STATISTIKA

STATISTICS AND ECONOMY JOURNAL

VOL. **103** (3) 2023

CZECH STATISTICAL OFFICE

Dear Readers,

We are happy to introduce this joint Czech-Hungarian *Statistika* issue, containing eight analyses, four from each country. After the previous publication of the common Czech-Slovak and Czech-Polish *Statistika* issues (No. 4/2019 and No. 3/2022) this instalment brings to completion the V4 cooperation in this scientific area, on the pages of the *Statistika* journal (granded by an Impact Factor this year, another fact to celebrate).

By this we would like to strengthen the international scientific cooperation, commemorate events, developments and current state and quality of research in official statistics. On the occasion of the Czech V4 Presidency in the second half of this year, we also consider its publication as a confirmation of a very successful cooperation of our national statistical offices and particularly between our two countries.

It is our hope that the papers published in this special issue will be interesting and beneficial for all its readers. We are looking for further cooperation (not only) with authors (and reviewers) from our two countries, and wish all our colleagues, partners, and collaborators plenty of creative thoughts and professional success.

Marek Rojíček
President, Czech Statistical Office
Prague

Áron Kincses
Hungarian Central Statistical Office
Budapest

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The Czech Statistical Office is an official national statistical institution of the Czech Republic. The Office´s main goal, as the coordinator of the State Statistical Service, consists in the acquisition of data and the subsequent production of statistical information on social, economic, demographic, and environmental development of the state. Based on the data acquired, the Czech Statistical Office produces a reliable and consistent image of the current society and its developments satisfying various needs of potential users.

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The Relationship between Monetary Aggregates and Inflation – the Case of the Czech Republic

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Received 4.4.2023, **Accepted** (reviewed) 2.5.2023, **Published** 15.9.2023

Abstract

Based on empirical data, this paper attempts modelling, in general terms, the relationship between money supply and inflation, i.e., the relationship between the inflation rate and monetary aggregates. Our basic idea is to estimate time-shift parameters and, subsequently, a leading indicator that would provide information on whether and with what delay changes in the money supply will be reflected in the price level evolution. The aim of the paper is to formulate and, on the basis of the data, to confirm or refute the hypothesis that changes in the value of monetary aggregates imply changes in the inflation rate and, therefore, whether or not monetary aggregates are certain indicators signalling further evolution of the inflation rate. Monthly data for the Czech Republic from the years 2002–2022 have been used to model and test our hypotheses. The analysis has failed to show a statistically significant relationship between the individual monetary aggregates and the inflation rate.[4]

Keywords	***DOI***	***JEL code***
Consumer price index, monetary aggregates, time lag, regression dynamic model, estimation of dependence intensity at a given lag	*https://doi.org/10.54694/stat.2023.14*	*C22, E31, E58*

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[4] This paper has been prepared under the Institutional Support for Long-Term and Conceptual Development of Research at Faculty of Informatics and Statistics, Prague University of Economics and Business.

INTRODUCTION

The high inflation rate in (not only) the Czech Republic in 2022 has raised a number of questions about the causes of price increases in this period, as well as about the differences between this period and other periods characterised by dramatic changes in inflation rate values. This approach also raises a broader economic issue of the monetary policy tools and the effectiveness of inflation targeting in unfavourable and, more recently, often very non-standard economic conditions. It also seems to have been changing the view of the relationship between price levels and the money supply and demand.

The theory of economic liberalism is based on the idea that a high inflation rate in the long run is caused by excessive growth of the money supply. However, the opposite view is also held, that growth in the money supply and deferred purchasing power do not primarily cause the price level to rise because they are not the cause but the effect of economic activity. The question then arises as to whether or not increased money supply (so-called quantitative easing, even in the broader international context) by central banks is a significant cause of price increases. Or whether the rise in the price level (as expressed by the inflation rate) is rather the result of other economic processes caused by specific phenomena at a given stage in the development of a national economy (such as wars, disasters, shortages of raw materials and supplies in supply chains, etc.). In other words, whether the growth of the money supply is not a cause but, in fact, a consequence of rising prices.

In this context, the aspect of time must also be considered. As we noted above, economists often talk about long-term high (or moderate) inflation when discussing the relationship between money supply and the inflation rate. But what is the measure of this 'long-term' aspect? It is clear that when prices rise due to a one-off price shock (a price spike in oil, gas, etc.), we cannot talk about a long-term high inflation rate in the sense of its definition. Nevertheless, such spikes are dramatically reflected in price movements for a wide range of goods and services and will be reflected in the inflation rate. The question is, of course, to what extent and for how long. And also to what extent they will disrupt the overall performance of the economy, particularly its fiscal parameters, which in turn must be reflected in the inflation rate.

This demand-side cause of the price level rise leads us to another idea. If input prices (of raw materials, energy, etc.) go up, output prices rise as well. This is soon reflected in the rise in final consumption prices and, consequently, in the rise of the consumer price index-based inflation rate. The fast-onset effect is then represented by problems in the household economy; households' standard of living falls when consumption prices rise rapidly. In such a situation, governments try to mitigate the impact of high price levels on households by increasing social benefits and introducing other measures to support low-income households. Moreover, because these measures are often not effectively targeted, they generally lead to massive inflows of money, even into segments of the economy where it is not strictly necessary. This phenomenon causes a rapid increase in general government spending and leads to a growing deficit. And, of course, it also leads to an increase in the volume of money in circulation, i.e., to an increased money supply. This is, in turn, reflected in the growth of monetary aggregates, which are indicators of the money supply or the amount of money in the economy. This is also the nature of the current inflation trend in the Czech Republic. However, is this just a short-term effect of rising input prices, or can we talk about a longer-term relationship between the inflation rate and monetary aggregates? Even in the sense that the high price level is the cause for the growth of the money supply, not its consequence.

So what is the true direction of the relationship between the money supply and the price level? Is price growth, as expressed by the inflation rate, a consequence of or a cause for the changes in the values of monetary aggregates? Or is it the ground truth that no statistically significant relationship between the evolutions of these variables can be meaningfully modelled?

We will try to answer these questions by analysing monthly data on the inflation rate and money supply (i.e., individual monetary aggregates) in the Czech Republic for the period 2002–2022.

1 STATE OF THE ART

A number of authors have addressed the relationship between inflation rates and monetary aggregates. The impact of the development of monetary aggregates or central bank interest rates on economic variables – employment, inflation rate, GDP, etc. – is used to assess the effectiveness of central bank's monetary policy. The relationship between the inflation rate and the evolution of individual monetary aggregates is probably one of the most frequently discussed topics regarding the existence of a dependency, but the conclusions of such discussions can certainly not be regarded as clear-cut.

The basic idea of the relationship between the evolution of monetary aggregates (which represent the money supply) and the evolution of prices (the inflation rate) is based on the quantity theory of money, which defines a direct relationship between the money supply and inflation.[5] According to this theory, an increase in the amount of money in the economy causes prices to rise (Friedman and Schwartz, 1963) and the amount of money in circulation affects prices through its impact on demand. This theory then formed the basis of the practical monetary policies applied by central banks (after WWII), whereby these institutions tried to predict and influence prices by restricting or increasing the money supply. However, this tool has been gradually proven to be ineffective and unreliable (especially in the short run) and central banks switched to direct inflation targeting. Guéné (2001) comments that strictly monetarist policies had already (i.e., by 2001) been virtually abandoned.

Questioning the direct relationship between the evolution of monetary aggregates and inflation has also resulted in analysts' efforts to confirm or refute this basic postulate of monetarism. Various models of temporal and spatial analysis have been applied to this end.

Using U.S. data, Halsag (1990) analysed the relationship between the monetary base (aggregate M0), aggregates M1 and M2, and price evolution. He concluded that the M0 and M2 aggregates, but not the M1 aggregate, appear to be useful for predicting the inflation rate. Guéné (2001), based on a detailed analysis of Eurozone data, concludes that price changes are (in the short run) only insignificantly explained by changes in the volume of monetary aggregates. He also argues that the quality of the predictive model used could be improved by incorporating asset price changes into the inflation rate.[6] Mischkin (2001) analyses the evolution of monetary policy in developed countries[7] in the context of inflation targeting. He concludes that monetary inflation targeting has proved successful in Germany and Switzerland, but not in other countries. The same conclusions for the case of Switzerland can be found in Baltensperger (2001), or Kirchgassner and Wolters (2010); Jordan and Peytrignet (2001) consider that the aggregate M3 (compared to M1 and M2) has been shown to have a better predictive power. A study by Černohorská and Maléř (2019) is based on an analysis of data from Switzerland, the Czech Republic and Israel to prove or disprove the hypothesis of the predictive ability of the M3 aggregate with regard to the inflation rate. The authors' choice of this trio of countries was driven by the central banks' decisions to introduce foreign exchange interventions, which naturally led to an increase in the value of the M3 monetary aggregate. Using co-integration analysis, they concluded that a long-term relationship between the evolution of the M3 aggregate and the inflation rate was not demonstrated in any of the countries studied. The impact of foreign exchange interventions as a monetary policy instrument on the evolution

[5] In the case of the relationship between money supply and inflation, we refer to the so-called equation of exchange derived by J. S. Mill in 1948. It holds that $M \cdot V = P \cdot Q$, where M is the money supply, V is the quantity of money, P is the price level, and Q is the quantity of goods and services.

[6] The problem of the absence of assets (houses and apartments purchased by households) in the consumer price index basket has become a subject of debate, especially in the context of their prices rising faster than those of short- and long-term consumption items after the 2008–2009 crisis. As a result, inflation rates in a number of countries now also take housing price developments into account.

[7] The U.S.A., Canada, the U.K., Germany, Switzerland, New Zealand, and Australia.

of the inflation rate was also examined by Fratzscher et al. (2019) on a sample of 33 countries. The authors conclude that money supply growth due to foreign exchange intervention does not significantly affect the inflation rate.

De Gregorio (2002) uses the example of twenty countries to show that even a very rapid growth in monetary aggregates is not necessarily associated with an increase in the inflation rate and that the time-series relationship between the inflation rate and monetary aggregates (specifically M1 and M2) appears to be significant only in years of high inflation. When the inflation rate is low, the dependence turns out to be statistically insignificant. In this context, King (2001) argues that the dependence of changes in monetary aggregates and inflation rates observed over a long time horizon becomes insignificant as the period under evaluation becomes shorter. On the other hand, he is concerned about the denial of monetarist principles and the neglect of the role of monetary aggregates in central banks' monetary policy models. Hale and Jorda (2007), based on an analysis of historical time series of monetary aggregates and inflation rates in the U.S. and the Eurozone, showed that, in the case of the U.S., monetary aggregates have virtually zero predictive power for forecasting the inflation rates; in the case of the Eurozone, their results were inconclusive. Woodford (2002) reached similar conclusions regarding the situation in the U.S.

Ramos-Francia, Noriega and Rodriguez-Perez (2017), on the basis of an extensive econometric analysis of data for Mexico from 2001–2014, show that money supply affects the price level only in the long run, but does not affect short-term deviations from that level. The predictive power of monetary aggregates is thus minimal for short-term forecasts of inflation rates. The problem of the inflation rate's volatility in relation to the evolution of monetary aggregates was addressed by Papadia and Cadamuro (2021). They confirmed the logical conclusion that, if the inflation rate is more or less stable (i.e., around the 2% target), the predictive ability of monetary aggregates is zero, and the variables under consideration appear to be independent of each other. They thus quite rightly called into question the general validity of the monetarist thesis of a "functional" relationship between monetary aggregates and the inflation rate. Monetary aggregates can help predict inflation rates only in the context of an unstable economy, unstable from the monetary and inflation-rate viewpoints (e.g., Italy in the 1970s and 1980s). A study by Csiki (2022) conducted on data for the U.S. over the period 2007 through 2022, looked at monetary expansion in the context of asset purchases after the 2008 crisis and partly during the COVID-19 pandemic. Money supply growth due to the asset purchase program and non-realised demand during the pandemic raised concerns about price increases. Using a vector autoregression model, the author showed that significant changes in monetary aggregates are built into inflation expectations and that asset purchase programs helped the central bank achieve its medium-term inflation target.

The specific situation of developing countries in terms of monetary inflation targeting was described and analysed by Abango, Yusif and Issifu (2019). Using data for Ghana in the period 1970 through 2015 and using an autoregressive distributed lag (ARDL) model, they showed that monetary inflation targeting implied keeping inflation rates in the lower band only in the short run. In contrast, direct inflation targeting proved to be more effective in keeping inflation rates lower in the long run. At the same time, they pointed out that it was difficult to stably keep the inflation rate within the target band in Ghana.

The view we mention in the introduction, namely, that the inflation rate may be an explanatory rather than the response variable in the relationship between the evolution of monetary aggregates and the inflation rate is, for example, held by Murayama (2017). Using Japan as an example, he shows that money supply growth is not a cause but a result of price growth. He therefore finds the excessive quantitative release by the Bank of Japan, which did not lead to the expected price increases, problematic and disruptive to a well-functioning financial system. The ambiguity of the real relationship between money supply growth and the inflation rate was summarised by Mandelman (2021). Referring to the period during and after WWII, he showed that a jump in the money supply may not cause a jump in prices. This is due to the existence of a number of factors affecting the behaviour of banks, households, the government and companies. During WWII, the U.S. money supply was doubled, but shortages of consumer goods limited the demand and the subsequent price increases. After the end of the war (1946–1947), the annual inflation rate reached 20%, but became stable in two years. The COVID-19 pandemic severely curtailed household and business demand, and meant an increase by 25% in the money supply in 2020. However, this growth did not lead to sudden inflationary pressures.

An analysis of the relationship between the monetary aggregate M3 and the inflation rate in the U.S., Japan[8] and the Czech Republic in the period 1960–2007 was conducted by Jílek (2015). Using annual data, he showed a strong correlation[9] between lagged aggregate M3 (or M2 for Japan) and the inflation rate for all countries studied. An obvious problem in this analysis was that it was only based on annual data (while both quarterly and monthly data were available) and the sole outcome of the analysis was the correlation coefficient. A high value of the correlation coefficient in the case of time series may reflect only an apparent correlation. Moreover, even with a high degree of correlation, the question is whether such a dependence can always be modelled and then factually justified.

The situation in the Czech Republic and in the Eurozone was, from the point of view of the conditions for monetary policy implementation, discussed by Kapounek (2010). By analysing data from the period 2002–2010 for the Czech Republic and from the period 1999–2010 for the Eurozone, he showed that there is no long-term stable relationship between the money supply and the expected inflation rate, or between the money supply and the interest rate.

A detailed analysis of the relationship between monetary aggregates and inflation rates using the U.S. as an example can be found in Michl (2019). Using quarterly data for the period 1959 through 2018, the author concludes that there is no close relationship between the money supply (aggregates M1, M2 and M3) and the inflation rate. He sees the reasons for this phenomenon in the long-run low inflation and in the declining velocity of money. If the inflation rate is low or its changes are insignificant within a certain range, it is clear that it is practically impossible to find a suitable explanatory variable in such a situation.

The review presented above shows that the theoretical monetarist concept of the inflation rate's dependence on the evolution of monetary aggregates is questionable and probably cannot be relied upon much in practical economic decision-making. If this relationship were generally valid, it would have to hold in both the short and long runs, at both low and high inflation rates, in both advanced and emerging economies. Economic theory establishes relationships between concepts and formulates them into formulae that give the impression of functional dependence.[10] In economics, however, functional dependences never hold; we are only able to model loose dependence, since the evolution of the variables under study is always influenced by a number of external factors that distort the "would-be-functional" relationship. In the case of the relationship between monetary aggregates and the inflation rate, these factors can undoubtedly include government spending, the changing tax system, the political situation affecting the behaviour of businesses and households, etc. It is therefore a very diverse combination of various causes for the behaviour of monetary aggregates and inflation rates, which are, moreover, time-varying and effectively non-repeatable. It is therefore practically impossible to find a model relationship that is a satisfactory and plausible summation of all these diverse and highly unstable causes over time. Moreover, a separate problem is whether we are able to substantively defend statistical free dependence at all. The explanation is simple: inflation is highly sensitive to its causal roots, and these roots may differ significantly from one another in different time periods. Therefore, the evolution of the inflation rate cannot be described by a lump-sum statistical dependence or a lump-sum econometric model.

8 In Japan, the respective aggregate was M2.
9 But not causality, as the author himself stressed in many instances in that article.
10 Inclusive of the "equation of exchange".

The validity of the relationships (concepts) defined by economic theory can only be demonstrated with the aid of data.[11] We must therefore work with statistical indicators and their values. In addition, here is another problem that disturbs the validity of the "functional" relationship – this is the discrepancy between the content of the concept and its quantifiable form, i.e. the indicator.[12] Unless a strong and valid dependence has been established between the variables under consideration, it is inappropriate to use such relationships to guide economic policy and to make major decisions on the policy. Such an instrument is bound to fail over time (as economic conditions change). And even if, despite all the problems mentioned above, the statistical data eventually prove that a dependency does exist, the causal character of this dependence is not proven.[13] It also goes without saying that two variables may only apparently be statistically dependent since they are both influenced by a third variable (sometimes overt, sometimes very well hidden). All this is a problem not only with respect to the relationships between monetary aggregates and inflation rates analysed here, but also to other relationships presented by economic theory, such as those given by the Phillips curve (see, e.g., Atkeson and Ohanian, 2001; Lansing 2002; Hindls and Hronová, 2015).

The controversial nature of the relationships between the evolution of monetary aggregates and the inflation rate has led us to the idea of checking whether it is possible to model their dependence in the case of long-run time series for the Czech Republic and to verify the direction of this dependence. Is it true that an increase in money in circulation leads to price increases, or is the price growth the cause of money supply growth? Or is the relationship between these variables insignificant? Or even the observed time series may indicate a certain level of formal correlation, but their relationship can in fact not be modelled and is therefore useless for the purposes of predictions?

2 BASIS OF ANALYSIS

In order to test the validity of the respective hypothesis, it is first necessary to identify and define the content and periodic nature of the indicators so that they, as closely as possible, to the theoretical economic assumptions and their values are capable of reflecting the changing situation during the years under evaluation. At the same time, it is necessary to decide how long a time series period should be chosen in order to satisfy not only the formal requirements for the use of time series analysis methods but also the substantive requirements, i.e., the requirements of adequate demonstrability and justifiability of the economic cycle phase.[14] The final task of this analysis will be to find (if any) the time lead or lag reflecting the response of the inflation rate to the evolution of monetary aggregates or vice versa. The definition of the indicators and their subsequent analysis will be based on data for the Czech Republic available on the websites of the Czech Statistical Office (see: <*www.czso.cz*>) and the Czech National Bank (see: <*www.cnb.cz*>); these indicators are methodologically internationally comparable.

The indicators initial for our analysis are the inflation rate and monetary aggregates, whose values will be monitored on a monthly basis. The inflation rate is defined as the relative increase corresponding to the consumer price index. The monthly inflation rate provides information on the percentage change in the price level (of consumer goods) in the month under review compared to the immediately preceding month. It is determined as the ratio of the underlying consumer price index in the month under review

[11] Lord Kelvin's (1824–1907) quote is certainly worth mentioning here: "When you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind".

[12] This is the so-called adequacy problem. Its striking example is the relationship between the economic concept of inflation and the statistical indicator of the inflation rate, which only characterises the development of consumer prices.

[13] This is a well-known problem in medicine – the statistical dependence may exist, but doctors are, at the current level of knowledge, often unable to reveal causal dependence.

[14] However, this requirement already contains a hidden seed of a "correlation" trap: the causes of changes in the inflation rate will be so different over the period under review that it will be virtually impossible to find a unifying view of these multiple causes.

and the underlying consumer price index in the preceding month, with the base being the same in both cases (in the Czech Republic, the base is the 2015 average).

Monetary aggregates represent the money supply in an economy. In general, a narrow (M1), medium (M2) and broad (M3) aggregates are defined. The M1 aggregate includes the currency in circulation, i.e., banknotes and coins, as well as balances that can be immediately converted into currency or used for non-cash payments, e.g., overnight deposits. The M2 aggregate includes M1 plus deposits with a maturity of up to two years and deposits with a notice period of up to three months. Depending on liquidity, these deposits can be converted into M1 components, but in some cases, there may be restrictions, such as the need to give notice, default, penalties or fees. The M3 aggregate includes M2 and negotiable instruments issued by the MFI subsector. This aggregate includes certain financial-market instruments, in particular financial market fund shares and units as well as repo operations. The high degree of liquidity and price certainty ensure that these instruments are close to deposits. Their inclusion and the cascading architecture of the aggregates mean that M3 is less affected by substitution between different categories of liquid assets, making it more stable. In our analysis, we have used both the month-on-month growth rates of the aggregates M1, M2 and M3, as well as their end-of-month balances (in CZK million).

We have faced certain formal problems when choosing the length of the monthly time series; the Czech monetary statistics do not provide such a long time series of the aggregates as encountered in most Western countries; and the Czech economy underwent an extensive transformation of ownership relations and economic management instruments in the early 1990s. These considerations have finally led us to choose the period of 2002 through 2022 (more than 240 observations are thus available when choosing a monthly periodicity).

This length is not only suitable for stochastic time series modelling tools; it is also sufficient to capture the phases of the business cycle as they manifested themselves in the Czech economy during this period. These phases, for example, include the accelerated dynamics of the Czech economy at the beginning of the millennium (with a peak around 2005–2007), the effects of the global crises in 2008–2009, and the recession in 2011–2013, then the recovery lasting until 2017, and the subsequent gradual slowdown in the performance of the Czech economy (noticeable since the beginning of 2018), and last but not least the economic downturn due to the global pandemic.

The uneven evolution of the average annual inflation rate in the Czech Republic between 2002 and 2021[15] (see Figure 1) requires a substantive analysis of the causes for this evolution in individual phases of the economic cycle.

