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Regional differentiation of human capital – analysis based on the Mincer wage equation

Introduction

Human capital has been an important field of research for economists for decades. Its level and quality seem to be crucial for societal development from the endogenous growth theory point of view. An analysis conducted by Acemoglu and Dell (2010) shows that approximately half of between-country and between-municipality differences could be explained by differences in human capital. Those disparities significantly affect the adoption and creation rates of innovations. The results obtained by Diebolt and Hippe (2019) suggest that human capital is the most significant historical factor of current prosperity in European regions. In that context, this type of capital has persistent positive long-term effects on regional development. This underlines the importance of analyses that concern the problems of regional diversification of human capital.

The purpose of this study was to capture the regional disparities in human capital. Based on previous studies (e.g., Roszkowska, 2013), we expected to find significant differences between regions, which suggests that those disparities have been maintained (or even growing) over a period of time. This may be one of the factors behind the process of real global-to-regional convergence not being achieved, as reported by most studies (see e.g., Dańska-Borsiak, 2011; Wójcik, 2018). For that purpose, we used the modified Mincer-based human capital index presented in Florczak (2011). The analysis was conducted at the NUTS-2 territorial-disaggregation level. Estimates of the Mincer wage regression parameters for every region were obtained with the use of non-identifiable microdata from the

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Central Statistical Office (CSO) – structure of wages and salaries by occupations – in the October survey (Z-12, 2016-year revision). These estimates were combined with a CSO Labour Force Survey (LFS) and life expectancy data to calculate final estimates of human capital indices (for the years 2016 and 2019). The results of the analysis will help identify the regions with the highest and lowest levels of human capital, as well as education-level premiums.

METHODS DESCRIPTION

Human capital is a very broad term. In a narrow sense, one can define it as the knowledge embodied within a human being (e.g., level of education, skills, etc.). Taking into account a broad definition, human capital incorporates factors such as health and vital energy, psychophysical and cultural characteristics (e.g., creativity, entrepreneurship), and social-economic activity or worldview (Becker, 1993; Domański, 1993; Florczak, 2011; Roszkowska, 2013; Schultz, 1961). In this context, this multidimensionality has created an opportunity for various approaches to analyse human capital levels[2].

In this study, we use the following extended Mincer wage equation as a base for further research (Kot, 2004; Kurkiewicz, Podolec, Sokołowski, 1999; Lemieux, 2006; Mincer, 1974):

$$\ln wage_i = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 edc_{m_i} + \beta_4 edc_{h_i} + \beta_5 gen_i + \\ + \boldsymbol{X}^T \boldsymbol{\alpha} + \varepsilon_i \qquad (1)$$

where:

$\ln wage_i$ – logarithm of the monthly wage for the i-th employee,
age_i – age of the i-th employee,
edc_{m_i} – dummy variable that takes the value “1” if the employee achieved a secondary education level and “0” otherwise,
edc_{h_i} – dummy variable that takes the value “1” if the employee achieved a tertiary education level and “0” otherwise,
gen_i – dummy variable that takes the value “1” for men and “0” for women,
$\boldsymbol{X}^T \boldsymbol{\alpha}$ – observation matrix of control variables and vector of parameters related to them, and
ε_i – random components.

In Equation (1), the variable age of the employee is an approximation of their level of experience and refers to the “on-the-job training” cycle that enhances the

[2] Overviews of the theoretical models and measurement concepts of human capital can be found, e.g., in: Domański (1993), Mačerinskienė and Viržintaitė (2003), Roszkowska (2013), and Woźniak, Jabłoński, Soszyńska, Firszt, Bal-Woźniak (2015).

employees' human capital level (Kot, 2004, p. 316). This variable is also included in the model in the second power, so the concavity of the relation between age and wage is achieved (Mincer, 1974). The "formal" part of the human capital level in the following model is reflected by the achieved educational level dummy variables grouped into three categories. The first category encompasses employees that are at the basic vocational, lower secondary, primary, or lower educational level. The second category covers employees that graduated from general secondary school. This group also includes post-secondary and vocational secondary education. The third category refers to the tertiary educational level.[3] In our model, we have included only the second and third groups, so we can interpret parameter estimates as a wage premium of the consequent education level in reference to primary education or lower (i.e., the first category). We also included a gender dummy variable to capture the effect of the gender pay gap.

