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Content

Development and Forecast of Unemployment in the Czech Republic

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Abstract

Unemployment is one of the key indicators of the state of the economy and labor market stability, and its development is sensitive to economic cycles and extraordinary economic shocks. The aim of this study was to evaluate the development of unemployment in the Czech Republic over the last ten years, identify the key factors influencing its dynamics, and propose a predictive model for estimating future developments. To achieve this goal, time series analysis, multivariate regression analysis, and the ARIMA seasonal model were used. The results showed significant seasonality in unemployment and its decline to historically low levels in 2017–2019. The impact of the COVID-19 pandemic was only a temporary disruption of the long-term trend, followed by a stabilization of the unemployment rate. The number of registered job seekers and the number of job vacancies had a significant impact on the development of unemployment. The prediction indicated a slight increase in the unemployment rate in 2026 without any indication of a significant structural break. The paper provides a comprehensive view of unemployment trends and, with the proposed model, offers a tool for further research and decision-making in the labor market. However, the scope of available data is a limitation.

Keywords: Unemployment, time series, regression model, ARIMA model, labour market, forecasting, economic trends.

Introduction

Unemployment represents one of the most important macroeconomic indicators, as it directly affects economic growth, inflation, household consumption, and the stability of public finances. In economic theory, unemployment is understood as an inevitable phenomenon that occurs even under full employment, where the so-called natural rate of

unemployment corresponds to stable inflation (Froncková et al., 2019). Therefore, the unemployment rate is a key indicator for economic policy-making and a tool for assessing labor market efficiency.

In recent years, the dynamics of unemployment in the Czech Republic have changed significantly due to the interplay of several external and internal factors. The COVID-19 pandemic led to a temporary collapse of the labor market, business closures, and job losses, disrupting standard employment mechanisms (Kapicka & Rupert, 2022). At the same time, the crisis highlighted the importance of frictional and structural factors affecting re-entry into the labor market. Current research shows that the pandemic had a disproportionate impact on young workers and women, with these groups facing higher unemployment than others (Fan et al., 2025).

In addition to short-term shocks, long-term structural influences also affect the Czech labor market, including digitalization, automation, and labor migration. The inflow of workers from Ukraine and other countries changes the structure of labor supply and influences the regional distribution of employment. Research confirms that migration, minimum wage levels, and minor changes in capital control and appropriation can significantly affect unemployment levels, with increases in the minimum wage in some cases even reducing unemployment (Pi & Duan, 2023).

Further studies emphasize the importance of information frictions and asymmetries in the labor market, which may lead to inefficient job allocation and greater wage rigidity (Bradley & Mann, 2024). This mechanism helps explain why unemployment may remain high even after an economic crisis ends, while newer models suggest that both workers and firms gradually learn, which better reflects real-world data.

The risk of a significant increase in unemployment is also linked to the credit cycle and developments in financial markets. Kiley (2022) demonstrates that when unemployment is low and credit growth is high, the likelihood of a subsequent sharp increase in unemployment rises, with short- and medium-term risk factors differing. These findings confirm that unemployment forecasting must consider not only economic cycles but also structural and behavioral characteristics of the labor market.

The choice of this topic is driven by a personal interest in the functioning of the labor market and its sensitivity to external shocks and structural changes. Unemployment is not merely a statistical indicator but has profound impacts on social stability, living standards, and

economic growth. The topic is both current and socially relevant, as the analysis and forecasting of unemployment provide practically useful insights for policymakers, businesses, and public institutions. This study aims to contribute to a deeper understanding of the factors shaping unemployment development in the Czech Republic and thereby support the creation of more effective economic policies.

The aim of this study is to evaluate the development of unemployment in the Czech Republic over the past ten years, identify the key factors influencing its dynamics, and propose a predictive model for estimating future development.

In relation to this aim, the following research questions are defined:

RQ1: What was the monthly development of unemployment in the Czech Republic in the period 2014–2024, and what main trends can be identified?