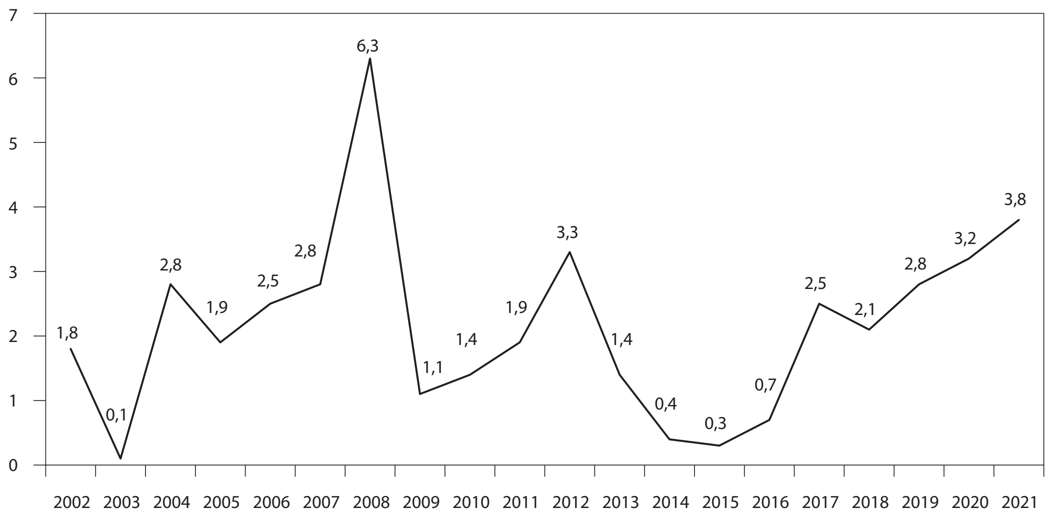
In the early years of this millennium, the inflation rate was kept around the inflation target (2%), the money supply did not show any significant trajectory, central bank and retail bank interest rates were kept low, and household consumption was also stable. All these parameters were rather indicators of positive expectations in the economy and stimuli for further gradual growth. Fiscal parameters were also in line with the potential of the Czech economy and were a harbinger of a rather upward trajectory. This was indeed evident in 2004–2007, when the performance of the economy started to increase and was still at the limit of its potential.

At that time, a sudden dramatic reversal occurred (beginning in 2008), caused by the global economic crisis. The U.S. mortgage crisis was the primary cause of that turning point, which gradually escalated into a global financial crisis. The high oil prices in early 2008 also played a significant role, leading to a fall in real GDP values worldwide and a sharp rise in consumer prices. The world oil price was fostered not only by speculative trades (pension and hedge funds buying commodities to reduce portfolio risk stemming from equity markets), but also by the weak dollar and growing demand from China prior

[15] The 2022 inflation rate was not yet available at the time of writing this text, but its real value will be extremely high, at least around 15%.

to the upcoming Olympics. Moreover, when the financial crisis hit in its full force in autumn 2008, it swept away not only the world's leading banks and stock markets, but also the oil prices. From a peak of USD 147 per barrel in July, it fell by a third in two months and continued to fall until it broke the USD 40 per barrel mark at the end of 2008.

Figure 1 Average annual inflation rate in the Czech Republic (%)



Source: Czech Statistical Office <*www.czso.cz*>

This situation naturally had a devastating effect on the small and open Czech economy. The annual inflation rate rose sharply (2008, see Figure 1), while the value of the monetary aggregate M3 rose by 13.6% year-on-year (December 2008 with respect to December 2007). The effect known as consumption smoothing also played a significant role, as Czech households gradually moderated their consumption. This led to a rapid decline in the inflation rate (2009), but monetary aggregates stagnated. This can be easily explained by the fact that Czech households' real income has naturally been falling since 2008, so there was not much to put aside into monetary aggregates. In the 2011–2013 period, which was characterised by a deterioration of fiscal parameters in the Czech economy (and not only in the Czech Republic), the inflation rate was below the inflation target; however, the money supply grew.[16] So did government spending.

By contrast, a different trajectory can be observed from the end of 2020 to the present day. As noted above, the COVID-19 epidemic knocked down household and business demand, and logically implied an increase in the money supply (by 10.0%) in 2020. Households and businesses were forced to postpone their consumption, only to subsequently plunge funds into purchases and consumption when pandemic restrictions were loosened. This turn of events, together with the injection of money into the economy, affected the inflation rate only about a year later; the latter began to rise more significantly from as late as autumn 2021, and was accompanied by an annual increase in monetary aggregates of about 6%.

Similarly, since the first months of 2022, when the "Czech" inflation rate started to pick up at an unusual pace,[17] the M1 aggregate has logically shown a certain decline[18] (this is about currency and also

[16] The annual monthly inflation rate amounted to 12.7% in March 2022, 17.2% in June 2022 and 18.0% in September 2022.
[17] The annual monthly inflation rate amounted to 12.7% in March 2022, 17.2% in June 2022 and 18.0% in September 2022.
[18] In July 2022, the value of the M1 aggregate M1 fell by 4.3% as compared to July 2021.

about balances that can immediately be converted into currency or used for non-cash payments), but the other aggregates, which are characterised by a more limited availability of liquidity, grew despite high commodity prices.[19] Households therefore postponed consumption, perhaps because of the extremely high prices during that period, or because they were "waiting" for a return to price stability, especially for medium- and long-term consumption items. It is therefore a slowdown in the velocity of money circulation that must logically have obscured the relationship between the movement of monetary aggregates and the evolution of the inflation rate. Therefore, the model's capture of this relationship (using the relevant correlation statistics) is, in fact, not sufficiently convincing.

It follows logically that the examined relationship between the evolution of the inflation rate and the evolution of monetary aggregates must be very loose. The substantive justification is also manifested in the model (see below), using stochastic techniques.

3 METHODOLOGY OF ANALYSIS

The cross correlation function (CCF) has been used to test the hypothesis whether there is a relationship between monetary aggregates and the inflation rate in the Czech economy and a certain time shift that needs to be found and confirmed by appropriate tests. See Box, Jenkins and Reinsel (1994), Pankratz (1991) or Wei (2006) for more details.

The CCF is defined as:

$$\rho_{XY}(k) = \frac{\gamma_{XY}(k)}{\sigma_X \sigma_Y}\,, \tag{1}$$

where X_t and Y_t are the time series to be analysed. The CCF's value at k is then defined as the covariance between X_t and Y_{t+k} for $k = 0, \pm 1, \pm 2, \ldots$, divided by a product of the standard deviation values of both series, where σ_X and σ_Y are the standard deviation values for the series X_t and Y_t (respectively). It is clear that, for the CCF relationship, the following formula holds true:

$$\rho_{XY}(k) = \rho_{YX}(-k)\,. \tag{2}$$

The CCF is defined for stationary time series and its advantage is that it measures not only the strength of the linear dependence between two time series, but also the direction of this dependence. From its values we can thus determine the time shift of the dependence between the analysed series.

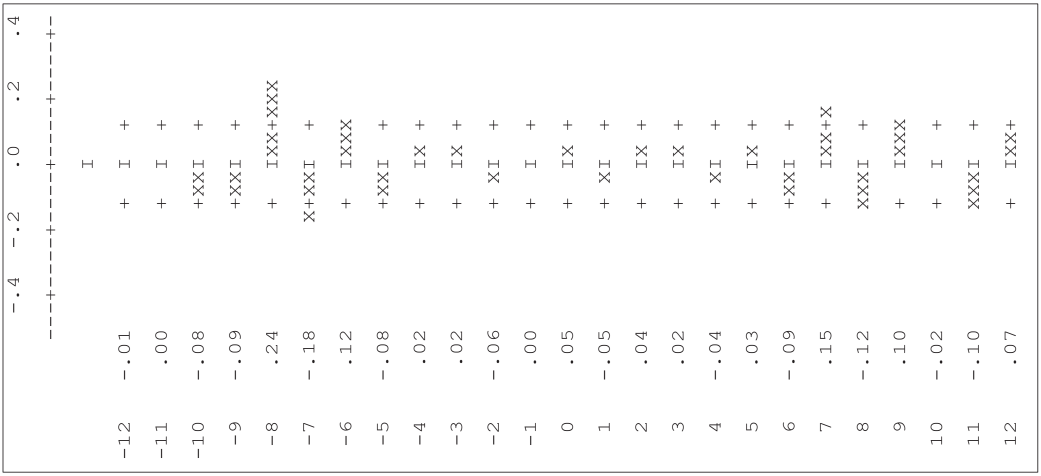
In order to apply the CCF, we first need to adjust the time series to be stationary; and to achieve stationarity, we use normal and seasonal differencing. Only then can we calculate the CCF values and decide whether there is a linear dependence between the series under analysis. This linear dependence will be examined not only at the same-time points t; we will also look for dependence including time shift to both sides, i.e., at times t, $t\pm1$, $t\pm2$, etc. For the purpose of this analysis, we will consider the time series of monetary aggregates M1, M2 and M3 in two forms. First, in the form of month-on-month relative growth rates (series labelled M1, M2 and M3), and second, in monetary balance values at the ends of the months (series labelled M1state, M2state and M3state).

First of all, we will study the time series correlograms of the inflation rate in relation to the aggregate M3, or M3state. Ordinary differencing (of order 1) and seasonal differencing (of order 12) have already been applied to all series. Let us look at the graphical progression of the CCF first for the M3 series

[19] In July 2022, the value of the M2 aggregate increased by 4.9% compared with July 2021; in the case of the M3 aggregate, the increase amounted to 5.9%.

(relative increments) and the inflation rate series (see Figure 2). We do not assume that the dependence either way from time point t might have a lag (or lead) longer than 1 year.

Figure 2 CCF between inflation rate and M3



Source: Authors' own calculations

We can clearly see in Figure 2 that a very strong linear dependence can be observed at time points t and t−8. In addition, there seems to be a weak linear dependence with lead times −8 and +7. Let us therefore try to construct a linear dynamic model to describe this dependence. The entire theory of linear dynamic models is described in detail in Box, Jenkins and Reinsel (1994), Pankratz (1991) or Wei (2006). The general model can be written as follows:

$$Y_t = c + \nu_0 X_t + \nu_1 X_{t-1} + \nu_2 X_{t-2} + \dots + \nu_K X_{t-K} + \frac{1}{(1-\phi_1(B))(1-\Phi_1(B^L))}\,\varepsilon_t\,, \tag{3}$$

where Y_t is the output series, X_t is the input series, c is constant, ν_i are unknown parameters for $i = 0, \dots, K$, $\phi_1(B)$ is the autoregressive operator of order 1, $\Phi_1(B)$ is the seasonal autoregressive operator of order 1, ε_t is the random variable (white noise), B is the shift operator ($BY_t = Y_{t-1}$), and L is the length of the season.

Let us now estimate the model parameters. All calculations are performed in SCA software. We consider the dependence at time point t and then with lags 1, 2, ..., 10. The variables $\nu 0$, $\nu 1$, ..., $\nu 10$ represent time lags of 0, 1, ..., 10. The output (cf. Table 1) shows that in none of these instances did the coefficient on the time lagged variable turn out to be significant, despite the coefficient of determination being almost equal to 1. It can be concluded that the occurrences of the significant CCF values at different time points are only accidental and cannot be described by the model.

Let us now have a look at the situation for the M3state time series (the M3 aggregate in monetary terms, i.e., the balances at the ends of the months). Figure 3 shows the CCF values for the inflation rate series and the M3state aggregate.

In none of these instances was the CCF value statistically significantly different from 0. The entire analysis is performed at a significance level of $\alpha = 0.05$; Figure 3 thus shows the 95% confidence interval from which the CCF value did not deviate in any of these cases.

Table 1 SCA software output

Summary for univariate time series model – INFM3

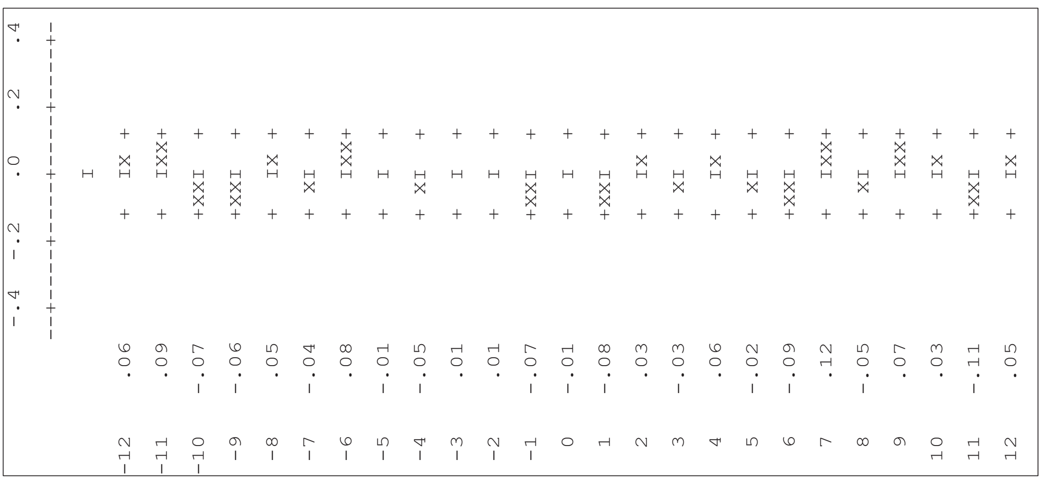
Variable	Type of variable	Original or centered	Differencing	
M3	Random	Original	$(1–B^1)$	$(1–B^{12})$
INF	Random	Original	$(1–B^1)$	$(1–B^{12})$

Parameter label		Variable name	Num./ denom.	Factor	Order	Constraint	Value	STD error	T value
1	V0	INF	NUM.	1	0	None	–3451.9047	4122.7372	–.84
2	V1	INF	NUM.	1	1	None	–7136.5605	5277.9051	–1.35
3	V2	INF	NUM.	1	2	None	–1434.0809	5836.6937	–.25
4	V3	INF	NUM.	1	3	None	265.2890	6047.2992	.04
5	V4	INF	NUM.	1	4	None	3312.9799	6147.3186	.54
6	V5	INF	NUM.	1	5	None	–347.1029	6192.5495	–.06
7	V6	INF	NUM.	1	6	None	–1466.1811	6199.3914	–.24
8	V7	INF	NUM.	1	7	None	9687.5670	6288.8980	1.54
9	V8	INF	NUM.	1	8	None	7539.9223	6153.4431	1.23
10	V9	INF	NUM.	1	9	None	11365.5169	5635.2959	2.02
11	V10	INF	NUM.	1	10	None	7046.1141	4313.0207	1.63
12	PHI1	M3STATE	MA	1	1	None	–.0993	.0699	–1.42

Effective number of observations	212
R-square	0.966
Residual standard error	.262371E+05

Source: Authors' own calculations

Figure 3 CCF between inflation rate and M3state



Source: Authors' own calculations

We have performed the same type of analysis for all of the time series considered and the relationships between them. In none of these instances is it possible to describe the relationship between the time series of the inflation rate and the variables M1, M2 and M3 with the aid of a suitable model that would properly capture the linear dependence. The same situation occurs when we consider the M1state, M2state, and M3state time series.

In result of our – at this point still just statistical – analysis we can conclude that, in the case of the Czech Republic, either there is no linear relationship between the time series of the inflation rate and the aggregates M1, M2 and M3 (respectively M1state, M2state and M3state), or the dependence is only accidental (including the time shift to both sides, so that the so-called feedback occurs here). In other words, this dependence cannot be truly described by any model. This observation holds true even though our analysis has been carried out on monthly data for a period of 20 years, which is characterised by relatively large fluctuations in the inflation rate in the Czech Republic. And not only in terms of its numerical values, but also in terms of the fundamental causes of these fluctuations.

CONCLUSIONS

The relationship between the inflation rate and monetary aggregates is an important issue in the implementation of the central bank's monetary policy. Is the relationship only one-sided (in terms of money supply), as theory suggests, or two-sided (also in terms of money demand), depending on specific economic realities? And if the latter case occurs, what are the lead/lag directions and magnitudes? A number of studies have attempted to demonstrate the validity of the theoretical relationship that provides the central bank with a tool to influence (and therefore target) inflation. However, central banks have gradually abandoned the targeting of monetary aggregates (especially M3), and hence the monetary influence on the inflation rate, and moved towards inflation targeting. The reason for this move has been the empirically demonstrated invalidity, or significantly limited validity, of the relationship of direct proportionality between money supply and price growth given by the equation of exchange.

When verifying and modelling the relationship between the inflation rate and the money supply (monetary aggregates), it is still necessary to bear in mind that the inflation rate derived from the consumer price index is quite distant from the concept of inflation in economic theory. Proving the validity of the theoretical relationship between the concepts when the quantifiable variable (indicator) expresses something else tends to be quite difficult. This can naturally lead to ambiguous conclusions in terms of the direction and strength of this relationship.

By means of deriving a dynamic linear model, we have been able to show that the dependence between the inflation rate and the money supply (M1, M2 and M3 – monthly relative growth) does exist, but it is accidental (with a time shift to both sides); so it cannot be modelled. The dependence between the inflation rate and the monetary aggregates M1, M2 and M3 expressed in absolute amounts in CZK (states at the ends of the months in CZK million) does not exist at all. The results of our analysis show that the intuitive view of the consequences of the high inflation rate in the Czech Republic at the present time (increasing government spending, i.e., the amount of money in circulation to compensate for the high cost of living of (mainly) households) is not confirmed by the data examined. Thus, the money supply is not growing as a result of the rise in the price level and the increase in government spending. Similarly, the inflation rate is not rising as a result of an increase in the money supply. This analysis has also shown that such a situation is a long-term phenomenon in the case of the Czech Republic and is therefore not simply an outcome of the current – extremely unfavourable – economic situation.

In other words, some dependence between the inflation rate and the monetary aggregates (M1, M2, M3) probably exists, but it is highly random in nature, so it cannot really be described by a model. The practical implication of such a conclusion is the impossibility of using the relationship between monetary aggregates and the inflation rate to make predictions. There may be several reasons based on factual considerations.

One of the reasons for the significant deviations in inflation rates in both directions is implied by very different, in some cases extremely non-standard and dominantly non-economic circumstances (most recently, for example, the COVID-19 pandemic, soon followed by Russian invasion of Ukraine, etc.). This leads to non-standard responses in the structure of the behaviour of economic actors, and such responses dramatically change the existing view of the evolution of monetary aggregates, i.e., the evolution of the values of such indicators as the velocity of money circulation (postponement of consumption, which significantly weakens gross domestic product), the current price level, and the money supply.

Another reason is probably the fact that if the reversals in the development of the analysed phenomena have economic roots (such as the 2008–2009 crisis, 2011–2013 recession, etc.), the magnitude of the changes is rather enormous and provokes unpredictable behaviour of individual economic entities and this behaviour cannot be properly modelled. One of the reasons for this unpredictability may be the phenomenon known as consumption smoothing, whereby households tend to reduce or postpone consumption in bad times. They therefore defer their consumption to other periods to ensure greater stability and predictability. This has been typical since 2008, and it has greatly obscured the relationship between monetary aggregates and the inflation rate.

The third cause is undoubtedly the so-called quantitative release, where global and national financial institutions have repeatedly injected money into economies in recent years; this has also been the case in the Czech economy. This instrument, used in adverse times, may have had some effect in boosting the growth of economies (including efforts to counter deflation), but as a non-standard element, it naturally also provokes non-standard behaviour of economic actors, with consequences for, on the one hand, the level of monetary aggregates, but also, on the other hand, the development of the inflation rate.

A fourth reason for the inadequate conclusiveness of the statistical modelling of the relationship may be the permanently present, so-called adequacy gap. A simple reasoning applies: what we cannot measure perfectly, we cannot model perfectly either. Of course, the consumer price index used as a measure of inflation does not fully correspond to the definition of inflation as an economic category. All these circumstances logically obfuscate the possibility of constructing an effective model for the relationship between monetary aggregates and the inflation rate.

The factual reasoning presented above shows that the relationship between monetary aggregates and inflation rate is in fact too inexplicable to admit a simple formal model from which meaningful implications might be drawn. This effort fails to do so even with variations of different time shifts in the two indicators. Having in mind the time lag that undoubtedly exists between a monetary policy measure and its impact on the real economy, the central bank can only partly be guided by the current situation, while it must also take into account, at least to some extent, the forecast of future economic developments. However, such a forecast is quite difficult to get, especially in the last 15 years.

The behaviour of households, the political establishment, non-standard foreign exchange interventions of the Czech National Bank,[20] and a great variety of the circumstances affecting the economic development do not give much chance of finding a formal model of the relationship that would also have a strong footing in substantive reasoning.

[20] The foreign exchange interventions were launched in 2013 to achieve the inflation target, which is set at 1–3%; therefore, the exchange rate of the koruna was kept above CZK 27 to 1 euro. In contrast, the Czech National Bank is currently intervening to strengthen the koruna to around CZK 24.50 to 1 euro in order to make imports cheaper and thus cool down the sharp rise in prices.

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Economic Relations between Hungary and Czechia

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Received 20.7.2023, **Accepted** (reviewed) 27.7.2023, **Published** 15.9.2023

Abstract

Trends of the economic relations between Czechia and Hungary – from Hungarian point of view – are reviewed, based mainly on the data of statistics office (KSH) and on the National Bank of Hungary (MNB). Developments are examined in EUR throughout the study, thus evaluation is exempt from HUF exchange rate changes. The first part presents, based on KSH data, the external trade turnover changes between Hungary and Czechia in 1994–2022. Czechia is an important trade partner of Hungary. Timely changes in product structure are emphasized, the most recent state is presented, based on SITC and BEC nomenclature. Car industry turnover size and structure is presented. The role of Czechia in the external trade of services is significantly smaller than in that of goods, but trade increases faster in this field. The second part compares, based on MNB data, the size and divisional structure of the outstanding capital stock, showing that Czech enterprises in Hungary are more productive than the average foreign subsidiary.

