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WAGE LEVELS AND WAGE DYNAMICS IN OCCUPATIONAL GROUPS RELATED TO NATIONAL SMART SPECIALISATIONS

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Purpose: The aim of the article is to assess the level and dynamics of wages in occupational groups related to the areas of national smart specialisations, in comparison to occupational groups not associated with these areas.

Design/methodology/approach: A review of scientific literature and official documents concerning smart specialisations was conducted. Occupational groups related to national smart specialisation (NSS) areas were identified, along with factors potentially influencing the level and dynamics of wages in the NSS sector. Subsequently, a statistical analysis was carried out based on data provided by Statistics Poland.

Findings: The results indicate that the average wages in occupational groups related to the areas of NSS were statistically significantly higher than in other occupational groups during the analysed period (p-value = 0.01). This suggests that occupational groups associated with the areas of NSS, as identified in the 2020–2030 strategy, are characterised by a higher average gross wage level.

Research limitations: The limitations of the study include the frequency and manner in which data are aggregated and published by Statistics Poland, the restriction of the research sample to a single country, and the absence of appropriate methods allowing for the unequivocal assignment of occupational groups to sectors identified as innovative.

Practical implications: Employees should develop competencies aligned with smart specialisations, as NSS-related occupations offer higher earning potential. Employers in NSS industries should maintain competitive wages. The government-initiated policy of supporting smart specialisations should be continued.

Originality/value: The study presents an original methodology aggregating occupations both related and unrelated to NSS sectors. It examines he relatively underexplored relationship between wage levels and dynamics in these groups. This analysis contributes to a deeper understanding of the economic effects of NSS development and provides insights that may inform future governmental policies and strategic initiatives in this domain.

Keywords: innovation, smart specialisations, wages, wage dynamics, labour market.

Category of the paper: research paper.

1. Introduction

Smart specialisations and their impact on the economy—particularly in the areas of innovation, sustainable development, and economic growth—have increasingly attracted the attention of researchers, as evidenced by numerous publications on the subject (Knefel, 2014; Marrocu et al., 2023). At the same time, the period that has passed since the implementation and conclusion of the Europe 2020 strategy provides an opportunity to examine the long-term effects of smart specialisations on the economies of EU countries and regions.

The aim of this article is to assess the level and dynamics of wages in occupational groups related to areas identified as national smart specialisations (hereinafter referred to as NSS), in comparison with other occupational groups. The analysis was conducted at the level of so-called medium-level occupational groups, for which aggregated data on average wage levels are published by Statistics Poland.

The article begins with a review of the literature on smart specialisations, with particular emphasis on documents published by executive authorities in the EU and in Poland. This is followed by an analysis of the relationships described in the literature between the implementation of the Europe 2020 Strategy and the level and dynamics of wages across different occupational groups. Secondary data concerning wages and the characteristics of work performed by individuals classified into various occupational groups (according to the methodology of Statistics Poland) were collected and analysed. The final section of the article presents the research methodology, the results of the analyses, and their interpretation. Based on the findings, recommendations for stakeholders are formulated. The article also outlines research limitations and potential directions for further study.

2. Smart Specialisations

In 2010, the European Commission adopted the Europe 2020 Strategy, aimed at long-term, intelligent development of the economies of the European Union member states. As a result of the decision to implement this strategy, the countries belonging to the community were obliged to select and indicate their smart specialisations at the national and regional level (European Comission, 2010). The document indicated three priorities on the basis of which the EU countries were to develop smart and sustainable economic growth in the coming years, these were:

- smart growth – understood as development strongly based on knowledge and innovation,
- sustainable growth – referring to the transformation of the economy into a low-emission and resource-efficient model, thereby enhancing competitiveness,
- inclusive growth – focused on supporting an economy that strives for high levels of employment and ensures economic, social and territorial cohesion (European Comission, 2010).

The concept of smart specialisations was initially introduced as a regional development strategy. By definition, its aim is to concentrate resources on areas of the economy with the greatest innovation and competitive potential. Foray, David, and Hall (2011) define smart specialisations as a process of strategic concentration in which regions and countries seek to identify and effectively exploit their unique economic, scientific, and technological strengths (Szymański, 2019). This approach makes it possible to support areas with the highest potential for creating added value and generating economic growth, while avoiding potentially inefficient fragmentation of investments (Foray, David, Hall, 2011).