The control variables set contains the following variables:

- sections for the main groups of the PKD 2007 classification for the enterprise in which a person is employed,
- the profession of employees using classification of occupations (so-called 'major' groups of occupations),
- ownership of enterprises (public or private), and
- size of the enterprise (measured by the number of people employed and grouped into three categories – small, medium, and large).

Parameter estimates of model (1) will be used as weights for the following human capital index construction (Florczak, 2011):

$$HLEXP_{t,j} = \left[\left(\exp\left(\beta_{5,j}\right) * NM_{t,j} * LEXPM_{t,j} + NK_{t,j} * LEXPK_{t,j}\right) * \right. \\ \left. * HCND_{t,j} * NDAGE_{t,j}\right] / ND_{t,j} \qquad (2)$$

where:

j – region subscript (j = 1, …, 16);
t – time subscript (t = 2016, 2019);
$LEXPK_{t,j}$ – women's life expectancy (in years);
$LEXPM_{t,j}$ – men's life expectancy (in years);
$NK_{t,j}$ – number of employed women;
$NM_{t,j}$ – number of employed men;
$ND_{t,j}$ – total number of employed persons;
$HCND_{t,j}$ – human capital level per employee that takes into account education level:

[3] We tested this grouping via model selection procedures and it was also found to be consistent with previous literature findings (e.g., Kurkiewicz, Podolec, Sokołowski, 1999).

$$HCND_{t,j} = \frac{\exp(\beta_{4,j})*NWYZ_{t,j}+\exp(\beta_{3,j})*NSR_{t,j}+NPO_{t,j}}{ND_{t,j}} \tag{3}$$

where:
$NWYZ_{t,j}$ – number of employees with a tertiary degree,[4]
$NSR_{t,j}$ – number of employees with a secondary degree,
$NPO_{t,j}$ – number of employees with a primary degree or lower; and
$NDAGE_{t,j}$ – age (job experience) index:

$$NDAGE_{t,j} = \sum_{k=15}\left[\frac{N_{kt,j}}{ND_{t,j}} * \frac{\exp\left(\beta_{1,j}*k+\beta_{2,j}*k^2\right)}{\exp\left(\beta_{1,j}*15+\beta_{2,j}*15^2\right)}\right] \tag{4}$$

Florczak (2011) proposed the above index, which encompasses three key components of widely understood human capital: education, experience, and health condition (approximated by life expectancy for women and men).

Estimation of the Mincer equation is not new in Polish studies. Most of them focus on educational wage premiums (e.g., Majchrowska, Roszkowska, 2013; 2014; Strawiński, 2006) and gender pay gap (e.g., Majchrowska, Strawiński, 2018). In the case of synthetic human capital index computations, Florczak (2011) and Szafrański (2006) use the Mincer equation estimation results from Kurkiewicz, Podolec, Sokołowski (1999). In contrast, our studies use our own estimate results to obtain the human capital index for each region.

DATA USED

In order to estimate the parameters of the Mincer wage equation for each voivodeship, we used non-identifiable microdata from the Z-12 survey addressing the structure of wages and salaries by occupations in October 2016 (CSO, 2018).[5] The survey is conducted every two years and covers national entities with employment exceeding nine people.[6] The database contains information on full- and part-time employees (without converting part-time employees into full-time ones) who worked the whole month of October 2016. The sample contains information on 795,900 employees. In our analysis, we excluded part-time employees in order

[4] We used the same three categories of aggregated education levels as in the Mincer equation.

[5] We used microdata for 2016 due to unavailability of newer data. Accessing microdata for the Z-12 survey requires the CSO's permission.

