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Human capital convergence in European NUTS 2 regions

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Abstract

Research background: The role of human capital in modern economy development is as important as that of material growth factors. According to the three-sector model theory, economic growth is associated with the process of labour force leaving the primary sector. The research issue addressed in this paper was the human capital level estimation in European NUTS 2 regions and the relationship between the human capital level and sectoral structure of the economy.

Purpose of the article: The article aimed to verify the hypotheses of absolute and conditional human capital convergence in European NUTS 2 regions. The analysis covered the 2005–2020 period for European NUTS 2 regions and two subgroups: the CEE regions and the Western European regions.

Methods: A composite indicator approach was adopted to measure human capital levels in NUTS 2 regions. In order to verify the absolute and conditional β -convergence hypotheses, dynamic panel data models were estimated. The Blundell and Bond system-GMM estimator with parameter standard errors robust to heteroscedasticity was used.

Findings & value added: The study positively verified the hypotheses of absolute and conditional convergence in each group of regions. Percentages of employees in sectors proved to be the steady-state determinants. The time needed to reduce differences occurring in human

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capital levels by half (a half-life) was about 11 times greater for the CEE regions than for the Western European ones. The value added of the article lies in proving the relationship between the sectoral structure of employees and the pace of human capital convergence in European NUTS 2 regions.

Introduction

Contemporary economy has the nature of a knowledge-based system with human capital becoming one of the key factors in economic development and growth. As a basic component of human capital, knowledge has become a factor co-determining the competitive advantage of economic entities. Economic growth and development are positively correlated with human capital. The relationship results from the fact that GDP growth stimulates increased capital investment, which, in turn, entails the need for qualified employees. Paces of regional growth are varied and depend, among others, on initial levels, economic structures and modernity of economies, the important determinant of which is human capital. As noted by Duran *et al.* (2015), the sustainable development of the society integrates three major components of human existence: economic, ecological and human. Differences in economic development paces and components, including human capital and sectoral structures of employees, may lead to the phenomenon of convergence, being absolute or conditional, depending on how the steady-state has been determined.

Regional convergence is the subject of numerous studies. They most often concern income convergence, while some of them consider economic convergence to be conditional on human capital. The role of human capital as a driver of convergence is also a matter of interest of the European Commission. The forthcoming report of the EU agency Eurofound-ETF *Role of human capital on cohesion and convergence* (planned publication date: 2024) focuses on the role that human capital plays in determining inequalities across the EU and within Member States.

Studies on human capital convergence appear in the literature, but they are relatively few and tend to focus on countries and, less often, on regions of a single country or group of countries. In recent years, research at country level has been carried out by Castelló-Climent and Doménech (2022) and Mendez (2020). Studies regarding the Visegrad Group NUTS 2 regions and Chinese provinces have been presented by Dańska-Borsiak (2018) and Valerio Mendoza *et al.* (2021), respectively. There is, therefore, a research

gap in analysing the regional convergence of human capital levels across Europe, and this article attempts to fill it in.

The principal aim of the article is to examine whether β -convergence occurred among European NUTS 2 regions in terms of human capital levels in the years 2005–2020 and whether the convergence pace was the same throughout Europe or was territorially diversified. The analysis covered 283 European NUTS 2 regions and two subgroups: regions of the countries which joined the EU after 2004 and regions of the countries that had already belonged to the EU before 2004, as well as Switzerland, Norway, Iceland and Liechtenstein. Hypotheses of absolute and conditional convergence were verified, the latter with percentages of working populations by sectors assumed as independent variables.

The novelty value and contribution of this paper in the literature are threefold. Firstly, to the author's knowledge, this is the first attempt to demonstrate that the sectoral structure of employees is a determinant of different steady-states of regional human capital levels. Secondly, a comparison was made among human capital convergence paces across Europe as a whole and in two subgroups: regions of Central and Eastern Europe and 'western' regions, i.e. those belonging to the 'old EU' along with ones closely economically linked to them. A comparison of the regions of the so-called old and new EU with respect to human capital had been made by Merło and Bogdański (2018), but it was carried out in the context of regional competitiveness and concerned levels of that variable. Thirdly, a composite measure of human capital was constructed, consisting of the same components as the World Bank's Human Capital Index. However, a proprietary set of diagnostic variables was proposed.

The composite measure of human capital was calculated as an unweighted sum of eight diagnostic variables describing its three dimensions: science, technology and education; demography; and health. Dynamic panel data models were applied to explore the β -convergence.

The remaining parts of this paper are as follows: Section 2 constitutes a literature review. Section 3 presents statistical data, the human capital measure construction method and the convergence testing procedure used in the study. Estimation results of absolute and conditional convergence models are described in section 4. They are preceded by a statistical analysis of key variables: human capital and sectoral structure of employment in the regions. The results are discussed in section 5, whereas the final section presents conclusions.

Literature review

Research background

According to the endogenous growth theory (compare Aghion & Howitt, 1999), human capital is one of the most important growth determinants. While neoclassical theories hold that the pace of economic growth is determined by an exogenously established long-term growth rate, the New Growth Theory strongly emphasises the importance of investing in new knowledge creation to sustain growth (compare Cortright, 2001, pp. 25–26).