According to the assumptions of the Europe 2020 strategy, smart specialisations may be defined at both national and regional levels, and EU Member States are expected to identify and indicate them at both of these levels (European Commission, 2012). The procedure for selecting smart specialisations has been described in documents published by the European Commission, as well as in numerous academic publications. The European Commission outlines a six-step process that includes: analysing the region's innovation potential; establishing an appropriate governance process and ensuring management structures; developing a shared vision that reflects the needs of the local community; identifying strategic priorities; defining an action plan and developing a policy mix; and continuously monitoring and evaluating the strategy (European Commission, 2012).

In Poland, the selection of NSS took place between 2012 and 2014. According to a description of this process published by the Ministry of Development, it consisted of multiple stages and was based on the principle of entrepreneurial discovery. The initial phase involved sectoral analyses and forecasting aimed at identifying areas with the greatest innovation and competitiveness potential. This was followed by public consultations with stakeholders and local communities. An important role in the entire process was played by the so-called NSS working groups, which analysed research, development and innovation (RDI) priorities and provided recommendations for further action (Ministerstwo Rozwoju, 2017). Researchers emphasise that the process, in line with EU recommendations, included extensive public consultations involving a diverse range of stakeholders—such as entrepreneurs, public administration representatives, scientists, and non-governmental organisations—and made significant use of the entrepreneurial discovery function (Michalak, 2016).

The above information indicates that the process of identifying National Smart Specialisations (NSS) in Poland—consistent with the smart specialisation concept promoted by the European Union—was based on a comprehensive analysis of the economic, scientific, and innovation potential of the entire economy. Researchers highlight that in Poland, smart specialisation strategies were developed with the active involvement of the regions. At the same time, efforts were undertaken at the national level to harmonise regional strategies within the framework of common priorities defined in strategic documents (e.g. the Strategy for Responsible Development). As a result of the proper implementation of this process, a flexible and well-defined system of priorities was established, aimed at enabling more effective use of public funds and contributing to the increase of innovation in the Polish economy (Ministerstwo Rozwoju, 2020).

The initial list of National Smart Specialisations (NSS) included 19 specialisations, which became the basis for investments under the Smart Growth Operational Programme and other related programmes. The selection process also incorporated the need for continuous monitoring and evaluation, in order to ensure flexibility in adjusting priorities to changing economic and technological conditions. This system was based on the analysis of implemented projects and market research findings, which made it possible to regularly update and adapt the NSS to the needs of the national economy (Ministerstwo Rozwoju, 2020). As a result, the list of smart specialisations has been updated several times over the years. The currently binding list, dated 13 February 2023, includes 13 smart specialisations (Ministerstwo Rozwoju i Technologii, 2023).

3. Job complexity and wage

Scientific literature frequently highlights that as the complexity of a given job increases—along with the level of creativity and innovation it requires—employee wages should also rise. Aufiero et al., in their 2023 study, demonstrated that greater occupational complexity is positively correlated with a higher level of abstraction, lower task routineness, and higher remuneration. Smart specialisations primarily focus on specialised sectors that demand substantial knowledge and creativity, which implies that these occupations should be characterised by a higher wage dynamic compared to others (Aufiero et al., 2023).

McCann and Ortega-Argilés note that occupations associated with smart specialisations are characterised by a high level of technological advancement and innovation. The authors point out that these professions often require specific, highly specialised competencies, such as knowledge of emerging technologies, analytical skills, and the ability to work in interdisciplinary teams. These occupations are frequently marked by a low degree of routineness and a high level of flexibility in adapting to rapidly changing market and technological conditions (McCann, Ortega-Argilés, 2015).

The issue of how job complexity and innovation influence wages in the context of smart specialisations has also been addressed by Gębska. In her article on value creation and intellectual capital in the process of identifying smart specialisations, she emphasises that they focus on sectors with high innovation and economic potential. The success of enterprises associated with these specialisations largely depends on the quality of human and intellectual capital at their disposal. The author states that occupations related to smart specialisations are characterised by high requirements in terms of qualifications, knowledge, and innovativeness. Her analysis indicates that in certain industries and occupations linked to smart specialisations, wages grow at a faster rate than in others, which reflects the dynamic nature of activities undertaken in these sectors (Gębska, 2018).

