EMPIRICAL ESTIMATE OF DEMAND FOR LABOUR TASKS BASED ON DATA FROM ONLINE VACANCIES IN SLOVAKIA

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Abstract: *The paper empirically estimates labour demand in Slovakia based on data from the online labor market platform Profesia.sk. It focuses on identifying the main trends in the number of job postings, their regional distribution, and occupational breakdown according to the ISCO classification. Data were collected using web scraping and subsequently processed through regression analysis and text analysis using Word Cloud visualization. The paper also analyzes factors influencing labour demand, such as technological innovations, automation, and employers' work preferences. Special attention is given to the differences between office-based work and remote work, as well as the development of offered wages across different regions. The results show that the Bratislava region dominates in the number of job postings, while eastern Slovakia has a higher unemployment rate. Remote work is associated with higher demand for specific skills.*

Keywords: *labour demand, online job postings, ISCO classifications, regional disparities, wages, automation*

JEL Classification: J21, O33, R23

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1 Introduction

In today's economy, the only certainty is uncertainty. This statement aptly captures the volatility of the modern labour market - jobs that seem ordinary today may become obsolete tomorrow. Technological innovation, automation, and artificial intelligence are reshaping the nature of employment and shifting labour demand toward more specialized professions. Labour demand today is not merely a matter of quantity, but also of the quality and accessibility of available positions.

This paper analyses labour market dynamics in Slovakia using data from *Profesia.sk*, one of the country's largest online job platforms. While this platform offers valuable insights into job demand, it is important to acknowledge that it is not the only source of labour market information. Other channels, such as employers' career websites, public employment portals, and professional social networks like LinkedIn, also play a significant role. As a result, although *Profesia.sk* provides a rich dataset, it may not fully represent the entire labour market. A more comprehensive analysis would ideally include data from multiple platforms. Nevertheless, several important conclusions can be drawn from the available data.

One of the key findings is the uneven geographical distribution of job opportunities across Slovakia. The Bratislava region clearly dominates in terms of the number of job advertisements—a pattern consistent with its status as the country's economic centre, home to international corporations, start-ups, and financial institutions. In contrast, some eastern regions exhibit a notably low number of job postings, suggesting limited opportunities and lower average wages. An interesting exception is the Košice region, which, despite a lower volume of job advertisements, shows higher average offered salaries than the Bratislava region.

These regional disparities indicate that although Bratislava remains Slovakia's primary employment hub, labour market dynamics in other regions are gradually evolving. Košice is emerging as a competitive centre for highly skilled professions, characterized by relatively higher average salaries.

The increasing pace of automation and digitalization is fundamentally altering the structure of labour demand in Slovakia. The labour market is increasingly oriented toward white-collar, high-skill occupations requiring technological proficiency, while demand for some manual and administrative roles is declining. This trend underscores the need for workforce adaptation and the realignment of education systems toward digital and technical competencies to meet the evolving requirements of the labour market.

This paper also explores the phenomenon of remote work and its implications for regional labour disparities. The findings indicate that some professions, particularly in the IT sector, offer not only higher wages but also greater flexibility compared to traditional on-site roles. Furthermore, the analysis reveals distinct skill requirements depending on the working mode—highlighting specific competencies needed for remote work versus office-based environments.

In recent years, research on labour demand using online job postings has expanded significantly, with influential contributions by Fabo & Kureková (2022) and Acemoglu et al. (2022). These studies emphasize methodological challenges in using online labour market data, such as representativeness, seasonal fluctuations, and inconsistencies in advertised positions.

While Fabo & Kureková (2022) focus on methodological issues in a global context, this study offers a Slovakia-specific perspective. It uses detailed geographic data down to the district level, drawing on *Profesia.sk* and enhancing it with geolocation information from the Google Maps API. This approach enables more accurate identification of regional disparities.

Whereas Acemoglu et al. (2022) primarily examine the impact of artificial intelligence on the decline in demand for certain skills and employment across sectors, this paper integrates vacancy data with employment rates at the regional level in Slovakia. Instead of isolating technological effects, it investigates broader regional labour market dynamics through regression analysis of the relationship between the number of registered job seekers and the volume of advertised vacancies. This approach allows us to uncover potential mismatches between supply and demand for skills and identify signs of regional imbalance—offering a new perspective on labour market adaptability amid technological change.

The first section outlines the theoretical framework, including concepts of labour supply and demand, the role of online job platforms, and the use of textual data in economic analysis. The second section presents the research

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objective, data collection, and methodological framework, including web scraping, geographic classification, and statistical techniques. The third section discusses the analytical results: trends in labour demand, regional differences, wage developments, and findings from both regression and text analysis of job postings.

2 Literature review

2.1 Demand

2.1.1 Changes in the demand for job tasks due to technological advancement

In recent decades, the labour market has become increasingly polarized as a result of technological change, with job opportunities concentrating at two ends of the spectrum—low-paid manual and service work, and high-skilled, abstract occupations such as managers or professionals (Acemoglu & Autor, 2011). The rapid growth of technological innovation, especially in the field of artificial intelligence (AI), is accelerating the demand for specialized skills while reducing the need for traditional manual or routine jobs. For instance, between 2010 and 2019, demand for AI-related skills in the United States increased fourfold (Alekseeva et al., 2021).

Labour demand evolves with emerging market trends. In recent years, there has been increasing demand in healthcare and social care, particularly for entry-level roles, whereas demand for entry-level IT workers has remained relatively stable. In contrast, there is growing demand for specialists capable of developing and applying AI technologies, which are becoming embedded in sectors such as finance, professional services, and logistics (Bessen, 2018).

Service and sales roles that do not require specific technical knowledge now commonly require digital literacy and familiarity with office software. These positions have increased in developed countries such as those in Europe and North America, as well as Singapore (ILO, 2020). Employment polarization occurred in these regions between 1993 and 2006, reducing the number of middle-income jobs while increasing low- and high-wage employment (Acemoglu & Autor, 2011). A similar trend is evident in AI-related work, where increased demand for AI specialists often precedes the creation of mid-level positions (Alekseeva et al., 2021).

Manual tasks requiring physical interaction that cannot be easily automated have remained stable (Acemoglu & Autor, 2011). Nonetheless, AI and automation are transforming specific industries through a combination of creative, cognitive, and technical skills (Squicciarini & Nachtigall, 2021).

Technological progress significantly reshapes the labour market profile, creating new jobs that require higher qualification levels while simultaneously threatening medium-skilled roles, especially in routine sectors like manufacturing (ILO, 2020). Technologies such as robots, automated systems, and data management software can effectively replace human labour. These changes increase demand for skills involving technological fluency, abstract reasoning, and creativity (Acemoglu & Autor, 2011). While medium-skilled roles decline, employer expectations remain relatively stable, emphasizing not only technical expertise but also adaptability to technological shifts (ILO, 2020).

