivity. It is obvious that on a global scale it is not, and even not advisable, that all economies undergo such a transformation. This process should be viewed as a process of sustainable development of traditional sectors of the economy, which are necessary for the proper functioning of society, as they satisfy basic human needs and the transition of human resources to modern production methods. On the other hand, in traditional sectors of the economy, their efficiency should be increased. As a result, basic human needs will continue to be met and compensation will increase at the same time.

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Summary

Employee compensation is the factor that determines the directions of economic development. Yet, at the same time, the structure of the economy influences employee compensation. Due to the importance of the structure of the economy, the purpose of the paper is to examine the structure factors that influence compensation in the EU Member States in the period 2013–2020. In particular, it investigates the importance of traditional and modern economic structures for employee compensation. In the paper, a multi-level analysis was applied. The research showed that the systematic transformation of the economy towards modern branches in favour of the traditional ones caused an increase of compensation. This is an alternative result in relation to some observations in the subject literature, where it is often emphasized that robotisation and AI cause an increase in unemployment and a decrease in employee compensation. On the other hand, it is impossible to completely replace the traditional sectors. Hence, the most appropriate direction seems to be a gradual increase in efficiency in underdeveloped sectors of the economy without abandoning them entirely.

Keywords: compensation of employees, economy, determinants, multi-level analysis.

Wynagrodzenia pracowników jako funkcja struktury sektorowej gospodarki

Streszczenie

Wynagrodzenia pracowników są czynnikiem, który wyznacza kierunki rozwoju gospodarczego. Jednocześnie można stwierdzić, że struktura gospodarki wpływa na wynagrodzenia pracowników. Ze względu na znaczenie struktury gospodarki, celem artykułu jest zbadanie czynników struktury wpływających na wynagrodzenia w krajach członkowskich UE w latach 2013–2020. W szczególności zbadano znaczenie tradycyjnych i nowoczesnych struktur gospodarczych dla wynagrodzeń. W pracy zastosowano analizę wielopoziomową. Badania wykazały, że systematyczna transformacja gospodarki w kierunku nowoczesnych gałęzi kosztem tradycyjnych spowodowała wzrost wynagrodzeń. Jest to wynik alternatywny w stosunku do niektórych obserwacji literaturowych, gdzie często podkreśla się, że wykorzystanie robotyzacji i sztucznej inteligencji powoduje wzrost bezrobocia i spadek wynagrodzeń pracowników. Z drugiej strony, całkowite zastąpienie tradycyjnych sektorów jest niemożliwe ze względu na ich znaczenie. Stąd najwłaściwszym kierunkiem wydaje się być stopniowe zwiększanie efektywności w słabo rozwiniętych sektorach gospodarki, bez ich całkowitego porzucania.

Słowa kluczowe: wynagrodzenia pracowników, gospodarka, determinanty, analiza wielopoziomowa.

JEL: E24, J30.