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The Czech Republic's Economy since the 1990s and its Development Forecasts: Selected Macroeconomic Indicators

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Using a comparative developmental analysis of wage levels and other indicators, the present paper aims to capture the changes in the economy and measurable aspects of living standards in the Czech Republic since the beginning of the then Czechoslovakia's transformation process launched in the early 1990s. To model the trend, analysis of the relevant time series was performed, exponential smoothing as an adaptive approach to trend modeling being applied. Interpolation and extrapolation criteria were used to verify the suitability of the selected exponential equalization; the Durbin-Watson test, determination index, residual autocorrelation functions, t-tests and Theil inequality coefficient were employed as well. The variables analyzed are the average wage, GDP and the rates of inflation and unemployment, supplemented by the minimum wage and the subsistence minimum. The data used come from the official website of the Czech Statistical Office. They were processed using SPSS and SAS statistical software and a Microsoft Excel spreadsheet. The results show economic downturns and gradual recoveries accompanied by repeated freezing and starting wage growth. High inflation rates in the transition from a centrally planned to a market economy or the GDP decline at the beginning of the financial crisis are evident, the labor market reacting with some delay, as reflected in the rise in the unemployment rate after the currency crisis in the late 1990s, and in average wage trends during the decline of the economic crisis in the early 2010s. The purpose of this research is also to predict further wage level and macroeconomic aggregate developments until 2023. This study aspires to be the starting point for subsequent research, comparing the original forecasts with the reality of further economic development interrupted by the COVID-19 pandemic.

Keywords: *Average Wage; GDP; Inflation Rate; Unemployment Rate; Time Series; Exponential Smoothing; Development Forecast; COVID-19 Pandemic.*

Introduction

Prior to 1989, the centrally planned economy of the then Czechoslovak Socialist Republic was based on heavy industry, failing to respond flexibly to population needs and technological challenges. Although foreign trade took place mainly with countries associated in the Council for Mutual Economic Assistance, the Soviet Union in particular, indebtedness to capitalist countries started to grow in the 1980s. Foreign exchange reserves were invested exclusively in household consumption, the lasting dominance of demand over supply impeding economic and social progress. The directive-driven economy was lagging behind the advanced countries' modernization and technological development. Its inefficiency (the decline in labor productivity having stopped at two-fifths of Western European performance) and stagnant standard of living increased the dissatisfaction of the population, thus contributing to the inevitable fall of the communist regime. Having been launched in the early 1990s, political and economic reforms began the country's transformation into a standard market economy. The present paper examines the development of the Czech Republic in terms of GDP, the inflation and unemployment rates and labor costs after the division of Czechoslovakia in 1993, taking account of the current situation and assessing the economic outlook.

Evidence of past economic developments makes it possible to infer future ones, thus facilitating political and economic decision-making at the national level. Considerations of future trends are also important for the business community when planning their activities and enhancing market opportunities. Therefore, the development of labor markets, wages and incomes (purchasing power), GDP and other macroeconomic aggregates is the subject of ongoing research worldwide, the selected publications being reviewed below.

Using data from 57 European regions, Head and Mayer (2006) demonstrate how wages and employment react to differentials in the real market potential. Beramendi and Cusack (2009) show that the OECD countries differ more in the distribution of labor earnings and disposable income than in that of market income, greater and persistent cross-national variation in the distribution of the former being attributable to political actors and economic institutions. Helpman, Itskhoki and Redding (2010) develop a new framework for examining wage distribution determinants which emphasizes within-industry reallocation, labor market frictions and differences in workforce composition across companies, maintaining that more productive firms pay better, and their exports raise wages. Applying wage income tax statistics, Moriguchi (2010) constructs continuous time series of upper-income shares in Japan between 1951 and

2005 to record the development of top incomes and explore their long-term determinants, pointing up that the middle-income group earned enormously over the period of high economic growth, while the top wage income class did comparatively better after 1975. Acharyya (2011) explores the effects of changes in trade restrictions on the intra-country wage inequality within a standard Heckscher–Ohlin–Samuelson model, indicating that the conversion of an import-quota to an equivalent voluntary export restraint raises wage inequality in a country importing unskilled-labor goods and reduces it in its trading partner country. Using sectoral panel data, Oyvat (2011) suggests that low-wage competition, followed by trade liberalization, reduces wage shares in the manufacturing industry, noting that rising capital flows and financial liberalization increase macroeconomic volatility, thus leading to a financial crisis that affects functional income inequality. Stockhammer and Onaran (2012) confirm that the euro-zone's aggregate demand regime is wage-led, an increase in wages having a positive effect on consumption – contrary to the impact on investments and exports. As the authors argue, credit- and export-based growth models – having emerged in the Euro area – gave rise to financial imbalances, wage flexibility proving insufficient to prevent them. To explain the growing market-driven wage dispersion as a central feature of income inequality, as Herr and Ruoff (2014) point out, neoclassical authors focused on technological change and underinvestment in education, while Keynesians considered other structural, social, and demand factors as well, deregulatory globalization trends playing a key macroeconomic role in recent decades. According to empirical research by Andriuskevicius, Ciegis and Dilius (2017), the effects of income inequality on sustainable economic growth in terms of savings are negligible in the four clusters of EU-25 countries examined over the period 2005–2013. US industries dependent on high-income consumers showing greater wage inequality, Wilmers (2017) identifies a new structural source of wage inequality, namely an increasingly unequal composition of consumer demand. Examining small-scale fishing in Spain, Outeiro, Villasante and Sumail (2018) found that at least the minimum wage was earned by almost 40 % of fishermen in the area studied, while only 8 % and 1.4 % earned twice and three times as much, respectively. Addressing the gender pay gap, with a focus on the wage distribution in the United Stetes, Gharehgozli and Atal (2020) concluded that, including part-timers, the ratio of women's to men's wages increased between 1986 and 2016 by 14 %, suggesting a slight decline in the overall gender wage gap. De Nardi, Fella, Knoef, Paz-Pardo and Van Ooijen (2021) compare male and household wage and income risks and distributions in the Netherlands and the United States, implying significant deviations from theoretical assumptions.

Using the British 1958 National Child Development Survey, Gregg (2001) looks at long-term unemployment, highlighting that low educational attainment, financial deprivation and childhood behavior problems raise the susceptibility to unemployment, especially among men. Kingdon and Knight (2004) explain why the unemployed in South Africa do not enter the grey economy, as is common in developing countries, unemployment not being largely voluntary. Unemployment growth in South Africa since the 1994 transition was documented by Banerjee, Galiani, Levinsohn, McLaren and Woolard (2008) who argued that seemingly stable unemployment rates would not decline without policy intervention. Nickell, Nunziata and Ochel (2005) empirically analyze unemployment patterns across OECD countries from the 1960s to the 90s, explaining them by changes in labor market institutions. Using regression modeling, Kochetkov (2012) revealed a negative correlation between inflation and unemployment in Latvia over the period 1996–2008. Gohmann and Fernandez (2014) apply a panel vector autoregressive model, determining the causal relationship between unemployment and ownership in the U.S. states using the 1976–2009 data. Marjanovic and Mihajlovic (2014) examine the presence of hysteresis in monthly unemployment rates in selected European OECD states and transition countries of Central and Eastern Europe in the 2000–2013 period, structural analysis suggesting that the hysteresis hypothesis can be rejected in the case of OECD countries, unlike the latter ones.