2.1.2 Employer demands

There is a persistent mismatch between employer demands and applicant preferences, largely caused by an educational system that fails to respond quickly or adequately to labour market needs. Companies increasingly seek skills in machine learning, natural language processing, and big data analytics—skills that are not yet sufficiently addressed in most educational programmes (Squicciarini & Nachtigall, 2021).

Recent years have seen growing discussion on aligning education with labour market requirements. Technological and economic shifts are causing some professions to disappear and new ones to emerge, requiring different qualifications. Although adaptation is necessary, the Slovak educational system has often failed to reflect real market needs (Institute of Employment, 2019). For example, in the 2017/2018 school year, the Slovak Centre for Scientific and Technical Information published a list of study fields with insufficient graduate numbers for the labour market (Institute of Employment, 2019). Despite clear evidence of labour shortages in certain fields, educational programs have not been updated accordingly. As a result, many graduates are unemployable in their field of study and are either unemployed or forced to

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work in unrelated sectors (Carneiro et al., 2023). Firms heavily using AI often offer higher wages even for non-technical roles in order to attract top talent. This trend pressures educational systems to incorporate interdisciplinary skills, including managerial and social competencies complementary to AI technologies (Bessen, 2018).In developed and emerging economies, job requirements remain relatively stable, although job titles and descriptions evolve with technological innovation. The mismatch between employer expectations and job seeker preferences is especially pronounced in digital labour. Employers increasingly use algorithmic monitoring systems to control performance, which reduces flexibility and increases job insecurity—clashing with workers' expectations for autonomy, social support, and stability. This tension results in worker frustration, reduced performance, and increased health issues.

Almost all jobs now require at least basic digital literacy, even in traditionally non-technical roles. Companies are investing heavily in technology and prioritise IT skills when hiring. However, the number of entry-level jobs for recent IT graduates is not growing as quickly as anticipated. Although the IT sector is considered high-growth and promising, the availability of junior roles does not reflect this potential (Carneiro et al., 2023).

2.2 Supply

The labour supply represents the quantity of labour services offered at a given time and wage. Workers provide their labour and skills, inseparable from their person, in exchange for pay. Labour supply is influenced by internal and external factors. Internal factors include motivation, physical and intellectual capacity, and preferences between work and leisure. External factors such as labour market trends, economic conditions, or tax policies significantly influence labour supply decisions (Bylkov, 2017). Changes in tax and social policy—such as the Earned Income Tax Credit (EITC) in the U.S. or the Family Credit in the U.K.—can motivate or dissuade labour market participation. These measures aim to increase work incentives but also highlight the risk of high marginal tax rates, which can discourage work when higher wages result in significant deductions (Blundell & Macurdy, 1999). Workers balance income and leisure. A wage increase can trigger an income effect (working less for the same income) or a substitution effect (working more due to higher hourly pay). Long-term labour supply models must also consider human capital accumulation and learning-by-doing, which influence behaviour over time (Blundell & Macurdy, 1999).

The decision to enter the labour market begins with the recognition of a need, often triggered by external factors such as economic conditions or personal finances. Motivation follows, where individuals weigh the benefits of work versus leisure. Labour supply is highly individual, shaped by preferences, qualifications, and priorities (Bylkov, 2017). Factors like future income expectations and family obligations also play a role in labour decisions (Blundell & Macurdy, 1999).

2.3 Online Labour Market Platforms

With the rapid expansion of internet access and the rise of online job platforms, the internet has become a central channel for connecting employers and job seekers. Platforms such as LinkedIn, Indeed, and Profesia.sk act as intermediaries. Globally, platforms like LightCast aggregate job listings from thousands of sources and analyse employment trends, providing a representative snapshot of labour demand (Fabo & Kureková, 2022).

The use of big data from online platforms enables detailed analysis of skill dynamics in both developed and developing countries. For example, in Uruguay, data from BuscoJobs helped compare employer demands with the cognitive, socio-emotional, and manual skills offered by job seekers (Bennett et al., 2022). Online data are useful for both microeconomic studies (skill demand shifts) and macroeconomic research (unemployment trends and skills shortages). These data are detailed, real-time, and complementary to traditional labour surveys. Their granularity allows analysis even below the national level. In Europe, Cedefop an institution under Eurostat provides valuable data on employment and skills trends (Fabo & Kureková, 2022).

2.4 Digitalization and Its Labour Market Impact

Online data are critical for understanding labour market functions. In some European countries, such as Estonia, Finland, and Sweden, nearly 100% of jobs are advertised online. In Denmark, this figure is about 50%. These patterns show that recruitment in developed economies is increasingly digital, improving access to real-time labour market insights. An analysis of two

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million U.S. job ads revealed that digitalization simplifies skills demand analysis and enables monitoring of geographical and sectoral trends (Beblavý et al., 2016).

However, online job data may not be fully representative. Online job ads tend to overrepresent sectors like IT and finance while underrepresenting areas like public administration or manual labour. This skews analytical accuracy. A U.S. study comparing online and official data (via Burning Glass) found overrepresentation in healthcare and finance and underrepresentation in hospitality, public administration, and manufacturing. Similar findings were observed in Europe, where the low presence of manual jobs online limits macroeconomic analysis accuracy (Acemoglu et al., 2022).

2.5 Text as a Data Source

2.5.1 Use of text data in economic research

Economic research increasingly uses text data as an alternative or supplement to traditional numerical data. Sources such as financial reports, political speeches, online platforms, or social media offer a unique opportunity to examine, analyse, and build various structured databases that can be applied in specific statistical methods. One of the main reasons for this growing trend is the availability of modern technological tools that allow for the transformation of large text corpora into structured data suitable for analysis (Gentzkow et al., 2019).

In finance, texts from financial reports and social media are used to predict asset price movements, with tools like sentiment analysis identifying and classifying text as positive or negative, enabling the prediction of market responses to new information (Gentzkow et al., 2017). Text data helps identify subtle relationships between expressions and the actual behaviour of economic actors (Jurafsky & Martin, 2024). In macroeconomics, text data is increasingly used to predict inflation and unemployment, for example, by analysing political debates and media commentary (Gentzkow et al., 2019). Political economy similarly analyses speeches and party programs to map changes in political agendas. For instance, analysing politicians' speeches can reveal how their preferences evolve over time (Gentzkow et al., 2017). These methods include regression models that use words and phrases to predict economic variables, or topic models that identify latent structures in documents.

To enable text analysis through statistical methods, it is necessary to transform text into numerical data, select the most informative words, and remove irrelevant elements (Gentzkow et al., 2017). This process includes selecting relevant elements from the text, removing redundant information such as frequent words or numbers, and constructing representations like term frequency vectors or document feature matrices (Gentzkow et al., 2019).