Keywords	***DOI***	***JEL code***
External trade in goods, product structure of foreign trade, external trade in services, foreign-controlled affiliates, FDI	*https://doi.org/10.54694/stat.2023.31*	*F10, F21*

INTRODUCTION

Economic relations between Hungary and Czechia go back to several centuries. The Visegrad agreement between kings Charles I of Hungary, Casimir III of Poland and John I of Bohemia included passages regarding the establishment of a more efficient trade between Hungary and Bohemia as early as 1335. These trade relations continued throughout the centuries.

Our study is looking for answers regarding how in the last 30 years, following the regime change, economic relations strengthened between the two countries, how significant is the role that Czechia is playing in the Hungarian economic processes. The short geographical distance as well as the fact that both countries joined the European Union at the same time, on 1 May 2004, are givens for an external trade related integration. The EU single market's four freedoms, launched in 1993, (free movement of people, goods, services and capital) are valid for both countries.

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1 EXTERNAL TRADE TURNOVER

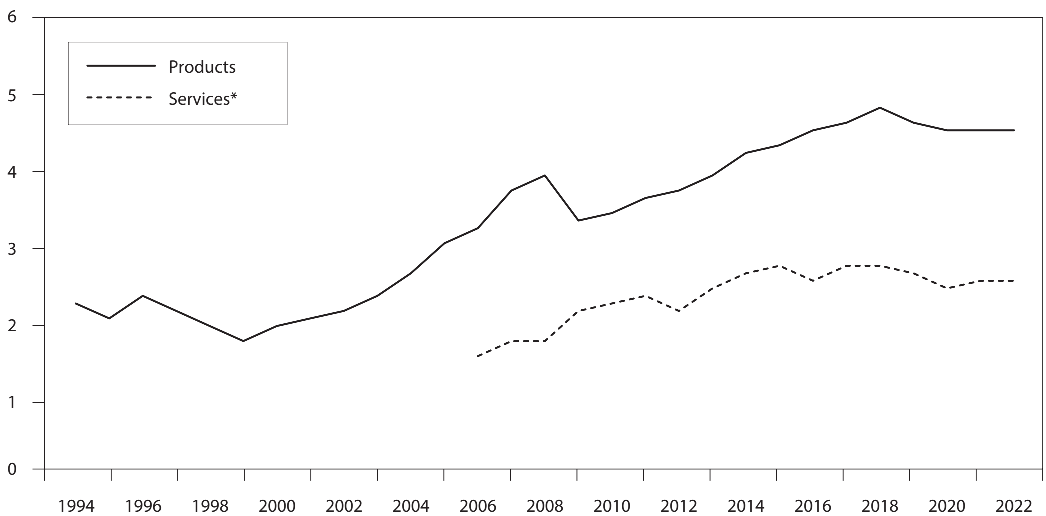
During the past nearly 30 years Czechia continued to be a significant trade partner of Hungary. The relatively short geographical distance between the two countries allows goods to be competitive on each other's markets, furthermore, both countries' production activity in the global value chains of multinational corporations follow each other in many cases, increasing trade turnover between them.

The observation of the Hungarian external trade turnover has been based on customs record data since 1991 up until the EU accession, in May 2004. Czechia and Slovakia already separated at the beginning of 1993, even so they figured as one country as the Czech and Slovak Republic for the given year in the Statistical Yearbook of External Trade[3] of the Hungarian Central Statistics Office (hereinafter HCSO); in consequence turnover analysis is only possible since 1994.

Between 1994 and 2003, the years preceding their adherence to the EU, Czechia had consecutively a 2% share in the Hungarian external trade turnover. CEFTA, a free trade agreement, applied as early as March 1993 for the Visegrad four countries (Slovenia, Romania and Bulgaria joined later on) helped in intensifying the economic cooperation between the two countries. In spite of this trade agreement – allowing for close to 90% of goods to be sold duty-free – the share of Czechia in the Hungarian external trade shrunk in the second half of the 90s, also in connection with the fact that Hungary's external trade as a whole grew dynamically in these years. Factors like the unification of customs tariffs, lower customs duties, elimination of non-customs related impediments, liberalisation of foreign direct investment regulations and the introduction of the HUF convertibility made the significant increase of foreign trade possible.

Turnover growth was based on the activity of industrial customs free zones, producing, in part, goods for export from base materials coming from Asia, machinery, first of all, to be distributed in developed

Figure 1 Czechia's share in Hungary's external trade turnover (%)



Note: * for 2006–2007 balance of payment based on data from methodology manual BPM #5., from there on # 6.
Source: Own calculations based on HCSO data (for the 1994–1998 period according to the HCSO Statistical Yearbooks of External Trade, for the 1999–2022 period upon HCSO databases)

[3] Similarly to the former Yugoslavia and the Soviet Union.

countries. All in all, the value of the Hungarian external trade turnover, calculated in ECU as well as EUR, increased 2.4-fold in the 1997–2000 period, meaning, on yearly average, a 25% growth.

In parallel with the outstanding increase the export's domestic added value content lessened considerably during these years; calculations performed based on the OECD Trade in Added Value database showed a 72% proportion in 1996 and a 54% one in 2000.

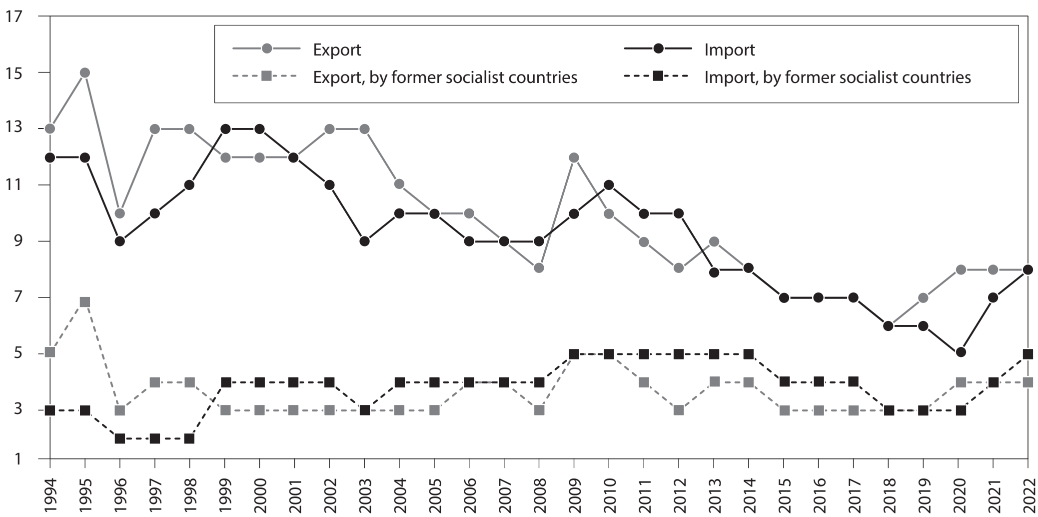
At the time when Hungary joined the EU close to 150 industrial customs free zones existed in the country, these ceased automatically with the accession.

Following the accession, the role of Czechia in the trade turnover to Hungary grew, its share surpassed each year 4% since 2014.

Czechia has continuously a larger share in Hungary's external trade in goods than in that of services. In the case of the latter geographical distances have a smaller importance, as such our turnover is rather targeting several western countries with highly developed service sectors (USA, United Kingdom, Switzerland).

Czechia was, during the 2011–2022 period, among the ten most important partners of Hungary in terms of trade in goods, in both directions, an improvement compared especially to the situation preceding the EU accession.

Figure 2 Czechia's place in Hungary's partners in external trade in goods (ranking place)



Source: Own calculations based on HCSO data

Hungary exports – in relation with the former Eastern Bloc countries – in larger values than into Czechia to the neighbouring Slovakia, to Poland, representing significantly larger market, and in Romania. In our import ranking China and Poland come before Czechia on a regular basis, Slovakia and Russia is occasionally a more significant partner, the value of import coming from the latter country is linked to energy price changes.

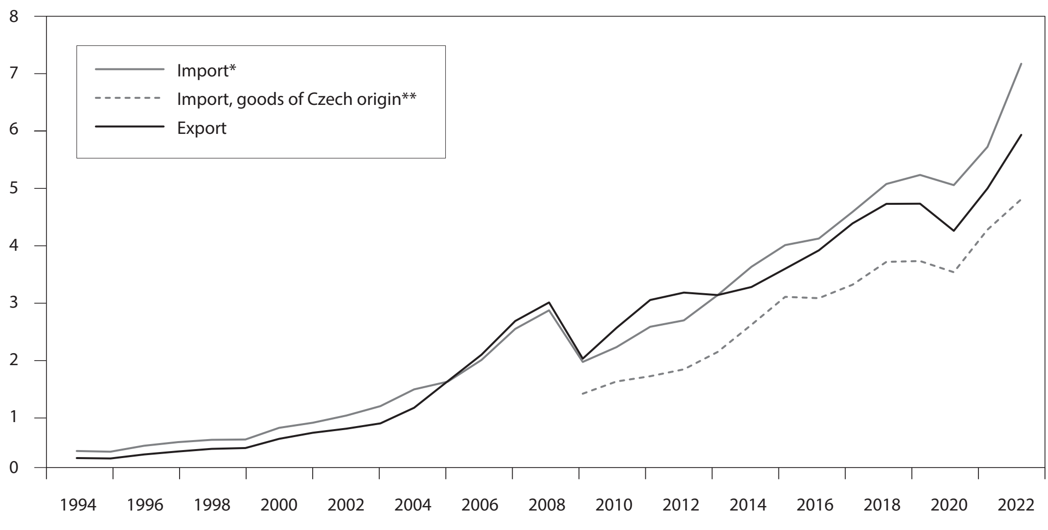
Credits, as they became more expensive during the 2009 financial crisis had a negative impact on demand, turnover shrunk from EUR 5.7 billion to 3.8 billion. Recovery was slow, aggregated trade flows only surpassed the 2008 level in 2013 (EUR 6.1 billion), after the eurozone crisis died out.

Table 1 Hungary's most significant trade partners in the external trade in goods, in 2022*

Export				Import			
Ranking	Country	Value, billion EUR	Change in value compared to 2021, %	Ranking	Country	Value, billion EUR	Change in value compared to 2021, %
1. (1.)	Germany	35.7	12.5	1. (1.)	Germany	31.9	14.4
2. (2.)	Italy	8.0	15.5	2. (3.)	Austria	10.8	50.5
3. (3.)	Romania	7.6	20.1	3. (2.)	China	10.2	23.5
4. (4.)	Slovakia	7.2	17.2	4. (4.)	Slovakia	10.0	44.6
5. (5.)	Austria	6.4	18.0	5. (11.)	Russia	9.3	157.2
6. (6.)	Poland	6.1	19.4	6. (5.)	Poland	8.4	25.3
7. (7.)	France	6.0	20.5	7. (6.)	The Netherlands	7.2	23.8
8. (8.)	**Czechia**	**5.9**	**19.2**	**8. (7.)**	**Czechia**	**7.2**	**25.9**
9. (9.)	The Netherlands	5.1	30.0	9. (8.)	Italy	6.1	17.8
10. (11.)	USA	5.0	43.4	10. (10.)	Korean Republic	5.8	59.4
	Total	**142.2**	**19.3**		**Total**	**150.8**	**28.2**

Note: * the number in bracket represents the 2021 ranking of the given country.
Source: HCSO

Figure 3 Hungary's external trade in goods with Czechia (billion EUR, ECU until 1998)



Note: * good of Czech origin up until 2002, from 2003, in connection with the EU accession, goods arriving from Czechia.
** in the years during the 2009–2022 period, 4.6–8.5% of Hungarian import had no country of origin, which might have included Czech turnover as well.
Source: For the 1994–1998 period calculations based on the HCSO Statistical Yearbook of External Trade, for the 1999–2022 period on HCSO databases

In 2020, when the Covid-19 pandemic spread worldwide, another setback occurred, in this case, however, turnover dropped only from EUR 9.9 billion to 9.2 billion. This drop was impacted by factory closures as well, therefore the crisis was supply based this time. It is worth mentioning, however, the so-called "crisis expectations" showing up as early as 2019, which can be experienced the Czech-Hungarian turnover, too, in form of a mere 2% growth rate, the slowest one of the 2010s. Finally, recession materialised as the pandemic reached worldwide dimensions, although no one expected a "great lockdown". Total turnover grew by 16% in 2021, to EUR 10.6 billion, surpassing already the pre-pandemic 2019 level. The pace of the turnover growth speeded up to 23% in 2022, the value of commodity exchange reached EUR 13.1 billion. The significant current price growth pace of the last two years has been impacted by the overall price hike on the world market, too. According to a study (Bod et al., 2020: 321–351) the introduction of the euro could markedly lower business expenses at external trade oriented companies, generating, first of all, additional external trade opportunities at smaller "domestic" companies. As in 2014–2021 Hungary registered a deficit in 2022, too, in the external trade of goods with Czechia, its amount grew in a year by more than half a billion EUR, reaching EUR 1.3 billion. The deficit to export ratio increased to 21%, showing its most unfavourable state from Hungary's point of view since joining the EU.

According to data calculated from the latest, 2018 data of the OECD Trade in Value Added database the domestic added value content in the Hungarian export (goods and services) had a 54% share, while the proportion was 58% for Czechia. (OECD average for this year was 72%). In the Hungarian export toward Czechia as well as in the Czech export to Hungary the domestic added value ratio was somewhat lower (2 percentage points).

Table 2 The domestic added value content of export in the bilateral turnover, 2018 (%)

	Hungarian export to Czechia	Czech export to Hungary
Manufacturing	44.4	50.6
out of this:		
manufacture of transport equipment	35.1	42.6
chemical products and non-metallic mineral products	52.0	49.0
Services	76.5	78.8
Export total (goods + services)	**52.0**	**56.3**

Source: Calculations performed according to the OECD „Trade in Value Added (TiVA) 2021 edition, Principal indicators" database

The structure of the trade in goods with Czechia underwent a big change before joining the EU. Up until 2001 manufactured goods represented the most significant main commodity group in both trade directions, their share in turnover characteristically surpassed 40% (at the same time fuels, electric energy main commodity group had the largest share, 43%, in the 1996 import). Between 1994–1997 (except for 1996) the second largest main commodity group on the import side was fuels, electric energy, the food, beverages, tobacco was on the export side, by and large in a proportion of one-third and one-fourth in the corresponding trade direction. When looking to a level lower, to the actual commodity groups, turns out that pharmaceuticals and pharmaceutical products have consecutively been among the five commodity groups with the largest turnover, while paper, cardboard, pulp and products manufactured from these, furthermore vegetables and fruits did not make into this group in one year only. Regarding import, iron and steel was continuously among the five commodity groups having the largest turnover between 1994 and 2012, this was true for coal, coke and briquettes up until 2002, for organic chemical products until 2000.

Machinery and transport equipment became the largest main commodity group on the export side in 2002, on the import one in 2005, with turnover shares of 44% (this was only 9% and 17% in 1994). Machinery and transport equipment are the most important main commodity group ever since, except for a few years, representing in both trade directions more than half of the turnover (their share, together with manufactured goods is close to 90% in the average of the export and import).

The commodity group with the largest turnover is unchanged in export since 2009, as can be seen on Table 3, while on the import side the telecommunications, sound recording and reproducing apparatus and equipment surpassed in 2022 the previous 23 years' number one, namely road vehicles', turnover.

Table 3 Commodity groups with the largest turnover in the trade of goods between Hungary and Czechia (based on the UN Standard International Trade Classification (SITC) double-digit groups)

<table>
<tr><th>Year</th><th>Export</th><th>Import</th></tr>
<tr><td>1994</td><td>Petroleum and petroleum products</td><td rowspan="2">Coal, coke and briquettes</td></tr>
<tr><td>1995–1997</td><td>Medical and pharmaceutical products</td></tr>
<tr><td>1998</td><td rowspan="2">Power generating machinery and equipment</td><td>Iron and steel</td></tr>
<tr><td>1999–2007</td><td rowspan="3">Road vehicles</td></tr>
<tr><td>2008</td><td>Telecommunications and sound recording and reproducing apparatus and equipment</td></tr>
<tr><td>2009–2021</td><td rowspan="2">Electrical machinery, apparatus and appliances</td></tr>
<tr><td>2022</td><td>Telecommunications and sound recording and reproducing apparatus and equipment</td></tr>
</table>

Source: For the 1994–2002 period the HCSO Statistical Yearbook of External Trade, for the 2003–2022 period the HCSO databases

Lithium-ion batteries for electric cars represented in 2022 the volume boosting products of the electrical machinery, apparatus and appliances commodity group, the most important one on the export side. Within the commodity group recording the largest turnover on the import side, i.e. the telecommunications and sound recording and reproducing apparatus and equipment, smart phones showed the most significant trade volume in 2022. Hungary had in the road vehicles group, including parts and accessories, too, a larger import only with Germany than with Czechia in 2022 as well. The importance of this commodity group is important also on the export side, being constantly since 2013 on the second place of the turnover. Within the group vehicle parts and accessories' trade value was in 2022 more than one-and a half times larger than that of road vehicles in both directions of the turnover. This structure is significantly different than in the case of all countries, where the situation is essentially reversed: export value of passenger cars surpassing by 57% that of parts and accessories. However, there is no surprise in the fact that Hungary is exporting a relatively small number of vehicles to Czechia, as in 2022 the four car factories in Czechia (Hyundai, Toyota and two Volkswagens) produced 1.2 million cars, placing Chechia, following Germany and Spain, in the third place regarding car manufacturing in the EU. The leading commodity group in export between 1997–2007, that of power generating machinery and equipment is worth mentioning, too, as being closely linked to car manufacturing, and it contains internal combustion engines. Cars related turnover is not limited to the machinery and transport equipment main commodity group however; it does include manufactured goods, too, for example car tires from the rubber manufactures group.

The bilateral trade consists almost exclusively of goods produced by manufacturing industry, their proportion in 2022 was 96% in both trade directions. The bulk of the turnover, however, is not executed by industrial, rather by commercial companies, their share from the total import was 58%, from the export 42% in 2022. In the last years commercial companies represented a larger proportion in our import, namely 57% in the average of the 2019–2022 period, in contrast with the 44% of the 2010–2018 one.

Two import data sets are available since 2009 (see Figure 3) as the HCSO is gathering data not only about the import coming from Czechia (this is used for calculating the balance) but (once again) about the goods originating from Czechia.[4] Regarding the years of the 2009–2022 period, the value of goods

[4] Goods are of Czech origin if they have been produced, extracted or processed in Czechia. If goods have been manufactured in several countries, they are considered of Czech origin if the last main processing operation took place in Czechia.

Table 4 The structure of the external trade with Czechia based on product as well as company's division classification, averages of 2019–2022 (%)

	Export		Import	
	Product	Company	Product	Company
Manufacturing (C)	**96.9**	**55.6**	**97.4**	**39.1**
out of this:				
Manufacture of food products, beverages and tobacco products (CA)	7.5	5.0	5.8	2.4
Manufacture of chemicals and chemical products (CE)	6.9	3.2	8.7	2.9
Manufacture of pharmaceuticals, medicinal chemical and botanical products (CF)	6.7	2.6	1.0	0.6
Manufacture of rubber and plastics products, and other non-metallic mineral products (CG)	5.8	3.8	7.3	2.9
Manufacture of basic metals and fabricated metal products, except machinery and equipment (CH)	6.4	5.8	9.3	3.1
Manufacture of computer, electronic and optical products (CI)	7.3	1.9	18.3	1.7
Manufacture of electrical equipment (CJ)	20.4	12.1	8.5	1.4
Manufacture of machinery and equipment n.e.c (CK)	5.1	1.8	8.5	1.1
Manufacture of transport equipment (CL)	21.7	17.0	20.9	20.0
The other (5) manufacturing subsections total	9.1	2.4	9.1	3.0
Wholesale & retail trade; repair of motor vehicles (G)	–	**42.7**	–	**57.3**
Other sections	**3.1**	**1.7**	**2.6**	**3.6**

Source: HCSO database

dispatched from Czechia to Hungary was at least 30%, at most 54% more than that of the ones based on origin, considering the average of 14 years the difference is 42%. (This difference is partly moderated by the fact that the HCSO could not always obtain country of origin-based data. If we allocate the missing turnover between countries according to the ratio by available data, then in the average of 2009–2021 our Czech import by sending country was not 40% but 32% more compared to the country of origin consideration.) The value of Hungarian import from Czechia (of any origin) in 2022 was EUR 2.4 billion (50%) more than the value of Czech origin goods coming from any country in the world. The largest value of goods Czechia is distributing to Hungary are goods of Chinese origin (EUR 847 million in 2022), which is more in itself than Czech origin goods delivered to Hungary from all countries in the world (EUR 393 million). (In conclusion only 8% of Czech origin goods came from other country into Hungary than from Czechia). The difference between the two import datasets was less prior to 2022, about EUR 1.5 billion. Table 5 enlists the commodity groups showing the largest value differences in 2022.