Using panel unit root and cointegration, Granger causality and long-run estimation, Narayan and Smyth (2008) find that capital formation, energy consumption and real GDP are interconnected, the first two processes having a positive long-term impact on GDP. Kubiszewski, Costanza, Franco, Lawn, Talberth, Jackson and Aylmer (2013) synthesized estimates of genuine progress indicator for 17 countries over the 1950–2003 period, comparing GPI with GDP human development index, ecological footprint, biocapacity, Gini coefficient and life satisfaction scores, revealing a significant variation between the countries studied. Stundziene (2015) seeks to create a practical, simple but accurate model for predicting Lithuanian GDP, a regression model with twelve lag independent variables meeting these criteria for short-term GDP forecasting. Varjan, Rovnanikova and Gnap (2017) carry out a long-term analysis of GDP per capita in Slovakia, recommending measures for the development of transport infrastructure in terms of sustainable growth. Krajnakova, Pilinkiene and Bulko (2020) analyze the impact of GDP, foreign investment and university R&D expenditure on the employability of HEI graduates in the Czech Republic and Slovakia, indicating a much higher correlation between graduate unemployment and GDP and investment in the latter country. Rawski (2001) argues that official Chinese statistics have been significantly exaggerating real output growth since 1998, speculating that cumulative GDP growth between 1997 and 2001 did not reach even a third of official claims. There are numerous studies suggesting a departure from GDP as the ultimate indicator of human well-being and progress, as Brinkman and Brinkman (2011) point out. It is the result of disillusionment that while the economy is experiencing GDP growth, many social indices and needs are not being addressed.

There is no study on the long-term development of wages and purchasing power in relation to trends in GDP and other macroeconomic indicators in the former Czechoslovakia and the Czech Republic since 1990. The present paper seeks to fill this gap and provide future research prospects. The principal objective is to explore the effects of economic recessions after currency and financial crises in the late 1990s and 2008 and to predict possible future wage and relevant macroeconomic developments, allowing follow-up research to investigate an economic fallout of the coronavirus pandemic aftermath on the Czech Republic.

Low-wage labor has long been a politically sensitive issue in most European countries. The current economic crisis has exacerbated it – many companies cutting payroll or making employees redundant. Further reduction of already low wages is not just a living standard threat, but even a potentially existential one. While the current dynamics of Czech GDP lags behind the rest of the Central European region, wage growth in the Czech Republic is higher compared to its neighbors. Both trends have a common denominator – a tight labor market.

The following variables were examined in the relevant time series (shortened versions used hereinafter are given in parentheses): average gross monthly nominal wage (average wage), gross domestic product at current prices (GDP) and the rates of inflation and unemployment. Two other variables were added to the study, namely the minimum gross monthly nominal wage (minimum wage) and the subsistence minimum. The data are drawn from the official website of the Czech Statistical Office (CZSO). (In the CZSO database, the umbrella term "wage" refers to employee earnings in both the private and public [salary] sectors, which is also applied in this paper.) The article includes two variants of predictions of the average wage, GDP and the rate of unemployment until 2023 – in anticipation of the economic slowdown or relative growth, respectively. Part of the research is the evaluation of the population's purchasing power in selected commodities in terms of units of measure of individual types of goods and services that customers could purchase in respective years. SPSS and SAS statistical software and a Microsoft Excel spreadsheet were utilized in the data processing.

To evaluate economic data, various statistical methods, including multidimensional ones, are commonly employed; see, e.g., Malec (2016) or Malec and Janovský (2019). In this research, standard analytical methods were used to model time series and construct predictions. An exponential smoothing technique was applied for capturing the trend. (This adaptive approach to trend time series modeling utilizes the weighted least squares method with weights decreasing exponentially toward the past, the latest observations having the highest weight. Appropriate exponential smoothing was chosen using interpolation and extrapolation criteria, the statistical software automatically evaluating the most advantageous combinations of smoothing constants α and β.)

All sample residual autocorrelation and partial autocorrelation functions indicate that the unsystematic component does not show autocorrelation, the corresponding exponential smoothing thus being satisfactory. The values of the Durbin-Watson statistic are in all cases close to 2, i.e., always in the interval (1.6, 2.4). Random failures can therefore be considered as independent. To evaluate the quality of the model, the Theil inequality coefficient was used. Annual and quarter time series were shortened by n_2 observations (n_2 = 5 observations in the case of average wage and GDP time series, and n_2 = 20 observations of quarterly unemployment rate time series), and the predictions for these n_2 values were made, applying appropriate exponential smoothing. (Taking only non-negative values, the Theil index acquires a lower zero limit in the case of error-free predictions. The more it deviates from zero, the more the prediction differs from the ideal error-free one, the square root of the Theil coefficient allowing to be interpreted as a relative prediction error.)

Theory and Methods

Exponential Smoothing of Time Series

Assume the time series y_1, y_2, …, y_n of length n. Exponential smoothing is the application of the weighted last squares method to all available observations of a given time series, the weights of particular observations decreasing exponentially towards the past. The values of the smoothed time series at time t, t = 1, 2, …, n, Y_t are determined to minimize the value of the expression

$$\sum_{j=0} (y_{t-j} - Y_{t-j})^2 d^j, \tag{1}$$

where δ is a discount constant satisfying the condition 0 < δ < 1. The given expression has the form of an infinite sum, although only a finite number of observations y_1, y_2, …, y_n are known in practice. In all variants of exponential smoothing, it is assumed that the smoothed time series has the form

$$y_t = T_t + \varepsilon_t, \tag{2}$$

where T_t is a trend component and ε_t is a random (unsystematic) component at time t, t = 1, 2, …, n.

Simple Exponential Smoothing

Simple exponential smoothing is used if the trend component is constant in short sections of the time series, i.e., it holds that

$$T_t = \beta_0. \tag{3}$$

It is necessary to estimate b_0 of the parameter β_0. Since this is an adaptive approach to the trend component, the estimate depends on the point in time at which it is made. The symbol $b_0(t)$ denotes the estimate of the parameter β_0 constructed at time t based on all observations y_1, y_2, …, y_n. This estimate is obtained by minimizing the expression

$$\sum_{j=0} [y_{t-j} - \beta_0(t)]^2 d^j. \tag{4}$$

The use of the least square method leads to the standard equation

$$b_0(t) \sum_{j=0} \delta^j \quad \sum_{j=0} \delta^j y_{t-j}. \tag{5}$$

If it holds that

$$\sum_{j=0} \delta^j = \frac{1}{1-d}, \tag{6}$$

the equation (5) can be modified into the form

$$b_0(t) \quad (1 \quad \delta) \sum_{j=0} \delta^j y_{t-j}. \tag{7}$$

The obtained estimate $b_0(t)$ represents not only the trend level at time t but also the smoothed value Y_t of the considered time series, so it can be written

$$Y_t = (1-\delta)\sum_{j=0}^{\infty}\delta^j y_{t-j} = (1-\delta)\,(y_t + \delta\, y_{t-1} + \delta^2 y_{t-2} + \ldots). \quad (8)$$

It is obvious from the expression (8) that the smoothed value of the time series at time t is the weighted sum of all time series observations up to the time t with exponentially decreasing weights

$$1-\delta,\ (1-\delta)\,\delta,\ (1-\delta)\,\delta^2, \ldots. \quad (9)$$

The expression (8) can be modified to the form

$$Y_t = (1-\delta)\, y_t + d\, Y_{t-1}, \quad (10)$$

which represents a recurrent expression for the calculation of the smoothed values of the analyzed time series. For practical purposes, the above expression is rewritten into the form

$$Y_t = a\, y_t + (1-\alpha)\, Y_{t-1} \quad (11)$$

where $\alpha = 1 - \delta$ is the smoothing constant. Equation (11) documents the above-mentioned advantages of exponential smoothing consisting in the simplicity of calculation of the smoothed values and low demand for data volume. The point is that at time $t-1$ it is enough to store only the smoothed value Y_{t-1} and the previous smoothed values Y_{t-2}, Y_{t-3}, … can be forgotten. Thus, the recurrent formula (11) can be used, and the smoothed value Y_0 must be obtained. It can be determined either:

- as the arithmetic mean of an appropriate number of initial observations

or

- by applying the so-called back-casting method relying on time-series extrapolation to the past.