This question provides an overview of the historical dynamics of unemployment and helps identify key trends. Understanding the development of unemployment is essential for detecting patterns that influence the labor market and for building a predictive model.

RQ2: Which factors (structural changes, labor migration, pandemic) most significantly influence unemployment dynamics?

Answering this question makes it possible to identify the main determinants of changes in unemployment. Knowledge of these factors is crucial for designing effective economic and social policies and for modeling future development.

RQ3: How can future unemployment development in the Czech Republic be predicted based on available data?

This question provides the practical output of the study—a predictive model that enables estimation of future unemployment dynamics. Its development is essential for planning measures and minimizing negative impacts on the labor market.

Data and methods

This chapter is devoted to the description of the data and methods that will be used in the empirical part of the study. The aim is to present the data sources, the method of data processing, and the analytical approaches that will enable the research questions to be answered and the objective of the study to be fulfilled.

Data

The empirical part of the study will be based on secondary data obtained from official statistical sources, specifically the Czech Statistical Office, the Ministry of Labour and Social Affairs, and the Kurzy.cz portal. These institutions provide long-term reliable and methodologically consistent data on the development of unemployment in the Czech Republic, both at the national and regional levels.

The analyzed data will include the registered unemployment rate, unemployment by gender, age, and educational attainment, as well as the number of job vacancies. The data are collected from secondary sources through content analysis of official statistical databases, specifically those of the Czech Statistical Office and the Ministry of Labour and Social Affairs. In this context, content analysis is used as a systematic procedure for selecting, classifying, and harmonizing relevant statistical indicators in order to create a consistent dataset suitable for subsequent quantitative analysis.

The analysis will focus on the period from January 2014 to December 2024, with monthly data frequency, allowing the development of unemployment to be captured both during periods of economic stability and during crisis years, particularly the COVID-19 pandemic and the economic impacts of the war in Ukraine. The dataset has subsequently been extended with the most recent available monthly data up to October 2025 to ensure the timeliness of the analysis and enable forecasting for 2026.

Before the analysis, the data will undergo consistency and completeness checks. Missing values will be handled through imputation based on the average of neighboring periods, taking seasonal fluctuations into account. Subsequently, potential outliers will be identified and verified using supplementary statistics to ensure data validity. To ensure comparability and eliminate short-term shocks, the time series will be normalized and smoothed using appropriate statistical techniques, such as moving averages.

The basic characteristics of the data will be described using descriptive statistics, specifically the arithmetic mean, median, mode, standard deviation, and coefficient of variation. These indicators will allow readers to understand the central tendency, dispersion, and variability of the observed variables. This step will also ensure that the subsequent regression analysis is based on a well-prepared dataset.

The data will be collected regularly from already published statistical time series and therefore represent secondary data. This approach complies with scientific research

standards and ensures transparency and reproducibility of results. Data sources will be properly cited according to relevant standards and are publicly available.

It is expected that data processing will enable the identification of long-term trends in unemployment development, differences between individual regions and socioeconomic groups, and the impacts of extraordinary events such as the COVID-19 pandemic or the economic crisis caused by the war in Ukraine. These findings will provide the basis for quantitative data processing in regression analysis and will enable the research questions of the study to be answered.

Methods

A quantitative approach will be used for data processing, enabling a comprehensive evaluation of unemployment development, identification of its key determinants, and description of both regional and temporal differences. This method provides a broader interpretative framework while allowing the identified relationships to be quantified using statistical models.

In the first phase, a content analysis of secondary data will be conducted, with the aim of systematically describing the main trends in unemployment development during the period 2014-2024. The content analysis will include classification and categorization of observed variables according to gender, age, educational attainment, and regional affiliation. This approach will make it possible to identify structural differences between groups and capture changes caused by macroeconomic shocks, seasonal fluctuations, or extraordinary events affecting the labor market (such as the COVID-19 pandemic or the impacts of the war in Ukraine). The outputs of the content analysis will serve as a basis for formulating assumptions regarding relationships between variables, which will subsequently be tested using quantitative methods.