Figures 4–5 show the main characteristics of the BEC (Broad Economic Categories) Rev. 4. nomenclature based structure of the commodity exchange with Czechia. Four among the approximately twenty BCE groups are worth mentioning regarding both trade directions, these represent jointly two-thirds on the export side and close the same size on the import side of trade. The ”parts and accessories of transport equipment” was the group with the largest turnover in the Hungarian export toward Czechia in 2020–2022, similarly to the 2002–2008 period. Their export fell back from the EUR 670 million in 2007 to EUR 333 million in 2009 and only the 2016 results (EUR 689 million) surpassed the pre-crisis level. The 2022 export value was EUR 1.7 billion, the average growth rate for 2014–2022 was 16%, 2022 showing the largest increase (31%). An opposing example is the “capital goods (except transport equipment)” category

Table 5 Commodity groups where the import arriving from/originating from Czechia shows a difference of at least EUR 100 million in 2022* (based on the UN Standard International Trade Classification (SITC) double-digit groups)

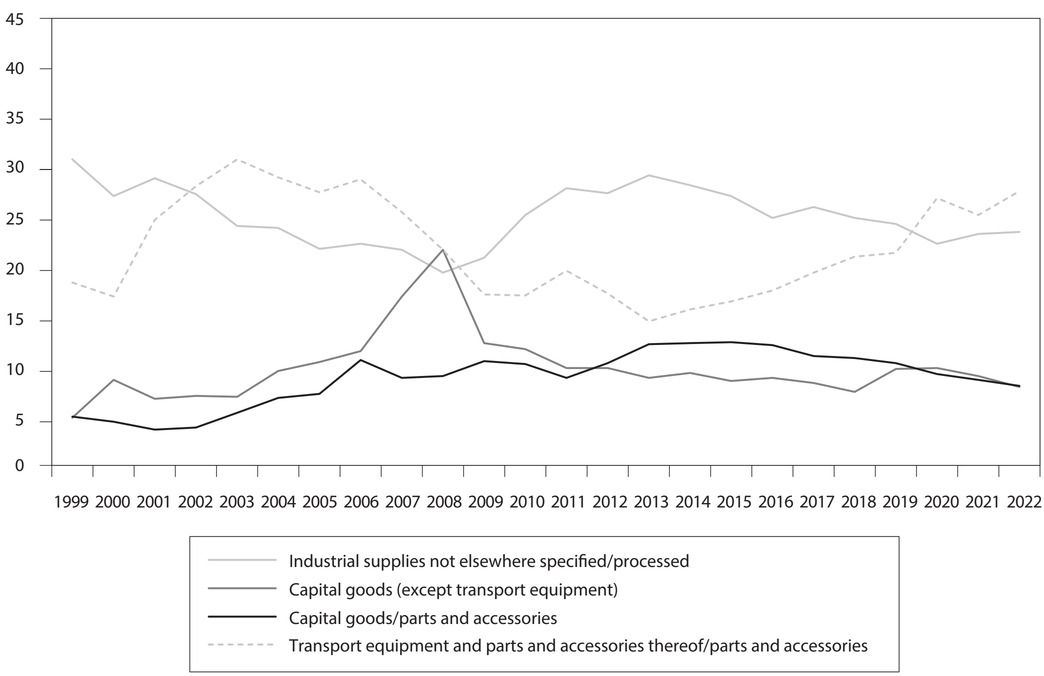
Commodity group	Import from Czechia	Import of Czech origin
	(million EUR)	
Telecommunications and sound recording and reproducing apparatus and equipment	1 170	410
Office machines and automatic data processing machines	332	30
Electrical machinery, apparatus and appliances	758	497
Road vehicles	1 150	903
Essential oils, perfume materials, cleaning preparations	217	95

Note: * there is no data available regarding the country of origin in 2022 for 6.8% of the total Hungarian import or EUR 10.2 billion in value. Part of this missing data may increase the Czech origin turnover of the commodity groups from the table.
Source: HCSO database

where the export grew from EUR 54 million to EUR 637 million between 2003 and 2008, however a sharp decrease came about in 2009 and it reached only EUR 475 million in 2022. The export of "non-durable consumer goods", - not on the diagram, - broadened by 35% in 2022, reaching a turnover share (8%) as large as one of the "capital goods" groups, represented on the chart.

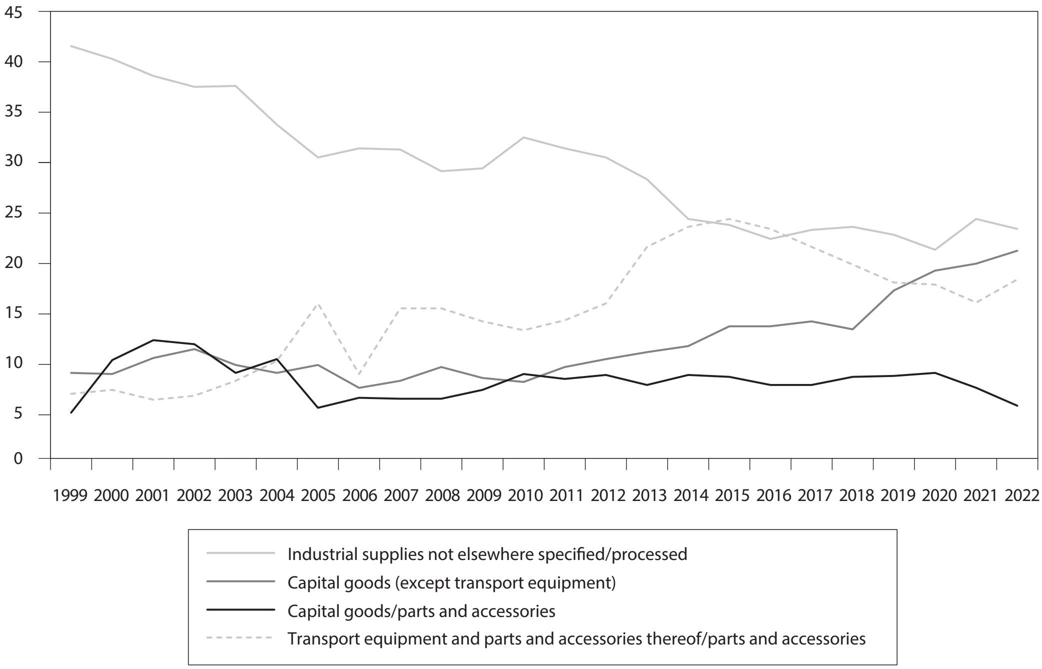
The turnover of the third most significant group on the import side "parts and accessories of transport equipment" grew in 2022 by 52% to EUR 1.4 billion, a record high flow of goods. In spite of the import

Figure 4 The structure of the Hungarian export to Czechia by the groups of the BEC Rev. 4 nomenclature (percentage share of the main groups in the export of the given year)



Source: Own calculations based on „DS-057555 – EU trade since 1988 by BEC/rev.4" Eurostat database hike there was still an EUR 307 million Hungarian surplus, the largest among the BEC groups. In the case of the second largest import group from turnover point of view the "capital goods (except transport equipment)" the value of arrivals grew by 40% in 2022, as a result its balance deteriorated in the largest extent (EUR 432 million) and its deficit was also the largest among the groups (EUR 1.1 billion). The most significant import group in 2022, too, was the "industrial supplies, processed, n.e.s." with a turnover growth from EUR 1.4 billion in 2021 to EUR 1.7 billion in 2022.

Figure 5 The structure of the Hungarian import* dispatched from Czechia by the groups of the BEC Rev. 4 nomenclature (percentage share of the main groups in the import of the given year)



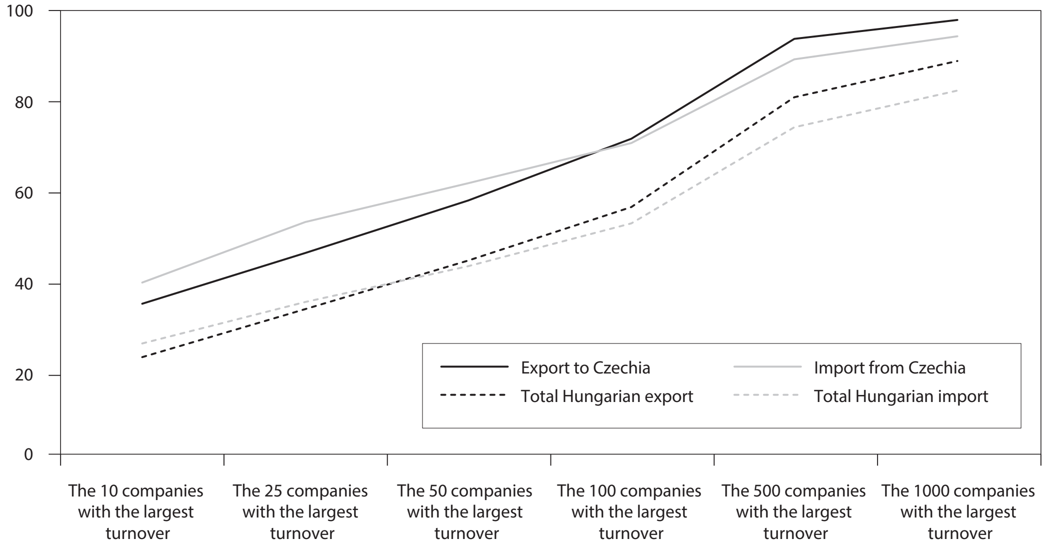
Note: * data by origin for 1999–2002.
Source: Own calculations based on „DS-057555 – EU trade since 1988 by BEC/rev.4" Eurostat database

Corporate concentration is significantly stronger in the external trade of Hungary with Czechia than in the total turnover. This fact contradicts our expectations, as the vicinity of the two states gave the impression that smaller Hungarian dealers may reach a greater share in this relation than in the total export or import. Interestingly the concentration of export overtakes that of import in both the Czech and the world context after taking into account a relatively small number of enterprises. The shift occurred in 2022 after the corporation with the 86^{th} and the 39^{th} largest turnover, respectively.

The Hungarian external trade in services with Czechia is one order in magnitude smaller in value than the external trade in goods. The value of our 2019 turnover with Czechia was 2.6 times the 2008 one, while the average growth rate of all countries of the world is 1.8-fold. The Czech turnover – in contrast with the total turnover – increased even in the 2009 crisis year.

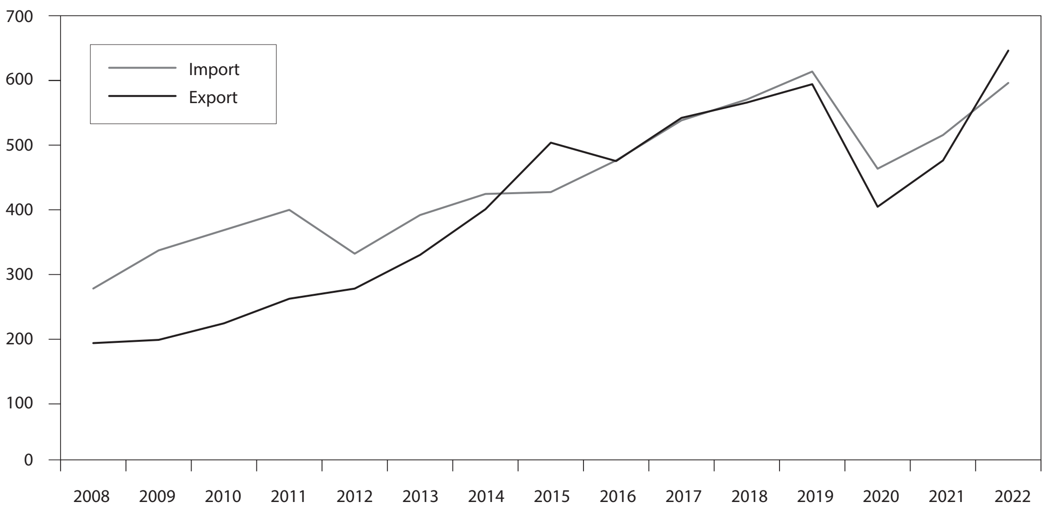
We observed a significant setback in 2020, a year loaded with the Covid19 pandemic, the bilateral turnover shrunk from EUR 1.2 billion to EUR 857 million. This change, surpassing the total turnover decrease, is in line with the fact that tourism has a more significant role in the turnover with Czechia

Figure 6 Company concentration in Hungarian external trade of merchandises, 2022 (%)



Source: Own calculations based on HCSO data

Figure 7 Hungary's external trade in services with Czechia (million EUR)



Source: The HCSO database

than in the average of all countries, and this division was severely affected by the pandemic related restrictions. Turnover expanded in 2021, however, it still lagged behind considerably the pre-pandemic 2019 level. Trade was 3% larger than its three years earlier amount, this pace, however, is 4 percentage points less than the growth in relation to all partner countries. In 2022, tourism had a 20% share in our external trade in services with Czechia, this was 8 percentage points less than in 2019, and 5 percentage points more regarding total turnover.

Table 6 Distribution of the external trade in services with Czechia by groups of services (%, calculated from EUR data)

Group of services	Export		Import	
	2012	2022	2012	2022
Transportation	**21.4**	**28.9**	**23.0**	**33.6**
out of this:				
maritime transportation	0.1	5.5	0.5	8.0
air transport	8.0	5.9	10.5	2.0
road transport	9.1	10.1	7.7	13.2
Tourism	**34.0**	**26.2**	**28.8**	**12.6**
Business services	**43.3**	**44.3**	**47.4**	**51.6**
out of this:				
other business services	29.6	28.5	32.2	34.6
out of this:				
management consultancy and PR-services	14.3	14.8	13.9	12.9
personal, cultural and entertainment services	4.8	7.5	5.8	4.4

Source: HCSO database

2 DEVELOPMENT OF THE CZECH-HUNGARIAN FDI (FOREIGN DIRECT INVESTMENT)

The European Union's framework (the base principle of free movement of capital, people, goods and services) is an unprecedented historical opportunity for the Central-European economic cooperation. Although Czech-Hungarian economic relations are evolving, there are still untapped potentials in this respect in comparison with other countries of the region.

In addition to trade relations the economic interconnection of two states is realised by FDI, too. The OECD definition states: Foreign direct investment (FDI) is a category of cross-border investment in which an investor resident in one economy establishes a lasting interest in and a significant degree of influence over an enterprise resident in another economy (OECD, 2008: 17). HCSO defines FDI as a long term, lasting investment realised in a different country than the direct investor's one (in an enterprise operating through direct investment). The lasting interest is long term and means a close relation between the direct investor and the company, significantly impacting the company management (HCSO).

There are many studies regarding the impact on FDI receiving countries, with diverging results, there is no consentaneity in the international literature. The literature does, however, highlight the major importance of technology.

A great number of studies concluded that FDI has a beneficial impact on the economy, as the capital arriving in the receiving country brings high-tech, which, in its turn, comes into general use in the given economy, increasing productivity and output, by more efficient use of the resources (Tőkés, 2021). Blomström–Kokko (1997) also concluded that foreign owned enterprises may have a positive influence on the economic performance of the receiving economy. Borensztein et al. (1998) studied developing countries and stated that technological catching up may – in part – bring about their development. Convergence may be speeded up if developed countries hand their high tech over to the developing ones through FDI. Large multinational corporations (MNC) spend usually a lot on research and development (R&D), their technological development is advanced and productivity is higher than that of their smaller competitors. MNCs are able to "export" their knowledge to the receiving countries (Borensztein et al., 1998). This knowledge flows through vertical and horizontal connections and by participating in the R&D, into the host country's economy (OECD, 2002).

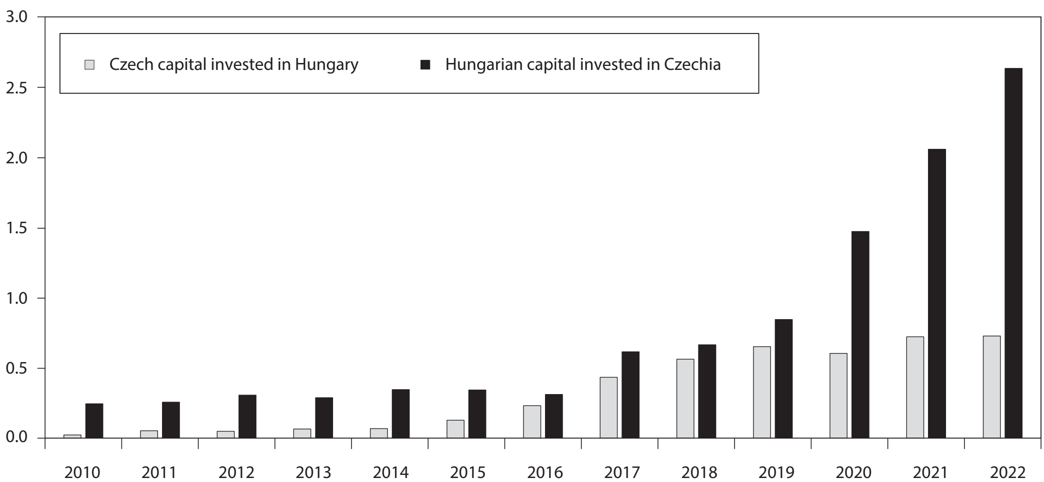
According to Lankes–Venables (1996) FDI may increase the production capacity of capital- and investment-poor receiving countries, could improve productivity and may speed up their economic development, could bring technology and know-how into the receiving economy, management and marketing knowledge, techniques to local companies by cooperating with these. May develop markets, the attitude and culture of local economic actors. These positive impacts, however, are not self-acting. Foreign owned companies may become isolated islands in the local economy, having few contacts with local economic actors. Also, these may "freeze" the low local technological development by activities of shallow added value. Excessive specialisation may occur in the receiving economy if only a few products are manufactured locally, increasing economic vulnerability from world economic processes and business cycles points of view.

Borensztein et al. (1998) stated that FDI was a major tool in transfer of technology, however, its potentials could only be used if the receiving country's human potential reaches a certain level, as new technologies require human knowledge and qualification.

All in all, many studies deal with FDI's impact on the economy. European central banks, overseeing financial markets, and statistical authorities offer reliable data for performing valid examinations based on international standards. The next part of this study reviews the Czech-Hungarian FDI development starting from 2008 based on these data, information.

Czech FDI stock has been growing continuously in Hungary since 2008[5] (except for 2012 and 2020), considering the country of the final investor, in 2022 it came close to EUR 728 million, being 32 times more than in 2010. The stock grew most dynamically in 2011, 2015 and 2017. In spite of the increasing volume still only 0.8% of Hungary's 2021[6] FDI came from Czech enterprises (this ratio was 0.1% ten years ago), placing it on the 15th place in the European countries' ranking.

Figure 8 Direct investment stock (at the end of the year) in billion EUR



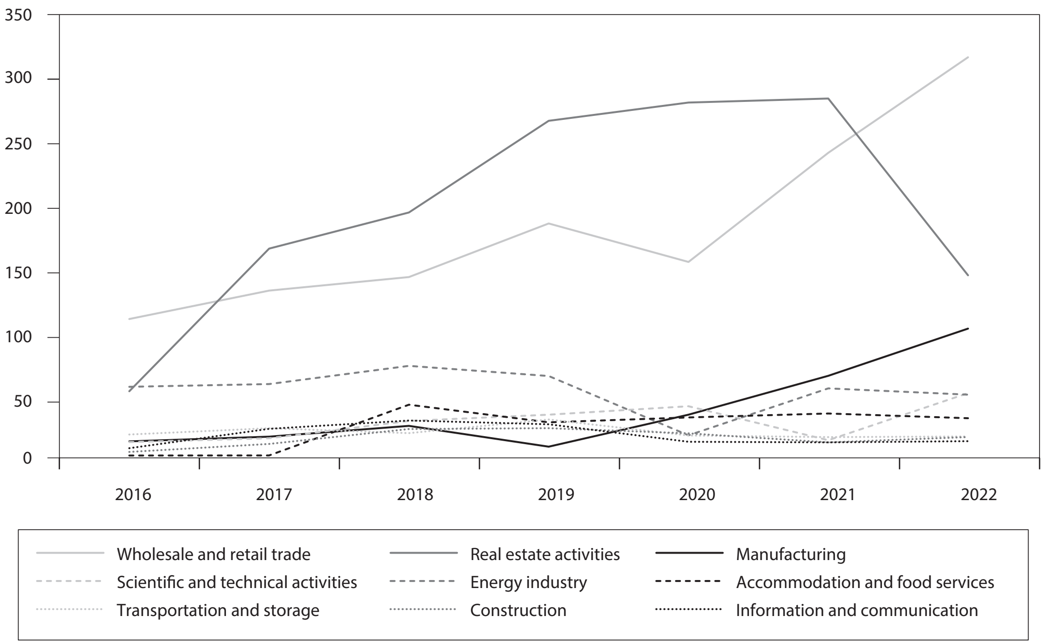
Source: Own design based on the data of the National Bank of Hungary

[5] The examination of the data at the sector-level is based on TEÁOR'08, introduced in 2008 and valid ever since. The period under study is starting with 2008, as previous data are based on earlier TEÁOR versions and their comparability is restricted.

[6] The 2022 value of the total FDI stock in Hungary was not available at the time.

By the end of 2022 Czech enterprises invested 78% of their capital in the services sections in Hungary. Trade took up 43% of their capital stock, real estate activities one-fifth, manufacturing 14% of it. Food industry, part of manufacturing, represented 9.9% of the Czech capital. 6.8% went into science and engineering activities, 6.6% into energy industry.