2.5.2 Converting text to structured data

To analyse text, it must be transformed into a numerical form. Text analysis includes three main steps. The first step is representing raw text as a numerical matrix using the "bag-of-words" model, which ignores word order and focuses on their occurrence in documents. Each document is represented as a vector where each element corresponds to the frequency of a particular word or phrase in the document (Gentzkow et al., 2017).

The next step involves using stemming and lemmatization techniques to reduce words to their base forms, thus decreasing the number of unique terms in the corpus. For example, the words "economy," "economic," and "economics" are unified as "economy". This normalization is used for further statistical or causal analysis (Gentzkow et al., 2019).

The following step is the prediction of unknown variables. To handle high-dimensional text data, the TF-IDF method (term frequency-inverse document frequency) is used. TF-IDF reduces the weight of common words and emphasizes those that are unique to specific documents (Gentzkow et al., 2019).

For effective analysis, a normalized version of TF-IDF is often applied to help identify the most important terms in a document based on their frequency and distribution across a text corpus (Gentzkow et al., 2019).

Statistical methods applied to text data include penalized regressions, such as LASSO, which are useful for selecting relevant features in texts. These models minimize the risk of overfitting when dealing with high-dimensional data (Gentzkow et al., 2017). The LDA method (Latent Dirichlet Allocation) identifies latent structures in texts. The model assumes that each document is a mixture of topics, and each topic is a mixture of words (Grimmer et al., 2022). Machine learning enables the classification of documents by topic, sentiment, or other features. For example, sentiment classification analyses the emotional tone of text and can identify relationships between textual properties and economic variables (Grimmer et al., 2022).

2.5.3 Validation of results

Validation is an essential part of text analysis that ensures the reliability of models. Cross-validation, which divides data into training and testing sets, helps detect potential overfitting. The use of gold standard data manually annotated data serving as a reference point allows for accurate model evaluation. Expert review involves domain experts assessing the results to verify their accuracy and contextual validity (Gentzkow et al., 2019). Precision and recall methods evaluate model performance in terms of correctly and completely identifying relevant elements (Jurafsky & Martin, 2024).

3 Methodology

The study focuses on labour market demand in Slovakia, with particular emphasis on regional disparities. The main research interest lies in the extent of these disparities and the influence of seasonal factors on labour supply. The analysis is based on quantitative research using extensive data extracted from the Profesia.sk online labour market platform.

3.1 Data Collection and Processing

3.1.1 Data source and collection method

The data were collected from Profesia.sk using web scraping a method for automatically extracting information from websites. This technique allowed efficient retrieval of current job postings and related data without manual browsing. Data were collected monthly, specifically on the 19th of each month. The scraping process involved loading the website, parsing its HTML structure, and extracting key information, which was then saved in CSV format. The variables extracted are summarized in Table 1.

Table 1: Overview of Extracted Variables

Variable name:	**Descritption**
Job title	Indicates the position offered and reflects the nature of the vacancy.
Employer	Identifies the company or organization offering the job.
Address	Enables geographic localization of the job.
Salary	Provides wage information for regional wage comparison.

Source: www.profesia.sk, own processing.

3.1.2 Dataset refinement and enrichment

For more detailed analysis, the dataset was enriched with additional variables due to inconsistencies in the raw Profesia.sk data. To obtain precise location data, the Google Maps API key was used to automatically append geographic coordinates and determine the exact location of each job listing at the city and regional level. We complemented these with administrative classifications from the Slovak Statistical Office, including streets, municipalities, districts, and regional divisions. Each locality was assigned to one of four main regions in Slovakia: Bratislava Region, Western Slovakia, Central Slovakia, and Eastern Slovakia.

This systematic approach enabled accurate analysis of the spatial distribution of job offers and identification of regional labour market differences.

Wage data were cleaned by removing symbols (€, EUR, EUR/month) to ensure suitability for quantitative analysis. Listings with salary ranges (e.g., "1200–1600 EUR") were split into two variables minimum and maximum wage for better variability assessment. Hourly wages were also isolated to avoid distorting results.

3.1.3 Classification of job positions

Job postings were categorized using ISCO-08 (International Standard Classification of Occupations), a global standard that ensures consistency and comparability across countries and sectors (Fabo & Kureková, 2022). Classification was performed using job title text and optimized with fuzzy matching to identify the closest ISCO category.

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To validate the classification, four experiments were conducted using different variable combinations to assign ISCO codes. Table 2 presents the variables used and the accuracy of each method based on a random sample of 100 job postings.

Table 2: ISCO Classification Experiment Results

	Variable 1	Variable 2	Accuracy of experiment
Exp. 1	Job title	X	80%
Exp. 2	Job title	Job description	48%
Exp. 3	Job description	X	21%
Exp. 4	Job description	English translation	57%

Source: www.profesia.sk, own processing.

Based on these results, experiment 1 showed the highest accuracy and was therefore chosen for the final classification of job postings.

We also linked ISCO codes to the ESCO classification (European Skills, Competences, Qualifications and Occupations), which assigns each job specific skills and qualifications. This enabled deeper analysis of job requirements.

The linkage was achieved using official ESCO mapping tables, allowing the assignment of relevant competencies to each position and enabling us to analyse qualification demand across sectors and regions.

3.2 Statistical Analysis of Regional Labour Market Disparities

3.2.1 Job availability

This section focuses on calculating the ratio of available job seekers (ages 15–64) to open job postings—a key indicator for assessing the supply-demand balance in each Slovak region. This metric reveals the extent to which job opportunities can absorb the number of active job seekers in each area.

We used the number of job-ready registered seekers aged 15–64 and compared it to the number of available jobs to assess competition for employment in each region:

$$\textit{Job seeker to vacancy ratio} = \frac{\text{Available job seekers aged } (15-64)}{\textit{Number of job postings}} \tag{1}$$

These calculations were conducted for each region and each month, providing insight into regional trends and seasonal variations in labour demand.

3.2.1 Regression model

We used linear regression to quantify the relationship between variables. Parameters were estimated using the Ordinary Least Squares (OLS) method, which minimizes the sum of squared errors and ensures unbiased and efficient estimates (Downward, 2017). The dependent variable Y is the number of job postings, and the independent variable X is the number of available job seekers aged 15–64. A separate linear model was created for each region (Downward, 2017):

$$\mathrm{Y_i} = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{2}$$

Equation (2) includes the following components, which are explained in Table 3:

Table 3: Components of Regression Model

Componenet	Explanation
Y_i	Number of job postings in region i
X_i	Number of available job seekers aged 15–64 in region i
β_0	Intercept
β_1	Regression coefficient (change in job postings per unit change in X)
ε_i	Error term

Source: own processing.

We estimated β_0 and β_1 using OLS and evaluated the model's ability to explain job demand variability. Results and interpretations are presented in section 6.2 using this methodology.