In the second phase, multivariate regression analysis will be applied. Its aim is to quantify the relationship between the unemployment rate as the dependent variable and selected socioeconomic indicators as independent variables. This approach will make it possible to determine the extent to which selected factors (e.g., the number of job vacancies) contribute to the variability of the unemployment rate and in what direction these factors influence it. The general form of the regression equation will be as follows (Source: Gujarati, 2015):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \quad (1)$$

where:

Y – unemployment rate [%],

$X_1 \ldots X_n$ – independent variables (selected socioeconomic indicators),

β_0 – model constant (intercept)

$\beta_1 \ldots \beta_n$ – regression coefficients expressing the strength and direction of the influence of individual factors,

ε – random component (error term / residual).

Before estimating the model, the basic assumptions of regression analysis will be verified. These include whether the variables exhibit an approximately linear relationship, whether the model errors are homoscedastic and do not show systematic bias, whether the explanatory variables are not excessively correlated with each other, and whether the residuals are approximately evenly distributed over the observed period. Assessing these assumptions is necessary to ensure the validity of the results and the correct interpretation of the estimated coefficients. Statistical significance will be evaluated based on p-values, and the overall quality of the model will be assessed using the coefficient of determination (R^2). Calculations and graphical outputs will be processed using appropriate statistical software.

As a supplementary quantitative method, the ARIMA model will also be used, allowing the analysis of time series dynamics independently of the influence of other variables. This model is suitable for identifying the trend, seasonal, and random components of a time series, and thus for an independent assessment of the temporal structure of the unemployment rate over the observed period. The general form of the ARIMA model is as follows (Source: Box & Jenkins, 2016):

$$\varphi(L)(1-L)^{d} Y_t = \theta(L)\varepsilon_t \qquad (2)$$

where:

$\varphi(L)$ – autoregressive operator,

$\theta(L)$ – moving average operator,

L – lag operator,

d – order of differencing,

ε_t – random component (white noise).

The ARIMA model will be estimated in the Python programming language, specifically using the "statsmodels" and "pmdarima" libraries, which implement the Box–Jenkins methodology, including the automatic identification of optimal model parameters. The estimation will be performed on monthly data for the period 2014-2025, with the subsequent forecast covering the months of 2026.

The ARIMA model will be used primarily to assess trend, seasonality, and short-term volatility, as well as to generate forecasts of future unemployment rate development. The results will serve as a complement to the regression analysis. Both approaches will make it possible to verify whether the identified trends remain consistent under an alternative modeling framework, thereby increasing the reliability of the conclusions.

The methodology will also include time series smoothing, aimed at reducing distortions caused by short-term fluctuations, extraordinary events, and seasonal effects. A moving average will be used for smoothing, contributing to greater comparability and interpretability of the time series.

The research procedure will include data collection and preparation, followed by content analysis and the calculation of basic descriptive statistics, the application of the regression model, and supplementary time series analysis using the ARIMA method. The results will be presented in the form of tables, visualizations, and interpreted forecasts to clearly address all research questions. It is expected that the combination of the selected methods will enable the identification of the main determinants of the unemployment rate, the description of temporal differences, and a comprehensive answer to the defined research questions.