Based on practical experience, it is recommended to choose the value of the smoothing constant α from the interval (0; 0.3>. A low value of α corresponds to the state when the time series generating mechanism does not change significantly, so the last observation is assigned a small weight. The α values are specified in two ways:

- using an empirical formula

$$\alpha = \frac{1}{m+1}, \quad (12)$$

where $2m + 1$ indicates the most suitable length of simple moving averages for smoothing a particular time series, and

- performing a simulation consisting in sequential selection of α = 0.01, 0.02, 0.03, …, 0.30, the value that provides the best predictions being finally chosen.

It is clear from the above that in the case of the simulation approach, the simple exponential smoothing is done in two phases. First, an optimal value of the smoothing constant α is determined. Then, the time series is adjusted by this value and the predictions are calculated.

Double Exponential Smoothing (Brown's Algorithm)

When applying the method of double exponential smoothing, it is assumed that the trend of the analyzed time series is linear in short sections, i.e., it is valid that

$$T_t = \beta_0 + \beta_1 t. \quad (13)$$

Estimates $b_0(t)$ and $b_1(t)$ of the parameters β_0 and β_1 are determined by minimizing the expression

$$\sum_{j=0}^{\infty}[y_{t-j} - \beta_0(t) + \beta_1(t)\, j]^2\, d^j, \quad 0 < \delta < 1. \quad (14)$$

The least squares method leads to the system of normal equations in the form

$$b_0(t) - \frac{\delta}{1-\delta}\, b_1(t) = (1-\delta)\sum_{j=0}^{\infty} d^j\, y_{t-j}, \quad (15)$$

$$\delta\, b_0(t) - \frac{\delta\,(\delta+1)}{1-\delta}\, b_1(t) = (1-\delta)^2\sum_{j=0}^{\infty} j\, d^j\, y_{t-j}. \quad (16)$$

To simplify the notation for the system of normal equations (15) and (16), two special variables are introduced, namely:

- a simple smoothing statistic S_t defined by the expression

$$S_t = (1-\delta)\sum_{j=0}^{\infty} d^j\, y_{t-j}, \quad (17)$$

and

- a double smoothing statistic $S_t^{[2]}$ defined by the expression

$$S_t^{[2]} = (1-\delta)\sum_{j=0}^{\infty} d^j\, S_{t-j}. \quad (18)$$

After introducing the smoothing constant $\alpha = 1 - \delta$, both smoothing statistics can be rewritten in the form

$$S_t = \alpha\, y_t + (1-\alpha)\, S_{t-1}, \quad (19)$$

$$S_t^{[2]} = \alpha\, S_t + (1-\alpha)\, S_{t-1}^{[2]}. \quad (20)$$

Using these smoothing statistics, the solution of the system of normal equations (15) and (16) can be rewritten in the form

$$b_0(t) = 2S_t - S_t^{[2]}, \quad (21)$$

$$b_1(t) = \frac{a}{1-a}\,(S_t - S_t^{[2]}). \quad (22)$$

For the predictions $Y_{t+\tau}$ constructed at time t, it holds

$$\begin{aligned} Y_{t+\tau} &= b_0(t) + b_1(t)\,\tau \\ &= 2S_t - S_t^{[2]} + \frac{a}{1-a}\,(S_t - S_t^{[2]})\,\tau \\ &= \left(2 + \frac{\alpha\,\tau}{1-\alpha}\right) S_t - \left(1 + \frac{\alpha\,\tau}{1-\alpha}\right) S_t^{[2]}. \end{aligned} \quad (23)$$

If $\tau = 0$ in expression (23), the following formula applies to the smoothed value of the time series at time t

$$Y_t = b_0(t) = 2S_t - S_t^{[2]}. \quad (24)$$

The recurrent formulas (19) and (20) are used to calculate the smoothing statistics. The initial values of S_0 and $S_0^{[2]}$ are usually derived from the formulas (19) and (20), in which the regression estimates $b_0(0)$ and $b_1(0)$ of the parameters of the line intersected by the initial section of the analyzed time series are substituted.

The selection of the smoothing constant α value is limited to the interval (0; 0.3>, the most suitable value being determined similarly to the case of simple exponential smoothing – either by the empirical formula

$$\alpha = \sqrt{\frac{1}{m+1}} \tag{25}$$

or by simulation.

Triple Exponential Smoothing

It is assumed that the trend component in short time sections is described by a quadratic polynomial, i.e.

$$T_t = \beta_0 + \beta_1 t + \beta_2 t^2. \tag{26}$$

Parameter estimates, smoothed values and predictions are calculated analogously to double exponential smoothing. The derived relations are considerably more complicated, a triple smoothing statistic being defined recurrently as

$$S_t^{[3]} = \alpha\, S_t^{[2]} + (1-\alpha)\, S_{t-1}^{[3]}. \tag{27}$$

Interpolation Criteria

After estimating the parameters of the trend model from the time series y_t, $t = 1, 2, \ldots, n$, it is a matter of finding out how accurately this model fits real time series data, in other words, examining the differences between the actual y_t values of a given indicator and the corresponding smoothed Y_t values at time t, $t = 1, 2, \ldots, n$. The differences

$$e_t = y_t - Y_t \tag{28}$$

are residual estimates of the unsystematic component ε_t at time t, $t = 1, 2, \ldots, n$. The accuracy of time series smoothing is measured by average residual characteristics that can be generalized for any time series model.

Measures of Exponential Smoothing Accuracy

There are different types of prediction errors that are to be taken into account, namely the mean error

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t = \frac{1}{n}\sum_{t=1}^{n}(y_t - Y_t), \tag{29}$$

mean square error

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 = \frac{1}{n}\sum_{t=1}^{n}(y_t - Y_t)^2, \tag{30}$$

mean absolute error

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| = \frac{1}{n}\sum_{t=1}^{n}|y_t - Y_t|, \tag{31}$$

mean absolute percentage error

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{y_t}100 = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - Y_t|}{y_t}100, \tag{32}$$

and mean percentage error

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\frac{e_t}{y_t}100 = \frac{1}{n}\sum_{t=1}^{n}\frac{y_t - Y_t}{y_t}100. \tag{33}$$

The lower the values of the given characteristics, the better the selected trend function.

Durbin-Watson Test

The non-correlation (absence of autocorrelation) of the unsystematic component is tested using the first autocorrelation coefficient, the following hypotheses being explored:

H_0: $\rho_1 = 0$, no autocorrelation, i.e. $cov(\varepsilon_t; \varepsilon_{t-1}) = 0$,

H_1: $\rho_1 \neq 0$, autocorrelation, i.e. $cov(\varepsilon_t; \varepsilon_{t-1}) \neq 0$.

Table 1

Durbin-Watson Test Results

DW	Result
$4 - d_L < DW < 4$	H_0 is rejected → autocorrelation
$4 - d_U < DW < 4 - d_L$	Cannot be decided; necessary to increase n
$2 < DW < 4 - d_U$	H_0 is accepted → no autocorrelation
$d_U < DW < 2$	H_0 is accepted → no autocorrelation
$d_L < DW < d_U$	Cannot be decided; necessary to increase n
$0 < DW < d_L$	H_0 is rejected → autocorrelation

Source: Arlt, Arltova, and Rublikova (2002)

The Durbin-Watson criterion has the form

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{34}$$

and it can take values from the interval <0; 4>. The decision not to reject or reject the null hypothesis at a 5% significance level requires the determination of critical values (d_L and d_U), which are listed in Arlt, Arltova and Rublíková (2002). Durbin-Watson test results are presented in Table 1.

Residual Autocorrelation Function

The coefficients of residual autocorrelation measure the linear dependence of the time-delayed variables ε_t and ε_{t-k}. They are defined by the relation

$$R_k = \hat{\rho}_k = \frac{\sum_{t=k+1}^{n} e_t e_{t-k}}{\sum_{t=1}^{n} e_t^2} \in \langle -1; 1\rangle. \tag{35}$$

A graph in which the time delays are on the horizontal axis and the autocorrelation coefficient of residues R_k on the vertical axis is called the residual autocorrelation function. If no autocorrelation coefficient R_k exceeds the limits of the 95% confidence interval

$$\left(-\frac{2}{\sqrt{n}}; \frac{2}{\sqrt{n}}\right), \tag{36}$$

it can be assumed that the unsystematic component is not autocorrelated.