In OECD (2001, pp. 17–18), human capital is defined as “The knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being”. The said individual attributes include physical, emotional and mental health as well as innate capacities. An increasing human capital level confers a range of personal, economic and social benefits and translates into faster economic growth and greater social development. Several authors, *e.g.* Faggian and McCann (2019), note that links between human capital and economic development at regional and national levels may differ.

Empirical research on the level and diversity of human capital, its sources and importance for socio-economic development is carried out at both national and regional levels. Measures of human capital for countries are constructed by organisations and research institutions, the examples of which are the United Nation’s Human Development Index (HDI) or the World Bank’s Human Capital Index (HDI). They can be divided into two broad categories: indicators-based and monetary measures, and are discussed at length *e.g.* by Fraumeni (2021). The book also presents international human capital comparisons for at least 130 countries based on the measures and, separately, single-country studies for the USA and China.

Interesting proposals of alternative measures were put forward by Lim *et al.* (2018), Campbell and Üngör (2020) and Demirgüç-Kunt and Torre (2022). Lim *et al.* (2018) generated a period measure of expected human capital defined for each birth cohort as the expected years lived from age 20 to 64 years adjusted for educational attainment, learning or education quality, and functional health status for 195 countries from 1990 to 2016. They proved that greater improvements in human capital were associated with faster economic growth. Campbell and Üngör (2020) constructed a measure

integrating three components: schooling, cognitive skills and health. They showed that, when understood in this way, human capital accounted for 19–28% of differences in output per worker in the sample of 122 countries. The differences decreased when the health component was excluded and fell even further if cognitive skills were excluded, decrease even further. Demirgüç-Kunt and Torre (2022) extended the World Bank's HCI by adding a measure of quality-adjusted years of higher education and an additional proxy for latent health status. The index was dedicated to European and Central Asian countries, where productive employment requires higher education graduate qualifications and good health is associated with low levels of risk factors.

The literature abounds in other worthwhile international human capital comparisons. Research by Teixeira and Queirós (2016) was performed for OECD countries based on data for 1960–2011 and assessed effects of human capital on economic growth, including the interaction between human capital and industrial specialisations of the countries. Cruz (2019) presented a multi-sectoral growth model, in which human capital induces structural change through changes in relative prices and investment rates in physical and human capital. The results indicate that imbalances between physical and human capital contribute to explaining cross-country differences in paces of structural change. Collin and Weil (2020) found that higher investment in human capital leads to significant improvements in a country's income with the largest gains in poor countries. Investing in human capital is a more effective means to achieve specified income or poverty goals than investing in physical capital.

The regional dimension is crucial to understanding economic growth, which is in line with Paul Krugman's words: "one of the best ways to understand how the international economy works is to start by looking at what happens inside nations" (Krugman, 1991, p. 3). The historical overview of human capital formation in European regions and analysis of the connection between regional human capital accumulation and economic growth in a long-term perspective was presented by Hippe (2020). Merlo and Bogdański (2018) analysed the level of human capital in the EU regions in the context of their competitiveness. They showed significant disproportions, especially between the so-called old and new EU. The impact of physical and human capital relocations on the growth of open economies was studied by Sardadvar (2016). Estimates of the spatial econometric

model for European NUTS 2 regions underlined the importance of human capital endowments and its relationship with spatial location.

There are also publications in the literature concerning differentiation of human capital within one or two neighbouring countries. Pasquini and Rosati (2020) showed large differences across Italian provinces in terms of human capital, driven mostly by education quality variation. Biedka *et al.* (2021) examined the effects of investment in human capital, as funded by the EU cohesion policy, on economic development in Poland at the level of municipalities. They proved that human capital investment exerted a positive impact on local revenues while the cohesion policy effectiveness depended on existing regional preconditions for development. In the case of Finland and Sweden over the 1987–2015 period, Eliasson *et al.* (2021) revealed statistically insignificant changes in the geographical dispersion of human capital on the inter-regional scale, large and persistent disparities between the core and hinterlands, and the largest intra-regional differences within the metropolitan labour markets. Jagódka and Snarska (2023) found human capital to be the main driver of regional disparities in Polish NUTS 2 regions and investigated whether it was fully utilised in creating innovations.

European NUTS convergence studies

According to Pina and Sicari (2021), the last two decades have been a period of uneven regional convergence paces. Apart from differences between fast growing Central and Eastern Europe and Southern Europe, often falling behind, gaps between large cities and rural areas have widened within most countries.

A majority of studies into regional convergence focus on income convergence (see *e.g.* Fischer & Pfaffermayr, 2018; Pietrzykowski, 2019; Peshev & Pirimova, 2020; Postiglione *et al.*, 2020; Bernardelli *et al.*, 2021). Papers on convergence in other variables are less common. Recent studies have included works by Kijek and Matras-Bolibok (2020) on technological convergence, Cismas *et al.* (2020) on employment convergence and Kijek *et al.* (2022) on the convergence of R&D expenditure.