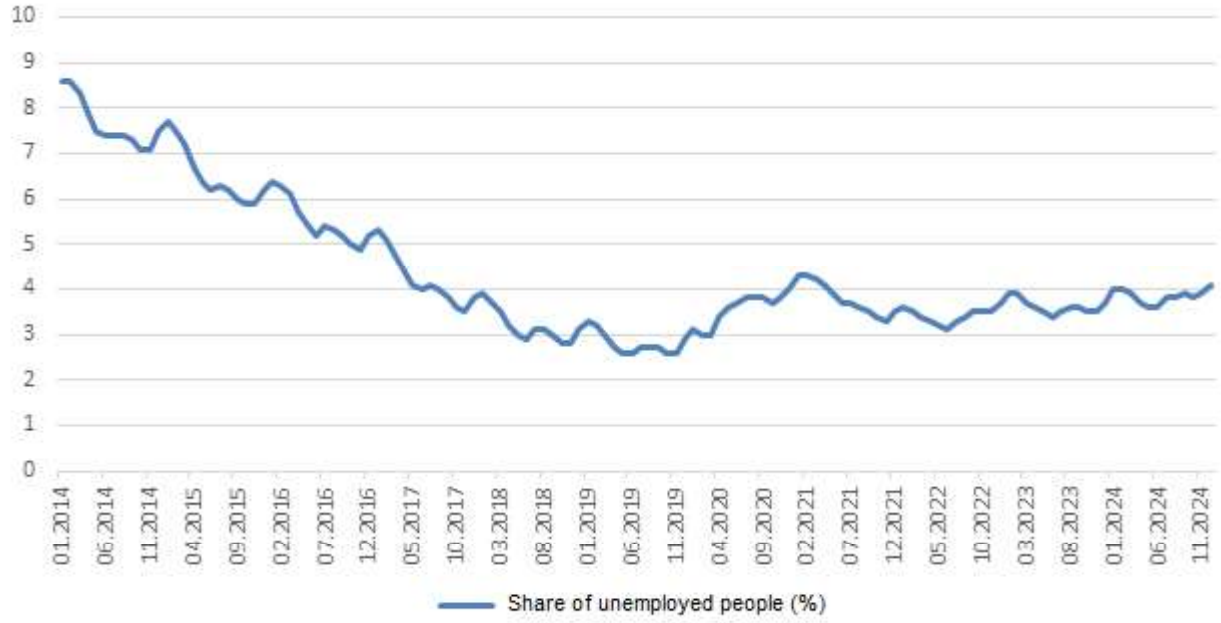
Results

This chapter presents the results of the empirical part of the study obtained based on the procedures described in the Methodology chapter. The results are structured according to the applied analytical approaches and include a description of the development of the unemployment rate in the period 2014-2024, the outputs of the multivariate regression analysis, and a forecast of future development using the ARIMA model. Each section of the chapter contains only the obtained values and statistical outputs, supplemented by graphical and tabular appendices.

Development of the unemployment rate in the period 2014–2024

For the analysis of unemployment development, monthly data for the period from January 2014 to December 2024 were used, totaling 132 observations. The time series of the unemployment rate is illustrated in Graph 1, which captures the development of values over the observed period.

Graph 1: Development of the Unemployment Rate in the Czech Republic (2014-2024)



Source: Own.

From the time series in Graph 1, it is evident that the unemployment rate in January 2014 was around 8.6%, representing the highest value of the entire observed period. This is followed by a long-term gradual decline, with the unemployment rate stabilizing at approximately 5% by the end of 2016. In 2017, the decline continues to values between 3.5% and 4%, with the lowest value of the entire period recorded in the first half of 2019, when the unemployment rate reached approximately 2.6%.