Figure 9 Changes in the Czech direct investment stock in Hungary by sections (in million EUR)



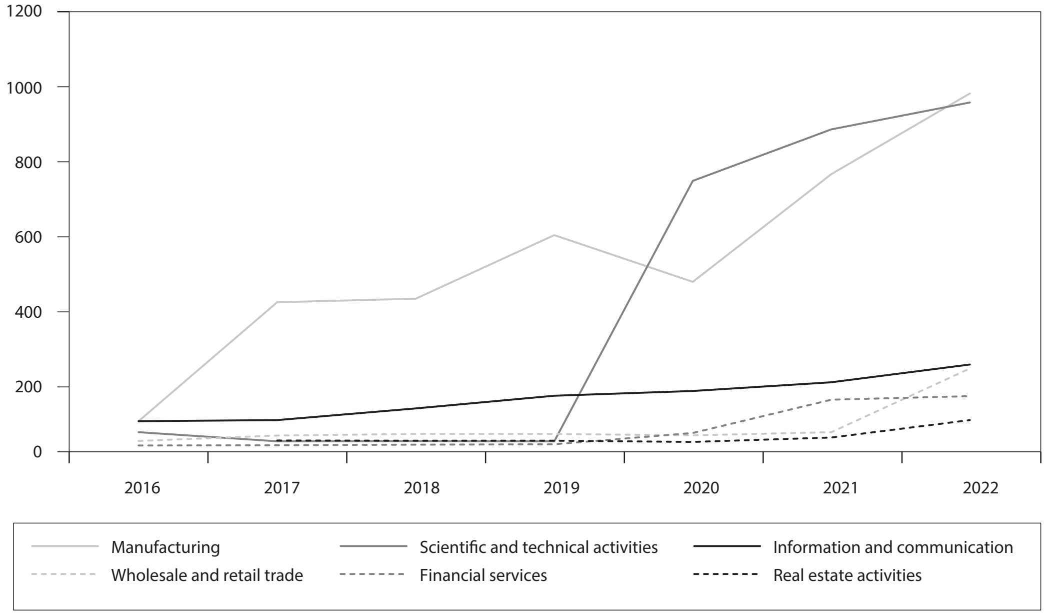
Source: Own design based on the data of the National Bank of Hungary

Hungarian enterprises' FDI stock in Czechia has also grew continuously since 2008 – except four years of setback – and surpassed by the end of 2022 EUR 2.6 billion. This was 3.6 times more than the Czech enterprises' FDI stock in Hungary and represented a 11-fold increase compared to the 2010 value. The stock almost doubled in 2017, year-on-year, also surpassed in 2020 by almost three quarters the 2019 one. Czechia was the country of destination for 5.9% of Hungarian owned FDI stock in 2021[7] (this ratio was only 1.2% ten years ago), granting among the European countries' ranking the honourable 5th place. Only the Netherlands, Cyprus, Croatia and Slovakia showed a larger capital investment amount than Hungary.

Based on the capital size of 2022, Hungarian enterprises invested 63% of their capital placed in Czechia in services sections. The remaining 37% served manufacturing development, where the stock, more than doubling since 2020, came close to EUR one billion. Within manufacturing the production of computers, electronics and optical products, production of chemicals as well as vehicle production were the most appealing investments for Hungarian companies. Scientific and technical fields were close behind manufacturing, where 2020 was a year of very significant investments and Hungarian capital investments are outstanding ever since.

[7] The value of the total Hungarian FDI stock for 2022 was not available at the time.

Figure 10 Changes in the Hungarian direct investment stock in Czechia by sections (in million EUR)



Source: Own design based on the data of the National Bank of Hungary

3 CZECH SUBSIDIARIES IN HUNGARY

The weight of Czech subsidiaries is not significant in the Hungarian economy on its own, among foreign controlled companies, however, their importance is non-negligible.

There were 284 companies controlled from Czechia in Hungary at the end of 2008. Their number shrunk to 210 by the end of 2010, then starting to increase once again reached 351 by the end of 2020, representing 2.3% of the total subsidiaries controlled from abroad, compared to 1.5% in 2008.

Turnover of Czech enterprises operating in Hungary – at current prices – surpassed each year, except two, the previous year's level in the period starting in 2008, at the highest extent (by 65%) in 2014. There was, however, a 23% setback in 2009 and 2020. While Czech companies' turnover represented in 2008 only 0.4% of the total of all foreign controlled enterprises operating in Hungary, this ratio reached 1.1% in 2020, its value surpassing EUR 1.7 billion.[8]

Production value at the very same companies changed in a similar way with the turnover, but in this case, there were four years of setback. Czech companies generated 0.8% of the production value of foreign controlled enterprises operating in Hungary in 2020, representing a 0.6 percentage points growth compared to 2008. Production value in 2020 was EUR 819 million, falling back by almost one-third in proportion to 2019.

The value added of Czech companies operating in Hungary – at factor cost – changed in a similar way as did the turnover and the production value. Their 2008 performance was only 0.3% of all foreign controlled companies' value added, growing by 2019 to 1.4%, and decreasing in the next year by a half. The 2020 value added realised by Czech companies, EUR 236 million, fell, at current price, by 46% compared to 2019.

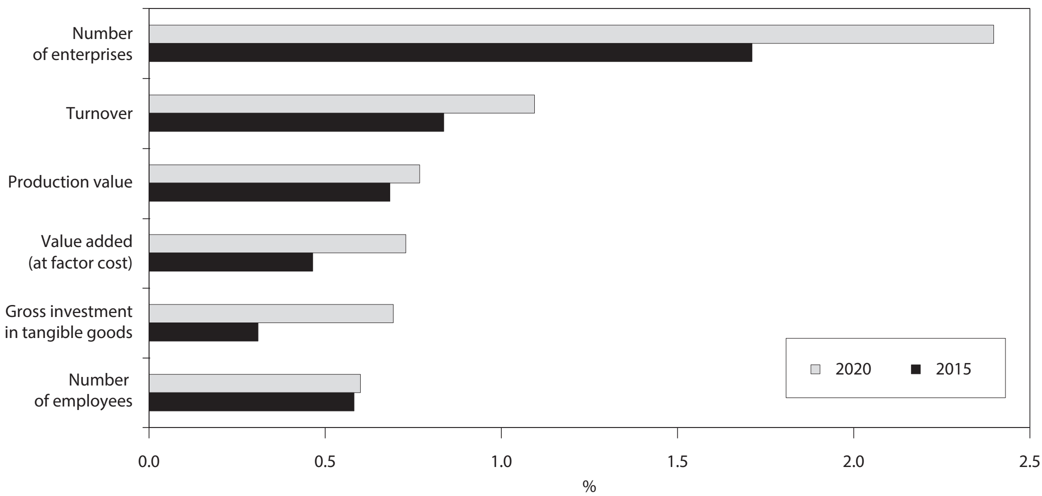
[8] Calculated at the 2020 average exchange rate of HUF 351.17/EUR of the National Bank of Hungary.

Their value added producing capability, at value added per employee index, was still higher (EUR 53.550) than the average of foreign subsidiaries (EUR 46.413). The 15% positive difference is a great improvement considering the base year of the data series, when the performance of Czech subsidiaries lagged behind the average by 45%.

Czech companies participated in 2008 in the gross investment in tangible goods of foreign enterprises by 0.1% only. This ratio increased to 0.7% by 2020. Czech companies operating in Hungary spent about EUR 68 million on development in 2020, at current prices 22% more year-on-year.

The number of employees at Czech enterprises, being more and more active in Hungary, grew from 2 975 people in 2008 to 4 409 in 2020 (coming close in 2018 to 5 500). The 48% increase in employee numbers at Czech companies excelled the foreign enterprises' 12% headcount-growth average. They gave by this 0.6% of the employees of foreign controlled companies in 2020, 0.1 percentage point more than in 2008. A foreign controlled enterprise in Hungary employed 33 people on average in 2008, this number at a Czech one was 10 on average. The foreign average reached 46 people in 2020, the Czech one grew to 12. The difference is due to the fact that Czech companies operating in Hungary are usually small and medium size.

Figure 11 Share of Czech-controlled subsidiaries in Hungary within total foreign-controlled enterprise population*



Note: * based on data of non-financial enterprises operating in Nace rev 2 sections B.
Source: Own design based on the data of the Hungarian Central Statistical Office

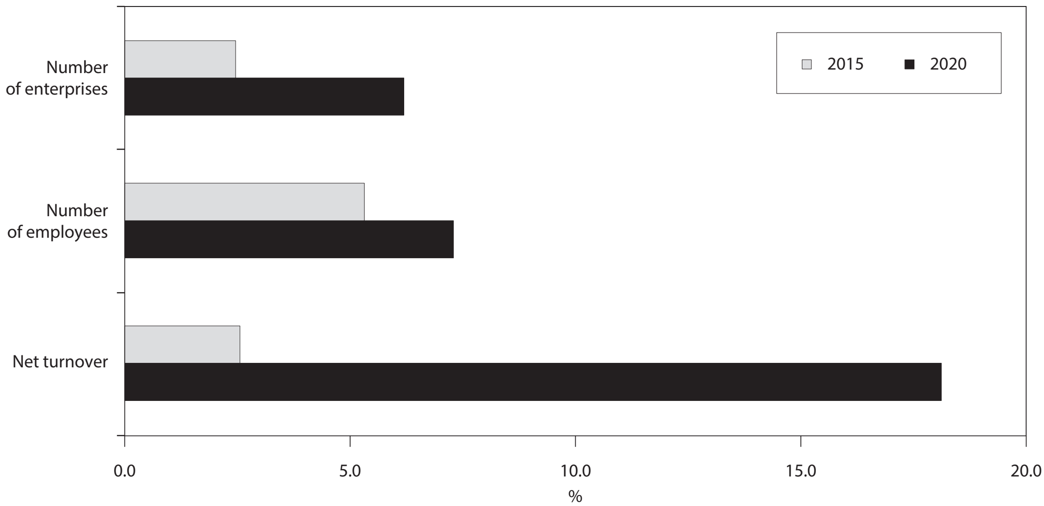
4 HUNGARIAN SUBSIDIARIES IN CZECHIA

Czechia had as of late in 2018 the largest number of Hungarian controlled subsidiaries, approximately 18 (6.2% of the total number of Hungarian controlled subsidiaries abroad by legal units), twice as many as in 2008, the start year of the period under study. 4 of them were active in the information and communication, and 3 in the field of scientific and technical activity. The number of Hungarian controlled subsidiaries did not grow in a calculated way, as statistics only registered three of them in 2019.

The previously mentioned 18 subsidiaries employed 1 722 people in 2020, the most of them (2 026 people) joined the 10 then existing enterprises in 2009. Their proportion in all those working at Hungarian controlled subsidiaries operating abroad was the highest in 2010 (8.8%), during the period under study and reached 7.3% in 2020. One quarter of employees performed scientific and technical activities, 19% have been employed by the energy industry.

Subsidiaries operating in Czechia, under Hungarian control reached EUR 2.6 billion[9] turnover in 2020, representing 18% of the total turnover realised by all Hungarian controlled subsidiaries operating abroad. This ratio was only 5.8% in 2008, and 6.9% on average between 2008 and 2020. (Based on available data, Hungarian companies operating in Czechia had an extremely low turnover in 2019, compared to the previous years.) Turnover of Hungarian companies working in Czechia came from the energy industry in a proportion of 52%, and from trade, 43% during 2020.

Figure 12 Share of Hungarian-controlled subsidiaries operating in Czechia within all Hungarian-controlled subsidiaries operating abroad*



Note: * based on data of non-financial enterprises operating in sections B-N based on TEÁOR'08 as well as in division S95.
Source: Own design based on the data of the Hungarian Central Statistical Office

The investments of the MOL are outstanding among the Hungarian enterprises' investments in Czechia, operating more than 300 gas stations, while MVM – through its subsidiary – provides natural gas and electricity for about 1.6 million Czech consumers.

Considering announced future investments, further increases may be expected in economic relations and investments, the Czech Nymwag Hungary Kft.'s railway vehicle manufacturing company in Nagykanizsa, a brownfield project stands out among these. It is going to provide employment to close to 1 500 people. The group of companies is also placing a research and development base near the factory equipped with high-end technology, this investment will be worth close to EUR 156 million;[10] according to plans 1800 freight cars and 4 800 railway carriages are going to be built here yearly. This development may be of great importance as the next 10 years could be the great decade of European railway development, being significantly more energy efficient and environmentally friendly than road transport. More than that, economic success of a country is highly dependent on logistics, inconceivable without modern railway.

The two countries' relations broaden in the arms industry, too. A joint handgun company has been established by the state owned Hungarian N7 Holding and the Czech Colt Group in Hungary. The factory is going to provide the Hungarian Army with firearms.

[9] Calculated at the 2020 average exchange rate of HUF 351.17/EUR of the National Bank of Hungary.
[10] Calculated at the February 2023 average exchange rate of HUF 384.91/EUR of the National Bank of Hungary.

In the light of direct investments and the operation of subsidiaries it may be stated that the Czech-Hungarian economic relations are continuously growing, developing. Given the relatively small number of subsidiaries there are significant fluctuations in the bilateral economic relations, unfortunately. The appearance or disappearance of a larger weight carrying economic actor may induce hectic movements. This is the reason why the diversifying of relations would be of tremendous significance in the stability of economic connections.

CONCLUSION

The first part of the study is dealing with the trends of the external trade between Czechia and Hungary, based on the data of the Hungarian Central Statistical Office, considering the last three decades regarding the trade in goods and the last one-and a half one in the case of the trade in services. Processes are examined in EUR throughout the study, evaluation is therefore exempt from HUF exchange rate changes – devaluation, characteristically. Following the regime change both countries suffered transformation setback, as a result Czechia participated in a small, 2% proportion in the goods turnover of Hungary during the 90s. Its share grew to 4.5% by the 2020s, and it is among the 10 most significant partners of Hungary in both trade directions. The structure of goods underwent a major change in time, the "machinery, transport equipment" main commodity group outrun the manufactured goods. Car industry products, occasionally not even from the "machinery, transport equipment" main commodity group, carry a big proportion in the trade of goods as such the crises affecting automotive industry have a greater impact on the Czech-Hungarian turnover than on the total Hungarian trade. Turnover in parts and accessories carries a greater value within car industry commerce than that of cars. It has been stated that the four largest turnover producing commodity groups, based on the BEC nomenclature, are the same in both trade directions. According to the most recent OECD data the Czech manufacturing industry exports to Hungary has a greater added value content than the Hungarian exports to Czechia (51% and 44% in 2018). Concentration of enterprises is stronger in relation with Czechia than in the average of all relations, this fact – considering the closeness of the markets – gives scope for a greater participation for SMEs in the commerce. In the average of 2019–2022 trade in goods consisted in 97% products of manufacturing industry, however, based on the classification of foreign trade enterprises, the role of the commerce division is significant (43% in exports, 57% in imports). As far as imports is concerned: the 2022 turnover coming from Czechia surpassed considerably (by EUR 2.4 billion or 50%) the Czech origin imports (coming from any country in the world). Czechia mediated to Hungary in greatest value Chinese origin goods last year. External trade in services with Czechia has a one order of magnitude smaller value than that of goods, its expansion between 2008 and 2022, however, had a faster pace than the total service trade of Hungary and surpassed the growth of the turnover of goods in relation with Czechia as well.

According to the data of National Bank of Hungary the Hungarian FDI stock invested in Czechia was EUR 2.6 billion, the Czech FDI in Hungary EUR 0.7 billion at the end of 2022. 37% of the Hungarian FDI in Czechia was invested in manufacturing, 43% of the Czech one in Hungary in trade. Based on business demography data at the end of 2020 there were 354 enterprises in Hungary controlled from Czechia. These had 4.4 thousand employees, value added per employee (EUR 53.6 thousand) was already 15% more than that of an average foreign subsidiary. Also at the end of 2020 there were only 18 subsidiaries in Czechia managed from Hungary, where 1.7 thousand people were employed. Their net sales revenue was EUR 2.6 billion in 2020, representing 18% of all revenues from Hungarian subsidiaries operating abroad. More than half of their sales revenue in Czechia came from the energy industry, 43% from trade. The MVM energy company, through its Czech subsidiary, provided natural gas and energy services for approximately 1.6 million consumers.

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The Impact of External Debt on Human Capital Development and GDP Growth in HIPCs: a Comprehensive Approach

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Received 6.3.2023, **Accepted** (reviewed) 3.4.2023, **Published** 15.9.2023

Abstract

The growth theorists argue that human capital development/accumulation (HCD/A) is vital for economic growth. However, the level of external debt accumulation determines HCA and its effect on economic growth. Besides, the impact of external debt on growth is still debatable. Further, the external debt-growth relationship could be non-linear instead of linear, and external debt can affect growth through the HCD channel. Therefore, this study aims to look at the impact of foreign debt on HCD and growth in heavily indebted poor countries (HIPCs) employing seemingly unrelated regressions (SUR) and other alternative simultaneous equations models (SEMs) from 1990–2017. The result indicates the link between foreign debt and HCD is negative and non-linear, but only non-linearity is observed between foreign debt and growth. Besides, external debt affects HIPCs growth through the HCD channel. Therefore, the study recommends essentializing solid macroeconomic policies, strengthening institutional performance, appropriate debt management strategies, and investing borrowed funds in productive projects.

Keywords	***DOI***	***JEL code***
External debt, HCD, economic growth, HIPCs	*https://doi.org/10.54694/stat.2023.10*	*F34, H63, O47*

INTRODUCTION

The Organisation for Economic Cooperation and Development (OECD, 2001: 18) broadly defined human capital by saying that "the Knowledge, skills, competencies and attributes embodied in the individuals that facilitate the creation of personal, social, and economic well-being". However, due to the demerits

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of conventional measurement of human capital, a new measurement approach is proposed by the United Nations Development Program (UNDP) and the International Labour Organization (ILO; Kwon, 2009). Hence, since 1990 UNDP has developed a new and more comprehensive measure of human capital called the human development index (HDI; Ivanova et al., 1999; Kwon, 2009). Therefore, according to UNDP (2019), HDI is a comprehensive measure of average performance in important areas of key human development, such as healthy and long life, knowledge, and decent living standards.

Human capital has been a topic of discussion in economics since the late 17th century. Smith (1776) and Farr (1853) argue that human beings and their acquired abilities were considered the primary input for national wealth. Besides, after the works of Schultz (1961), Becker (1964) and Mincer (1974), the concept of human capital regained recognition and began to apply to various economic issues. Even since the new millennium, the two main development plans, Millenium Development Goals (MDGs) and Sustainable Development Goals (SDGs), broadly focus on achieving either of the three-elements of HDI.

Besides, the endogenous growth models emphasized the role of endogenous factors (i.e., human capital stock and research & development activities) as the main engines of economic growth. According to Lucas (1993), human capital accumulation is an engine of growth. Countries vary in their quality of life because of the differences in their accumulated human capital. Further, Mankiw (1992) argues that the rise in human capital accumulation directly increases the growth rate (Hasan and Butt, 2008). The two broad categories of studies that investigate the link between economic growth and human capital accumulation are: (a) the growth accounting framework theorist (Baumol, 1986; Barro and Lee, 1993), argues that human capital accumulation through education, increases individuals' productivity and a pillar for growth, and (b) endogenous growth theorists like Lucas (1988), Romer (1990), and Grossman (1991), argue that human capital creates new ideas which are transformed into scientific knowledge and ultimately leads to accelerating the process of economic growth. Human capital is an important source of long-term growth because it directly inputs research (Romer, 1990) or because it shows positive externalities (Lucas, 1988). The integration of human capital variables in endogenous growth models is intended to capture quality differences in the labour force, as non-physical capital investment increases the productivity of the existing labour force (Barro and Lee, 1993).

However, the effect of human capital accumulation on GDP growth depends on foreign debt accumulation. According to Pattillo et al. (2004), foreign borrowing increases investment in human capital at low debt levels, hence boosting growth. However, if the debt burden is very high, debt overhang and crowding out effect conditions may happen, adversely affecting human capital and growth. Concerning this, evidence shows that the high external debt level was one of the causes of the failure to achieve the MDGs because debt servicing absorbs resources that could be used for essential spending on poverty reduction and diverts resources away from investment in education and health.

There is a contradictory school of thought concerning the impact of external borrowing on growth – the Keynesians and Classical economists. The Keynesians argue that external debt positively contributes to growth, but the classical postulates the reverse. Besides, based on the type of functional model, empirical findings concerning the impact of foreign debt on GDP growth can be broadly categorized into two groups. The first group considered a linear relationship between external borrowing and growth, while the second group used a non-linear model. However, similar to the theories, empirical studies about external debt's impact on growth are mixed and inconclusive. Besides the direct effect of foreign debt on growth, scholars noted that there were channels through which external debt was transmitted to the economy and affects nations' economic growth.

The existing empirical studies regarding the impact of foreign debt on human capital/welfare can be categorized into two groups. The first group used a composite HDI as a dependent variable (Egungwu, 2018; Zaghdoudi, 2018). The other group examined the effects of external debt on either of the three components of the HDI such as health, education and living standards (poverty; Pattillo et al., 2004; Fosu, 2007, 2010; Eduardo and Mauricio, 2007; Shabbir and Yasin, 2015; Zaghdoudi and Hakimi, 2017; Saungweme and Mufandaedza, 2013). However, there are no empirical studies about the impact of external borrowing on HCD in HIPCs though the countries experienced a bad history of external debt accumulation and its adverse effect on macroeconomic variables since the 1970s debt crisis.

Besides, except for Pattillo et al. (2004) and Zaghdoudi (2018), all other studies neglected the optimal threshold beyond which external debt can positively or negatively affect human capital, which means that previous studies examined the linear relationships between the variables. Also, except for Zaghdoudi (2018) and Egungwu (2018), all others narrowly investigated the effect of foreign debt on health, education, or living standards. Further, most of previous studies evaluated the direct impact of external debt on economic growth rather than an indirect effect through the HCD channel. Also, except for a few studies, most of previous findings did not consider a non-linear relationship between external debt and growth and neglected the most concerned countries – HIPCs. For example, only Pattillo et al. (2004) examined the human capital channel through which external debt affects growth using a non-linear model for 61 developing countries from 1969–1998. This implies empirical studies that analysed the non-linear impact of external debt on growth, considering the human capital channel is not found in HIPCs.

Therefore, unlike others, this study focuses on the most concerned countries. Hence, investigating the impact of foreign debt on HCD and growth in the case of HIPCs is vital to provide policy recommendations that help overcome the adverse effect of debt accumulation. Besides, since the 1970s external debt crisis, HIPCs experienced external debt accumulation, making their debt unsustainable and qualified for repeated debt cancellation and relief. Therefore, examining the effect of external debt HCD and growth is an important research area for HIPCs. Also, unlike other studies, this study uses a more comprehensive measurement called HDI to measure HCD. Further, in recent times, an essential feature of the research in this area indicates that the impact of external debt on HCD and growth could be non-linear rather than linear; therefore, this study considers the non-linear relationship. Also, previous studies did not show the HCD channel through which foreign debt affects growth and consider the cross-sectional dependence (CD) in the errors in their methodologies. Therefore, this study's primary objective is to examine the impact of foreign debt on HCD and GDP growth in HIPCs using the SUR model from 1990–2017.