There have also been several works examining the convergence of human capital across countries and regions. According to Castelló-Climent and Doménech (2022), convergence in human capital preceded convergence in *per capita* income. For 140 countries in the years 1970–2020,

σ -convergence in human capital started around 1977, while divergence in GDP *per capita* was the dominant force until the 1990s and started to decline around 2000. The pace of β -convergence in human capital has been increasing since the 1980s onward. Moreover, for *per capita* income, the conditional β coefficient on the initial level of human capital was twice as high as the unconditional convergence β coefficient. Mendez (2020) examined convergence in capital accumulation across developed and developing countries. A non-linear dynamic factor model was used to evaluate the cross-country dynamics of physical and human capital in the years 1990–2014. The estimation results indicated the occurrence of club convergence in human capital in the case of developed countries, for which two clubs were distinguished, with weakly separating trends. However, for developing countries, the dynamics of human capital was characterised by three largely separated and parallel clubs. Dańska-Borsiak (2018) analysed absolute convergence of human capital and spatial relationships in its distribution for the Visegrad Group NUTS 2 regions in the years 2001–2015. No spatial autocorrelation was detected, but evidence of absolute convergence was found and regions that contributed to the weakening of its pace were identified. Stamatakis (2016) empirically analysed human capital convergence in three groups of countries: G7, developed and developing ones. He found moderate evidence of conditional convergence for alternative determinants of human capital.

According to the New Growth Theory, investing in human capital is crucial for sustaining growth (compare Cortright, 2001, pp. 25–26). Economic growth brings about changes in the structure of employees observed in the economies of developed countries in the form of an increasing GDP share of services, in their broad sense. Thus, a question arises about the relationship between the human capital level and sectoral structure of employees. The only studies that addressed the issue were, to the author's knowledge, Čadil *et al.* (2014) concerning EU member states and Valerio Mendoza *et al.* (2021) regarding Chinese provinces. Hence, a research gap seems to exist in the area and this study attempts to fill that in by analysing the relationship between the human capital level and sectoral structure of employees in European NUTS 2 regions in the context of human capital convergence.

Research methods

Human capital is intangible and its different interpretations and definitions in the specialist literature give rise to various quantification methods. Currently existing human capital measures can be divided into two categories: indicators-based and monetary measures. In this study, an indicators-based measure was constructed. According to Fraumeni (2021), these measures have a wide array of components, such as demography, education, health and know-how. Also, the HCI (World Bank, 2021) for countries combines demographic, education and health dimensions.

The composite measure constructed in this study included the same dimensions as the HCI. The study used data for 283 NUTS 2 European regions in the years 2005–2020, obtained from the Eurostat website¹. Diagnostic variables for each dimension were as follows, with letters (S) or (D) denoting a stimulant or destimulant, respectively:

Education, science, technology:

- prim* individuals with less than primary, primary and lower secondary education (levels 0-2) as percentage of population aged 25-64 (D)
- tert* individuals with tertiary education (levels 5-8) as percentage of population aged 25-64 (S)
- noedu* young people neither in employment nor in education or training as percentage of population aged 15-24 (D)
- trng* participation rate in education and training (last 4 weeks) as percentage of population aged 25-64 (S)
- hrst* individuals employed in science and technology as percentage of active population (S)

Demography:

- ddr* demographic dependency ratio (expressed as the number of “dependants” aged 0-14 and 65+ for every 100 “workers” (aged 15-64) (D)

¹ <http://ec.europa.eu/eurostat/data/database>.

Health:

life life expectancy, population aged less than 1 year (S)
cdr crude death rate (D)

When constructing the composite human capital measure, it was assumed that each of the diagnostic variables had the same impact on its value. The human capital measure in region i (hc_i) was calculated as an unweighted sum of the eight individual diagnostic characteristics listed above, using the formula:

$$hc_i = \frac{1}{8} \sum_{j=1}^8 z_{ij}, \quad (1)$$

where z_{ij} was the unitised value of variable x_{ij} , calculated according to the formula:

$$z_{ij} = \begin{cases} \frac{x_{ij} - x_{j \min}}{x_{j \max} - x_{j \min}} & \text{if } x_j \text{ is a stimulant} \\ \frac{x_{j \max} - x_{ij}}{x_{j \max} - x_{j \min}} & \text{if } x_j \text{ is a destimulant} \end{cases} \quad (2)$$

in which x_{ij} was the value of the j -th variable in region i , $x_{j \min}$ and $x_{j \max}$ denoted the maximum and minimum of the j -th variable, respectively.

In this study, the hypotheses of the absolute and conditional β -convergence were verified. The absolute (unconditional) β -convergence hypothesis assumes that regions tend to the same level of a variable, regardless of the initial conditions, and thus basic parameters describing economies of different regions are similar. All economies, therefore, converge to the same steady-state equilibrium. Conditional β -convergence means that each of the regions tends to its own steady-state, depending on features specific to its economy. Therefore, the hypothesis assumes the diversification of basic indicators describing various regions' economies and arises from neoclassical growth models.

In order to verify the absolute β -convergence hypothesis, a panel data model was estimated, where the dependent variable was the mean rate of changes in the variable and the explanatory variable was its initial level. The model took the following form:

$$\frac{1}{T} \ln \frac{y_{i,t+T}}{y_{it}} = \alpha_0 + \gamma \ln y_{it} + u_{it} \quad (3)$$

where:

$y_{i,t+T}$ level of variable y in region i in the final period,
 y_{it} level of variable y in region i in the initial period,
 T number of periods included in the analysis (number of years for which the growth rate was calculated),
 $u_{it} = \alpha_i + \varepsilon_{it}$, α_i group effects specific to region i , and ε_{it} was the error term.