Downward (2017) provides a standard regression model framework, its limitations, and interpretation methods. Huang & Aldeeb (2023) discuss regression analysis applications to economic indicators and emphasize the

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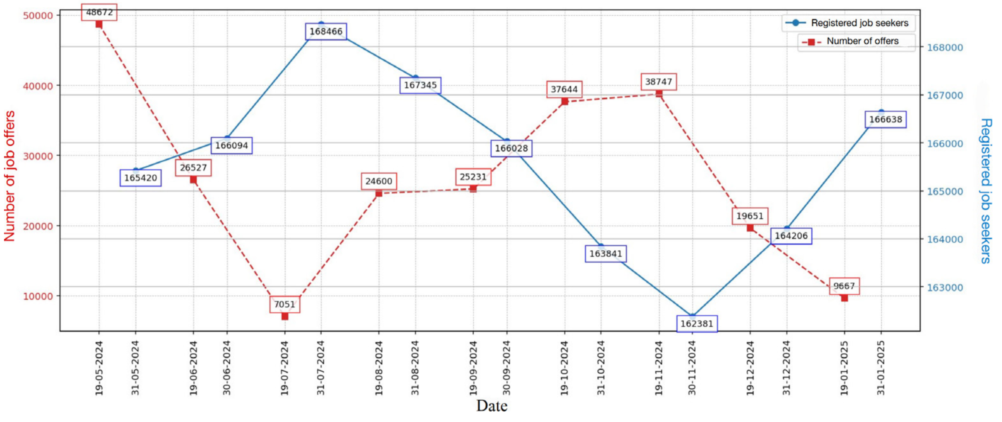
importance of assumption testing.

4 Results

4.1 Statistical Analysis of Regional Labour Market Disparities

This chapter focuses on the analysis of the number of job postings over time and the identification of labour demand trends in Slovakia. The volume of job postings reflects labour market dynamics and its response to economic changes. Variability in job postings is driven by seasonal fluctuations, economic conditions, and specific factors such as legislative changes or crises (Blundell & Macurdy, 1999). For instance, during an economic recession, the number of job postings tends to drop due to decreased demand for labour, while in times of economic growth, employers increase the number of advertised positions (Institute for Employment, 2019).

Figure 1: Registered job seekers and job postings over time



Source: www.profesia.sk, ÚPSVAR, own processing.

Figure 1 shows the development of the number of job postings and registered job seekers (RJS) over time. According to the methodology described in section 3.1.1, data on job postings were collected monthly via data scraping from the online labour market platform Profesia.sk. Data on the number of registered job seekers were taken from monthly statistics published by the Central Office of Labour, Social Affairs and Family (UPSVaR) at the end of each month.

A comparative analysis across months revealed an increase in the number of job postings in the second and fourth quarters of 2024. The x-axis indicates time periods, the left y-axis shows the number of job postings, and the right y-axis presents the number of registered job seekers.

The figure clearly reveals significant volatility in job supply and registered unemployment, highlighting several key trends. At the beginning of the monitored period, the number of job postings was relatively high (48,672), but a sharp decline followed, reaching a low of 7,051, which may suggest seasonal variation or economic conditions affecting the labour market. Another sharp decline is observed toward the end of the period, where the number of postings again drops below 10,000. The chart supports the assumption of seasonal fluctuations, with peak job postings occurring during periods of economic growth or heightened employer activity.

Simultaneously, we tracked the number of registered job seekers. Overall, the trend indicates that when job postings decrease, the number of job seekers increases and vice versa. For example, during a job posting drop in July 2024, the number of job seekers rose to 168,446. Conversely, when job postings peaked in November 2024, the number of job seekers dropped to 162,381.

The comparison of job postings and registered job seekers suggests that periods with more job postings generally correspond to lower unemployment, and vice versa. For instance, a surge in job postings in some periods may result from seasonal factors temporarily reducing registered unemployment. Conversely, a decline in job postings toward the end of the period is often accompanied by a rise in unemployment due to the termination of seasonal jobs.

Figure 1 confirms a strong correlation between labour demand and the number of job seekers, emphasizing the role of seasonal effects in labour market dynamics. Such analyses are essential for understanding unemployment trends and formulating employment support measures throughout the year.

4.2 Dynamics of Equilibrium between Job Seekers and Job Vacancies

Based on data from the Central Office of Labour, Social Affairs and Family on the number of available job seekers of working age and the number of job vacancies from Profesia.sk, we analyse the ratio between these two variables.

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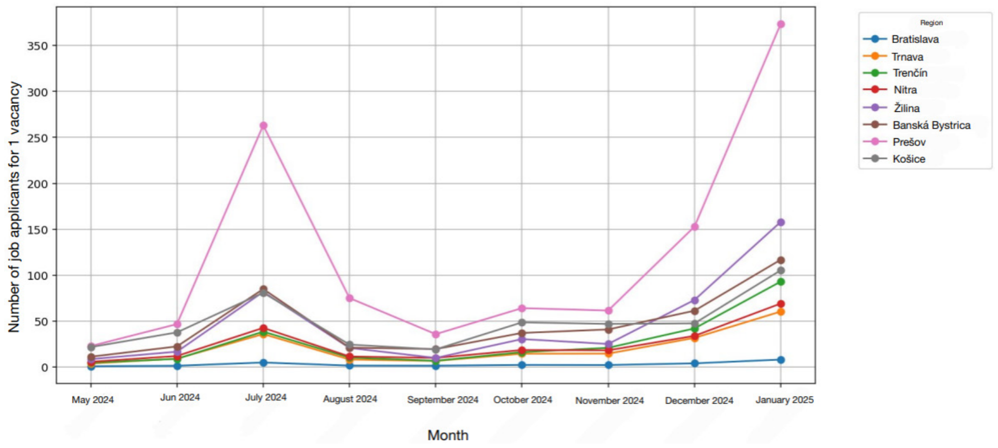
This indicator enables us to identify regions with overheated or underutilized labour markets. Section 3.2.1 of the methodology describes how the data on the ratio of job seekers to job vacancies were obtained using formula (1).

Figure 2: Ratio of Available Job Seekers to Job Vacancies by Region over Time



Source: www.profesia.sk, ÚPSVAR, own processing.

Figure 2 illustrates the development of the ratio of job seekers per job vacancy across Slovak regions over time. The x-axis represents individual months, and the y-axis shows the number of job seekers per vacancy. Each line represents a separate region.

The main observation is that all regions follow similar upward and downward trends but with varying intensity. Common seasonal fluctuations are evident throughout the year, with the most significant increases in the number of job seekers per vacancy observed during the summer months (June – July) and winter months (December – January).

Regional differences lie in the intensity of these fluctuations. The Prešov region experiences the most pronounced swings, with the number of job seekers per vacancy rising sharply in July and January to levels exceeding 200–300. This indicates the highest labour market imbalance in terms of supply and demand. The Žilina, Banská Bystrica, and Košice regions show milder fluctuations but still display noticeable increases in the winter months.