[6] Every revision of the survey is published in the form of a report with a 2-year delay. The newest revision contains data on wages and salaries from 2018.

to avoid Mincer equation estimate bias (that is, we excluded 7.6% of the whole sample). Obviously, the mentioned database is, of course, not the only one that contains information useful for estimating the Mincer equation. A cross-comparison of popular Polish databases can be found in Strawiński (2015). The most important advantage of using the Z-12 survey microdata is that the information comes from an accounting system of the entities surveyed. They are not declared by individuals, as in the Household Budget Survey (HBS). Another important aspect is that the Z-12 survey focuses on distributing the characteristics of individual employees (in contrast to the HBS, where the family is the main unit of interest).

The second source of data that we used is the CSO Labour Force Survey database. It contains information on the employment structure by educational level, gender, and age. Additionally, we also used data on life expectancy. The data were downloaded from the CSO Local Data Bank (CSO, 2021) for the years 2016 and 2019.

Results

The following section provides a short analysis of the diversity of the level of human capital by Polish voivodeships in 2016 and 2019. We will also provide some basic interpretation of the wage regression results that concern the educational premiums and gender pay gap.[7] Table 1 presents the estimated values of parameters of interest for Equation (1).[8]

Table 1. Mincer wage equation estimation results (NUTS-2 level)

Voivodeship	$\hat{\beta}_{1,j}$	$\hat{\beta}_{2,j}$	$\hat{\beta}_{3,j}$	$\hat{\beta}_{4,j}$	$\hat{\beta}_{5,j}$
1	*2*	*3*	*4*	*5*	*6*
Dolnośląskie	0.03691	-0.00037	0.10220	0.28852	0.18777
Kujawsko-Pomorskie	0.02953	-0.00027	0.10494	0.28883	0.15952
Lubelskie	0.02793	-0.00023	0.07581	0.25406	0.13681
Lubuskie	0.03439	-0.00035	0.04437	0.20636	0.17525
Łódzkie	0.02643	-0.00025	0.07529	0.23626	0.16140
Małopolskie	0.03705	-0.00035	0.12135	0.31930	0.17199
Mazowieckie	0.04591	-0.00045	0.11186	0.38597	0.17710

[7] The relation of age and wage is non-linear; thus, the proper interpretation requires at least that wage-age profiles (for each region) be presented. Instead, we will concentrate on interpreting the synthetic human capital index.

[8] We are not presenting the estimates for the control variables due to their large number (multiplied by the number of regions) and the fact that we do not use them in the further analysis. Full estimation results are available on request.

1	*2*	*3*	*4*	*5*	*6*
Opolskie	0.02910	-0.00027	0.07785	0.27719	0.21009
Podkarpackie	0.02241	-0.00019	0.07236	0.23399	0.14846
Podlaskie	0.02651	-0.00023	0.04447	0.19391	0.12105
Pomorskie	0.03788	-0.00036	0.12559	0.32772	0.16921
Śląskie	0.03190	-0.00031	0.06644	0.25082	0.20599
Świętokrzyskie	0.02453	-0.00019	0.08457	0.25379	0.13440
Warmińsko-Mazurskie	0.02454	-0.00022	0.08069	0.24847	0.15103
Wielkopolskie	0.03251	-0.00032	0.06488	0.28408	0.19879
Zachodniopomorskie	0.03186	-0.00030	0.06126	0.23170	0.17977

Source: own estimates based on Z-12 2016 data, sample weights have been applied.