1 LITERATURE REVIEW

1.1 External debt, human capital and growth

Since human capital can be measured using HDI, which considers better achievements in education, health, and living standards, any activities that hinder these elements adversely affect countries' human capital. Besides, HDI's scope is broad and sometimes considered human welfare.

The debt overhang and crowding out effect hypotheses are the two basic arguments for the relationship between increasing foreign debt and human capital (welfare) and growth. According to the debt overhang theory, increasing foreign debt has a negative impact on both growth and welfare. When there is an excessive build-up of external debt, both domestic and international investors believe that the government would finance the debt by unfavourable measures, such as high taxes, seigniorage, or a reduction in useful public investment. Investors would thus decide to hold back, spend less, or invest abroad, negatively impacting growth and welfare-related investments (education and health).

On the other hand, the crowding out argument contends that excessive external debt accumulation results in huge debt payments and diverts resources away from the social sector, particularly health and education (Fosu, 2008). According to Shabbir and Yasin (2015), government spending is a key driver of economic growth, and governments in emerging nations must make wise social sector investments. However, countries' budgetary allocations may suffer due to debt payments. The fundamental purpose of foreign borrowing, which is to support growth and development, is undermined by the cost of servicing debt, which takes a significant portion of the limited resources generated through exports and/or foreign remittances and leaves little to finance growth.

1.2 Theoretical framework of the study

This study considers endogenous growth models and adopts Zaghdoudi's (2018), Cunningham's (1993), and Mallick and Moore's (2008) theoretical models to examine the relationship between external borrowing, human capital, and GDP growth.

Zaghdoudi (2018) illustrated how external debt affects human development. On the other hand, to investigate the effect of external debt on economic growth, Cunningham (1993) introduced debt burden into the production function.

However, Mallick and Moore (2008) comprehensively established an endogenous growth model and demonstrated how human capital affects growth. Additionally, they looked at the significance of foreign capital in supporting growth and investments in both human and physical capital.

Given country's production can be characterised by the augmented aggregate production function (Y), homogenous of degree one with respect to physical and human capital, as:

$$Y_t = A(K_t^{\gamma})\,(HL)_t^{\eta} \text{ and } HL = E^{\delta} \Rightarrow \frac{Y}{E} = A\left(\frac{K^{\gamma}}{E^{1-\delta\eta}}\right) \Rightarrow y = Ak^{\gamma} \text{ if } \gamma = 1 - \delta\eta\,, \tag{1}$$

where y is real output per unit of human capital, K is capital, L is raw labour input, HL is the average level of human capital, which is more likely to improve productivity, A is technical progress or TFP, which is exogenous and different across countries, that is, low in low-income countries, E is the measure of education level, δ is the return to education.

Assuming the capital stock depreciates at the rate Ψ, the evolution of k (K/E) is given by the following:

$$\dot{k} = \frac{I}{E} = \Psi k - kh, \text{ where } h = \frac{\dot{E}}{E}\,. \tag{2}$$

In the long-run $\dot{k} = 0$. This long-run relation implies that as human capital growth increases, physical capital stock per unit of human capital remains constant. Now substituting the steady-state level of K in the production function, we write:

$$Y_t = A\left(\frac{I}{\Psi + h} I_t^{\gamma}\right) (E^{\delta})_t^{\eta}\,, \tag{3}$$

There are two sources of financing this domestic investment (I) (physical and human capital). One is domestic savings[3] and foreign savings.[4] Since foreign debt is one source of inflow of foreign capital, it can contribute to growth by relaxing financing constraints (saving, foreign exchange, and fiscal gaps) and financing investment in physical and human capital (Morrissey, 2004; Mallick and Moore, 2008).

1.3 Empirical literature

Even though there are several empirical studies concerning the linear impact of external debt on growth, this section focuses on non-linear[5] ones for the interest of scope and space. Furthermore, it reviews findings on the impact of external debt on HDI or its element(s).

[3] Part of the gross national disposable income that is not consumed.
[4] Complementary source of financing investment outlays.
[5] Pattillo et al. (2004), Checherita-Westphal and Rother (2012), Senadza et al. (2017), and Zaghdoudi (2018).

There are only two empirical studies that used the comprehensive measure of human capital or human development or welfare: Egungwu (2018) and Zaghdoudi (2018). Zaghdoudi (2018) found an inverted U-shape relationship between external debt and human development. Besides, Egungwu (2018) found that external debt stock and external debt servicing adversely affected HCD. However, Egungwu (2018) study is only for Nigeria, but the country is not found in the current IMF list of HIPCs. It also neglected the optimal threshold beyond which external debt can positively or negatively affect human capital. Further, it used conventional estimation techniques and included I(0), I(1) and I(2) variables in its estimations, and it neglected the cointegration test. Hence, its policy recommendations may not be appropriate and represent HIPCs. Therefore, this study overcomes Egungwu's (2018) limitations by considering the most concerned countries, the non-linear relationship, and better estimation technique that considers basic steps in econometrics such as CD, unit root, and cointegration tests.

Zaghdoudi (2018) used HDI to measure human development, considered the non-linear relationship between external debt and HDI, used a good estimation technique, and many countries. However, the study mixed countries suffering from massive & unsustainable external debt with others. That means around 70% of sampled countries are not in the list of HIPCs; hence, its results and policy recommendations may not represent HIPCs. Besides, the study neglected two basic tests – CD and panel cointegration. However, ignoring CD tests leads to biased estimates and spurious inferences. Further, the CD test determines the type of panel unit root, cointegration tests, and estimation techniques the study should follow. Therefore, unlike Zaghdoudi (2018), this study focuses on the most concerned countries that experienced accumulated & unsustainable external debt and repeated debt cancellations & relief and conducting basic econometric tests before estimation. Moreover, our study is relatively latest (until 2017).

Unlike the above studies, Pattillo et al. (2004), Fosu (2007), Eduardo and Mauricio (2007), Fosu (2010), Saungweme and Mufandaedza (2013), Shabbir and Yasin (2015), and Zaghdoudi and Hakimi (2017) examined the relationship between external debt on either of three HDI elements.[6] This implies these studies did not use a comprehensive measurement of HCD, which can limit their scope of analysis.

Concerning empirical studies on the debt-growth relationship, Pattillo et al. (2004), Checherita-Westphal and Rother (2012), Abdelaziz et al. (2019), and Silva (2020) examined the channels through which external debt is transmitted to the economy and affects the economic growth of nations. However, among channel studies, only Pattillo et al. (2004) investigated the human capital channel through which external debt affects growth using a non-linear model for 61 developing countries. This implies that, to the best of the writer's knowledge, no study shows the non-linear effect of external debt on HCD and growth in the case of HIPCs. Also, the HCD channel through which external debt affects growth is not investigated in HIPCs, leading to a literature gap.

2 METHODOLOGY OF THE STUDY

2.1 Data type and sources

This study uses secondary panel data and all, except for institutional quality (INSQ) and HDI, were collected from the World Development Indicator (WDI) (see Table 1).

This study employs a sample of 15 HIPCs[7] (which achieved a post-completion-point)[8] from 1990 to 2017 due to a lack of pertinent data, and its scope (sampled nations (N) and period (t)) is sufficient to describe all HIPCs. In other words, the study's $N \cdot t = 420$ observations satisfy Kennedy's (2008) suggestion about the significance of a high sample size. The findings and policy suggestions from this

6 They found that high level of external debt or its service negatively affects either of the three elements of HDI.

7 Benin, Burundi, Cameron, Central Africa Republic, Mauritania, Mozambique, Niger, Rwanda, Senegal, Sierra Leone, Tanzania, Togo, Honduras, Bolivia, and Nicaragua.

8 Countries that completed the HIPC initiative process (a program aimed to reduce the debt burden of developing countries) and obtained 100% debt relief from international communities (creditors).

Table 1 Definitions, measurement and sources

Variables	Definition	Source
HCD	Human capital development proxied by human development index (HDI). HDI is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living	UNDP
GDPGR	The annual GDP growth rate (%)	WDI
ED	External debt (% of GDP)	WDI
ED^2	External debt (% of GDP)2	WDI
DSR	Debt service (% of GDP)	WDI
INF	Inflation, GDP deflator (annual %)	WDI
INSQ	Institutional quality proxies as Polity 2, which is measured as the country's elections competitiveness and openness, the nature of political involvement in general, and the degree of checks on administrative authority. The estimate gives the country's score on the aggregate indicator, in units of standard normal distribution, ranging from –10 to +10	Polity 2 data series from Polity IV
OPPN	Trade as a proxy variable for openness and measured the sum of exports and imports of goods and services (% of GDP)	WDI
EXCH	Official exchange rate (LCU per US$, period average)	WDI
POP	Population growth (annual %)	WDI
NBTOT	Net barter terms of trade index (2000 = 100)	WDI
LAB	Labour force (% of total population)	WDI

Source: Authors construction

study can thus reflect and used for the other HIPCs. Additionally, the study's time frame is relevant since it covers a variety of global development programs and occasions connected to the title.

2.2 Model specification

This study considers HCD and GDPGR as dependent variables. Additionally, the study treats the dependent variables as independent because of their reciprocal interaction. Therefore, the estimated models specified as:

$$HCD_{it} = \alpha_0 + \alpha_1 ED_{it} + \alpha_2 ED^2_{it} + \alpha_3 DSR_{it} + \alpha_4 GDPGR_{it} + \alpha_5 POP_{it} + \alpha_6 NBTOT_{it} + \alpha_7 INSQ_{it} + \eta_{it}\,, \quad (4)$$

$$GDPGR_{it} = \beta_0 + \beta_1 HCD_{it} + \beta_2 ED_{it} + \beta_3 ED^2_{it} + \beta_4 DSR_{it} + \beta_5\, LAB_{it} + \beta_6 OPPN_{it} + \beta_7 INF_{it} + \beta_8 EXCH_{it} + \eta_{it}\,, \quad (5)$$

where, α_0 is an intercept term, η_{it} is a stochastic error term, and (+) α_1, (–) α_2, (–) α_3, (+) α_4, (–) α_5, (+) α_6, and (+) α_7 are the long-run coefficients of Formula (4). For Formula (5), β_0 is an intercept term, and (+) β_1, (+) β_2, (–) β_3, (–) β_4, (+) β_5, (+) β_6, (–/+) β_7, and (–/+) β_8 are the long-run coefficients. The signs in the parenthesis refer to the hypothesised signs.

2.3 Basic panel econometric tests

All countries are susceptible to the effects of financial and economic crises (Pesaran, 2006). As a result, the cross-sectional unit, its explanatory variables, and the error terms are often subject to CD. Therefore, disregarding the CD in panel data results in distorted estimations and erroneous results (De Hoyos and Sarafidis, 2006; Pesaran, 2007). As a result, it is crucial and the first step in panel data econometrics to examine the CD. There are several tests for CD in the literature; however, among the CD tests currently in use, this study uses Friedman (1937), Frees (1995), and Pesaran (2021).

Following the CD test, doing the panel unit root (UR) and cointegration tests is a usual practice. First-generation and second-generation panel UR tests are the two different varieties. However, O'Connell (1998), Pesaran (2007), Baltagi (2008), Chudik and Pesaran (2015), and Eberhardt and Presbitero (2015), among others, have criticized the first-generation tests for assuming cross-sectional independence. Consequently, second-generation tests have been suggested to account for CD; hence, this study uses the 2^{nd} generation of Pesaran (2007) cross-sectional augmented panel UR (CIPS) test.

Several panel cointegration tests allow CD; however, except for a few, most are not coded in Statistical Software (STATA) or Econometrics Views (EViews). Besides, some of them suffer from insufficient observation and cannot accept many regressors in their model. For example, even though Westerlund and Edgerton (2007) do not take many regressors, it is based on the McCoskey and Kao (1998) Lagrange Multiplier (LM) test. Thus, we can use a residual-based cointegration test in the heterogeneous panels' framework proposed by McCoskey and Kao (1998) using an efficient estimation technique, such as fully modified OLS (FMOLS) and dynamic OLS (DOLS) (Barbieri, 2008). However, relatively the DOLS is better than FMOLS (Kao and Chiang, 2000); thus, this study uses DOLS. Further, Banerjee and Carrion-i-Silvestre (2017) cointegration test is a residual-based one that allows a CD (for more detail, see Dajčman, 2019); thus, this study also employs it.

2.4 Estimation techniques and justifications

Several panel data estimation techniques allow CD; however, most require many observations over groups and periods. For instance, Driscoll and Kraay (1998) standard error estimates need a large number of countries (N) than period (t) (Hoechle, 2007). However, panel-corrected standard error (PCSE), feasible generalised least squares (FGLS), and SUR need more t than N (Hoechle, 2007; Breitung and Pesaran, 2008). Unlike others, the SUR approach is SEM; therefore, this study employs it. The SUR model was developed by Zellner (1962) and later adopted by Abdelaziz et al. (2019).

In contrast to conventional panel data methods (pooled OLS, Least Square Dummy Variable (LSDV), or fixed effect (FE) and random effect (RE), the SUR model captures the dynamic characteristics of the data. The correlation among equations is not taken into account by the pooled OLS estimate, FE, or RE. However, the SUR-generalized least squares (GLS) estimator presupposes the cross-equation correlation (Baltagi and Pirotte, 2011). Moreover, the SUR technique estimates the parameters of all equations together (simultaneously), allowing each equation's parameter to take into consideration the data supplied by the other equations. Consequently, the parameter estimations are more accurate since the system is described using more information. Additionally, if t>N, the SUR technique is feasible (Coakley et al., 2006; Breitung and Pesaran, 2008). Additionally, the SUR method's motivation came from the effectiveness in estimating it provides by combining data from many equations. The SUR model is more effective than OLS estimators, the two-stage generic least square, and Maximum Likelihood (ML) estimators (Abdelaziz et al., 2019). Thus, the SUR estimation technique is more effective in preventing erroneous findings than conventional panel data techniques since this research considers the data's dynamic behaviour and has a greater number of t than N. Therefore, this study estimated Formula (4) and (5) together (simultaneously) under the SUR approach. However, even though this study primarily uses the SUR approach, it employs other alternative SEMs, FGLS, and RE methods with alternative variables for robustness checks.

3 EMPIRICAL RESULTS AND DISCUSSION

3.1 Descriptive statistics and basic econometric tests

This study conducts descriptive statistics of all variables and CD tests for both models. Unfortunately, all the CD tests fail to accept the H0 of no CD (to save space, we do not report the results, but they are available from the authors). However, the Pesaran (2007) unit root result confirms that all the variables are highly significant (at 1% level) at the first difference.

Table 2 Panel UR test

Variables	CIPS (intercepts only)				Critical values		
	HCD model		Growth model				
	Levels	1st diff.	Levels	1st diff.			
	Statistic	Statistic	Statistic	Statistic	10 %	5 %	1 %
HCD	–2.073	–3.656 ***	–2.073	–3.656 ***			
ED	–2.086	–4.691***	–2.086	–4.691***			
ED2	–1.785	–4.149***	–1.785	–4.149***			
DSR	–2.678***	–5.731***	–2.678***	–5.731***			
INF	–	–	–3.968 ***	–5.897***			
GDPGR	–4.584***	–3.533***	–4.584***	–3.533***	–2.14	–2.25	–2.45
INSQ	–2.661***	–5.175***	–	–			
OPPN	–	–	–2.266**	–4.650***			
EXCH	–	–	–1.748	–3.460***			
LAB	–	–	–0.996	–0.996***			
POP	–1.91	–3.533***	–	–			
NBTOT	–1.925	–5.167***	–	–			

Banerjee and Carrion-i-Silvestre (2017)

Models	All variables without a square of external debt	All variables with a square of external debt	Critical values		
	Levels statistic	Levels statistic			
HCD	–4.228***	–4.289***	–2.14	–2.25	–2.45
Growth	–5.763***	–5.887***			

DOLS residuals test

Models	Tests		All variables without a square of external debt		All variables with a square of external debt	
			Statistics	p-value	Statistics	p-value
HCD	LLC	unadjusted t	–9.3433	0.0003***	–11.7954	0.0000***
		adjusted t*	–3.4687		–6.7374	
	IPS	t-bar	–3.2916	0.0000***	–3.1347	0.0000***
		t-tilde-bar	–2.4246		–2.4563	
		Z-t-tilde-bar	–4.8895		–5.0458	
Growth	LLC	unadjusted t	–25.6571	0.0000***	–54.7585	0.0000***
		adjusted t*	–26.8490		–58.8967	
	IPS	t-bar	–1.1821	0.9777	–1.7133	0.4850
		t-tilde-bar	–1.0250		–1.4402	
		Z-t-tilde-bar	2.0091		–0.0377	

Note: *** refers to significant at a 1% level.
Source: Authors calculation using STATA 15

The study conducts the residual-based cointegration (long-run relationship) tests using the DOLS of McCoskey and Kao (1998) and Banerjee and Carrion-i-Silvestre (2017). The Banerjee and Carrion-i-Silvestre (2017) result strongly rejects H0 of no cointegration at a 1% significance level for both models, implying a long-run relationship among the variables. Similarly, the DOLS result of the HCD model rejects the H0 of no cointegration while mixed for the growth model. This difference might be the LLC is more restrictive than IPS because it does not allow for heterogeneous coefficients. Since the DOLS result partially rejects the H0, this study uses Banerjee and Carrion-i-Silvestre's (2017) cointegration for further investigation. The result strongly rejects the H0 of no cointegration in the growth model. Therefore, we can conclude that a long-run relationship exists among the variables (see Table 2).

3.2 Long-run estimation results

Table 3 shows the estimated results (but to the interest of space, this section discusses only the target variables). The finding confirms the theory that foreign debt negatively affects HCD computed as HDI. In other words, a percentage change in foreign debt lowers HCD by 0.18%. This implies that when HIPCs increase their external debt, their HCD declines relative to prior years. This inverse relationship supports the debt overhang and crowding out effect hypotheses. This outcome is also in line with Egungwu (2018).

Even though their relationship defies the theoretical notion of an inverted U-shape, the link between external debt and HCD is non-linear, as represented by the quadratic term of the external debt coefficient. The findings show that the relationship between foreign debt and HDC is negative up to 236% of the external debt to GDP, but positive above this threshold. However, they do not have a U-shaped relationship. This is because, in most periods, 98% of the studied HIPCs' foreign debt remained below the threshold; as a result, the relationship is predominately negative. Therefore, in HIPCs, the link between foreign debt and HCD is negative and non-linear. Moreover, the individual country estimation results show that the relationship between external debt and HCD is inverted U-shape (in four countries), U-shape (in two countries), positive and non-linear (in one country), only non-linear (in three countries), only linear (in one country), and insignificant (in four countries).

This outcome contrasts with Zaghdoudi's (2018) inverted U-shape conclusion. Likely, 70% of the sampled countries in Zaghdoudi's (2018) study were not HIPCs; some were European and emerging nations with more effective debt management plans. Additionally, Zaghdoudi (2018) computed the square of foreign debt differently than we did, calculating it as (foreign debt · growth of external debt), which might account for the discrepancy in the estimated findings.

The finding in Table 3 further supports the notion that, over time, servicing foreign debt significantly raises the HCD of HIPCs. The HCD rises by 2.2 percentage points for every percentage point increase in debt service. In this regard, Fosu (2007; 2010) independently looked into the effect of actual and predicted debt service on social expenditures, such as those for education and health, and concluded that the expected debt service reflects the debt burden compared to actual debt service exhibits negative impact on social expenditure. Therefore, our analysis uses the actual debt service rather than the predicted debt service. Therefore, potential investors prefer to invest more if the government pays its obligation in the long term, which benefits investments connected to welfare (education and health).

The result of the growth model demonstrates that foreign debt has a negligible impact on HIPCs' GDP growth, contradicting both the debt overhang and crowding out effect theories. However, the external debt quadratic factor, which is positive and significant, suggests that the relationship between foreign debt and GDP growth is not linear. Furthermore, a single-country estimation result reveals that the relationship between external debt and GDP growth is U-shape (in two countries), insignificant (in 12 countries), and only non-linear (in one country). The reciprocal association between HCD and GDP growth is the other important result. A one-point rise in HCD leads to a boost in GDP growth by 9.6 percentage points, and a one-point increase in GDP growth leads to an increase in HCD of 0.31 percent. Higher levels of

HCD impact the economy by improving individuals' capabilities, creativity and production. Various studies contend that persons possessing either of the HDI components indirectly contribute more to the economy through better exports, improved technology, more investment from abroad, and higher labor productivity. This finding is thus compatible with the traditional theories of economic growth, the growth accounting framework, and endogenous growth theorists that assert the crucial importance of human capital as a production component.