Determination Index and Adjusted Determination Index

The determination index is defined by the relation

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - Y_t)^2}{\sum_{t=1}^{n}(y_t - \bar{y})^2} \in \langle 0; 1\rangle. \tag{37}$$

The closer the value of the determination index R^2 is to one, the better the model captures the time series trend and vice versa. The drawback to the determination index lying in the fact that it depends on the number of model parameters (trend function) is eliminated by the adjusted determination index. It has the form

$$R^2_{adj} = R^2 - \frac{(1 - R^2)(k - 1)}{n - k}, \tag{38}$$

where k is the number of model parameters, i.e., the trend function.

T-Test for Model Parameters (Trend Function)

Using the t-test, the following hypotheses are verified:

H_0: $\beta_i = 0$,

H_1: $\beta_i \neq 0$, for $i = 1, 2, \ldots, k$.

The test criterion has the form

$$t_i = \frac{b_i}{s_{b_i}} \quad i = 1, 2, \ldots, k, \tag{39}$$

where b_i is the estimate of the model parameter (trend function) and s_{bi} is the estimate of the standard error of the tested parameter estimate. Assuming the validity of the null hypothesis, the test criterion (39) has a Student's t-distribution of $n - k$ degrees of freedom. The null hypothesis is rejected, the alternative hypothesis being accepted at the 100-α% significance level if the test criterion (39) value falls into the critical range

$$W_\alpha = \{t; |t| \geq t_{1-\alpha/2}(n-k)\}, \tag{40}$$

where $t_{1-\alpha/2}(n - k)$ is the 100 (1 – α/2)% quantile of the Student's t-distribution of $n - k$ degrees of freedom. If the null hypothesis is rejected, the t-test is significant, and the model is correct for the tested parameter.

Extrapolation Criteria

The extrapolation criteria are based on the division of the time series y_t, $t = 1, 2, \ldots, n$ into two parts. The first (test) part comprises n_1 observations and is used to select the trend model, estimate the parameters and verify suitability using interpolation criteria. The second part of the time series has $n_2 = n - n_1$ observations for $t = n_1 + 1$, $n_1 + 2$, $n_1 + 3$, …, $n_1 + n_2 = n$ and it is used to make predictions of a known fact (so-called ex-post predictions) and verify their accuracy. According to appropriately adjusted equations (29)–(33), ex-post prediction accuracy is evaluated using the mean error (ME), mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and mean percentage error (MPE).

For example, the ex-post ME criterion

$$ME = \frac{1}{n_2} \sum_{t=n_1+1}^{n=n_1+n_2} e_t(n_1), \tag{41}$$

is a measure of bias. If $ME > 0$, the model systematically underestimates the reality, if $ME < 0$, it overestimates the reality.

If the predictions are systematically biased, it is appropriate to examine the statistical significance of this bias using the test criterion

$$t(ME) = \frac{ME}{\dfrac{\hat{\sigma}_\varepsilon}{\sqrt{n_2}}}, \tag{42}$$

where $\hat{\sigma}_\varepsilon$ is the standard deviation of residues in the interpolation period and ME is determined using (41). Testing the null hypothesis H_0 – predictions are not systematically biased; testing against the alternative hypothesis H_1 – predictions are systematically biased. Assuming the validity of the null hypothesis, the test criterion (42) has a Student's t-distribution of $n_2 - l - 1$ degrees of freedom, where l is the degree of a polynomial of the trend function. The null hypothesis of non-biased predictions is rejected, and the alternative hypothesis of biased predictions accepted at the 100-α% significance level if the value of the test criterion (42) falls into the critical range

$$W_\alpha = \{t(ME); |t(ME)| \geq t_{1-\alpha/2}(n_2 - l - 1)\}. \tag{43}$$

Heteroscedasticity of prediction errors, which increase over time, can be verified employing the test criterion

$$F = \frac{1}{\hat{\sigma}_\varepsilon^2 \, n_2} \sum_{t=n_1+1}^{n=n_1+n_2} e_t^2. \tag{44}$$

Testing the null hypothesis H_0 – the prediction errors are homoscedastic; testing against the alternative hypothesis H_1 – they are heteroscedastic. Assuming the validity of the null hypothesis, the test criterion (44) has a Fisher-Snedecor F-distribution of n_2 and $n_1 - l - 1$ degrees of freedom. The null hypothesis of homoscedasticity of prediction errors is rejected, and the alternative hypothesis of heteroscedasticity of prediction errors accepted at the 100-α% level of significance if the value of test criterion (44) falls into the critical range

$$W_\alpha = \{F; F \geq F_{1-\alpha}(n_2; n_1 - l - 1)\}. \tag{45}$$

If the null hypothesis is rejected, prediction errors are systematically biased, and the trend model is not suitable for prediction. A suitable prognostic model based on extrapolation criteria can be applied to the whole time series y_t, $t = 1, 2, \ldots, n$ allowing predictions ex ante to be made.

Theil Inequality Coefficient (Theil Index II)

The time series were shortened by n_2 observations, and predictions for these values were made using appropriate exponential smoothing. Deviations between the predicted and actual values were calculated as

$$\Delta_t(i) = P_t(i) - y_{t+i}, \tag{46}$$

where $P_t(i)$ is the prediction of the monitored indicator performed at time t of i time units ahead (prediction horizon), and y_{t+i} is the real value of the predicted indicator at time $t + i$. These deviations are called prediction errors for a given time t and the prediction horizon i. If $\Delta_t(i) < 0$, it is the so-called underestimated prediction, if $\Delta t(i) > 0$, an overestimated prediction occurs.

A very frequent measure of the variability of relative prediction errors is the Theil inequality coefficient (II)

$$T_H^2 = \frac{\sum_{t=n_1+1}^{n=n_1+n_2} [P_t(i) - y_{t+i}]^2}{\sum_{t=n_1+1}^{n=n_1+n_2} y_{t+i}^2}. \tag{47}$$

This index can take only non-negative values, acquiring a lower zero limit in the case of error-free predictions when $P_t(i) = y_{t+i}$. The more the Theil inequality coefficient deviates from zero, the more the prediction differs from ideal error-free predictions.

The square root of the Theil index

$$T_H = \sqrt{\frac{\sum_{t=n_1+1}^{n=n_1+n_2} [P_t(i) - y_{t+i}]^2}{\sum_{t=n_1+1}^{n=n_1+n_2} y_{t+i}^2}} \tag{48}$$

can be interpreted as a relative prediction error.

Results

Figures 1 and 2 illustrate the development of the average wage and GDP in the Czech Republic between 1990 and 2018, both at current prices in the given year and at prices after conversion to purchasing power parity (PPP) as of 1990. These figures also show the development of the rate of inflation, which peaked in the transformation period, reaching 56.6 and 20.8 % in 1991 and 1993, respectively.

The overall growth of GDP and average nominal wage at current prices is relatively fast throughout the monitored period. After converting to the PPP of the population relative to the 1990 price level, however, a marked drop in the average wage and GDP in the early 90s becomes apparent. The 2009 decline in GDP is clearly seen in Figure 2. While GDP at current prices was growing year on year in the following period, GDP converted to the 1990 PPP value continued to go down until 2013. This was triggered by the 2008 financial crisis that pushed the economy further into recession leading already in 2009 to a 3.3% decline in the Czech economy. Only mild signs of recovery appearing, GDP growth did not exceed 1.8 % until 2013. The threat of a double-dip recession announced by economists in 2010 became real, its long-term effects being more harmful than the 1997–1998 economic downturn. The wage level reacted to the onset of the recession with some delay as seen in Figure 1, the average wage showing only slight fluctuations.