The Trnava, Trenčín, Nitra, and Bratislava regions exhibit the most stable trends with relatively minor fluctuations. The Bratislava region consistently reports the lowest number of job seekers per vacancy, indicating the most favourable employment conditions and higher labour demand.

Seasonal effects significantly influence unemployment trends and highlight the need for employers to adapt their strategies during these periods. This analysis indicates that regional labour market disparities persist and require targeted employment support measures in regions with high job seeker-to-vacancy ratios.

4.3 Analysis of Regression Indicators in Slovak Regions

Regression analysis provides key insights into the relationship between the analysed variables. The dependent variable Y is the number of job vacancies, and the independent variable X represents the number of available job seekers of working age. Section 3.2.2 of the methodology explains the construction of the regression model. In this section, we focus on the regression indicator values for each Slovak region, specifically Multiple R, R Square, Adjusted R Square, Significance F, the regression coefficient X (Variable 1), P-value, and the 95% confidence interval. The results are presented in Table 4.

The aim of this analysis is to evaluate how well the model explains the variability of the observed data and the reliability of the estimated regression parameters.

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Table 4: Regression Indicators by Region

Region	Indicators						
	Multiple R	R Square	Adjusted R Square	Signif. F	Coefficient X (Variable 1)	P-value	Conf. interval (95%)
Bratislava	0,854	0,739	0,605	0,00024	0,5366	0,00165	(0,2703; 0,8036)
Trnava	0,792	0,627	0,502	0,00799	0,1014	0,00634	(0,0376; 0,1652)
Trenčín	0,792	0,627	0,502	0,00803	0,0893	0,00637	(0,0331; 0,1454)
Nitra	0,822	0,676	0,551	0,00464	0,0782	0,00349	(0,0341; 0,1223)
Žilina	0,789	0,623	0,498	0,00835	0,0534	0,00664	(0,0195; 0,0873)
Banská Bystrica	0,818	0,668	0,543	0,00509	0,0455	0,00386	(0,0194; 0,0716)
Prešov	0,804	0,646	0,521	0,00652	0,0212	0,00507	(0,0084; 0,0339)
Košice	0,891	0,794	0,669	0,00086	0,0354	0,00054	(0,0207; 0,0501)

Source: www.profesia.sk, ÚPSVAR, own processing.

The Multiple R indicator represents the correlation coefficient between the independent and dependent variables. Values close to 1 indicate a strong linear relationship (Huang & Aldeeb, 2023). The highest values are observed in the Bratislava (0.854) and Košice (0.891) regions, suggesting a strong correlation.

The coefficient of determination (R Square) indicates the proportion of the dependent variable's variability explained by the model. High values in Bratislava and Košice suggest a good fit, with Košice explaining 79.4% of the variability. Lower values, such as 0.623 in Žilina, suggest other factors may influence demand more heavily.

The Significance F indicator tests whether the model is statistically significant. All regions have values below 0.01, confirming the significance of each model. The lowest value in Bratislava indicates the highest reliability.

The regression coefficient X (Variable 1) shows the expected change in the number of job vacancies per one-unit change in the number of available job seekers. Bratislava has the highest coefficient (0.5366), indicating a stronger influence of available labour supply. Prešov has the lowest (0.0212).

The P-value tests the statistical significance of the regression coefficient (Huang & Aldeeb, 2023). Values below 0.05 confirm its reliability, with all regions reporting values below 0.01.

The 95% confidence interval indicates the range in which the true coefficient value likely lies. Bratislava's wider interval suggests greater variability, while Prešov's narrow interval indicates greater precision.

Based on the results in Table 4, the regression analysis confirms a strong relationship between available job seekers and job vacancies. Regional differences suggest that local factors influence the strength of this relationship.

4.4 Geographical Distribution of Job Postings

During the observed period, a total of 237,790 job postings were recorded, of which only 118,176 could be assigned to specific territorial units. This geographic assignment enabled a more detailed analysis of regional differences in the availability of job opportunities across Slovakia.

However, it is important to note that not all job postings could be linked to a specific region. Reasons include incomplete data, missing location information, or inaccurate geographic identifiers in the source. Additionally, some positions were advertised for jobs abroad and do not belong to any Slovak region, while others offered remote or home office work, making geographic categorization ambiguous. These factors can distort regional statistics and must be considered when interpreting the data. A more detailed methodology is described in section 3.1.2, where the use of the Google Maps API for adding geographic coordinates and accurately assigning jobs to regions is explained.

To better visualize regional disparities, we decided to display the Bratislava region separately due to its significantly higher number of job postings.

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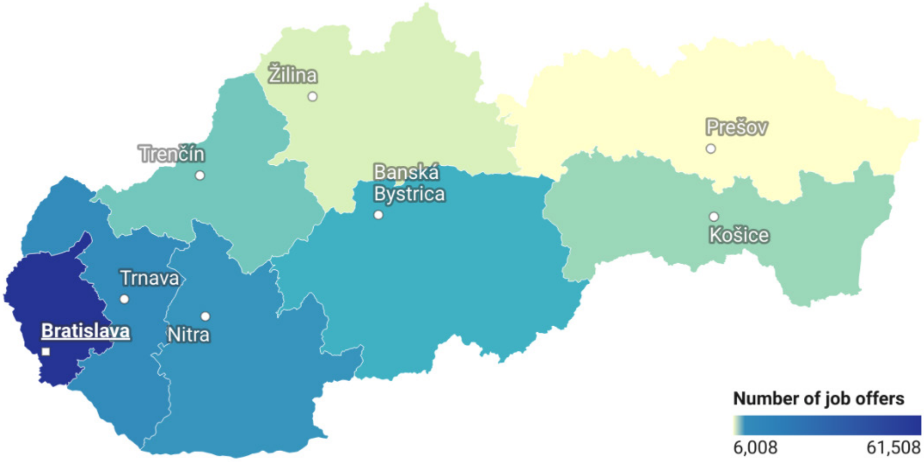
Figure 3: Regional Distribution of Job Postings in Slovakia



Source: www.profesia.sk, own processing.

As shown in Figure 3, the Bratislava region recorded 61,508 job postings, significantly more than other regions. This can be attributed to the higher concentration of companies, tech centres, and administrative positions in the capital city.

The second-highest number of job postings was found in the Banská Bystrica region (8,875), followed by the Trnava region (9,230) and the Nitra region (9,040). These regions demonstrate stable job availability, primarily in industry, manufacturing, and logistics.

Conversely, the lowest number of job postings was recorded in the Prešov region (6,008), indicating economic disparities between western and eastern Slovakia. Similarly, the Žilina (6,947) and Košice (8,066) regions fall on the lower end of job availability.