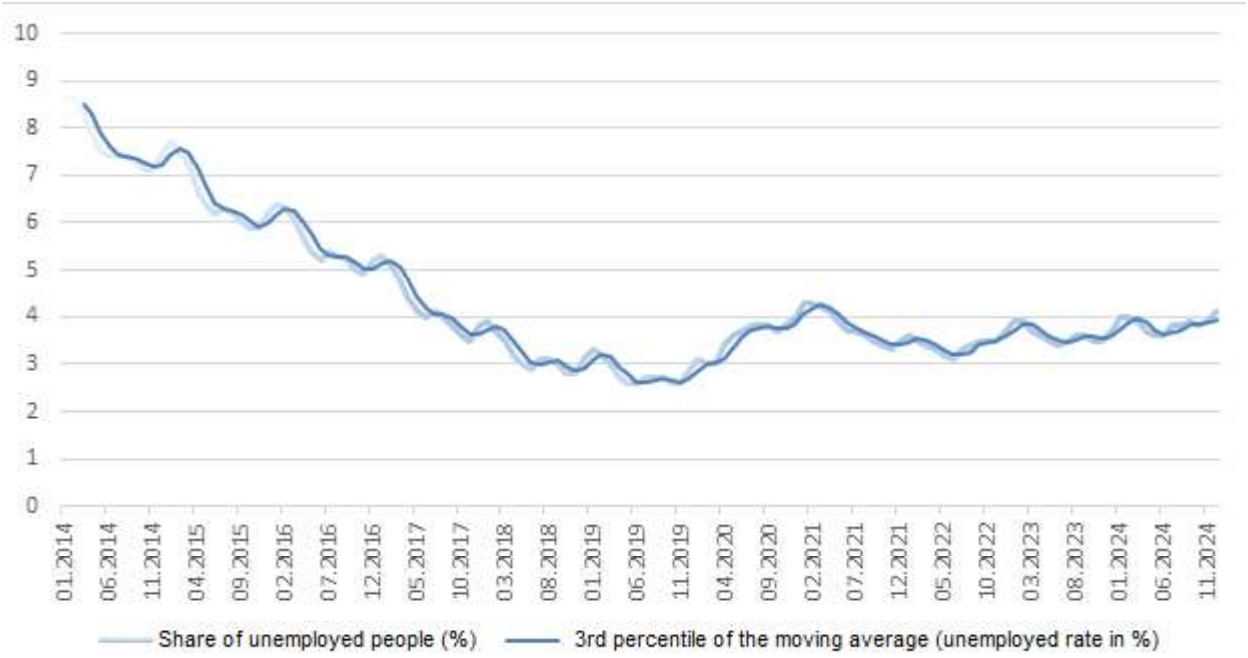
The time series also exhibits regular seasonality. This recurring pattern is clearly visible in Graph 1. In most years, an increase in the unemployment rate can be observed in January and February, while the lowest values are typically reached during the summer months, particularly in July and August. This seasonal cycle is evident throughout the entire observed period, regardless of the overall level of unemployment.

From a year-by-year perspective, periods of increased volatility can also be identified. In 2020, there is a more pronounced fluctuation, with the unemployment rate rising from

approximately 2.9% in January to more than 3.8% in July. In the following months of 2021 and 2022, the unemployment rate mostly ranges between 3.3% and 4%, with fluctuations remaining mild and regular. In 2023, a slight increase is observed, with unemployment generally ranging between 3.5% and 3.9%. The year 2024 concludes the observed period with values around 4%, representing a slight increase compared to the previous year.

To clarify short-term fluctuations, a three-point moving average was applied to the time series. The smoothed curve shown in Graph 2 better illustrates the overall trend and confirms the long-term decline in unemployment until 2019, followed by its stabilization at around 3–4%.

Graph 2: Smoothed Development of the Unemployment Rate



Source: Own.

To complement the presentation of the results, the basic statistical characteristics are presented in Table 1 below.

Table 1: Descriptive characteristics of the unemployment rate, 2014–2024

Share of unemployed persons [%]	
Aritmetmetic mean	4.37
Median	3.8
Mode	3.5
Standard deviation	1.52
Minimum	2.6
Maximum	8.6
Number	132

Source: Own.

Results of the regression analysis

The regression analysis was conducted on a dataset of 132 monthly observations covering the period from January 2014 to December 2024. The dependent variable was the unemployment rate expressed as a percentage. Two labour market variables were included as independent variables: the number of registered job seekers and the number of job vacancies. The estimation was carried out using a multiple linear regression model, with all values processed at the same monthly frequency.

The results of the model are presented in Table 2, which includes the estimated coefficients, their standard errors, t-statistics, and p-values. The table also contains key model characteristics such as the coefficient of determination (R^2), adjusted R^2, the F-test value, and the number of observations included.

Table 2: Results of the multiple regression analysis

	Coefficients	**Standard error**	**t – Statistics**	**Value P**
Limit	1.99802060	1.15812957	1.72521335	0,08688382
Job seekers (UoZ)	0.00008433	0.00001741	4.84385364	0,00000359
Job vacancies (VPM)	-0.00000576	0.00000164	-3.51164903	0,00061431
Model statistics				
R^2	0.8715			
Adjusted R^2	0.8695			
F	437.54			
p	<0.001			
n	132 observations			

Source: Own.