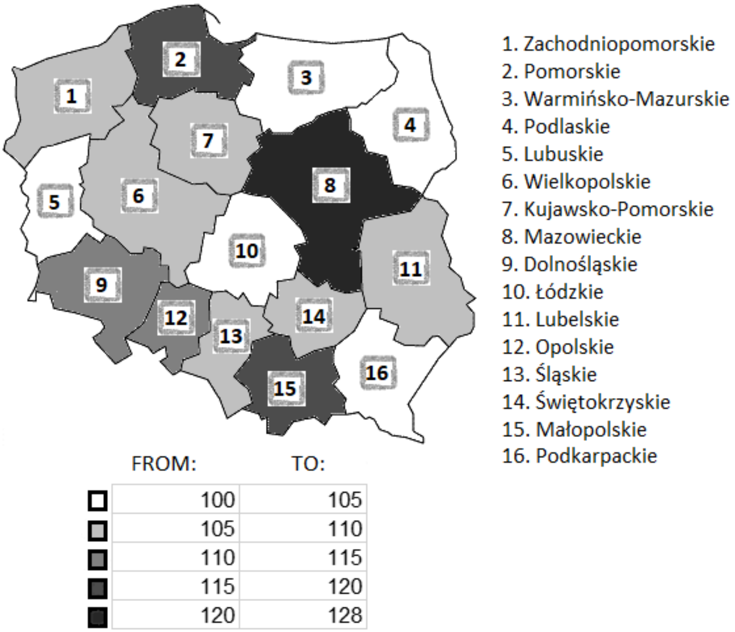
Regarding the gender pay gap estimates ($\hat{\beta}_{5,j}$), we draw the following conclusions:

- The highest disparities were observed in Opolskie. On average, men's wages were about 21% higher than women's (holding all other factors constant).
- A relatively high gender pay gap was also observed in Śląskie (approximately 20.6%) and Wielkopolskie (approximately 19.9%).
- The lowest disparities were observed in Podlaskie. On average, men's wages were about 12.1% higher than women's (holding all other factors constant).
- Relatively low gender pay gaps were also observed in Świętokrzyskie (approximately 13.4%) and Podkarpackie (approximately 14.8%).

The following conclusions were reached regarding the diversification of regional educational premiums ($\hat{\beta}_{3,j}$, $\hat{\beta}_{4,j}$):

- Considering tertiary education levels, the highest premiums were observed in Mazowieckie. On average, wages were about 38.6% higher than for employees with primary education or lower (keeping all other factors constant).
- Relatively high tertiary educational premiums were also observed in Pomorskie (approximately 32.8%) and Małopolskie (approximately 31.9%).
- The lowest tertiary educational premiums were observed in Podlaskie (appro-ximately 19.4%) and Lubuskie (approximately 20.6%).
- As expected, the overall secondary education level premiums were relatively low. Similarly to the tertiary level, the highest education premiums were observed in Pomorskie, Małopolskie, and Mazowieckie (approximately from 11.2% to 12.6%).
- The lowest secondary educational premiums were observed in Podlaskie and Lubuskie (approximately 4.4%).

Figure 1 presents the regional diversification of human capital levels computed using formula (2). The same weights (estimated values of parameters from the Mincer wage regression) were applied to the Labour Force Survey and demographic data from 2016 and 2019. The following conclusions were drawn:



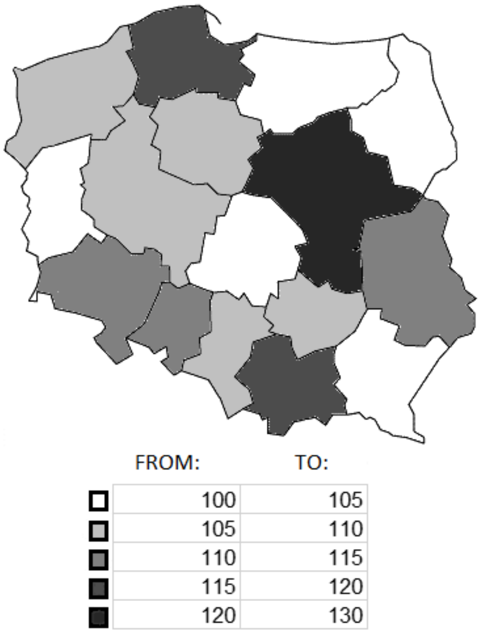


Figure 1. Regional diversification of human capital based on the HLEXP index for years 2016 (upper) and 2019 (lower), Lubuskie voivodeship = 100

Source: own work based on CSO data and own estimates.