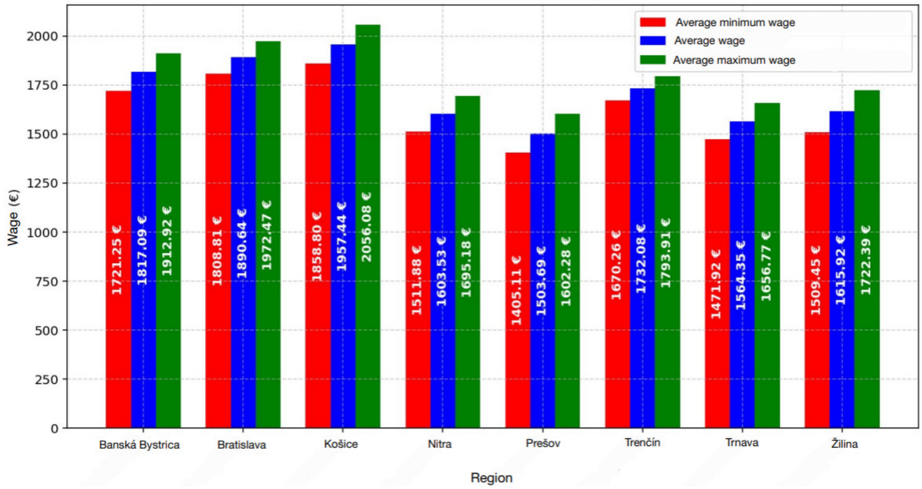
These disparities reflect the regional economic structures of Slovakia and highlight the need for more balanced development of job opportunities in less developed areas. The collected data can support better planning for employment and regional development, promoting more even distribution of job opportunities across the country.

4.5 Wage Structure of Job Postings

To perform this analysis, the salary variable was cleaned by removing symbols such as €, EUR, and EUR/month to retain only numerical wage values. Section 3.1.2 describes how the data were formatted for subsequent analysis.

Based on the cleaned and adjusted data, we created a visualization comparing the offered average wages across Slovak regions according to job postings.

Figure 4: Average Wage by Region



Source: www.profesia.sk, own processing.

Figure 4 displays three key indicators – minimum, average, and maximum wages in each region. The bar chart provides an overview of regional differences in offered wages and enables the identification of regions with the highest and lowest values. It is important to note that this figure does not represent actual employee salaries in each region but reflects the wage levels specified by employers in job advertisements.

Košice and Bratislava regions show the highest average wages, while the Prešov and Trnava regions fall on the opposite end. This disparity points to economic differences across regions, influenced by factors such as job availability, economic activity, and industrial specialization.

Interestingly, the highest average offered wages are not limited to western

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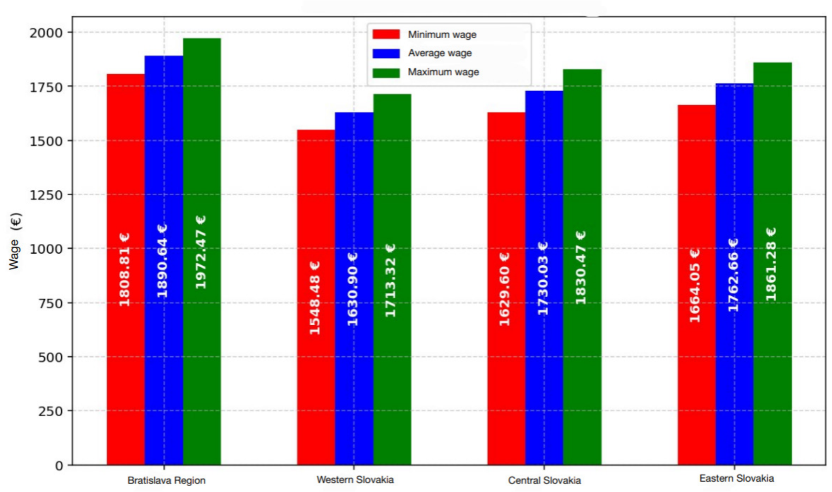
Slovakia (Bratislava) but also appear in the east, particularly in Košice. Conversely, the lowest average offered wages are seen in both the west (Trnava) and east (Prešov). This distribution suggests that wage disparities are not strictly divided between west and east but are shaped by local economic conditions and sectoral focus.

To take a broader view, we visualized average wages at the regional level.

Figure 5: Average Wage by Broader Regions



Source: www.profesia.sk, own processing.

Figure 5 shows that the highest offered wages are in the Bratislava region, where the maximum wage approaches €2,000 and the average wage reaches €1,890.64. Conversely, the lowest wages are found in western Slovakia, where the average minimum wage drops below €1,550. It is noteworthy that the difference between minimum and maximum offered wages is relatively wide in central and eastern Slovakia, indicating variation between sectors and job roles.

Figure 5 provides a comprehensive view of regional differences in offered wages, highlighting that wage levels are not evenly distributed across Slovakia. The inclusion of both minimum and maximum values helps to better understand the wage range within each region.

In some regions, a narrow range between minimum and maximum offered wages suggests uniform compensation structures, while others show greater variability, pointing to sectoral wage disparities. This analysis provides valuable insights for shaping regional employment and wage policies and supports both job seekers and employers in understanding wage dynamics across Slovakia.

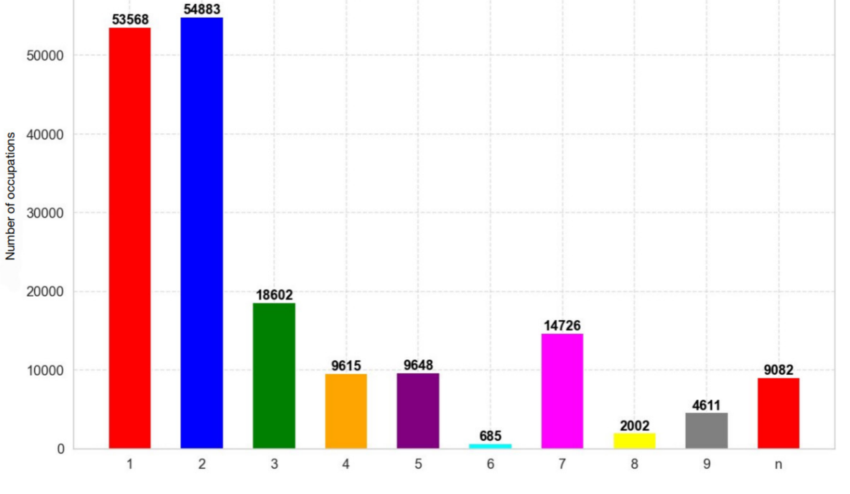
4.6 Job Position Structure According to ISCO Classification

Another important part of the data processing was the integration of the ISCO-08 classification, which is the international standard for classifying job positions.

In our analysis, we incorporated the ISCO-08 classification into the dataset, categorizing each job position into major groups based on job descriptions and responsibilities. This classification enabled a detailed examination of job distribution within specific occupational groups and the identification of trends across professional sectors. Section 3.1.3 explains how individual ISCO codes were assigned to positions extracted from the Profesia.sk online job platform.