The coefficient of determination (R^2) reached a value of 0.8715. This value indicates how much of the variability of the dependent variable is explained by the selected independent

variables. The adjusted coefficient of determination is 0.8695, which is very close to the original R^2 value, confirming that the inclusion of both explanatory variables is appropriate and does not compromise the stability of the model. The F-test of the model reached a value of 437.54, and its p-value is significantly lower than the 0.01 significance level, indicating that the model as a whole is statistically significant.

The results of the regression analysis show that both included variables have a statistically significant effect on the unemployment rate at the 1% significance level. The coefficient for the number of registered job seekers has a positive value of 0.00008433, with a t-statistic of 4.84 and a p-value lower than 0.001. The coefficient for the number of job vacancies has a negative value of -0.00000576, a t-statistic of −3.51, and a p-value also below 0.001. The low values of the standard errors for both variables indicate the stability and reliability of the regression model results.

The constant term of the model reached a value of 1.998; however, its p-value is 0.086, which is higher than the commonly used significance level of 0.05. Therefore, its statistical significance appears lower compared to the two explanatory variables. Nevertheless, it is included in the table as it represents an integral part of the estimated model.

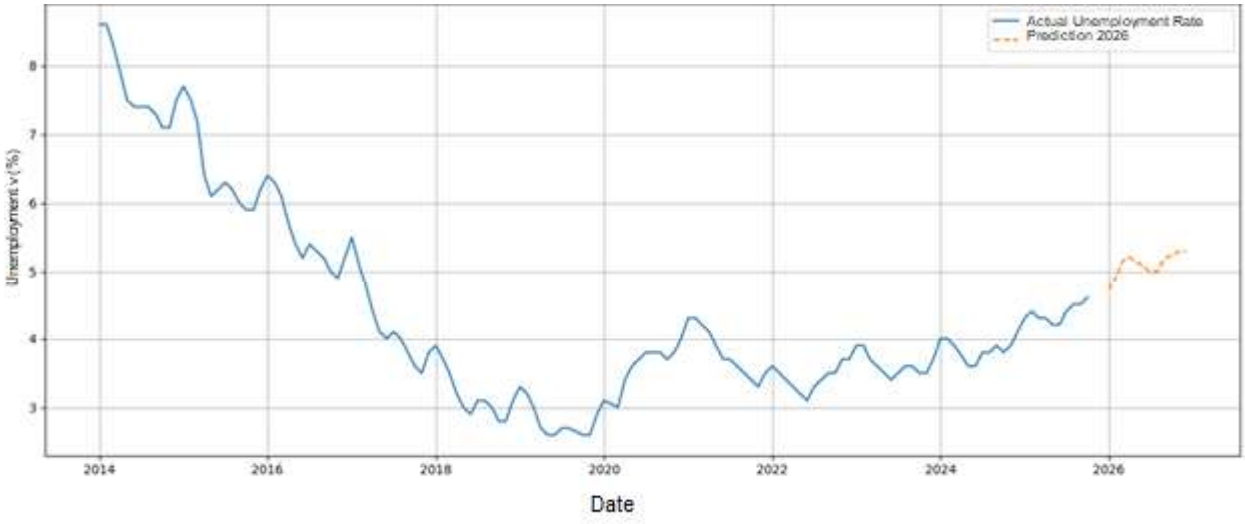
The assumptions of linear regression were verified using basic diagnostic procedures. The residuals are evenly distributed around the zero axis and do not form any systematic patterns. Their variance remains consistent across the range of values, indicating no significant heteroscedasticity. No strong multicollinearity was detected among the explanatory variables. Based on these findings, it can be concluded that the model meets the assumptions required for linear regression.