The explained variable in model (3) was the average growth rate of the variable in the studied period. A negative value of the estimated γ parameter means that absolute β -convergence occurs (because the value indicates the direction of the relationship between the initial variable level and its growth rate).

In order to write (3) in a form convenient for estimation, it should be converted to:

$$\ln y_{i,t+T} = T\alpha_0 + (T\gamma + 1) \ln y_{it} = \theta_0 + (\theta_1 + 1) \ln y_{it} + u_{it} \quad (4)$$

Verifying the conditional convergence hypothesis required modifying equation (4) to the following form:

$$\begin{aligned} \ln y_{i,t+T} &= T\alpha_0 + (T\gamma + 1) \ln y_{it} + \delta^T \mathbf{x}_{it} + u_{it} = \\ &= \theta_0 + (\theta_1 + 1) \ln y_{it} + \delta^T \mathbf{x}_{it} + u_{it} \end{aligned} \quad (5)$$

where \mathbf{x}_{it} was the vector of explanatory variables characterising steady-state heterogeneity. In the presented study, elements of vector \mathbf{x} were percentages of employees in three sectors of the economy: agriculture, forestry and fishing (u_{ag}); industry and construction (u_{in}); and services (u_{sv}). They were calculated based on Eurostat data on employment by economic activity and NUTS 2 regions².

The value of the β coefficient, indicating the pace of convergence, *i.e.* what percentage of distance towards a long-term equilibrium is covered by the economy over one period, can be estimated based on the formula:

$$\hat{\beta} = -\frac{1}{T} \ln(1 + T\hat{\gamma}), \quad (6)$$

² <http://ec.europa.eu/eurostat/data/database>.

where $\hat{\gamma}$ is an estimate obtained from equation (4) or (5). As pursuant to the convergence theory, parameter γ in model (3) equals $\gamma = -(1 - e^{-\beta T})/T$ (see Barro & Sala-i-Martin, 1992).

Based on the β -convergence parameter estimate, the so-called half-life (length of a half of a convergence period, a half convergence period) interpreted as time needed for existing differences to be reduced by half, can be worked out as follows:

$$T_{1/2} = \frac{\ln 2}{\hat{\beta}}. \quad (7)$$

Dynamic panel data models of forms (4) and (5) are most often estimated with the system-GMM estimator developed by Blundell and Bond (1998). Their approach was used in this study. Alternatives would be the first-differenced GMM estimator proposed by Arellano and Bond (1991) or the instrumental variables technique by Anderson and Hsiao (1982). The system-GMM estimator has better properties than the latter in the case of regressor endogeneity and short time dimension of the panel. It is much more effective than the first-differenced GMM, especially if the autoregressive parameter is close to one or the ratio of the group effects variance to the error term variance is growing.

Results

Human capital distribution

An empirical analysis was conducted for (I) all 283 European NUTS 2 regions and two subgroups: (II) 225 regions of the countries that belonged to the EU before 2004, as well as Switzerland, Norway, Iceland and Liechtenstein³; (III) 56 regions of Central and Eastern Europe (hereinafter called the CEE regions)⁴. Group II comprised the regions of the “old EU” member states and countries closely linked to them by economic agreements: EFTA (Switzerland and Norway since 1960) and EEA (Iceland and Liechtenstein

³ NUTS-2 regions of the following countries were excluded: Bulgaria, Croatia, Cyprus, the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia and Slovenia.

⁴ The set comprised NUTS-2 regions of countries listed in footnote 4, except for Cyprus and Malta.

since 1992). The group is further referred to as the Western European (WE) group of regions.

In the first step of research, values of human capital measure *hc* were calculated according to formulas (1) and (2) based on the set of diagnostic variables described in section 3.

Basic characteristics of the *hc* composite human capital measure in the extreme periods of the sample (years 2005 and 2020) are presented in Table 1. These statistics indicate that the mean human capital level in 2020 was about 3.3% higher than in 2005. Although the growth was considerably faster in the CEE (about 7.7%) than in the WE (about 2.6%) regions, the final level in the former group remained significantly lower. The quicker human capital growth in the CEE regions may, however, suggest convergence among all the analysed regions. The Central European regions showed the fastest growing diversification – the coefficient of variation (CV) in 2020 increased by almost 8 pp. compared to 2005. Moreover, in contrast to the WE regions, the minimum *hc* measure value declined, which reflected the outflow of human capital from certain regions to other, more modern ones.

An analysis of spatial distribution of the *hc* measure (Figure 1) allowed indicating the weakest and strongest regions. The highest human capital levels were observed in Scandinavian, German, Austrian, British and Dutch regions, while the lowest – in Bulgarian, Romanian, Greek and Portugal ones. In 2020, compared to 2005, an improved situation could be noticed in some Norwegian, Polish and French regions, with the biggest drops in the *hc* measure occurring in a part of East German and South Italian regions. In 2005, there were two “upper outlier” regions: Zurich and Inner London, while in 2020 the group was joined by the regions of: Stockholm, Oslo and Akershus as well as Central Switzerland. That means that the number of regions with significantly high human capital concentration increased to five. They are leading academic, research and development centres, as well as Knowledge and Innovation Communities created by the European Institute of Innovation and Technology.