In the context of the growing importance of smart specialisations and innovative sectors in Poland—as well as the research conducted by Gębska—it is worth noting that between 2014 and 2022, the share of innovative enterprises among all enterprises in Poland increased significantly. According to data from Statistics Poland, in 2022 the average share of innovative enterprises in the total number of enterprises was 32.2%, compared to 14.5% in 2014. The increasing innovation potential of Polish enterprises is also reflected in the rising value of innovation-related expenditures per economically active person. These expenditures grew from PLN 2,210 in 2014 to PLN 3,136 in 2022, alongside an increase in the number of employed persons from approximately 15.5 million to around 17.25 million[1]. However, it should be noted that innovation expenditures did not increase in relation to GDP. Over the past decade, they have fluctuated between 1.5% and 2.5% of GDP.

Higher wages in occupations related to areas identified as smart specialisations may therefore be driven by multiple factors. First, these professions are closely linked to high value-added sectors, where labour productivity exceeds the average. Second, the educational and skill requirements result in a limited supply of qualified workers, which naturally leads to higher remuneration. Finally, these occupations are often essential for the implementation of innovation strategies and the attraction of investment, making them important for the development of both regions and countries. This, in turn, increases their associated prestige and enables employees in such roles to negotiate their wages more effectively (McCann, Ortega-Argilés, 2015).

The literature referenced above, along with statistical data, suggests that smart specialisations should not only support economic growth and innovation at the national or regional level, but also stimulate the development of employee competencies in innovative sectors and positively influence wage levels—and thus wage dynamics. At the same time, there is still a lack of scientific studies focused on wages in sectors and occupations related to

[1] Statistics Poland data.

smart specialisations, particularly at the national level, that could empirically validate the hypotheses proposed by researchers.

4. Methods

In order to assess the level and dynamics of wages in occupational groups related to the areas defined within the framework of national smart specialisations, in comparison to other occupational groups, data on average gross wages in occupational groups in Poland for the years 2014-2022 were collected. The data, obtained from the resources of Statistics Poland, are published at two-year intervals and cover 115 occupational groups. The research sample is representative. The analysis was conducted at the level of so-called medium-level occupational groups[2], excluding those included in the first major group ("Legislators, senior officials and managers"). The decision to exclude occupations assigned to this group was based on three main reasons. First, in many enterprises, the wages of managers are influenced by factors different from those affecting the wages of other employees. It should be noted that the scope of responsibilities and the nature of work performed by individuals in managerial positions differ significantly from the characteristics of other occupations (Tyrańska, 2004). Second, managers generally receive higher wages than specialists, which could distort the comparative analysis if most of them were assigned to one of the two groups under study. Third, aggregated data on the wages of a large group of individuals employed in managerial positions do not allow for an unambiguous assignment of representatives of this group to either the occupational groups related or unrelated to the areas defined within national smart specialisations. Although assigning occupations to one of the two categories—related or unrelated to smart specialisations—is a challenging and potentially ambiguous task in the case of other occupational groups as well, it is particularly problematic for managers. In their case, such a classification appears risky and potentially highly impactful on the results.

Each occupational group was classified as either related or unrelated to the areas identified as national smart specialisations in the most recent strategy, published on 13 February 2023. To achieve this, a researcher-designed methodology was employed, consisting of several stages of the research procedure, namely:

1. Identification of areas related to the NSS.
2. Definition of the set of occupational groups to be included in the analysis.
3. Analysis of connections between occupational groups and NSS areas.

[2] Statistics Poland publishes wage data for so-called major, sub-major, and medium-level occupational groups. This means that the occupational groups used in the study are the most detailed (i.e., the narrowest) for which wage data are available in the Statistics Poland databases.

4. Classification of occupational groups into one of two categories – those related to NSS sectors and those unrelated or only weakly related.
5. Verification of the resulting classification.

In the first stage, based on the reviewed literature—particularly government documents and publications—areas related to NSS were identified. The analysis resulted in the identification of 13 such areas, which can be grouped into five major categories: (1) healthy society, (2) agri-food, forestry, wood, and environmental bioeconomy, (3) sustainable energy, (4) circular economy: water, fossil resources, and waste, and (5) innovative technologies and industrial processes.

Next, data were collected for all occupational groups for which Statistics Poland (SP) regularly publishes wage data. For this purpose, the publications Structure of Wages by Occupation, issued by SP, were used. In the subsequent stage, the potential relationship between occupational groups and NSS areas was analysed. If a given occupational group could be classified as related to at least one broadly defined NSS area, it was assigned to the group of occupations related to NSS sectors. Otherwise, the group was classified as unrelated or only weakly related to NSS areas.