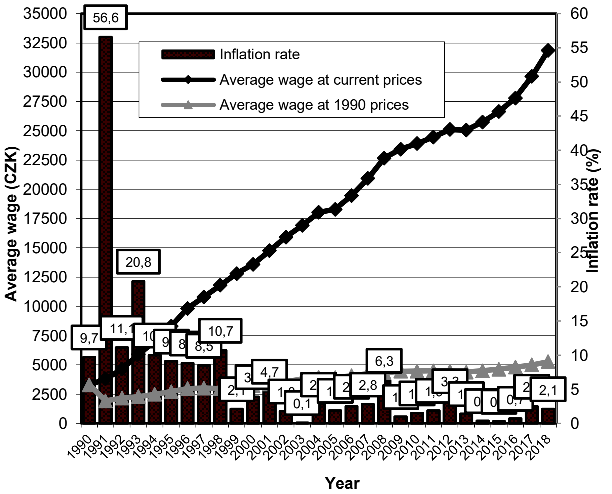

Figure 1. Average wage development since 1990

Source: Own research

Figure 3 shows the average price growth rates of the selected foods since 1990. High price volatility is clearly visible. (An extreme example is ware potatoes. In 1994, consumers paid an average of 161 % more per kilogram of potatoes than in 1993, and in 1996 almost 45 % more than in the previous year. After a price jump of more than 77 % in 2003, there was a steep decline of over 53 % in 2004. Having increased sharply by almost 130 % in 2006, the average price of potatoes decreased by nearly 38 % in the following year. Compared to 2009, the price soared again in 2010, this time by over 70 %, falling by more than 41 % the following year.) As illustrated in Figure 4, growth rates of average prices of clothing and footwear are on average lower than those of foodstuffs. Their development is free of significant fluctuations (except for the prices of walking shoes and women's winter coats and summer dresses at the beginning of the monitoring period). The same applies to consumer goods and fuels whose average prices grew at a reasonable rate throughout the research period as can be seen in Figure 5. (Higher volatility was recorded only for refrigerators, men's mountain bikes, pencil batteries and diesel fuel.)

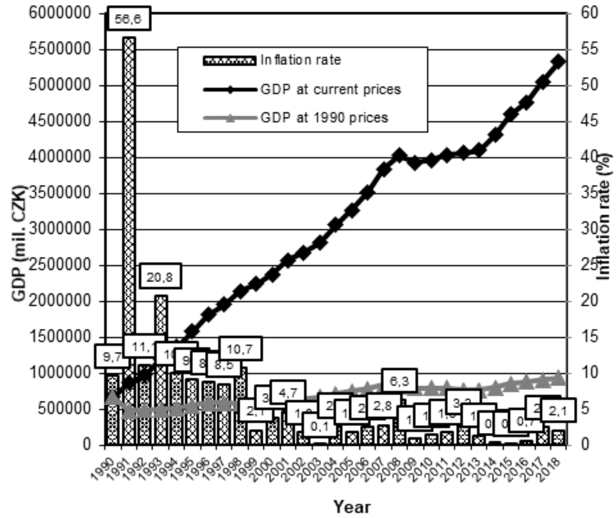

Figure 2. GDP Development Since 1990

Source: Own research

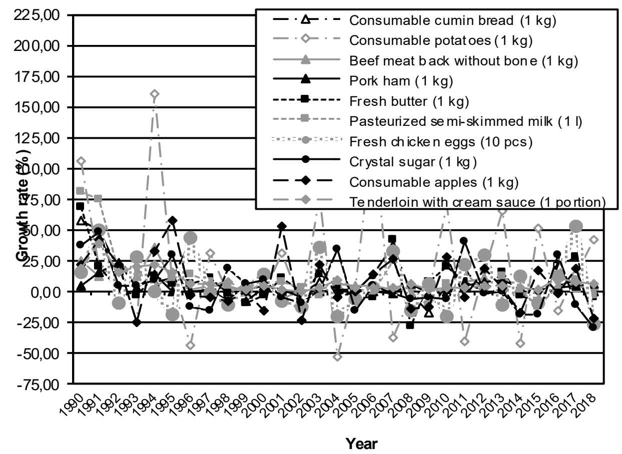

Figure 3. Average Price Growth Rates of Foods Since 1990 (in %)

Source: Own research

Figure 6 provides data on the development of average prices of some public, cultural and gastronomic services. Price developments were relatively stable for most of the reference period, the most dramatic fluctuations occurring at the onset of social transformation in the early 1990s. (In 1991, for instance, waste disposal charges and public transport fares increased by 211 % and 188 %, respectively, compared to the previous year, waste collection services becoming more expensive by over 91 % in 1993, too. In 1992, the average price of postage increased by 200 % and gentlemen also paid extra 80 % at the barber between 2010 and 2011.)

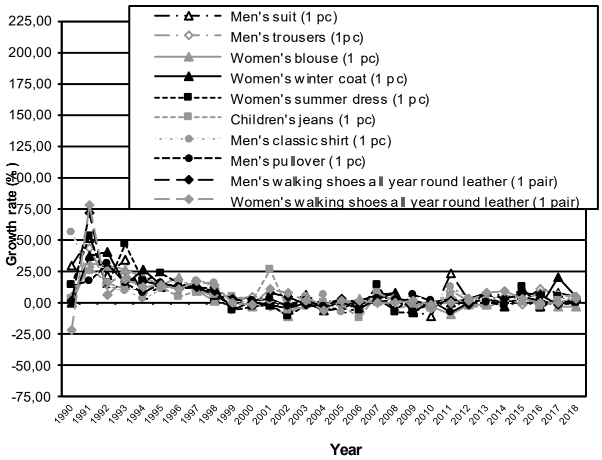

Figure 4. Average Price Growth Rates of Clothing and Footwear Since 1990 (in %)

Source: Own research

Tables 2–5 document the development of the purchasing power of the population of the Czech Republic from 1990 to the present at ten-year intervals. Table 2 presents the amount of the selected food items that could be purchased for an average wage. (For example, people could buy on average only 935 kilograms of consumable cumin bread in 2000, compared to 1,174 kg in 1990 and 1,289 kg in 2018. As regards pork ham, e.g., while in 1990 consumers could buy only 33 kg for an average wage, in 2018 it climbed to 157 kg.)

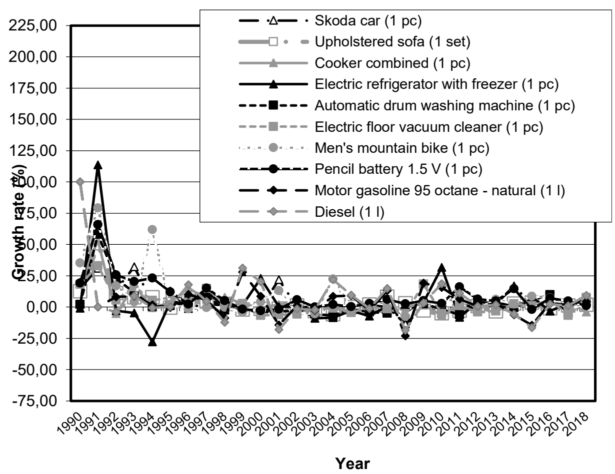

Figure 5. Average Price Growth rates of Consumer Goods and Fuels Since (in %)

Source: Own research

Table 3 maps the purchasing power in terms of clothes and footwear. (While in 1990, for example, men could buy an average of 3,402 suits and women 11,207 summer dresses, in 2018 it was already 4,539 and 30,270 pieces, respectively.)