- The lowest human capital level for both years was observed in Lubuskie (this region serves as a reference region).
- We can also assign Warmińsko-Mazurskie, Podlaskie, Podkarpackie, and Łódzkie (all regions below 105% of the human capital level for Lubuskie) to the class of regions with very low human capital.
- The highest level of human capital for both years was observed in Mazowieckie and was approximately 128% and 130% of the level of Lubuskie for 2016 and 2019, respectively.
- We can also assign Pomorskie and Małopolskie (from 115% to 120% of the human capital level for Lubuskie) to the class of regions with relatively high human capital levels.
- The highest "between years" human capital dynamic from the lower level regions was noted in Lubelskie (for the class changes between the years 2016 and 2019, see Figure 1).
- The highest overall "between years" dynamic was noted in Mazowieckie (the HLEXP index was approximately 2.25% higher in 2019 than in 2016).
- A high dynamic was also observed in Pomorskie, Małopolskie and Dolnośląskie (approximately 1.4%).
- The lowest overall "between years" dynamic was observed in Kujawsko-Pomorskie (approximately 0.20%).
- A lower dynamic was also observed in Warmińsko-Mazurskie and Lubuskie (approximately 0.62% and 0.75%, respectively).

CONCLUSIONS

The estimation results of the Mincer wage model for Polish voivodeships reveal significant differences in terms of the returns for schooling and experience, as well as in the gender pay gap. However, one should be aware of the limitation of the Mincer equation (see e.g., Lemieux, 2006). An unambiguous advantage of the presented approach is that we can use those estimates as a weight in computing the human capital index. In many cases, during synthetic index construction, researchers use arbitrary weights for partial characteristics. In this case, our weight is more 'data and theory' driven.

We found that, in the period analysed, Mazowieckie, Pomorskie, and Małopolskie show the highest level of human capital. On the other side were Lubuskie, Warmińsko-Mazurskie, Podkarpackie, Podlaskie, and Łódzkie. A similar ranking could be obtained for the dynamics of the human capital index. We noted that regions with a lower index value also have the lowest change rate of that index between the analysed years. In fact, we only analysed two years, but these results may premise that regions in Poland are characterised by divergence in human capital (also, the variance of the HLEXP index was higher in 2019). The one exception is Lubelskie, in which the human capital dynamic was significantly greater among lower class regions. The result could be partially explained by the fact that big academic centers are often located in Polish regions and by the unequally distributed high-tech industry. The latter often requires a significant level of financial capital and good infrastructure that can only be fulfilled by higher-developed regions. This will most likely lead to a human capital drain effect from one region (less developed) to another (higher developed).

Finally, it is worth mentioning that the silent assumption about the constant parameters of the Mincer equation across years could be violated, although, as is likely in this analysis, they could remain stable for a reasonably short period of time. Of course, the presented approach also does not encompass all aspects of human capital, so it would be very interesting to extend the analysis through a wider set of characteristics (and a broader time span). Further research will also involve efficiency wage hypothesis testing. In that analysis, we will try to combine the results of the Mincer wage equation with regional estimates of the total factor productivity.

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Summary

The main objective of this paper was an attempt to assess the differentiation of human capital at the level of Polish regions (voivodeships, NUTS-2 level). For this purpose, we used unidentifiable unit data from a survey the Central Statistical Office conducted on the structure of wages and salaries in October 2016 (Z-12), data from the Labour Force Survey (LFS), and data on the life expectancy of women and men. The GUS microdata from the Z-12 study was used to estimate the parameters of the Mincer-type extended wage regression, separately for each voivodeship. In the next step, these estimates were used as weights to calculate the human capital index, taking into account the health condition, education, and professional experience of employees. The values of the aforementioned measure were estimated for 2016 and 2019 (the assumption of weight stability over a short time period was made).

The analysis conducted made it possible to determine which regions are characterised by the highest and lowest levels of human capital. The highest levels of human capital were found in Mazowieckie, Pomorskie, and Małopolskie. The voivodeships with the lowest level of the considered measures were Lubuskie, Warmińsko-Mazurskie, Podlaskie, Podkarpackie, and Łódzkie. When comparing the values of the human capital index between 2016 and 2019, it can be concluded that the regions with the lowest value of this measure were also characterised by lower dynamics (the only exception was Lubelskie). Such a situation will probably favor the divergence of human capital between regions. This may, therefore, translate into the persistence (or deepening) of differences in the levels of development of these voivodeships, compared to more developed regions.