The results also show that HIPCs' GDP growth positively impacts their HCD. This implies governments will have enough funds to invest in public health and education when the economy expands. Additionally,

Table 3 Results of SUR model

Variables	Dependent variable HCD			
	HIPCs		HIPCs in SSA	
	Coef.	Std. err.	Coef.	Std. err.
ED	–0.0018***	0.00035	–0.0018***	0.00031
ED^2	3.80e-06***	1.39e-06	3.89e-06**	1.27e-06
DSR	0.0225***	0.00272	0.0091***	0.00267
GDPGR	0.0031***	0.00082	0.003***	0.00064
POP	–0.0096**	0.0040	0.011***	0.0033
NBTOT	0.00023**	0.00011	–0.0001	0.00011
INSQ	0.0057***	0.0009	–0.0027***	0.00084
Constant	0.4302***	0.0226	0.428***	0.0197

Other statistics						
	Obs.	Parms	RMSE	R-sq	Chi2	P
HIPCs	420	7	0.0920	0.328	220.72	0.0001***
HIPCs in SSA	336	7	0.07117	0.27	157.74	0.0000***

Dependent variable GDPGR				
HCD	9.601***	3.190	22.159***	5.320
ED	–0.0303	0.0223	–0.0302	0.0277
ED^2	0.00016*	0.00008	0.00024**	0.00001
DSR	–0.1508	0.1887	0.0081	0.247
LAB	0.0882*	0.0468	0.090*	0.054
OPPN	0.02075	0.0140	0.022	0.0196
INF	–0.0012	0.00090	–0.0284	0.0261
EXCH	0.0005	0.00035	0.00055	0.00039
Constant	–4.1454	2.6565	–9.258***	3.443

Other statistics						
	Obs.	Parms	RMSE	R-sq	Chi2	P
HIPCs	420	8	5.661	0.044	68	0.0046***
HIPCs in SSA	336	8	6.223	0.048	47.58	0.0000***

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.
Source: Authors calculation using STATA 15

ceteris paribus, a country's GDP growth improves its residents' per capita income, enhancing their standard of life. Mulligan and Sala-i-Martin (1992), using the endogenous growth model, argue that economic growth can enhance the return rate on human capital and people can invest more. The two-chain model of Ranis and Stewart also explains the powerful connection between human capital and economic growth (2005). They contend that economic expansion offers the means to enable long-term advancements in human development.

3.3 Robustness checks

To assure the validity of results in Table 3, this study splits the dataset into HIPCs in sub-Saharan Africa (SSA) and HIPCs in non-SSA. However, the estimation was only done for 12 HIPCs in SSA due to only three HIPCs in non-SSA. According to Kennedy (2008), large sample size determination in econometrics has some important implications for the asymptotic properties of an estimator. Therefore, the results of HIPCs in SSA coincide with HIPCs.

For further robustness checks, this study employs alternative SEMs (there-stage least squares (3SLS) and multivariate multiple regression estimates (MVREG)). Besides, it uses the RE to compare the SUR results with other standard approaches. Except for the impact of external debt on growth under RE for HIPCs in SSA, all robustness checks support SUR results (see Table 4).

Table 4 3SLS+, MVREG++, RE+++ estimation results of target variables

Variables	Dependent variable HCD+		HCD++		HCD+++	
	HIPCs	HIPCs in SSA	HIPCs	HIPCs in SSA	HIPCs	HIPCs in SSA
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
ED	–0.0018***	–0.0018***	–0.0018***	–0.0018***	–0.00187***	–0.00181***
ED^2	3.80e-06***	2.89e-06**	3.80e-06***	2.89e-06***	3.52e-06***	2.61e-06***
DSR	0.0225***	0.0092***	0.0225***	0.0092***	0.0015	0.00067
Dependent variable GDPGR						
HCD	9.602***	22.1597***	9.608***	22.178***	7.704*	10.165*
ED	–0.0303	–0.0302	–0.0303	–0.03021	–0.0375	–0.0522*
ED^2	0.00016*	0.00024**	0.00016*	0.00024**	0.00016*	0.00027**
DSR	–0.151	0.008	–0.151	0.0079	–0.0504	0.1307

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.
Source: Authors calculation using STATA 15

In Tables 3 and 4, the proxy variable for HCD is HDI, which is a combination of three indices (health, education, and income), but the contribution of the income index is not substantial. Moreover, the income index measures the economic well-being of the people and its impact on GDP growth may be insignificant and create some correlation with GDP growth. Therefore, this study calculates and uses HDI without income index (HCDWoI) and employs SEMs for robustness checks. The result supports the findings in Tables 3 and 4 (see Table 5).

Furthermore, this study employs a non-SEM and non-conventional model called FGLS to test the validity of SUR results and found similar results with SUR and other SEMs. However, the impact of external debt on growth is significant under FGLS. This might be because the FGLS estimates the models separately (see Table 6).

Though this study mainly employed the SUR approach and cleared up, the SUR method is efficient. However, since it uses the dependent variables as independent variables in each other's specifications,

Table 5 SUR+, 3SLS++, MVREG+++ estimation results of target variables

Variables	Dependent variable HCDWoI+		HCDWoI++		HCDWoI+++	
	HIPCs	HIPCs in SSA	HIPCs	HIPCs in SSA	HIPCs	HIPCs in SSA
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
ED	–0.0021***	–0.0022***	–0.0023***	–0.0022***	–0.0023***	–0.0022***
ED^2	5.06e-06***	4.47e-06***	5.06e-06***	4.47e-06***	5.06e-06***	4.48e-06***
DSR	0.0234***	0.0088***	0.0234***	0.0088***	0.0234***	0.0088***
Dependent variable GDPGR						
HCD	9.111**	19.259***	9.111***	19.259***	9.117***	19.276***
ED	–0.0269	–0.0266	–0.0267	–0.0267	–0.027	–0.027
ED^2	0.00014*	0.00021*	0.00015*	0.00021*	0.000148*	0.00021*
DSR	–0.1598	0.0258	–0.1598	0.0258	–0.16	0.0256

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.
Source: Authors calculation using STATA 15

Table 6 FGLS estimation results of target variables

Variables	Dependent variable HCD		Dependent variable HCDWoI	
	HIPCs	HIPCs in SSA	HIPCs	HIPCs in SSA
	Coef.	Coef.	Coef.	Coef.
ED	–0.0021***	–0.0022***	–0.0023***	–0.0022***
ED^2	5.06e-06***	4.47e-06***	5.06e-06***	4.48e-06***
DSR	0.0234***	0.0088***	0.0234***	0.0088***
Dependent variable GDPGR				
HCD	5.453***	8.633***	–	–
HCDWoI	–	–	3.439***	3.959*
ED	–0.0251**	–0.0291*	–0.0292***	–0.0367**
ED^2	0.00013***	0.000197***	0.00014***	0.000212***
DSR	0.0398	0.068	–0.0375	0.0478

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.
Source: Authors calculation using STATA 15

endogeneity can be a problem. Thus, the SEM can overcome the problem of endogeneity (Li and Xu, 2021). Further, this study tested endogeneity after estimation, but the test is not valid under the SUR estimation.

CONCLUSION

Human capital development is essential for economic growth, according to both the growth accounting model and proponents of endogenous growth. However, human capital development and its impact on economic growth depend on the amount of external debt. In addition, since Keynesian and Classical economists disagree on this point, the effect of foreign debt on growth is still up for debate. Scholars have pointed out that the link between foreign debt and growth could not be linear but somewhat non-linear and that foreign debt might influence growth via the HCD. However, HIPCs pay little attention to empirical studies regarding the ways and effects of foreign debt on the development of HIPCs. Therefore, using the SUR and alternative SEMs from 1990 to 2017, this study examines the effect of external debt on HCD and growth by focusing on the HCD channel via which external debt influences the growth of HIPCs. According to the findings, external debt significantly and negatively affects HCD. Additionally, the correlation between external debt and HCD is negative and non-linear, although the correlation between external debt and growth is just non-linear. Additionally, the outcome demonstrated that the HCD channel was the mechanism through which external debt impacts HIPCs development.

The research also suggests HIPCs establish strong macroeconomic policies, improve institutional performance, and put in place appropriate debt management tools to manage the accrued external debt and minimize its detrimental effects on HCD and growth. External debt hurts HCD, implying borrowed funds are neither properly allocated nor efficiently used for productive activities. Hence, HIPCs need to invest and efficiently use the borrowed funds on education, health, and growth-driven activities. Moreover, creditors should give loans to feasible and development projects, and they have to follow up on their implementations. By examining the status of HIPCs projects, creditors should provide the funds step by step. In addition, improving the skill and knowledge of HIPCs concerning debt-related issues is crucial. Furthermore, HIPCs must prioritize and fund the three components of HDI. Finally, since the threshold value of external debt-HCD is 236% of GDP, creditors need to cancel some portion of HIPCs debt.

Even though this study attempts to fill the existing gaps such as measurement, literature, scope, and methodology, it has also limitations. For instance, due to the lack of data on some important variables, this study is constrained to 15 HIPCs. Besides, for the sake of scope, this study focused on the HCD channel and did not include other channels. Moreover, this study did not employ a panel threshold model due to the unique characteristics of our model (data) and several limitations of the threshold model (Seo and Shin, 2016; Seo et al., 2019). Therefore, future research can broaden their scope by considering these aspects.

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The Czech Republic and Austrian Tourism in Scope of German Visitors

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Received 16.6.2023, **Accepted** (reviewed) 18.7.2023, **Published** 15.9.2023

Abstract

Tourism demand modelling is one of the most studied areas in tourism economics, particularly focused on time series and econometric research. In this study, directly interpretable one-equation techniques are utilised, i.e. the autoregressive distributed lag model (ADLM) and the derived error correction model (ECM). To complement the sharing of information and habits in tourism, we apply regressors derived from wages, general prices, and dummies. For the Czech and Austrian data, short- as well as long-run sets of outputs act differently, regarding the specific situation. Such information can straightforwardly be applied to the effective planning of various activities covering the public and private sectors. The results are completed by the standard cointegration testing procedure and residual analysis.

Keywords	***DOI***	***JEL code***
Autoregressive Distributed Lag Model, Error Correction Model, cointegration, multipliers, tourism	*https://doi.org/10.54694/stat.2023.27*	*C01, Z31*

INTRODUCTION

In addition to its direct, indirect, and potentially induced effects, tourism plays a significant role in the economy of the country, both nationally and internationally. Indirect impacts result from the overall multilateral and mediated activity of tourism on economic development (Beránek, 2013). According to the Czech Statistical Office, the economic contribution of tourism is most often expressed by its share in the creation of the gross domestic product and by the share of tourism in overall employment. It contributes to the creation of new jobs and the growth of employment, with important areas including accommodation, catering and transport services, support of travel offices and agencies, tourist attractions, etc. Generally, many factors influence tourism, such as the economy, demography, geography, psychology, and ecology. Despite predominantly positive influences on people, the risks and negative impacts associated with tourism should be mentioned, e.g. the influence on the environment. In this study,

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the economic view is selected to model supply and demand, for selected products or services in destinations classified as tourism products. Moreover, according to Palatková and Zichová (2014), tourism can be studied based on the platform of a certain product and various segments, as well as for territorial units. In the following, we have selected the scope of tourism destinations, which is the approach most often used in data processing studies.

The classification of tourism as an economic sector is the result of offices such as the United Nations World Tourism Organisation, which gathers and publishes data on tourism, organises thematic conferences, supports educational programmes, and maintains the sustainable development of tourism. Among others, the Organisation for Economic Co-operation and Development and the European Statistical Office ensure the methodology and standards of collecting, sorting, and processing data in the field of tourism. The outputs of the offices represent the fundamental core of successful data analysis (Palatková and Zichová, 2014). Individual methodologies for statistical surveys are presented, e.g. in the materials Methodological Manual for Tourism Statistics, International Recommendations for Tourism Statistics, and Tourism Satellite Account: Recommended Methodological Framework. Covering European Union, Regulation (EU) No 692/2011 of the European Parliament and of the Council of 6 July 2011 concerning European statistics on tourism and repealing Council Directive 95/57/EC is mandatory. This obliges member states to monitor and provide harmonised data on tourism in the specified time intervals, structure, and details.

The number of visitors to Europe had been almost increasing recently, up to 2020. For example, two drops in previous years, 2010 and 2014, were registered that especially influenced residents. In 2020, tourism became one of the sectors most affected by the Covid pandemic (Mrázková, 2020), as this also is the case in the Czech Republic and Austria we focus on. Despite the best accommodation result in history with a record 22 million people visiting the Czech Republic in 2019 (about 3.5% more than in 2018), a major decrease followed in 2020. The share of tourism in the total gross domestic product of around 3% fell from previous values to 1.48% (about CZK 84.3 billion). Tourism in Austria, which can be quantified by 41 million visitors in 2019, employed around 314 thousand people and the share of total employment in the national economy was about 7.9%. The largest number were employed by hotels and restaurants. Being more concentrated on non-residents (68%) in comparison to the Czech Republic, the drop in 2020 was severe.

In addition, both territories differ in tourist attractions and the structure of visitors (Palatková and Zichová, 2014; Jeřábek, 2018). While non-residents in the Czech Republic concentrate on historical monuments (specifically in Prague and other locations), culture and cities, it is more about natural wealth in Austria. Most visitors to the Czech Republic in 2019 came from Germany, Slovakia, Poland, the United Kingdom, and Italy. Meanwhile, the dominant number of visitors to Austria came from Germany, Holland, Switzerland, the United Kingdom, and Italy.

There exists a variety of models for tourism demand based on different variables describing economic theory, limited by a lack of available data (Lim, 2006). Although tourism is influenced by a range of factors that are economic, environmental, and political in nature, the large number of studies covering economic parameters is decisive (Song et al., 2010). For the quantitative and qualitative distribution of methods (Dwyer et al., 2012), note the use of artificial intelligence for forecasting in tourism research is currently overcoming the gap between both approaches. Quantitative methods are used the most, which Song and Li (2008) represent by time series and econometric models. The autoregressive integrated moving average techniques dominate the time series models, with an alternative seasonal component. The other branches are generalised autoregressive conditional heteroskedasticity methods, applied, e.g. by Chan et al. (2005), and a basic structural model with better forecasting performances than the univariate autoregressive moving average approaches (Turner et al., 1997). The basic structural model is also used by Greenidge (2001) for forecasting tourism arrivals to Barbados from the most significant source countries.

On the other hand, econometric models based on fundamental econometric theory identify potential causal relations between exogenous and endogenous variables, covering errors in the exogenous ones, see, e.g. Malec and Žák (2021). These models analyse the impact of tourism but moreover help in planning various activities in the public and private sectors (Pech, 2010). Econometric models enable us to examine the relationships between tourism demand and the factors that influence it (Abdou et al., 2021). According to Dwyer (2022), ADLM and error correction approaches dominate here. In this study, we apply and demonstrate the power of the ECM derived from a fundamental autoregressive distributed lag, being a straightforwardly interpretable technique for tourism research. This method allows short-run relations with short memory knowledge, continuously arising and ceasing, to be studied separately from long memory in time series. Due to one approach being selected from the range of existing techniques, the outputs are supported by standard testing cointegration and other additional tests, thus contributing to the correctness of the application. The results can be used by airlines, travel offices and agencies, and accommodation and catering establishments to reach various business decisions or devise tourism policy strategies (Song and Turner, 2006).

1 EXPERIMENTAL

1.1 Data used

The combination of Czech, Austrian and European Statistical Offices are used to gather monthly and quarterly information from 2003 to 2022. For analysing the tourism industry, the periods of monthly data in the source are transformed into quarterly information. With Song et al. (2010), demand can be measured using the number of arrivals and overnight stays, presence, income from tourism, or the criterion of distance to the target destination. Although arrivals are the leading indicator, see, e.g. Lim et al. (2006), Song and Li (2008), and Jeřábek (2018), we concentrate on the endogenous variable number of nights spent (NTS). It is considered superior to arrivals because the length of stay is included (Bakkal and Scaperlanda, 1991). We focus on hotels, holiday and other short-stay accommodations, camping grounds, recreational vehicle parks and trailer parks. The ratio of German visitors to domestic tourism (NRR), gathered with the same methodology, is included as an optional parameter. Note that tourist expenditures are usually ascertained through visitor surveys (Song et al., 2010). On the other hand, the number of tourists is generally recorded at the borders of a given destination through border controls, surveys of visitors at the borders or close to it, and using questionnaires at accommodation facilities (Jeřábek, 2018).

Covering exogenous variables, the first factor is wages and salaries (WSA) in source Germany. Wages and salaries (D.11), together with social contributions for employees (D.12) selected for their eligibility, form the employee compensation item in the national accounts (D.1) that the employer has to pay the employee for the work performed in the given accounting period. We select current prices in millions of Euros as part of the gross domestic product. Generally, income is a subjective variable and some authors supply this by using real capita consumption, recreational expenditure, or the production index to estimate income elasticities (Dwyer and Forsyth, 2006). Next is the relative prices (RPR) indicator gathered by European Statistical Office. This is the harmonised indicator of consumer prices in the source country to the target one. This indicator, in the form of an index, measures the change in the prices of goods and services purchased by ordinary households over time. It is based in 2015 and focuses exclusively on segments covering tourism and related activities. Due to the monthly periodicity, its values are averaged. In the case of the Czech Republic, the exchange rate is included in the formula. Prices (PRI) in the target destination are included as well. It is also based on the harmonised indicator of consumer prices focused on tourism, but with it reciprocal to positively influence tourism in the country visited. In the case of the Czech Republic, again the exchange rate parameter is incorporated. We do not include the exchange rate directly, due to evidence that tourists react to exchange rate movements but not to any real relative change in inflation rates in the process of their decision to travel (Bekaert and Gray, 1998; Artus, 1978).

The consumer confidence indicator (CCI), reported on unadjusted data (i.e., neither seasonally adjusted nor calendar adjusted data), measures future developments in households, including consumption and saving. It is based on a questionnaire about their expected financial situation, opinion on the general economic situation, unemployment, and on their ability to save. If the indicator is greater than 100, it signals a boost in confidence towards the future economic situation, with consumers being less prone to save and more inclined to spend money on major purchases. Less than 100 demonstrates a pessimistic opinion on developments in the economy, less consumption and more saving. Visitor expectations, any information sharing, the word-of-mouth effect, and the persistence of habit, reflecting supply constraints in the form of the lagged endogenous variable, are also included. According to Song et al. (2003), this is one of the most important factors in tourism demand. Dummy variables then cover the economic crisis of 2008 with its consequential impact and the Covid pandemic with a value of 1 from the second quarter of 2020. Marketing, consumer expectations, habit persistence and population size in the origin country can serve other potential factors influencing tourism for the cross-elasticities of competing destinations. The transport cost variable is rarely used due to the lack of data (Lim, 2006), sometimes replaced by the price of oil.

In this study, the current version of the R software platform with RStudio contribution (R Core Team: Vienna, Austria, 2023) is selected for preprocessing the data and consequent analyses. All the variables were evaluated for the Kruskal-Wallis test using *isSeasonal* function from the seastests library. For those significant at 5%, the *seas* function from the seasonal library applies X-13ARIMA-SEATS for automatic seasonal adjustment. It is omitted, e.g. in some cases of PRI and CCI. Note that this method belongs to one of the most used covering statistical offices over Europe. The Augmented Dickey-Fuller test using *ur.df* with the critical values given by Dickey-Fuller tables, and the KPSS test (Kwiatkowski et al., 1992) from the urca library, are used to test the unit root in time series. The results of both tests, although the null is reversed, demonstrate very close conclusions, as the time series almost always (and in all cases for endogenous variables) are of I(1). There are some exceptional cases of prices (RPR and PRI) and CCI being rather stationary. To improve heteroskedasticity, the non-linearity and asymmetry of the data, the Box-Cox technique is applied with a typical parameter value of 0.3. Using the methodology in the MASS library, this is handled by the maximum likelihood estimation with usual values of 0 for logarithmic, and 0.5 for square root transformations.

1.2 Methods

The straightforward way in the case of a stationary time series is the application of vector autoregressive models for describing long-run dynamics. When the time series are non-stationary, the differencing approach can be used to apply the model for a stationary time series, however, long-run information is lost by this procedure. If the target is to analyse long- as well as short-run data, we can apply some of the approaches for a non-stationary series, such as ECM. It originates from the cointegration principle for a non-stationary time series with the long-lasting relation expressed by the error correction mechanism. As Engle and Granger (1987) stated, variables that are cointegrated can always be transformed into an error correction problem and *vice versa*. This covers an adjustment process preventing a time series from excessively drifting from the expected equilibrium time path. When we analyse the mixture of stationary and non-stationary time series, the majority (and always endogenous in this study) are non-stationary. Although such properties can influence inductive conclusions, the interpretation is more direct than in the case of procedures developed exclusively to analyse a mixture of various orders of integration. I(2) series, being rare in tourism, are not included either, as well as the oscillatory convergent, explosive, mean and fractionally integrated time series are excluded.

Based on the Engle and Granger (1987) methodology, we study one cointegrating relationship among variables, a reasonable approximation in tourism (Song et al., 2008). Although there exist some alternatives (Johansen, 1988; Arlt and Arltová, 2007) where there are more such vectors possible, the average cointegrating vector over them is revealed herein. While the ADLM methodology is relatively unique, there are variant approaches to applying error correction. Song et al. (2008) introduce three fundamental methods for estimation, i.e. the two-step procedure of Engle and Granger (1987), the one-step approach given by Wickens and Breusch (1988), and the third method is based on the ADLM background published by Pesaran and Shin (1995). In this study, we process the data using the last procedure mentioned, applied in tourism research (Song and Turner, 2006). The technique starts with the autoregressive model specification to study any change in the endogenous variable for unit change in the lagged endogenous variable, and the current and delayed exogenous variables (*ceteris paribus*). Then, the model is transformed into ECM, connecting short-run dynamics with a long-run equilibrium in time series. This technique is in close connection to the cointegration analysis. We restrict error correction for the linear trend below.