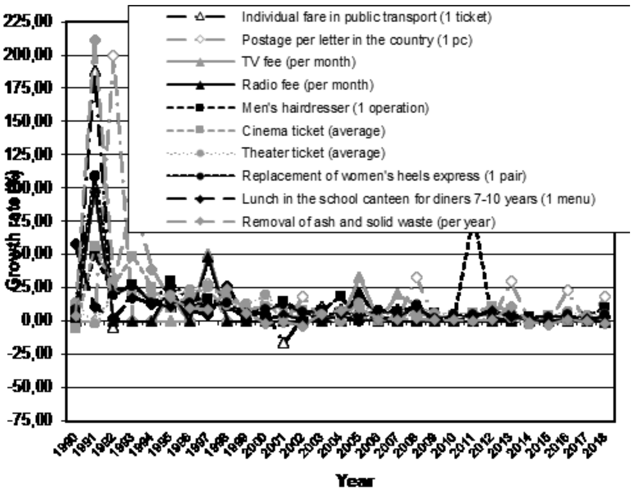

Figure 6. Average Price growth rates of Services and Cultural and Gastronomic Experiences Since 1990 (in %)

Source: Own research

Table 4 gives an overview of the purchasing power in the sphere of consumer goods and fuels. Since these are usually more expensive items, for some of them (marked with the upper index 1) it is stated how many average wages are needed to purchase them. (For example, in 1990, people had to save an average of 25.75 full wages so that they could buy one Skoda car, while in 2018 it was only 9.15 full wages.) It is clear from the table that throughout the period, inflation in the electronics sector was very low and the purchasing power of the population grew considerably, which also applies to the fuel sector. (In 2010 and 2018, for example, customers could buy an average of 2.444 and 3.024 automatic washing machines, respectively, for one average wage. Statistically, in 1990, people could buy on average 438 liters of diesel fuel for one wage, while in 2018, it was 1,073 liters.)

Table 2

Purchasing Power – Foods

Item	Number of items that can be purchased for an average wage			
	1990	**2000**	**2010**	**2018**
Consumable cumin bread (1 kg)	1,174	935	1,273	1,289
Consumable potatoes (1 kg)	2,054	1,885	2,612	2,219
Beef meat back without bone (1 kg)	71	98	134	150
Pork ham (1 kg)	33	87	155	157
Fresh butter (1 kg)	82	144	213	147
Pasteurized semi-skimmed milk (1 l)	1,643	1,152	1,560	1,568
Fresh chicken eggs (10 pcs)	253	531	878	638
Crystal sugar (1 kg)	450	667	1,251	1,791
Consumable apples (1 kg)	469	733	1,103	908
Tenderloin with cream sauce (1 portion)	289	315	419	407

Source: Own research

Table 3

Purchasing Power – Clothing and Footwear

Item	Number of items that can be purchased for an average wage			
	1990	**2000**	**2010**	**2018**
Men's suit (1 pc)	3.402	2.815	4.854	4.539
Men's trousers (1 pc)	8.990	11.260	21.389	22.984
Women's blouse (1 pc)	12.473	13.536	31.272	45.998
Women's winter coat (1 pc)	2.755	2.796	5.936	5.941
Women's summer dress (1 pc)	11.207	8.937	25.221	30.270
Children's jeans (1 pc)	17.762	29.239	49.469	70.694

Item	Number of items that can be purchased for an average wage			
	1990	2000	2010	2018
Men's classic shirt (1 pc)	26.742	27.571	47.217	50.669
Men's pullover (1 pc)	11.836	15.630	29.625	43.200
Men's walking shoes - all-year-round, leather (1 pair)	9.441	10.203	16.740	19.480
Women's walking shoes - all-year-round, leather (1 pair)	8.647	11.525	18.657	21.876

Source: Own research

Table 4

Purchasing Power – Consumer Goods and Fuels

Item	Number of items that can be purchased for an average wage			
	1990	2000	2010	2018
Skoda car (1 pc)	25.75[1]	16.96[1]	9.54[1]	9.15[1]
Upholstered sofa (1 set)	2.97[1]	1.72[1]	1.022	1.419
Cooker combined (1 pc)	1.08[1]	1.331	2.762	3.699
Electric refrigerator with freezer (1 pc)	1.76[1]	1.361	2.629	2.457
Automatic drum washing machine (1 pc)	1.81[1]	1.07[1]	2.344	3.024
Electric floor vacuum cleaner (1 pc)	2.42	3.56	7.33	10.71
Men's mountain bike (1 pc)	2.15	1.95	2.55	2.49
Pencil battery 1.5 V (1 pc)	2,347	1,934	2,789	2,212
Motor gasoline 95 octane - natural (1 l)	411	523	840	1,047
Diesel fuel (1 l)	438	612	887	1,073

Source: Own research

Table 5 reflects on the purchasing power in terms of services and cultural and gastronomic experiences. (Public transport and postage in particular were extremely cheap in 1990. While a person could travel 3,286 times by public transport on average and send the same number of letters for one wage, in 2018 it was only 2,610 public transport rides and 1,992 letters. For a common customer, prices developed unfavorably, which also applies to most items in cultural and catering services, except for meals in school canteens and television and radio fees.)

Table 5

Purchasing Power – Services and Cultural and Gastronomic Experiences

Item	Number of items that can be purchased for an average wage			
	1990	2000	2010	2018
Individual fare in public transport (1 ticket)	3,286	2,108	2,395	2,610
Postage per letter in the country (1 pc)	3,286	2,955	2,390	1,992
TV fee (per month)	131	181	177	236
Radio fee (per month)	329	367	531	708
Men's hairdresser (1 operation)	469	345	279	173
Cinema ticket (average)	448	251	270	257
Theatre ticket (average)	137	126	114	119
Replacement of women's heels express (1 pair)	411	247	223	217
Lunch in the school canteen (7–10 years) (1 menu)	865	936	1,239	1,377
Removal of ash and solid waste (per year)	54	11	15	18

Source: Own research

Table 6

Forecasts of Average Gross Monthly Nominal Wage (in CZK) and GDP at Current Prices (in mil. CZK) – Pessimistic Variant

Indicator	Year				
	2019	2020	2021	2022	2023
Average wage	33,325	35,170	37,015	38,859	40,704
GDP	5,573,651	5,837,185	6,100,724	6,364,256	6,627,798

Source: Own research

Table 7

Forecasts of Average Gross Monthly Nominal Wage (in CZK) and GDP at Current Prices (in mil. CZK) – Optimistic Variant

Indicator	Year				
	2019	2020	2021	2022	2023
Average wage	35,377	39,273	43,854	49,118	55,067
GDP	5,908,652	6,490,815	7,173,969	7,958,084	8,843,197

Source: Own research

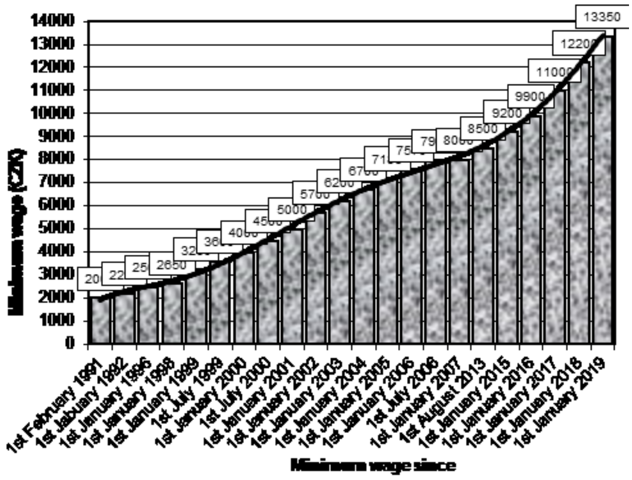

Figure 7. Minimum Wage (in CZK) Ssince its Introduction

Source: Own research

Documenting the development of the minimum wage and the subsistence minimum since their introduction, Figures 7 and 8, respectively, indicate that neither of these indicators has been regularly valorized, the sections of different lengths for both of them being clearly visible on the horizontal and vertical axes, respectively. It can be seen, for example, that the minimum wage did not change at all from January 2007 to July 2013, i.e., roughly over the period of global economic downturn, remaining at CZK 8,000. The subsistence minimum also kept stagnating (at CZK 3,126) until the end of 2011.