Keywords: human capital, Mincer wage equation, regional analysis.

Regionalne zróżnicowanie kapitału ludzkiego – analiza na podstawie równania płac Mincera

Streszczenie

Głównym celem niniejszego artykułu była próba oceny zróżnicowania kapitału ludzkiego na poziomie polskich regionów (województwa, poziom NUTS-2). W tym celu wykorzystano nieidentyfikowalne dane jednostkowe pochodzące z badania przeprowadzonego przez Główny Urząd Statystyczny dotyczącego struktury wynagrodzeń w październiku 2016 roku (Z-12), dane pochodzące z badania aktywności ekonomicznej ludności (BAEL) oraz dane o oczekiwanej długości życia kobiet oraz mężczyzn. Mikrodane GUS z badania Z-12 posłużyły do oszacowania parametrów rozszerzonej regresji płac typu Mincera, osobno dla każdego województwa. W kolejnym kroku oszacowania te zostały wykorzystane jako wagi do obliczenia indeksu kapitału ludzkiego uwzględniającego stan zdrowia, poziom wykształcenia oraz doświadczenie zawodowe pracowników. Wartości wspomnianej miary oszacowano dla lat 2016 oraz 2019 (przyjęto założenie o stałości wag w krótkim czasie).

Przeprowadzona analiza pozwoliła na ustalenie, które regiony cechują się najwyższym, a które najniższym poziomem kapitału ludzkiego. Zdecydowanie najwyższy poziom kapitału ludzkiego odnotowano w województwach mazowieckim, pomorskim oraz małopolskim. Do województw o najniższym poziomie rozważanej miary zaliczono lubuskie, warmińsko-mazurskie, podlaskie, podkarpackie oraz łódzkie. Porównując wartości indeksu kapitału ludzkiego pomiędzy latami 2016 oraz 2019 można stwierdzić, że regiony o najniższej wartości tej miary cechowały się również niższą jej dynamiką (wyjątek stanowiło województwo lubelskie). Taki stan rzeczy będzie prawdopodobnie sprzyjał dywergencji kapitał ludzkiego pomiędzy regionami. Przełożyć się to może tym samym na utrzymywanie się (bądź pogłębianie) różnic w poziomach rozwoju tych województw, względem regionów lepiej rozwiniętych.

Słowa kluczowe: kapitał ludzki, równanie płac Mincera, analizy regionalne.

JEL: C20, C43, C51, C55, J24, J31.

APPENDIX

Table 2. Basic description of the sample used

Voivodeship	No. of men	No. of women	No. of employees with primary degree	No. of employees with secondary degree	No. of employees with tertiary degree	Total
Dolnośląskie	30,007	29,936	15,446	20,625	23,872	59,943
Kujawsko--Pomorskie	17,219	16,284	9,770	11,359	12,374	33,503
Lubelskie	14,917	16,197	6,409	10,449	14,256	31,114
Lubuskie	8,087	7,894	4,721	5,728	5,532	15,981
Łódzkie	21,995	22,802	10,766	16,239	17,792	44,797
Małopolskie	29,265	30,231	13,384	19,468	26,644	59,496
Mazowieckie	75,112	73,461	23,045	48,021	77,507	148,573
Opolskie	7,962	8,102	4,262	5,371	6,431	16,064
Podkarpackie	21,138	18,408	10,861	13,889	14,796	39,546
Podlaskie	7,597	8,005	3,670	5,024	6,908	15,602
Pomorskie	19,710	19,590	9,817	12,536	16,947	39,300
Śląskie	52,286	42,130	25,087	34,602	34,727	94,416
Świętokrzyskie	8,650	8,915	4,086	5,830	7,649	17,565
Warmińsko--Mazurskie	9,054	10,653	5,654	6,167	7,886	19,707
Wielkopolskie	38,245	36,513	22,223	26,136	26,399	74,758
Zachodnio-pomorskie	11,736	13,479	6,274	8,100	10,841	25,215

Source: own calculations based on Z-12 2016 data.