Working population sectoral structure

Differences in human capital resources among regions reflect differences in knowledge-based economy development. Such an economy is considered to be characterised by the developed service sector, with de-

creasing shares of the other sectors, particularly the primary sector, encompassing agriculture, hunting, forestry, fishery, fishing and mining.

The diversification of NUTS 2 regions in respect of their working population sectoral structures was measured using coefficients of variation for percentage shares of populations working in the three sectors: agriculture, forestry and fishing (u_{ag}); industry and construction (u_{in}); and services (u_{sv}). Their values are presented in Table 2.

Results contained in Table 2 show that the highest interregional diversification of employee shares was observed in agriculture, forestry and fishing. Coefficients CV indicate higher diversification of the WE regions compared to the CEE ones. The agricultural sector seemed to be shrinking, particularly in the WE regions, where the maximum u_{ag} value dropped by 27 pp., compared to a fall of 12 pp. in the CEE ones. The mean percentage was declining too, although it was several times higher in the CEE regions than in the other ones. As for the shares of employees working in industry, the coefficients of variation and ranges were comparable for each group of the regions. The diversification of shares of industry employees slightly increased over the studied period. The lowest diversification characterised regional shares of employees in the service sector with a decrease over the period under consideration. Moreover, the minimum values of shares of employees in that sector increased: by 26.7 pp. in the WE regions and by 37.1 pp. in the CEE ones, respectively.

Results of absolute convergence analysis

Most convergence studies based on panel data use observations of five-year frequency. Due to relatively short time series available for NUTS 2 regions, this study was based on data for three-year periods. Thus, the sample included 6 periods (years: 2005, 2008, ..., 2020), while the cross-sectional dimension comprised from 283 to 56 NUTS 2 regions, depending on the study range. In order to verify the absolute convergence hypothesis, model (4) was applied. Its parameters were estimated based on data for all the regions and two groups described in section 4. The models were estimated using the Blundell–Bond system-GMM with parameter standard errors robust to heteroscedasticity. Two tests were performed for each model, the results of which are given in Tables 3 and 4: the Arellano–Bond autocorrelation test and the Sargan test for over-identification restrictions. No serial autocorrelation at an order greater than one was found in any

case (Arellano-Bond test), indicating that the models were correctly specified. The GMM instruments are valid according to the Sargan test results.

The estimates of parameters at the lagged dependent variable in models I, II and III, presented in Table 3, differ considerably. The estimated coefficient β , *i.e.* the three-year convergence pace, equalled 11.6% for all the 283 regions, being about twice as high (24%) for the WE regions. A significantly slower convergence pace, at about 2.7%, was found for the CEE regions. The time needed to reduce the occurring differences by half (*half-life*) was the shortest for the WE regions, *i.e.* an area whose economies have been functioning according to stable rules for more than 75 years, with developed knowledge-based economies and high mean expenditures on R&D. Different results were received for the CEE regions, where the annual convergence pace was 0.87% and it would take about 77.5 years to reduce the existing differences by half. Such a slow pace of catching-up may arise from the considerable diversification of the initial *hc* variable levels in a relatively small number of regions: the CV coefficient in the group was more than 3 pp. higher than in the WE regions, with the numbers of regions in the groups being 56 and 225, respectively.

Results of conditional convergence analysis

The economies of the European NUTS 2 regions are diversified in many respects, in particular as to their wealth or sectoral structures of their working populations. Therefore, the next step in the analysis was to verify the conditional β -convergence hypothesis, according to which regions converge to different steady-states but at the same speed. For this purpose, the model of the form (5) was used, with shares of employees in the sectors considered endogenous variables. The estimation results are presented in Table 4.

For the groups of all regions and the WE regions, results of models IVa, IVb, Va and Vb indicate a negative impact of percentages of agriculture employees (u_{ag}) on the human capital level, whereas the impact of percentages of service employees (u_{sv}) is positive. If, however, both the variables were included in the model, u_{sv} was statistically insignificant. These variables are strongly correlated – Pearson's $r = -0.71$. A different situation was observed in the case of the CEE regions (models VIa and VIb) in which Pearson's $r = -0.35$. A statistically significant, positive impact on human capital levels was found for percentages of industrial employees, whilst

variables u_{ag} and u_{sv} were significant together but not separately. The conclusions are consistent with results received by Čadil *et al.* (2014), who observed that human capital in agricultural regions negatively affects economic growth, and Ramos (2012), according to whom the so-called effect of over-education occurs in regions.

The hypothesis that the percentage of the working population by sectors is the characteristic of steady-state heterogeneity was, thus, positively verified. Although the impact of exogenous variables on human capital levels was slight, taking them into account influenced the estimates of parameters at lagged dependent variables in all the models. As a result, the human capital level in all the European regions and in the WE group converged faster when assuming that steady-states might be different. That was indicated by comparing β -convergence parameter estimates in Tables 3 and 4. They increased from 0.116 to 0.188 (0.163) and from 0.242 to 0.209 (0.195) respectively, depending on the independent variable. This means the shortening of the half-life from almost 18 to 11-12 years for all the regions and from 8.5 to about 7.5 years for the WE regions.