Based on this data, we performed statistical analyses to identify and quantify regional differences in the labour market and seasonal fluctuations in labour demand. The research analysed the distribution of job positions according to ISCO-08 classification throughout the observed period.

Figure 6: Occupational Distribution According to ISCO



Source: www.profesia.sk, own processing.

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Figure 6 shows the number of job positions in each major ISCO category, clearly highlighting differences in their representation:

ISCO 1 – Legislators, senior officials, and managers. These roles involve strategic decision-making, organizational leadership, and policy implementation, requiring high-level education and managerial experience. This is the second most numerous category on Profesia.sk, with 53,568 job postings.

ISCO 2 – Professionals. The most represented category with 54,883 positions, indicating growing demand for highly qualified specialists such as doctors, lawyers, IT professionals, engineers, and academics (ILO, 2023).

ISCO 3 – Technicians and associate professionals. Includes mid-level professionals assisting specialists, requiring secondary or vocational education. Example roles include nurses, lab technicians, IT technicians, and inspectors. This is the third largest category with 18,602 postings.

ISCO 4 – Clerical support workers. Encompasses administrative and office roles like secretaries, receptionists, and customer support. This group totals 9,615 postings.

ISCO 5 – Service and sales workers. Includes salespeople, waiters, chefs, hotel staff, and personal service workers, often requiring communication skills and customer interaction. This group has 9,648 job postings.

ISCO 6 – Skilled agricultural, forestry, and fishery workers. The least represented category with 685 postings. Includes jobs like farmers, foresters, and beekeepers, requiring knowledge of plants, animals, and machinery.

ISCO 7 – Craft and related trades workers. Involves technically skilled trades such as electricians, carpenters, welders, and mechanics. This is the fourth most represented category with 14,726 postings.

ISCO 8 – Plant and machine operators, and assemblers. Focused on operating manufacturing equipment, heavy machinery, and vehicles. This category includes 2,002 job postings.

ISCO 9 – Elementary occupations. Includes unskilled or low-skilled labour such as cleaners, packers, warehouse workers, and construction assistants.

This category has 4,611 postings.

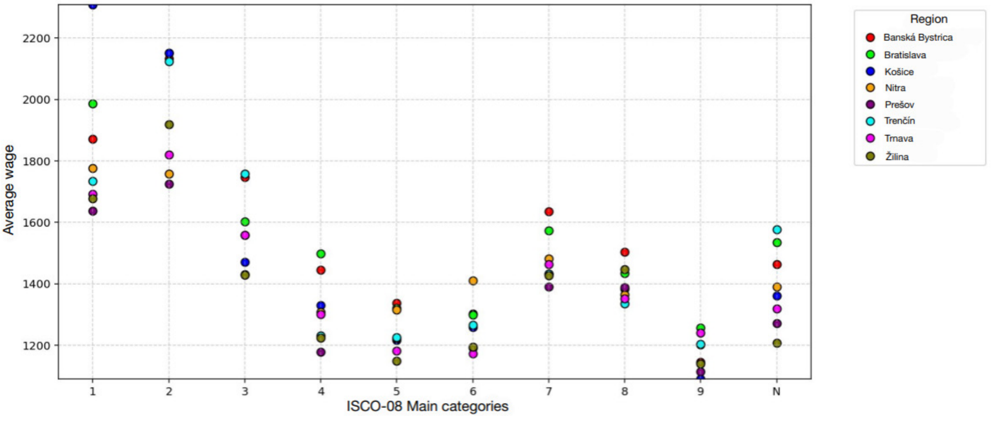
ISCO N – Unclassified positions. Includes emerging or niche roles not found in standard ISCO categories. This group accounts for 9,082 postings.

The results show that the largest demand is for professionals (ISCO 2) and managers (ISCO 1), highlighting the high demand for skilled labour. In contrast, manual and unskilled jobs (ISCO 6, 8, and 9) are much less represented, likely due to automation, technological advancements, and declining demand for physically intensive roles.

4.7 Analysis of Average Wages by Main ISCO Categories

This subsection focuses on comparing average wages across Slovak regions by main ISCO categories. Each point in Figure 7 represents the average wage for a given category in a specific region. Regions are color-coded and labelled in the legend. The x-axis shows the main ISCO categories, while the y-axis represents the average wage in each region for the respective ISCO category.

Figure 7: Average Wages for Main ISCO Categories by Region



Source: www.profesia.sk, own processing.

Several trends can be observed from Figure 7. The highest average wages occur in ISCO categories 1 and 2, confirming that managerial and specialist professions are the best paid. In the Košice Region, average wages exceed €2,200. Mid-level income is seen in categories 3, 7, and 8. The lowest wages

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are observed in categories 5, 6, and 9, which include positions with the lowest remuneration in certain regions.

From this scatterplot, it is possible to identify which ISCO categories receive the highest average wages in specific regions:

ISCO 1 (Managers): The Košice Region leads, suggesting that managerial positions there may be better compensated than in Bratislava, possibly due to fewer high-paid managers.

ISCO 2 (Professionals): The highest average wage appears in the Trenčín Region.

ISCO 3 (Technicians and associate professionals): The highest average is also found in the Trenčín Region, likely influenced by its industrial history.

ISCO 4 (Clerical support workers): The Bratislava Region dominates due to typically higher wages in the capital, influenced by living costs and the presence of state institutions.

ISCO 5 (Service and sales workers): The Banská Bystrica Region offers the highest average wage.

ISCO 6 (Agricultural and forestry workers): The Nitra Region ranks highest, possibly influenced by the presence of the Slovak University of Agriculture.

ISCO 7 (Craft and trades workers): Banská Bystrica Region again leads.

ISCO 8 (Machine operators): The highest average is also in Banská Bystrica, potentially due to industrial enterprises.

ISCO 9 (Elementary occupations): The Trenčín Region leads in average wage for unskilled jobs, possibly due to higher demand for manual labour.

Figure 7 highlights regional disparities in wage levels by profession. Wages are not evenly distributed across occupations or regions. This analysis can inform employers, job seekers, and policymakers when making career or investment decisions within Slovak regions.