[1]Number of average wages needed for the purchase of one piece.

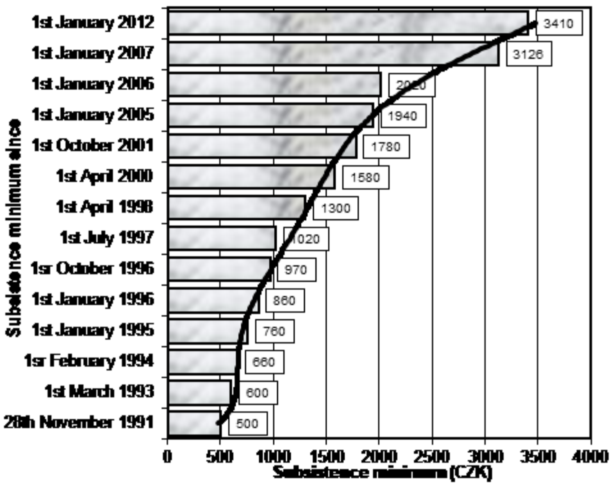

Figure 8. Subsistence Minimum for a One-person Household (in CZK) Since its Introduction

Source: Own research

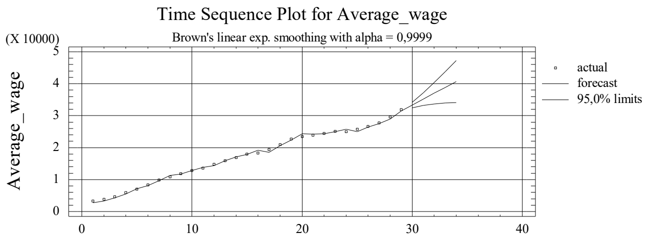

Figure 9. Brown's Linear Exponential Smoothing for Aaverage Wage Time Series – Pessimistic Variant

Source: Own research

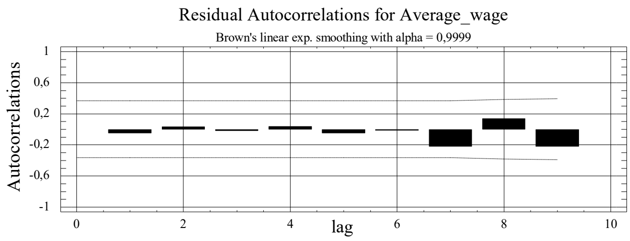

Figure 10. Sample Residual Autocorrelation Function for Average Wage Time Series – Pessimistic Variant

Source: Own research

Figure 9 shows the Brown's linear exponential smoothing model of the average wage trend used to extrapolate (rather pessimistic) predictions based on the developments up to 2023. Figures 10 and 11 present sample residual autocorrelation and partial autocorrelation functions applied to check the suitability of the model. (This was also verified using the techniques described in the second section of the paper.)

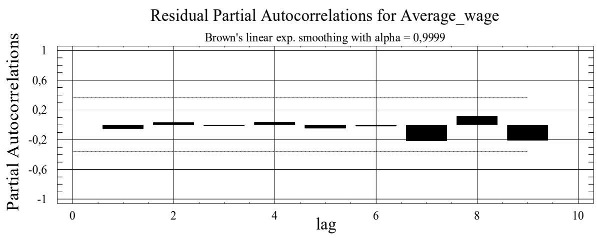

Figure 11. Sample Residual Partial Autocorrelation Function for Average Wage Time Series – Pessimistic Variant

Source: Own research

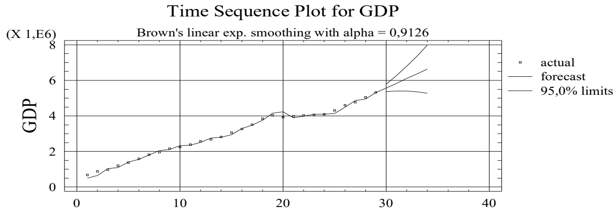

Figure 12. Brown's Linear Exponential Smoothing for GDP Time Series – Pessimistic Variant

Source: Own research

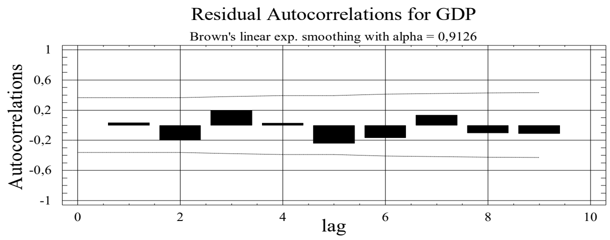

Figure 13. Sample Residual Autocorrelation Function for GDP Time Series – Pessimistic Variant

Source: Own research

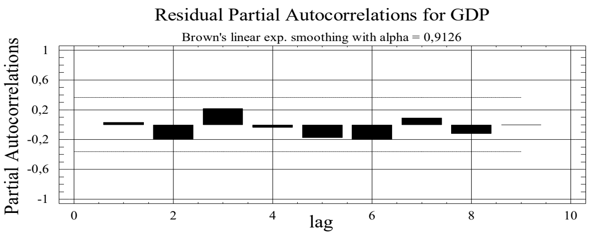

Figure 14. Sample Residual Partial Autocorrelation Function for GDP Time Series – Pessimistic Variant

Source: Own research

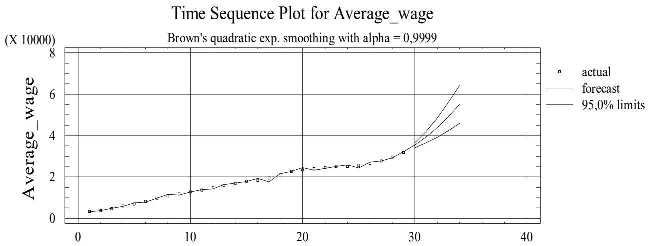

Figure 15. Brown's Quadratic Exponential Smoothing for Average Wage Time Series – Optimistic

Source: Own research

Similarly, Figure 12 shows Brown's linear exponential smoothing used to model the trend of GDP time series and its pessimistic forecast variant. Figures 13 and 14 again present the sample residual autocorrelation and partial autocorrelation functions. The respective predictions of the average wage and GDP in a pessimistic variant up to 2023 are displayed in Table 6, Table 7 reporting the same in an optimistic variant. The corresponding Brown's quadratic exponential smoothing models of average wage and GDP trends as well as the subsequent optimistic variants of predictions up to 2023 are plotted in Figures 15 and 16.

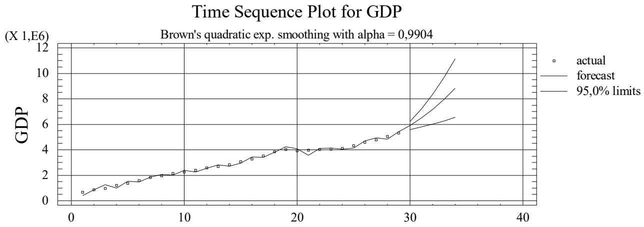

Figure 16. Brown's Quadratic Exponential Smoothing for GDP Time Series – Optimistic Variant

Source: Own research

Table 8

Seasonal Deviations of Unemployment Time Series Additive Model (in %)

Quarter of a year	1st quarter	2nd quarter	3rd quarter	4th quarter
Seasonal deviations	0.21838	-0.16464	0.01524	-0.06898

Source: Own research

Table 9

Forecasts of Unemployment Rate Time Series (in %) – Pessimistic Variant

Quarter of a year	Year				
	2019	2020	2021	2022	2023
1st quarter	2.839	4.267	6.840	10.557	15.418
2nd quarter	2.706	4.420	7.279	11.282	16.429
3rd quarter	3.207	5.207	8.352	12.641	18.075
4th quarter	3.516	5.802	9.233	13.808	19.528

Source: Own research

Table 10

Forecasts of Unemployment Rate Time Series (in %) – Optimistic Variant

Quarter of a year	Year				
	2019	2020	2021	2022	2023
1st quarter	2.314	2.252	2.191	2.130	2.070
2nd quarter	1.915	1.854	1.793	1.732	1.672
3rd quarter	2.080	2.019	1.958	1.897	1.836
4th quarter	1.981	1.919	1.859	1.798	1.752

Source: Own research

As regards the rate of unemployment, there is an additive seasonal time series of the length four, the amplitude of the seasonal fluctuation remaining relatively constant over time. In this case, seasonality is described by seasonal deviations as shown in Table 8.