The estimated half-life for the CEE regions differs considerably – it equals about 84–88 years, depending on the control variables. Although the theta parameter estimate is negative and statistically significant, which should be interpreted as the occurrence of convergence, its extremely slow pace suggests the need for gaining more insight into the regions' situations.

Discussion

The literature concerning the regional convergence of human capital is sparse. Although there is a large number of studies on convergence of European NUTS regions, most of them address income convergence in the context of the endogenous growth theory with human capital regarded as a factor that differentiates steady-state parameters. The novelty of the presented research lies, therefore, in addressing the issue of human capital convergence at the NUTS 2 level in Europe and, above all, in demonstrating that the sectoral structure of employees is a factor that determines steady-states.

Based on a review of the available literature, a majority of studies on human capital convergence are country-specific and global in their scope. Castelló-Climent and Doménech (2022) established σ -convergence and

absolute β -convergence for a sample of 140 countries in the years 1970–2020. When analysing smaller subgroups, they found that a subgroup of 20 countries in Europe and Central Asia showed the lowest growth rates of human capital across almost all the decades. The results of a study by Mendez (2020) indicated club convergence in human capital in developed countries in the years 1990–2014, with weakly separating trends. Stamatakis (2016) examined three groups of countries: G7, developed and developing. The results were inconclusive. Moderate evidence of conditional convergence or signs of divergence, the latter especially for poor economies, were found, depending on the method of human capital measurement. At the regional level, Dańska-Borsiak (2018) found evidence of absolute β -convergence for the Visegrad Group NUTS 2 regions. Valerio Mendoza *et al.* (2021) observed club convergence, but no evidence of overall human capital convergence at the province level in China.

The human capital level should correspond to the structure of the region's economy. Otherwise, it will result in imbalances in the labour market and a crowding out effect. In consequence, unemployment will increase and economic growth will slow down. This issue was addressed by Ramos *et al.* (2012), Čadil *et al.* (2014) and, more recently, by Bye and Faehn (2022). Ramos *et al.* (2012) stressed that human capital represented by the education level can have a negative effect on employment, associated with overeducation. That occurs when human capital is mismatched with the economy structure, *i.e.* its supply exceeds regional demand for highly skilled workers, especially if geographical labour mobility is limited. Čadil *et al.* (2014) analysed the impact of human capital on regional economic growth at the NUTS 2 level, controlling for economic structure. Their analysis was conducted for all the regions and for clusters of regions with similar economic structures. The results obtained for the agriculture-oriented cluster, which exhibits low shares of the secondary and tertiary sectors, indicated that human capital endowment was slowing down regional economic growth instead of accelerating it. Based on a case study of Norway's small open economy, Bye and Faehn (2022) showed that the fastest growing sectors were those in which human capital, R&D and trade interacted and increased absorptive capacity. For 31 Chinese provinces, Sun *et al.* (2018) indicated that dependence on natural resources was significantly and negatively correlated with human capital accumulation.

The presented study verified the hypothesis that percentage shares of employees in particular sectors may be the exogenous variables characteris-

ing the heterogeneity of steady-states. To the author's knowledge, this is the first attempt at capturing the impact of the structure of employees on the pace of human capital convergence.

Human capital is an intangible phenomenon, hence considering its convergence requires establishing a method of its measurement first. Indicators of human capital proposed by institutions such as the World Bank or the United Nations are only available at the national level. In order to measure regional human capital, some authors used simple indices, like the average or compulsory schooling period or the Gross Enrolment Index at various levels of education (*e.g.* Eliasson *et al.*, 2021; Stamatakis, 2016). Other researchers constructed proprietary measures, often based on the World Bank HCI (Merło & Bogdański, 2018) for European NUTS 2 regions, Pasquini and Rosati (2020) for Italian provinces). Within the first approach, human capital is understood in a narrow sense, in terms of educational inputs and expected future benefits. The second approach follows a broad understanding of human capital as a wide range of components, such as demography, education, health and know-how (see *e.g.* Fraumeni, 2021, Lim *et al.*, 2018). This paper contributes to the literature by proposing a set of variables to construct a composite measure of broadly understood human capital, based on the Human Capital Index.

Conclusions

This study examined the human capital convergence of European NUTS 2 regions. Both absolute and conditional convergence was considered, the latter being conditional on sectoral structures of employees. Although there have been many studies examining convergence at the regional level, most of them have assessed income convergence. Convergence in other variables is still a relatively unexplored area.

The analysis of convergence was preceded by the analysis of human capital dynamics in the years 2005–2020. Apart from all the NUTS 2 regions, two subgroups were compared: the CEE regions and the Western European (WE) regions, comprising regions of the so-called “old EU” and regions of countries closely economically linked to them. The CEE regions were characterised by the greatest increase both in the human capital mean value and in its differentiation. In the WE regions, the initial mean human capital level was higher, but the increase was very slow. At the same time,

the CEE regions were characterised by a higher percentage of employment in agriculture and industry and a lower share of employment in services compared to the WE regions. For that reason, a question arises as to whether the sectoral structure of employees is a factor that differentiates the steady-states.

The estimation results of econometric models indicated that the European regions were converging in human capital, but the pace of the process was diversified. In the light of the analyses, the steady-states tended to be different and depended on percentages of employment in agriculture and services. A comparison of half-lives estimated applying absolute and conditional convergence models supported that conclusion. The time needed to reduce the occurring differences by half was almost twice as long assuming the same steady-state.