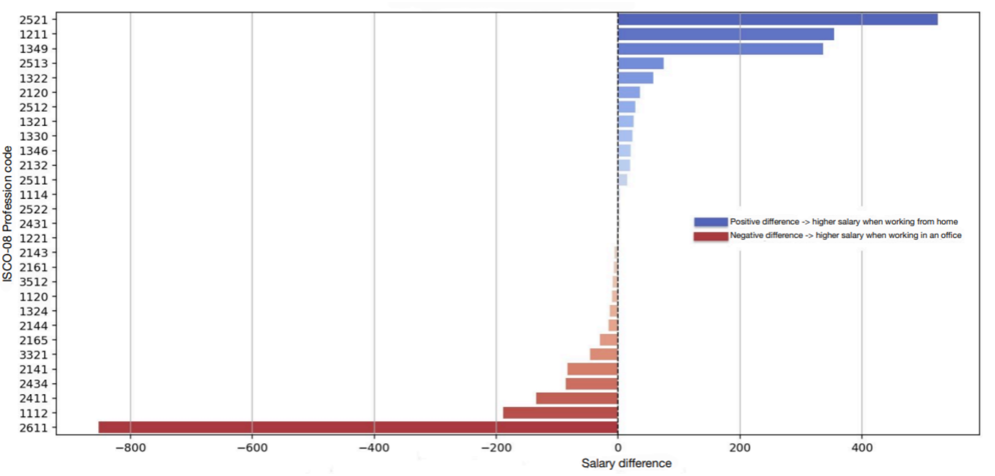
4.8 Comparison of Remote Work and Office Work in Identical Positions

This section focuses on wage differences between remote work and office work for the same job positions. In addition, we examine how the required skills differ between these two work modalities. We identified the 10 most common skills required for remote and office-based work for identical positions.

4.8.1 Wage differences

Wage differences between these two modes of work can be influenced by factors such as commuting costs, demand for specific skills, level of autonomy, or the geographic location of the employer. Figure 8 illustrates the difference in average wages for the same job positions based on whether the work is performed remotely or in an office setting.

Figure 8: Average Wage for Remote vs. Office Based Work



Source: www.profesia.sk, own processing.

As shown in Figure 8, some professions offer higher wages when performed remotely, while others favour office-based work. Blue bars represent positions with higher average wages when performed remotely. These mostly include IT positions, analytical roles, and specialized technical tasks. According to ISCO-08 classification, code 2521 refers to database administrators and analysts. These roles offer wages that are €524.5 higher when performed remotely. IT

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specialists working with databases can perform their tasks from any location, and the global demand for their expertise enables higher pay. On average, remote jobs earn €95.3 more than their office-based counterparts.

Red bars represent professions where office-based employees earn more. For ISCO-08 code 2611, which includes legal and attorney positions, office work offers significantly higher wages €852.6 more due to the necessity of in-person interaction, court appearances, and collaboration. On average, office-based jobs earn €106.1 more than those performed remotely.

4.8.2 Skill Differences Based on Work Modality

Apart from wage differences, there are notable disparities in required skills between remote and office-based positions. For the following analysis, ISCO codes were matched with ESCO-defined skills as explained in Section 4.1.3.

Table 5: Regression Indicators by Region

Remote work – Top 10 skills	Frequency	Office work – Top 10 skills	Frequency
Defining technical requirements	2 449	Manage budgets	62 496
Building business relationships	2 122	Supervising employees	62 389
Interpreting technical documentation	2 078	Project management	58 931
Gathering customer feedback	1 919	Writing reports	48 951
Analysing software specifications	1 901	Communicating with managers	45 036
Using application interfaces	1 857	Using multiple communication channels	43 510
Conducting scientific research	1 845	Applying health and safety standards	41 245
Creating diagrams and flowcharts	1 725	Problem - solving	41 125
Project management	1 706	Complying with legal regulations	40 216
Designing processes	1 635	Supervising team members	39 020

Source: www.profesia.sk, own processing.

Table 5 shows the 10 most frequent skills required for remote and office-based work. Each skill includes a frequency count representing how often it appeared in job listings.

Remote work demands primarily technical and analytical skills. These capabilities allow employees to work independently without frequent interaction. Key skills include defining technical requirements, interpreting documentation, managing projects remotely, and using digital platforms.

Remote work is ideal for programmers, analysts, and researchers who perform tasks independently.

In contrast, office work emphasizes management, communication, and coordination. Office roles often require intensive interaction with colleagues and clients. Dominant skills include budget and staff management, writing reports, and complying with legal standards.

Office work is ideal for managers, administrative staff, financial analysts, and legal professionals who require ongoing in-person collaboration.

5 Conclusion

This paper focused on a comprehensive analysis of labour demand in Slovakia based on data from the online job platform Profesia.sk. It offers a complete overview and insights into regional disparities, occupational distribution of job postings, and the factors influencing labour market dynamics.

The analysis identified several key trends affecting the Slovak labour market. Regional disparities remain significant, with the Bratislava Region dominating in the number of job postings. However, an interesting finding is that the Košice Region reports higher average offered wages than Bratislava, indicating a shifting labour market dynamic and a growing importance of Eastern Slovakia for highly qualified professions.

Another crucial aspect was the analysis of temporal demand, which highlighted seasonal fluctuations and their impact on unemployment. The number of job postings typically decreases in the summer and winter months, leading to an increase in registered job seekers. In contrast, periods of higher economic activity bring an uptick in postings and a decline in unemployment.

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Regression analysis confirmed that the number of available job seekers significantly influences the number of advertised job positions, with the strength of this relationship varying by region. The most pronounced effects were observed in the Bratislava and Košice Regions.

Rising automation and digitalization are shifting labour demand toward technology-driven professions. The occupational structure of postings according to the ISCO classification showed that professionals and managers are the most in demand. Employers increasingly seek specialists and technical workers, while demand for manual and administrative roles is relatively low.

Remote work is another factor reshaping the labour market. The analysis revealed that especially in IT and analytical professions, more job offers are emerging that allow remote or home-based work. These positions often offer higher wages and require specific skill sets. Additionally, it was found that the skill requirements differ for the same job depending on the work modality. Wage differences were also identified between remote and office roles within the same job categories. While some technical and IT roles offer better compensation remotely, legal and managerial jobs tend to pay more in-office.

In conclusion, the Slovak labour market is undergoing significant transformation driven by technological progress, regional differences, and changing employer preferences. While Bratislava remains dominant in terms of job postings, the increasing attractiveness of Eastern Slovakia for skilled professionals suggests a gradual decentralization of the labour market. The growing demand for technology and analytical roles, along with the rise of flexible employment formats such as remote work, are becoming key factors in employment decisions for both employers and workers. These trends suggest that the future of Slovakia's labour market will depend not only on innovation but also on the ability of regions and industries to adapt to evolving conditions and demands.

One key limitation of this analysis is that the data is sourced exclusively from Profesia.sk. Although it covers approximately 80% of the market, it may not fully represent the entire Slovak labour market, especially in the case of manual, seasonal, and low-skilled positions. Another limitation is the relatively short observation period, which supports a cross-sectional rather than a long-term trend analysis.

For a more complete understanding of labour market dynamics in Slovakia, future research should incorporate data from multiple job portals, public institutions, and social networks like LinkedIn. Analysing a longer time frame would also support more robust identification of trends, cyclical patterns, and the impact of technological change on labour market structure. Nevertheless, the results obtained offer valuable insights that contribute to a deeper understanding of labour market developments.

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