After the initial classification of occupations into the respective categories, the assignments were verified to ensure their consistency with the previously established criteria. The final classification served as the basis for further analysis, including the comparison of wage levels between occupations related and unrelated to the sectors identified as NSS.

As a result of the adopted procedure, the following occupational groups were classified within the first identified category:

Table 1.
Occupational groups related to the areas identified as NSS sectors

Healthy society; Agri-food, forestry, wood and environmental bioeconomy; Sustainable energy; Circular economy: water, fossil resources and waste; Innovative technologies and industrial processes	medical doctors, nursing professionals, other health professionals, pharmacists, health professionals not elsewhere classified, life science professionals, physical and engineering science technicians, engineering professionals (excluding electrotechnology), electrotechnology engineers, software and applications developers and analysts, mining, manufacturing and construction supervisors, process control technicians, life science technicians and related associate professionals, ship and aircraft controllers and technicians, medical and pharmaceutical technicians, dietary and nutritional associate professionals, traditional and complementary medicine associate professionals, other health associate professionals, sports and fitness workers, information and communications technology operations and user support technicians, telecommunications and broadcasting technicians, personal care workers, market gardeners and crop growers, animal producers, mixed crop and animal producers, forestry and related workers

Source: own elaboration based on data from Statistics Poland.

Following the classification of the 115 occupational groups in the sample, 38 groups were identified as related to broadly defined NSS areas, while 77 were classified as unrelated or potentially only very weakly related to these areas.

The secondary data were published in an aggregated form, which means that information was available only on the average wages within entire occupational groups and their sizes, rather than on individual observations (i.e., individual employees in the economy). This necessitated the artificial calculation of variance and standard deviation for both major groups. For this purpose, formulas (1) and (2) were applied. Subsequently, the corresponding standard deviations were calculated.

$$\mu = \frac{\sum_{i=1}^{k} n_i \mu_i}{\sum_{i=1}^{k} n_i} \tag{1}$$

where:
$n_i - the\ size\ of\ the\ i - th\ sample$;
$\mu_i -$ the mean of the $i - th\ sample$;
$k - number\ of\ samples.$

$$\sigma^2 = \frac{\sum_{i=1}^{k} n_i \sigma_i^2 + \sum_{i=1}^{k} n_i (\mu_i - \mu)^2}{\sum_{i=1}^{k} n_i} \tag{2}$$

where $\sigma_i^2 - the\ variance\ of\ the\ i - th\ sample.$

The use of statistical tests makes it possible to verify hypotheses concerning the values of specific variables in the entire population based solely on a sample, while accounting for a certain probability of error. To compare the means of the two identified groups, a Z-test for the equality of two means was applied. This test allows for the verification of the hypothesis that, in the full population as well, the average wage in occupations related to NSS sectors would be higher.

The lack of access to raw data made it impossible to verify the assumption of normal distribution. However, the existing literature clearly indicates that wage distributions do not meet this condition. The application of the Z-test is justified by the use of the Central Limit Theorem (CLT). This theorem states that if X_i are independent and identically distributed random variables with the same expected value (mean) μ and a finite σ^2 greater than 0, then the random variable defined as:

$$\frac{\sum_{i=1}^{n} X_i - n\mu}{\sigma\sqrt{n}} \tag{3}$$

where $X_i - i - th\ observation$;
converges in distribution to the standard normal distribution as n approaches infinity.

This means that with a sufficiently large sample size, the assumption of normality in statistical testing can be considered satisfied, provided that the distribution has a finite expected value and variance[3]. Since the size of the collected sample significantly exceeds the threshold required for the application of the Central Limit Theorem, it was assumed that the sample means and variances could be subjected to the selected statistical tests. As a result, the Z-test for the equality of two means was considered applicable in this case (Magiera, 2002).

It should be noted that the applied research methodology has its limitations. The main limitation concerns access to statistical data, which in certain respects may be considered insufficient or incomplete. While the data obtained from Statistics Poland are of high quality, the information regarding the occupational group to which an employee belongs is not always a sufficient criterion for classifying that individual as working in a sector related or unrelated to NSS areas.