In the conditional convergence models, a negative effect of an increase in the percentage of agricultural workers was observed. Such a direction may reflect an outflow of highly skilled workers from regions with large agriculture shares to industrial or service-oriented ones. It may also be related to the effect of over-education. Highly skilled workers either do not accept wages below their qualifications and remain unemployed or accept them, pushing out of the market lower skilled workers who, thus, become unemployed. In many European regions, a very large share of the service sector is accounted for by services that provide advanced information and technology. For that reason, an increase in the share of service employees positively impacts on regional human capital levels.

The limitations of this study are related to several issues. Firstly, there is no widely accepted measure of human capital constructed for regions along the lines of the HCI or HDI. The measure presented in the article was chosen for its simplicity of construction. Alternative measures were also constructed using other methods (means of sub-indices, which are means of variables describing each of the three dimensions; TOPSIS method), but their use in the models did not change the essential estimation results. However, it is important to be aware that full comparability of the results of different studies can be ensured by using a unified measure of human capital. Secondly, the half-life estimated for CEE regions was, depending on the model specification, 6.5 or even 8 times greater than for all regions, suggesting the existence of significant differences within that group of regions. Those differences were not investigated in this study. Another issue is that NUTS 2 regions are large entities, with populations of 800,000 to 3

million people, which conceals substantial heterogeneity inside the regions. Moving the analysis to the NUTS 3 or NUTS 4 level would allow an insight into that heterogeneity. However, a barrier to overcome would be the much lower availability of statistical data on diagnostic variables.

The topics for further research are, to some extent, related to the limitations of this study. In the light of the exceptionally long half-life in the CEE regions, the club convergence hypothesis emerged. The range of variation in the human capital measure in 2020 was greater than in 2005, so there is likely a group of leaders (in particular regions of: Praha, Bratislava, Mazowieckie) and groups of particularly weak regions located mostly in Bulgaria and Romania, as well as intermediate groups. Further research is planned to verify the hypothesis. It would also be interesting to replicate the study for regions at lower levels of the NUTS classification. Those are much more homogeneous and more prone to spatial dependencies. They would be able to be incorporated into convergence studies through the use of spatial models. Finally, the internal heterogeneity of traditionally distinguished sectors, especially the service sector, is worth noting. Splitting that into smaller components in a convergence study, especially distinguishing the so-called knowledge sector, which includes technology industries, advanced manufacturing and business service centres, could also yield interesting results.

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Annex

Table 1. Basic characteristics of the *hc* measure

Year	all regions		WE regions		CEE regions	
	2005	2020	2005	2020	2005	2020
min	0.284	0.246	0.323	0.341	0.284	0.246
max	0.893	0.908	0.893	0.908	0.773	0.758
mean	0.546	0.564	0.563	0.578	0.471	0.524
CV (%)	20.71	20.859	18.48	19.11	21.68	23.41

Table 2. Coefficients of variation (*V*) of employment shares by sectors

year	all regions		WE regions		CEE regions	
	2005	2020	2005	2020	2005	2020
agriculture forestry and fishing (u_ag)						
min	0	0	0	0	0.54	0.26
max	51.08	44.91	33.98	24.89	51.08	44.91
mean	7.11	4.34	5.09	3.53	14.67	8.76
CV (%)	121.09	122.61	111.08	119.93	84.17	93.95
industry (u_in)						
min	6.61	6.30	6.61	6.30	18.69	17.33
max	46.98	47.74	42.52	37.29	46.98	47.74
mean	27.68	23.58	26.25	21.72	32.40	32.12
CV (%)	26.11	33.13	25.17	29.88	21.79	22.34
services (u_sv)						
min	23.96	33.02	42.99	54.54	23.96	33.02
max	93.4	94.56	93.41	94.02	78.39	83.24
mean	64.82	72.07	68.01	74.91	51.79	58.92
CV (%)	17.35	14.23	12.62	9.58	21.35	16.80

Table 3. Estimation results of the absolute convergence model (4)

The estimated parameter	Model I <i>all regions</i>	Model II <i>WE regions</i>	Model III <i>CEE regions</i>
$\theta_1 + 1$	0.705 (0.000)	0.484 (0.000)	0.923 (0.000)
const	0.142 (0.000)	0.213 (0.000)	0.058 (0.008)
γ	-0.098	-0.172	-0.026
β	0.116	0.242	0.027
$T_{1/2}$	5.960	2.863	25.820
<i>half-life (in years)</i>	17.88	8.59	77.46
Result of the Arellano – Bond test:			
m_1 (<i>p-value</i>)	-7.567 (0.000)	-6.652 (0.000)	-4.635 (0.000)
m_2 (<i>p-value</i>)	-0.857 (0.391)	-1.275 (0.202)	0.698 (0.485)
Result of the Sargan test			
chi-2(13)	12.295 (0.504)	18.207 (0.149)	14.119 (0.366)