Using the time series trend model, seasonally adjusted time series forecasts for the twenty periods ahead (until 2023) were constructed. Finally, seasonal deviations were added to those forecasts. Pessimistic and optimistic variants of quarterly predictions of the unemployment rate until 2023 are listed in Tables 9 and 10, respectively.

Conclusion and Discussion

GDP, the average wage and the rates of unemployment and inflation are commonly used to internationally compare and evaluate long-term socio-economic trends. The present paper outlines the development of selected macroeconomic indicators in the former Czechoslovakia and the successor Czech Republic from the state-to-market-economy transition throughout the periods of the currency and financial crisis in 1997 and 2008, respectively, and the economic downturn aftermath, the current crisis caused by the covid pandemic not being covered as the necessary data are not available yet. The research shows the effect of crisis fluctuations on individual indicators and their subsequent development.

The Czech Republic's GDP at current prices exhibits an upward trend with an average annual growth rate of 7.66 % per year for the entire period analyzed. Year-on-year decline in GDP is recorded only in 2009, specifically by 2.33 % compared to 2008, presumably in connection with the onset of the global economic crisis. The rapid pace of GDP growth is evident especially at the beginning of the economic transformation in 1991, 1992 and 1993, when GDP grew by 29 %, 12 % and 23 % year-on-year, respectively. However, data on inflation and GDP in 1990 suggest that the sharp rise in GDP in the period immediately after 1990 is mainly due to rising price levels, the 1991 year-on-year inflation rate exceeding 56 %, and GDP at 1990 prices falling by 28 % in 1991, stagnating or showing only a creeping growth in the following period. A slight decline in GDP at 1990 prices – around 1 % year-on-year – is evident in 1997 and 1998, which is probably due to the onset of the currency crisis in the Czech Republic in 1997. This decline continued more significantly between 2008 and 2013 (in 2009 even by more than 3 % year-on-year), which may be related to the onset of the 2008 financial crisis that later turned into an economic downturn. Closely related to the development of GDP at current prices is that of the inflation rate, which did not fall below 8.5 % year-on-year until 1998, having even exceeded 56 % and 20 % in 1991 and 1993, respectively. At the turn of the millennium, the inflation rate stabilized and the year-on-year value of over 6 % was not reached until 2008 at the dawn of the economic downturn.

Inflation rate changes in the 1990s are also related to the development of the average wage at current prices, which grew considerably by 15 %, 22 % and 27 % year-on-year in 1991, 1992 and 1993, respectively, its growth not falling below 18 % over the period 1994–1996, the average annual increase in the average wage throughout the 1990s being almost 14 %. The growth of the average wage in the Czech Republic practically stopped over the 2010–2014 period, which can be explained by the impact of the global economic downturn, taking into account the delay with which wages react to the economic situation. Within the last decade examined, the development of the average wage at 1990 prices can be described as stagnant. (Also having stagnated for a long time, the minimum wage remained at CZK 8,000 between 2007 and 2013. Its substantial increase to CZK 15,200 did not occur until 2021, which, however, is not covered by the present analysis.)

The dynamics of the labor market is significantly affected by the rate of unemployment. Until the 1997 currency crisis, it did not exceed 5 %. Since then, however, the unemployment rate has gained momentum, reaching almost 10 % in 2000. Having fallen slightly to around 7 % in 2002, unemployment was ranging from 7 % to 9 % over the next five years. After decreasing to about 4 % in 2008, it rose again to 8 % in 2010. In the 2010s, the rate of unemployment fluctuated, following a declining trend down to 2 % in 2018.

An equally important benefit of this research are the forecasts of selected economic indicators for the period up to 2023, whose optimistic and pessimistic versions are based on developments in the previous period. This approach will make it possible to quantify the effects of the current coronavirus crisis on the development of the indicators examined.

The Czech Republic has moved significantly forward economically in the last three decades. The path to a market economy was not smooth, with many traditional businesses and several banks disappearing. The transformation also brought about a considerable redistribution of wealth, timely and reliable information playing an important role. Accompanying difficulties having been overcome, in 2018, the Czechs were enjoying a period of the greatest economic prosperity in their history.

The Czech Republic's accession to the European Union in May 2004 was the most significant event since 2000. The promise of joining the EU accelerated the inflow of foreign capital, especially from the Netherlands, Germany, Austria and the U.S. The Czech economy then showed solid GDP growth until the outbreak of the global financial crisis in 2008. In 2012, the Czech Republic surpassed the first "old" EU country, namely Portugal, in terms of GDP per capita, and shortly afterwards it got ahead of Greece.

Overall economic performance will decline due to the COVID-19 pandemic reverberations. Many companies will not restart their business, others will only survive at the cost of significant losses. A short-term decline in GDP, rising unemployment and stagnant wages are expected. Although current figures do not indicate major downward changes in the economic trend, there are some elevated risks whose impacts cannot be quantified at present. The economic forecasts presented in this paper are therefore given in two – optimistic and pessimistic – variants, both based on the assumption of maintaining the conditions of the current development. Other predictions cannot be currently quantified. The impact of the coronavirus crisis on the performance of the Czech economy cannot yet be measured. In the near future, however, the present forecasts will make it possible to compare the economic development at the time of the pandemic with that predicted on the basis of past data, thus exploring the effect of COVID-19 on the Czech economy.

Subsequent research will focus on evaluating the further development of indicators by comparing their predictions with the reality, outlining the perspective of the post-pandemic economy in the Czech Republic. Another line of future research is a similar analysis of economic indicators in the Visegrad Four countries and a comparison of the impacts of economic and health crises on V4 economies.

The economic situation of Czechoslovakia in the early 1990s was generally favorable compared to other post-communist countries. However, it was marked by the technological backwardness and a considerable structural burden due to cumbersome central state planning. Unlike Hungary and Poland, the then Czechoslovakia had a balanced government budget and a low monetary surplus. Thus, there was a relatively reasonable basis for rapid liberalization and stabilization without the risk of widespread inflation. Microeconomic conditions, on the other hand, were problematic. Centralized management and planning, including pricing policy, and the lack of modern business management bore nothing but the risk of a dramatic decline.

Poland experienced socio-economic destabilization in the 1980s due to the depression, high inflation and supply chain problems. After the change of political regime, the Polish economy continued to face structural difficulties (unprofitable coal mining, high share of agricultural workers and heavy engineering, etc.), which required fundamental reforms through immediate market liberalization accompanied by stabilization measures (budgetary and monetary restrictions, wage regulation and currency fixation against the US dollar).

In terms of economic reforms, Hungary was in a different position than Czechoslovakia and Poland in 1990. State-controlled prices were deregulated and private enterprise on the basis of free-market pricing was allowed as early as the 1980s. The advantage of Hungary was also a more suitable structure of the economy, which corresponded to its dispositions, imposing a minimal burden on the environment. However, there was a high external debt, significant currency surplus and economic imbalance caused by a double deficit in the government budget and trade balance, foreign capital playing a major role in the two-phase privatization.

A comparison of the neighboring V4 countries suggests that starting positions of their transforming economies were different, their subsequent development taking different paths as well. Using universal mathematical-statistical methods, the present paper explores the quantifiable development and predictions of macroeconomic aggregates for the Czech Republic only, not allowing broader generalization of the findings. A general aspect of this research is the reflection of crisis factors' effects on the economy over the past three decades. The relevance and scope of the impact assessment remain an issue for follow-up research.

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