Moreover, the process of assigning occupations to the appropriate group is inherently difficult and, to some extent, arbitrary. In addition, data for certain occupational groups may have been collected by Statistics Poland from individuals employed in both enterprises operating in areas related to NSS sectors and those unrelated to them. This ambiguity introduces a risk of classification error, as it prevents a precise and objective determination of the extent to which a given occupation—and, consequently, the individuals surveyed by Statistics Poland—was related to the areas identified as part of NSS.

Another research limitation, directly related to data quality, concerns the manner in which the statistical office collects, processes, and publishes wage information. Data from Statistics Poland (SP) are published with a two-year delay and only once every two years. This prevents the real-time monitoring of trends as well as short-term analysis on a yearly or quarterly basis.

The available datasets include wage information only for major, sub-major, and medium-level occupational groups, while data for smaller occupational groups are not publicly available. This limits the level of detail in the analysis and makes it more difficult to gain insight into the characteristics of specific occupational categories.

In the context of the statistical methods used, it should be noted that conducting research based solely on a small portion of the population limits the ability to draw general conclusions from the obtained results. Even when a representative sample is collected—such as the one on which Statistics Poland bases its research—there is no guarantee that the results will fully align with those that would be obtained from a study conducted on the entire population. Moreover, when analysing wage levels and wage dynamics within specific occupational groups, macroeconomic, microeconomic, legal, and financial factors should also be taken into account—factors that were omitted in the present study. As such, the conducted analysis leaves room for further research by scholars from other disciplines.

[3] This does not mean that the distribution itself becomes normal as n increases. It only implies that the sampling distribution of the mean converges to normality, which allows for the application of appropriate statistical tests.

5. Results

Table 2 presents the average gross salaries in total in the analysed period and their dynamics. Over 8 years, the nominal increase in total salaries amounted to 70.40%. In real terms, the increase in wages was not so high and, according to Statistics Poland's estimates, amounted to 27.05%[4]. The recorded increases in nominal and real terms may reflect a continuous and systematic improvement of the economic situation in Poland.

Table 2.
Average gross wage (in PLN) and wage dynamics in Poland in the years 2014-2022

Year	Overall wage level	Overall wage dynamics
2014	4,107.72	-
2016	4,346.76	5.82%
2018	5,003.78	15.12%
2020	5,748.24	14.88%
2022	7,001.28	21.80%

Source: own elaboration based on data from Statistics Poland.

Based on the known average wages and variances for individual occupational groups, the average wages, variances, and standard deviations were calculated for the groups of occupations related and unrelated to NSS areas. Appropriate comparisons were then made in accordance with the principles of mathematical statistics.

Using the Z-test for the equality of means in two independent groups, the hypothesis was tested that the average wages of individuals employed in occupations related to smart specialisations are equal to the wages of individuals in other occupations. The results of the tests are presented in Table 3.

Table 3.
Results of one-sided statistical tests for the equality of means in two populations

Year	Statistics	Occupational groups related to the areas of the National Fiscal Information System	Other groups of professions
Year 2014	**Average**	4,489.05	3,556.93
	Standard deviation	2,776.19	2,168.31
	Sample size (in thousands)	1,464,50	5,070,80
	Critical Value (Z-Test)	374.65	
	p–value (Z-test)	0	
Year 2016	**Average**	4,737.56	3,786.06
	Standard deviation	2,840.37	2,274.77
	Average dynamics (until 2014)	5.54%	6.44%
	Sample size (in thousands)	1,601,30	5,492,70
	Critical Value (Z-Test)	389.09	
	p–value (Z-test)	0	

[4] Notices available at: https://stat.gov.pl/sygnalne/komunikaty-i-obwieszczenia/2024,rok.html.

Cont. table 3.

Year 2018	**Average**	5,609.89	4,359.62
	Standard deviation	3,357.30	2,525.75
	Average dynamics (until 2016)	18.41%	15.15%
	Sample size (in thousands)	1,627,10	5,622,50
	Critical Value (Z-Test)	440.33	
	p–value (Z-test)	0	
Year 2020	**Average**	6,150.94	5,024.05
	Standard deviation	3,479.53	2,790.05
	Average growth rate (until 2018)	9.64%	15.24%
	Sample size (in thousands)	1,700,50	5,753,00
	Critical Value (Z-Test)	387.14	
	p–value (Z-test)	0	
Year 2022	**Average**	7.660.36	6,047.97
	Standard deviation	4,555.30	3,503.24
	Average growth rate (until 2020)	24.54%	20.38%
	Sample size (in thousands)	1,814,70	5,965,50
	Critical Value (Z-Test)	438.96	
	p–value (Z-test)	0	

Source: own elaboration, performed in R-studio.