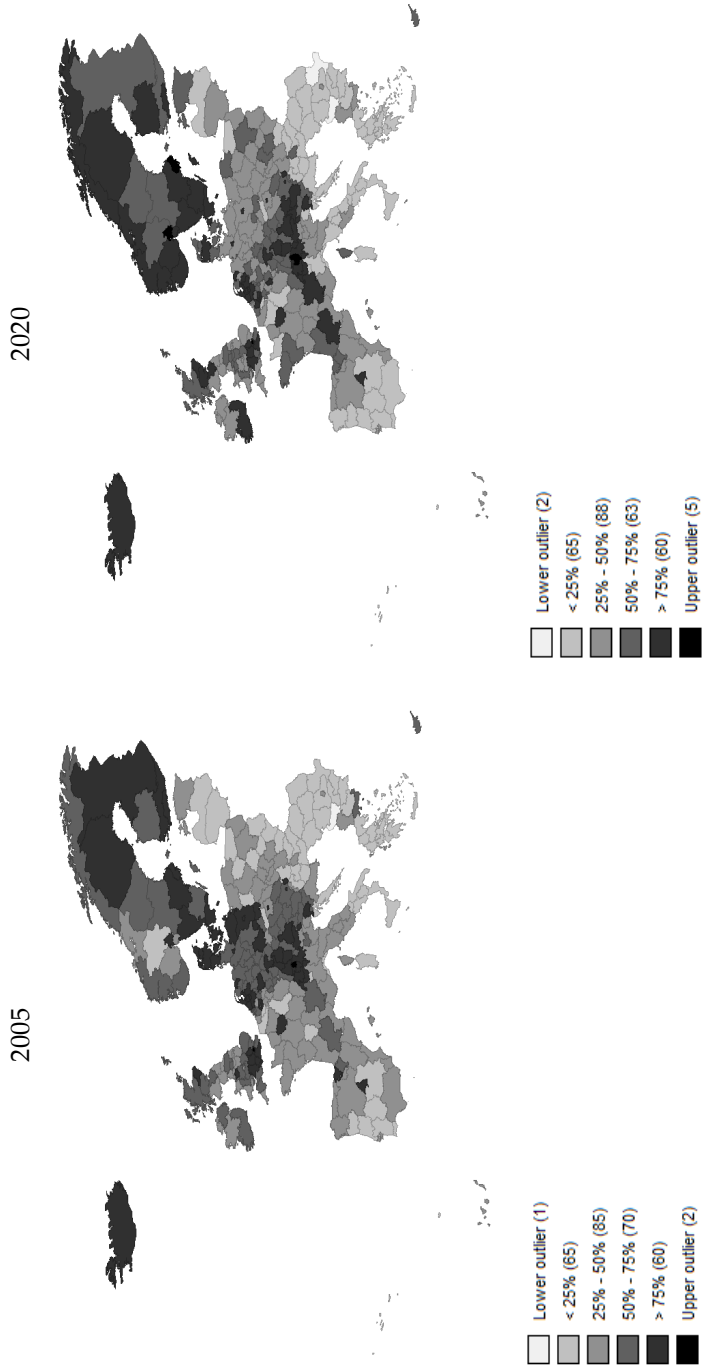
Note: Along with structural parameter estimates, *p-values* were indicated in brackets.

Table 4. Estimation results of the conditional convergence model (5)

The estimated parameter	Model IVa all regions	Model IVb all regions	Model Va WE regions	Model Vb WE regions	Model VIa CEE regions	Model VIb CEE regions
$\theta_1 + 1$	0.569 (0.000)	0.613 (0.000)	0.434 (0.000)	0.457 (0.000)	0.931 (0.000)	0.928 (0.000)
u_{lag}	-0.003 (0.000)	-	-0.003 (0.000)	-	-	-0.001 (0.047)
u_{sv}	-	0.001 (0.000)	-	0.004 (0.035)	-	0.001 (0.008)
u_{in}	-	-	-	-	0.001 (0.030)	-
const	0.198 (0.000)	0.073 (0.000)	0.216 (0.000)	0.104 (0.000)	-0.028 (0.029)	0.111 (0.000)
γ	-0.144	-0.129	-0.189	-0.181	-0.023	-0.024
β	0.188	0.163	0.278	0.261	0.024	0.025
$T_{1/2}$	3.691	4.245	2.491	2.654	29.175	27.880
<i>half-life (in years)</i>	11.072	12.734	7.472	7.963	87.524	83.640
Result of the Arellano – Bond test:						
m_1 (<i>p-value</i>)	-9.010 (0.000)	-10.283 (0.000)	-7.628 (0.000)	-8.894 (0.000)	-4.747 (0.000)	-4.867 (0.000)
m_2 (<i>p-value</i>)	-0.797 (0.426)	-0.759 (0.447)	-1.246 (0.213)	-1.204 (0.228)	0.639 (0.523)	0.572 (0.567)
Result of the Sargan test						
chi-2(27)	27.479 (0.438)	24.224 (0.618)	24.224 (0.618)	28.478 (0.387)	19.278 (0.859)	19.376 (0.856)

Note: Along with structural parameter estimates, *p-values* were indicated in brackets.

Figure 1. Spatial differentiation of the human capital measure (*h_{ic}*) in the years 2005 and 2020



Note: *Upper outlier* and *lower outlier* are observations which lie more than 1,5 times the interquartile range (the difference between the 75th percentile and the 25th percentile) above or below the value for the 75th percentile and 25th percentile respectively.