Forecast of the unemployment rate for 2026

To predict future developments, a time series of monthly unemployment rate values was used, extended with the most recent available data for 2025 (January-October). The forecasting model was constructed using the ARIMA method, estimated in the Python programming environment. The model selection process involved automatic parameter identification based on the AIC information criterion. The result was a seasonal model with a 12-month seasonality, whose parameters enabled the creation of a forecast for the period January-December 2026.

The resulting forecast values are illustrated in Figure 3. The visualization captures both the actual development up to October 2025 and the subsequent projection of values for the entire year 2026.

Figure 3: Development of the unemployment rate in the Czech Republic (2014-2025) + prediction 2026



Source: Own.

The forecasted time series suggests that the model expects a gradual increase in the unemployment rate throughout 2026. The initial value in January is 4.71%, while by the end of the year the predicted values reach approximately 5.30%. Within the year, slight seasonal variability is evident, with lower values estimated for the summer months and higher values for the autumn and winter months. A complete list of the forecasted values is provided in Table 3 in Appendix 1.

Discussion

This chapter interprets the results of the empirical part of the thesis and systematically answers the research questions posed. The findings are interpreted in the context of the literature review and supplemented with key relationships derived from the empirical data. The discussion focuses on the main characteristics of unemployment development, the importance of individual factors, and the suitability of the applied methodology.

RQ1: What was the monthly development of unemployment in the Czech Republic in the period 2014–2024 and what main trends can be identified?

The time series results show several distinct phases in the development of unemployment. At the beginning of the observed period (2014-2016), higher values above 7% are evident, which may be associated with the gradual fading of economic stagnation described by Kapáska (2022). This interpretation is largely consistent with the data; however, the graph also shows that the decline in unemployment was relatively smooth, without significant short-term shocks. This suggests that the Czech labour market was structurally quite resilient at the time, even though literature often emphasizes its sensitivity to economic cycles.

The period 2017-2019 is characterized by a significant decline in unemployment to around 2.6%. This development corresponds with the findings of Pošta (2023) regarding strong labour demand; however, the data indicate that the decline was unusually steep. This may suggest that short-term factors (e.g., labour shortages in industry) played a more significant role than is typically emphasized in the literature. In other words, the actual development may have been more sensitive to specific domestic conditions than general theories about the European labour market suggest.

The pandemic period of 2020 brought fluctuations that are also visible in the data. Unlike some studies (e.g., Zubíková et al., 2023), which expect a more pronounced shock, the time series shows only moderate deviations. This confirms that the impact of the pandemic in the Czech context was weaker than international analyses might suggest. It is possible that government support measures, the specific structure of employment (strong industrial base), and already low unemployment levels before the pandemic mitigated the potential increase.

After 2022, the development stabilizes within the range of 3.5-4%. The stability described in the literature for developed and digitalized labour markets (Priede, 2023) is consistent with this observation. However, the graph also shows that this stability has a strong seasonal component. Regular winter increases and summer decreases occur consistently each year and, in practice, have a stronger influence than long-term structural changes. This seasonality represents the most prominent and reliable pattern in the entire series, as it is more stable than the trend and more pronounced than the impact of the pandemic.

RQ2: Which factors (structural changes, labour migration, pandemic) most influence unemployment dynamics?

The regression analysis confirmed that the most significant determinants of the unemployment rate are two key variables: the number of registered job seekers and the number of job vacancies. Both variables were found to be statistically significant, and their direction aligns with expectations. However, several additional insights emerge that are not always emphasized in the literature.

The positive relationship between the number of job seekers and unemployment is intuitive, but the increase in unemployment is not always linear, suggesting the influence of factors not captured by the model, such as duration of unemployment, structure of job seekers, or seasonal hiring patterns. While literature (e.g., Pošta, 2023) often explains this relationship through regional qualification structures, the data suggest that the dynamics may be more heterogeneous than commonly described.

The negative relationship between job vacancies and unemployment corresponds with findings by Priede (2023); however, the analysis shows that the intensity of this relationship changes over time. During periods of strong economic growth (2017-2019), unemployment decreased significantly even with a smaller increase in vacancies, whereas after 2022 the changes are more moderate. This indicates that the number of vacancies alone may not be sufficient, and their structure, qualification requirements, and regional distribution also play an important role—factors not captured by the model.