The obtained results make it possible, at the p-value level of 0.01, to reject the null hypothesis formulated at the outset—that there are no significant differences in the average wages of individuals in occupational groups related to national smart specialisation (NSS) areas and those in other occupational groups—and to accept the alternative hypothesis, which states that wages in occupations related to NSS areas are significantly higher than those in other occupational groups. This means that there is a very low probability of obtaining a different result if the entire population were examined. Therefore, it can be stated with high confidence that wages in occupational groups related to the NSS areas identified in the most recent strategy are higher than in the remaining occupational groups.

The wage dynamics for occupational groups related to NSS sectors and for other occupational groups were calculated and compared. The obtained results do not provide sufficient grounds to claim that wage dynamics consistently remain higher in the group of occupations related to NSS sectors. In two out of the four analysed periods, wage dynamics were higher in the group of occupations related to NSS sectors, while in the other two periods, they were higher in the group of other occupations. Moreover, the wage dynamics in occupations related to NSS sectors exceeded the overall wage dynamics in only two of the four analysed periods.

6. Discussion

The aim of the conducted study was to assess the level and dynamics of wages in occupational groups related to national smart specialisation (NSS) areas in comparison to occupational groups unrelated to those areas. To achieve this objective, one-sided statistical tests for the equality of means in two independent samples were performed.

The obtained results indicate that, during the analysed period, the average wages in occupational groups related to NSS areas were statistically significantly higher than in other occupational groups (p-value = 0.01). Based on the conducted analysis, it can be concluded that occupational groups related to the NSS areas identified in the 2020–2030 strategy are characterised by a higher average gross wage level.

The results obtained are consistent with the findings presented in the literature. Gębska (2015) and McCann and Ortega-Argilés (2015) emphasise that sectors related to smart specialisations are characterised by high innovation and technological potential, which should naturally translate into higher wage levels. Aufiero et al. (2023) confirm that a higher level of job complexity—measured, among other things, by low task routineness and a high degree of technological advancement—is positively correlated with average wage levels.

The higher wage levels and faster wage growth observed in occupational groups related to NSS areas are consistent with the theory of wage growth in high value-added sectors, as well as with the theory of higher wages in occupations characterised by greater complexity and a higher degree of technologisation (Gębska, 2018; McCann, Ortega-Argilés, 2015; Aufiero et al., 2023).

The findings on wage dynamics in both groups may indicate that the NSS areas were correctly identified, and that the higher wages in occupations related to these areas are due to the greater difficulty and complexity of the work performed. However, this does not necessarily translate into faster wage growth in these occupation groups.

In light of the considerations presented, it should be emphasised that the results should be interpreted within the appropriate context and with full consideration of the identified research limitations, which clearly indicate the need for caution when drawing conclusions. These limitations highlight the necessity of further research in this area—particularly through the use of more detailed datasets on wages in occupations and occupational groups, or through the improvement of methods for assigning occupations and occupational groups to areas related to NSS. The study conducted may also serve as a basis for reflection and the development of academic works aimed at a more in-depth analysis of wage levels and wage dynamics in occupations or occupational groups, taking into account the priorities set out in strategies supporting regional or national smart specialisations in Poland and other EU countries.

The study's findings allow for the formulation of recommendations for relevant stakeholders. Employees should invest in the continuous development of competencies necessary to secure employment in workplaces that prioritise smart specialisations, as occupational groups related to NSS offer the potential for significantly higher earnings compared to other occupational groups. Employers operating in industries associated with smart specialisations should ensure the competitiveness of their enterprises in terms of employee remuneration, as these workers are well compensated on the market and may reject job offers that do not meet their financial expectations. From a macroeconomic perspective, it should be noted that the government's efforts to select and support smart specialisations appear to be yielding the desired effects. It is therefore advisable to continue this policy, while simultaneously increasing the availability of education and training programmes aligned with labour market needs and focused on smart specialisations. Moreover, attention should also be directed toward regional smart specialisations in terms of wage levels and wage dynamics, in order to ensure their balanced and local development.

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