Broader influences such as structural changes, digitalization, or technological progress are not directly reflected in the regression. This is mainly due to the lack of suitable monthly indicators. While literature (e.g., Bachmann et al., 2024) often highlights these as key drivers, the analysis suggests they act more as long-term background factors affecting the trend rather than short-term dynamics.

A similar conclusion applies to migration. Although it may theoretically affect labour supply structure, it does not create significant shifts in the time series. This finding aligns with Yılmaz and Günel (2022), although the impact may be even weaker in the Czech context due to relatively low migration levels.

The COVID-19 pandemic appears in the data as a short-term disruption rather than a long-term structural shock. This contrasts with expectations from international studies and may

reflect the effect of rapid policy responses, economic structure, and low pre-pandemic unemployment.

RQ3: How can future unemployment developments in the Czech Republic be predicted based on available data?

The forecast was developed using a seasonal ARIMA model, which is generally recommended for monthly economic time series. Parameter optimization based on AIC led to the selection of a model capable of capturing both recurring seasonal patterns and long-term trends.

The results suggest that unemployment may slightly increase in 2026. This is consistent with broader expectations of a slowdown in the European economy (Priede, 2023). The forecast indicates a gradual rise in unemployment, continuing the relative stability observed in 2022-2024.

However, it is important to critically acknowledge that the ARIMA model relies solely on historical values of a single variable and has limited ability to account for sudden shocks or structural changes. If significant events occur in 2026 (e.g., recession, changes in industrial demand, geopolitical developments), the model cannot anticipate them. In this sense, the forecast may appear somewhat "over-smoothed."

The literature suggests that more advanced hybrid models (e.g., ARIMA-ARNN, ARIMA-SVM; Ahmad et al., 2023) can provide more accurate predictions due to their ability to capture nonlinear patterns. However, their application was beyond the scope of this study due to data and complexity requirements. The use of a seasonal ARIMA model can therefore be considered a reasonable compromise—offering a simple, transparent, and sufficiently reliable forecast given the available data, albeit less flexible than more advanced approaches.

Conclusion

The aim of this thesis was to evaluate the development of unemployment in the Czech Republic over the past ten years, identify the key factors influencing its dynamics, and propose a predictive model to estimate future developments. This objective was achieved through time series analysis, regression modelling, and the ARIMA forecasting model, which together provided a comprehensive view of the functioning of the Czech labour market.

The time series analysis showed that the observed period was not homogeneous in terms of development. In 2014-2016, the data reflected the effects of previous economic stagnation, while the period 2017-2019 was characterized by historically low unemployment around 2.6%. The COVID-19 pandemic caused a temporary disruption of the trend; however, due to stabilisation measures, there was no sharp increase in unemployment. Since 2022, the development has stabilised within the range of 3.5-4%. Throughout the entire period, a strong seasonal pattern is evident, which represents one of the characteristic features of the Czech labour market.

The regression analysis confirmed the importance of two main factors: the number of job seekers and the number of job vacancies. These variables best explain short-term fluctuations in unemployment. Structural or technological changes could not be included in the model due to the lack of data at a monthly frequency, and therefore their influence is only indirectly reflected in long-term trends. The pandemic was confirmed as a short-term shock that only temporarily disrupted the trend.

The predictive part of the thesis used a seasonal ARIMA model, which forecasts a slight increase in unemployment in 2026 and a continuation of stable development without major structural breaks. The model captured both the seasonal pattern and the long-term trend and provided a realistic outlook that can serve as a basis for practical use and further research.

The thesis thus fulfilled its objective by describing the development of unemployment, identifying key factors, and producing a forecast of future trends. A limitation of the research remains the restricted range of explanatory variables, which were not available at the required frequency. Nevertheless, the results form a consistent and methodologically appropriate whole. The contribution of the thesis lies in the integration of multiple analytical approaches and in providing a comprehensive view of the development and expected direction of the Czech labour market.

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