The starting ADLM is selected as a combination of Akaike, Schwarz and Bayesian information criteria in this study, although the Bayesian approach is preferred to annual data (Pesaran and Shin, 1998). Due to the collinearity issue, the maximum lag of 4 is accepted for NTS modelling. The *auto_ardl* function in R is used to select the best model, supplemented by criteria such as autocorrelation tests, and more. The one-equation ADLM(p, q_1, …, q_k) without the deterministic trend (Natsiopoulos and Tzeremes, 2022) can be stated

$$y_t = c + \sum_{i=1}^{p} b_{y,i} y_{t-i} + \sum_{j=1}^{k} \sum_{l=0}^{q_j} b_{j,l} x_{j,t-l} + \varepsilon_t \,, \tag{1}$$

for $t = 1, 2, \ldots, T$. Then, the corresponding ECM has the form

$$\Delta y_t = c + \sum_{i=1}^{p-1} \psi_{y,i} \Delta y_{t-i} + \sum_{j=1}^{k} \sum_{l=1}^{q_j-1} \psi_{j,l} \Delta x_{j,t-l} + \sum_{j=1}^{k} \omega_j \Delta x_{j,t} + \pi_y y_{t-1} + \sum_{j=1}^{k} \pi_j x_{j,t-1} + \varepsilon_t \,. \tag{2}$$

The equation can be reformulated using the error correction term $ect = y_{t-1} - \sum_{j=1}^{k} \theta_j x_{j,t-1}$ in the formula, stated with the corresponding coefficient. There, short- and long-run multipliers exist, where the short-run ones are expressed by ω_j. Above that, the long-run multipliers are given by the term

$$\frac{\partial y_{t+\infty}}{\partial x_{j,t}} = \frac{\pi_j}{-\pi_y} \,. \tag{3}$$

We apply tests for no cointegration in ECM, i.e. Wald bounds F-test with H_0: $\pi_y = \pi_1 = \cdots = \pi_k = 0$ and bounds t-test for H_0: $\pi_y = 0$.

If the endogenous variable is I(1), the ADLM methodology allows a mixture of I(1) and I(0) variables (Grant and Lebo, 2016; Pesaran and Shin, 1998) to be studied. Moreover, the value of *ect* depends also on the order of integration, sample size and the number of variables. This is remarkable, especially using the traditional t-test. Note that in covering macroeconomics analyses the *ect* coefficients are often relatively small, due to the intervention of governments, actions of external factors, etc. If the coefficient is high, close to 1, it means the error correction takes place in almost the time one period only. Although the range of exclusion and exogeneity tests are not utilised due to background economic theory, an analysis of residues evaluates the nature of the time series. The tests used cover autocorrelation, heteroskedasticity and normality, concentrating on the efficiency of estimates and inductive conclusions.

Cointegration is also tested by a standard procedure using residue from the static regression model, for which the function *lm* from the stats library is applied. We use the Augmented Dickey-Fuller test discussed by Song et al. (2008) for critical values given by the formula $\beta_\infty + \beta_1/T + \beta_2/T^2$. Here, the parameters

β_∞, β_1 and β_2 are given by the work of MacKinnon (2010) and T is the number of observations. From the results of analyses and 5% significancy is detected, there exists at least one cointegrating relationship in all the cases considered.

2 RESULTS AND DISCUSSION

Although there are many interpretational aspects, we initially apply the ADLM, and then the ECM with short- and long-run multipliers. Some original variables multiplied by 10 in the case of modelling NTS are used for clarity in the interpretation. In all the cases, the influence of the Covid pandemic is significant and negative. The effect of the event of a crisis is diverse, and it can be concluded that it does not play a significant role globally. Covering Table 1, both bounds F- and t-tests for no cointegration with the values of test statistics about 22.811 and –9.970, respectively, are significant with p-values < 1e-06.

Table 1 The Czech Republic ADLM and ECM for nights spent

ADLM(4,2,2,3,1)				ECM			
Parameter in model	Estimate	Std error	*p*-value	Parameter in model	Estimate	Std error	*p*-value
Intercept	–22.818	41.275	0.5827	Intercept	–22.818***	1.995	0.0000
L(NTS, 1)	0.507***	0.105	0.0000	d(L(NTS, 1))	0.480***	0.091	0.0000
L(NTS, 2)	0.371***	0.105	0.0009	d(L(NTS, 2))	0.852***	0.119	0.0000
L(NTS, 3)	–0.467***	0.074	0.0000	d(L(NTS, 3))	0.385***	0.098	0.0002
L(NTS, 4)	–0.385**	0.113	0.0012	d(WSA)	16.036***	2.124	0.0000
WSA	16.036***	2.740	0.0000	d(L(WSA, 1))	–14.632***	2.364	0.0000
L(WSA, 1)	–28.985***	3.435	0.0000	d(RPR)	–0.367	1.280	0.7753
L(WSA, 2)	14.632***	3.126	0.0000	d(L(RPR, 1))	–4.474**	1.593	0.0068
RPR	–0.367	1.588	0.8181	d(PRI)	2.082	3.102	0.5048
L(RPR, 1)	1.622	2.133	0.4506	d(L(PRI, 1))	–4.037	3.023	0.1871
L(RPR, 2)	4.474*	1.738	0.0130	d(L(PRI, 2))	–7.879**	2.694	0.0050
PRI	2.082	3.531	0.5580	d(CCI)	1.660.	0.940	0.0829
L(PRI, 1)	–6.321	5.305	0.2389	D_cri	1.335***	0.271	0.0000
L(PRI, 2)	–3.842	4.917	0.4381	D_cov	–3.526***	0.696	0.0000
L(PRI, 3)	7.879*	3.065	0.0131	*ect*	–0.974***	0.088	0.0000
CCI	1.660	1.069	0.1264				
L(CCI, 1)	–2.169*	1.067	0.0473				
D_cri	1.335***	0.348	0.0003				
D_cov	–3.526***	0.868	0.0002				

Notes: ADLM: Residual standard error: 5.050 on 52 degrees of freedom, Multiple R-squared: 0.9687, Adjusted R-squared: 0.9579, F-statistic: 89.38 on 18 and 52 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 4.866 on 56 degrees of freedom, Multiple R-squared: 0.9297, Adjusted R-squared: 0.9121, F-statistic: 52.86 on 14 and 56 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

The significant sharing of information and habit in tourism is evident (see Table 1), covering the first and second lagged quarters positive and the rest of negative action. The negative signs probably mean the turning effect from preceding periods. German wages and salaries are also important, depending positively on the current quarter, to make a prompt decision. Relative prices and prices are almost insignificant and cover only the last lag considered. For the error correction model in the short run, the sharing of information and habit is also evidently decisive, as well as wages and salaries for the given quarter. Partially, the positive action of the consumer confidence indicator is visible. The coefficient estimated at *ect* means a prompt return to equilibrium about one period in turn. For Table 2, wages and salaries and relative prices are decisive in the long run, both positively influencing NTS.

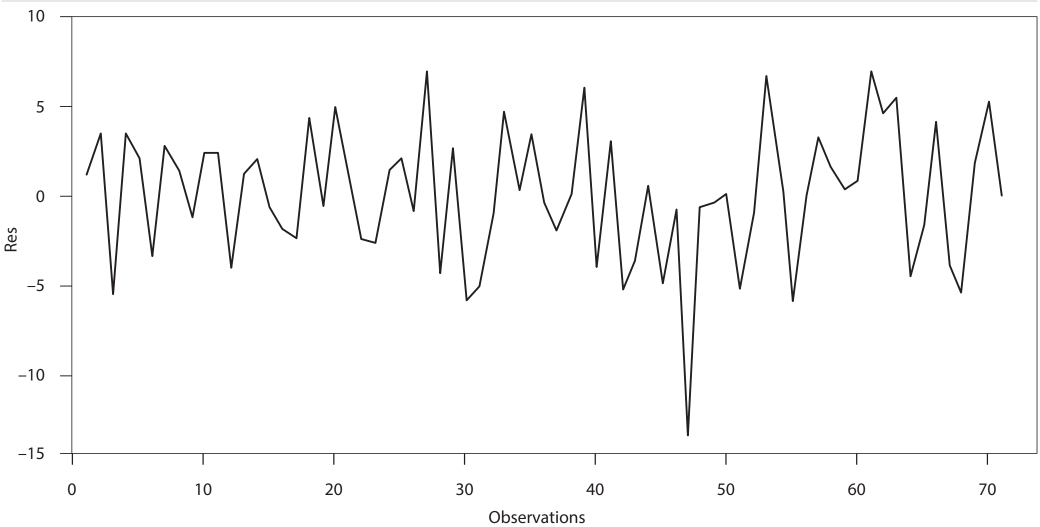
Analysing the residual part, the graphical representation contributed to selected hypothesis testing is demonstrated in Figure 1. No issues are evident in the scope of the statistics used.

Table 2 The Czech Republic long-run multipliers for nights spent

Parameter in model	Estimate	Std error	*p*-value
Intercept	–23.433	42.815	0.5865
WSA	1.728	0.316	0.0000
RPR	5.883	1.393	0.0001
PRI	–0.207	1.791	0.9084
CCI	–0.522	0.755	0.4926

Source: Own construction

Figure 1 ECM residual diagnostics for nights spent



Durbin-Watson test for autocorrelation by *durbinWatsonTest* with the value of test statistic 2.08779 and *p*-value 0.6523; Breusch-Godfrey test for serial correlation of order up to 1 by *bgtest* with the value of test statistic 0.39516 and *p*-value 0.5296; Breusch-Godfrey test for serial correlation of order up to 3 by *bgtest* with the value of test statistic 0.65231 and *p*-value 0.8844; Studentized Breusch-Pagan test for homoskedasticity by *bptest* with the value of test statistic 11.05342 and *p*-value 0.9221; Jarque Bera test for normality by *jarque.bera.test* with the value of test statistic 4.44014 and *p*-value 0.1086.
Source: Own construction

Covering Table 3, both bounds *F*- and *t*-tests for no cointegration with the values of test statistics about 12.155 (*p*-value < 1e-06) and –5.673 (*p*-value < 1e-03), respectively, are significant.

Table 3 The Czech Republic ADLM and ECM for the German and domestic tourism ratio

ADLM(3,3,1,2,1)				ECM			
Parameter in model	**Estimate**	**Std error**	***p*-value**	**Parameter in model**	**Estimate**	**Std error**	***p*-value**
Intercept	–0.179	0.676	0.7932	Intercept	–0.179***	0.023	0.0000
L(NRR, 1)	0.699***	0.099	0.0000	d(L(NRR, 1))	0.421***	0.063	0.0000
L(NRR, 2)	–0.441***	0.084	0.0000	d(L(NRR, 2))	–0.020	0.075	0.7918
L(NRR, 3)	0.020	0.086	0.8163	d(WSA)	–0.042	0.029	0.1484
WSA	–0.042	0.038	0.2807	d(L(WSA, 1))	–0.183***	0.030	0.0000
L(WSA, 1)	–0.146**	0.042	0.0012	d(L(WSA, 2))	0.293***	0.033	0.0000
L(WSA, 2)	0.477***	0.043	0.0000	d(RPR)	1.255	2.230	0.5759
L(WSA, 3)	–0.293***	0.051	0.0000	d(PRI)	–0.301	0.544	0.5816
RPR	1.255	2.665	0.6402	d(L(PRI, 1))	–0.598	0.484	0.2216
L(RPR, 1)	2.592	2.601	0.3234	d(CCI)	0.026	0.016	0.1016
PRI	–0.301	0.606	0.6206	D_cri	0.079.	0.045	0.0843
L(PRI, 1)	–0.639	0.879	0.4703	D_cov	–0.454***	0.071	0.0000
L(PRI, 2)	0.598	0.539	0.2718	*ect*	–0.721***	0.089	0.0000
CCI	0.026	0.017	0.1401				
L(CCI, 1)	–0.024	0.018	0.1959				
D_cri	0.079	0.063	0.2164				
D_cov	–0.454***	0.131	0.0006				

Notes: ADLM: Residual standard error: 0.088 on 55 degrees of freedom, Multiple R-squared: 0.9506, Adjusted R-squared: 0.9362, F-statistic: 66.13 on 16 and 55 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 0.085 on 59 degrees of freedom, Multiple R-squared: 0.8781, Adjusted R-squared: 0.8533, F-statistic: 35.42 on 12 and 59 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

For the ratio of German to domestic visitors, the significant sharing of information and habit is evident (see Table 3), covering the first lag for positive and the second lag for negative relation. Wages and salaries in Germany are important, especially covering historical values with first and third lags opposite to second. The rest of the parameters are not significant to a great extent. In the short run, sharing information and habit covers the first lag. Wages and salaries are important, covering the negative value in the first and positive value in the second lag, similarly as in ADLM. The error correction term means returning to equilibrium for one period of 72.1%, approximately. For Table 4, the significance of the coefficients is lower in the long run. Possibly, the most influencing parameter is relative prices with a positive effect. Our case of a strong significant *ect* and insignificant long-run multipliers could be caused by partial collinearity reasons in regressors. It can be handled simply by reducing the order of some variables, keeping *ect* and cointegration tests significant. However, we apply the criterion for minimum information criteria due to the fact, that the interpretation of the reduced model is almost the same.

Covering Table 5, both bounds F- and t-tests for no cointegration with the values of test statistics about 24.775 and –9.060, respectively, are significant with p-values < 1e-06.

Note the similar results to analysing the NTS parameter in the Czech Republic and Austria (see Table 5). The significant sharing of information and habit in tourism is evident, covering the first and

Table 4 The Czech Republic long-run multipliers for the German and domestic tourism ratio

Parameter in model	Estimate	Std error	*p*-value
Intercept	−0.247	0.945	0.7943
WSA	−0.007	0.007	0.3497
RPR	5.332	3.025	0.0835
PRI	−0.475	0.382	0.2194
CCI	0.003	0.017	0.8432

Source: Own construction

Table 5 Austrian ADLM and ECM for nights spent

ADLM(4,3,1,3,2)				ECM			
Parameter in model	Estimate	Std error	*p*-value	Parameter in model	Estimate	Std error	*p*-value
Intercept	2.569	77.740	0.9738	Intercept	2.569	1.829	0.1658
L(NTS, 1)	0.285**	0.089	0.0024	d(L(NTS, 1))	0.112	0.088	0.2085
L(NTS, 2)	0.867***	0.108	0.0000	d(L(NTS, 2))	0.979***	0.134	0.0000
L(NTS, 3)	−0.240**	0.090	0.0099	d(L(NTS, 3))	0.739***	0.094	0.0000
L(NTS, 4)	−0.739***	0.099	0.0000	d(WSA)	8.079***	1.402	0.0000
WSA	8.079***	2.001	0.0002	d(L(WSA, 1))	−0.508	1.609	0.7536
L(WSA, 1)	−6.059*	2.475	0.0178	d(L(WSA, 2))	−5.423**	1.640	0.0017
L(WSA, 2)	−4.916.	2.585	0.0629	d(RPR)	−6.274*	2.407	0.0118
L(WSA, 3)	5.423*	2.281	0.0212	d(PRI)	5.450**	1.695	0.0022
RPR	−6.274*	2.944	0.0379	d(L(PRI, 1))	0.093	1.857	0.9601
L(RPR, 1)	5.590.	2.908	0.0602	d(L(PRI, 2))	−4.628*	1.809	0.0133
PRI	5.450**	1.977	0.0081	d(CCI)	−0.616	0.940	0.5154
L(PRI, 1)	−3.565	2.968	0.2352	d(L(CCI, 1))	2.510**	0.856	0.0049
L(PRI, 2)	−4.722	2.998	0.1214	D_cri	−0.152	0.210	0.4733
L(PRI, 3)	4.628*	1.973	0.0229	D_cov	−3.936***	0.462	0.0000
CCI	−0.616	0.999	0.5406	*ect*	−0.827***	0.072	0.0000
L(CCI, 1)	2.527.	1.267	0.0514				
L(CCI, 2)	−2.510*	1.225	0.0456				
D_cri	−0.152	0.342	0.6599				
D_cov	−3.936***	0.716	0.0000				

Notes: ADLM: Residual standard error: 3.701 on 51 degrees of freedom, Multiple R-squared: 0.9808, Adjusted R-squared: 0.9736, F-statistic: 136.80 on 19 and 51 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 3.564 on 55 degrees of freedom, Multiple R-squared: 0.9230, Adjusted R-squared: 0.9020, F-statistic: 43.95 on 15 and 55 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

second quarters positive and the rest negative action. Wages and salaries in Germany are both significant parameters, depending positively on the given period, for making a prompt decision. The other periods are with various signs, but less significant. Although not so significant, the relative prices in a given period influence the NTS negatively and prices positively. The consumer confidence indicator is small significant in the first lag, with the turning point in the lag following. For the error correction model, in the short run, the word-of-mouth effect is significant with lags 2 and 3. This means a delay in covering response. Decisive are also wages and salaries and prices in the current period. The consumer confidence indicator acts positively but with a delay. The error correction term means returning to equilibrium for one period of 82.7%, approximately. For Table 6, wages and salaries and prices are important, as both positively influence the NTS in the long run.

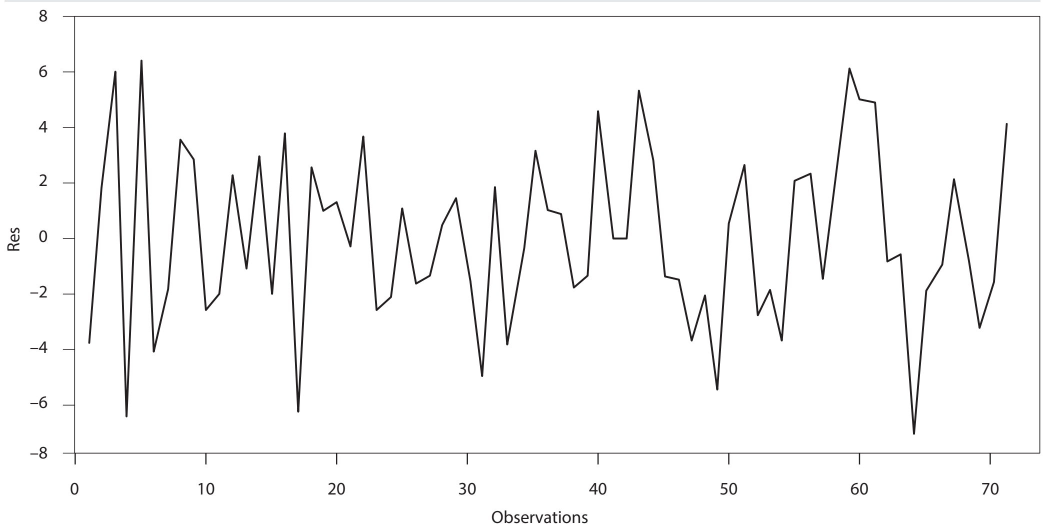
Table 6 Austrian long-run multipliers for nights spent

Parameter in model	Estimate	Std error	*p*-value
Intercept	3.107	93.880	0.9737
WSA	3.056	0.656	0.0000
RPR	–0.827	2.153	0.7025
PRI	2.166	0.420	0.0000
CCI	–0.724	1.244	0.5632

Source: Own construction

Analysing the residual part, the graphical representation contributed to selected hypothesis testing is demonstrated in Figure 2. No issues are evident in the scope of the statistics used.

Figure 2 ECM residual diagnostics for nights spent



Durbin-Watson test for autocorrelation by *durbinWatsonTest* with the value of test statistic 2.12725 and *p*-value 0.8722; Breusch-Godfrey test for serial correlation of order up to 1 by *bgtest* with the value of test statistic 0.94268 and *p*-value 0.3316; Breusch-Godfrey test for serial correlation of order up to 3 by *bgtest* with the value of test statistic 1.43285 and *p*-value 0.6978; Studentized Breusch-Pagan test for homoskedasticity by *bptest* with the value of test statistic 22.47086 and *p*-value 0.2614; Jarque Bera test for normality by *jarque.bera.test* with the value of test statistic 0.89051 and *p*-value 0.6407.
Source: Own construction

Covering Table 7, both bounds *F*- and *t*-tests for no cointegration with the values of test statistics about 5.220 (*p*-value = 0.0078) and –4.445 (*p*-value = 0.0151), respectively, are significant.

Table 7 Austrian ADLM and ECM for the German and domestic tourism ratio

ADLM(3,1,3,2,1)				ECM			
Parameter in model	**Estimate**	**Std error**	***p*-value**	**Parameter in model**	**Estimate**	**Std error**	***p*-value**
Intercept	0.877	1.077	0.4188	Intercept	0.877***	0.172	0.0000
L(NRR, 1)	0.041	0.119	0.7324	d(L(NRR, 1))	–0.494***	0.108	0.0000
L(NRR, 2)	0.272*	0.110	0.0166	d(L(NRR, 2))	–0.221	0.136	0.1080
L(NRR, 3)	0.221	0.151	0.1497	d(WSA)	0.005	0.021	0.8044
WSA	0.005	0.024	0.8301	d(RPR)	–12.096***	3.280	0.0005
L(WSA, 1)	–0.010	0.024	0.6668	d(L(RPR, 1))	8.464*	3.310	0.0132
RPR	–12.096**	3.510	0.0011	d(L(RPR, 2))	9.835**	3.358	0.0048
L(RPR, 1)	15.190**	5.017	0.0038	d(PRI)	5.995**	2.203	0.0085
L(RPR, 2)	1.371	5.469	0.8030	d(L(PRI, 1))	–2.886	2.358	0.2260
L(RPR, 3)	–9.835*	3.745	0.0112	d(CCI)	–0.024.	0.012	0.0567
PRI	5.995*	2.718	0.0316	D_cri	0.038	0.027	0.1634
L(PRI, 1)	–7.886*	3.809	0.0431	D_cov	–0.507***	0.057	0.0000
L(PRI, 2)	2.886	2.612	0.2741	*ect*	–0.465***	0.088	0.0000
CCI	–0.024.	0.013	0.0746				
L(CCI, 1)	0.027.	0.015	0.0830				
D_cri	0.038	0.039	0.3453				
D_cov	–0.507***	0.063	0.0000				

Notes: ADLM: Residual standard error: 0.051 on 55 degrees of freedom, Multiple R-squared: 0.9646, Adjusted R-squared: 0.9543, F-statistic: 93.57 on 16 and 55 DF, *p*-value: < 2.2e-16. ECM: Residual standard error: 0.049 on 59 degrees of freedom, Multiple R-squared: 0.8410, Adjusted R-squared: 0.8086, F-statistic: 26.07 on 12 and 59 DF, *p*-value: < 2.2e-16. Here, L(variable, order) states lag with corresponding order, and d is differencing. Significance codes: < 0.001 as ***, < 0.01 as **, < 0.05 as * and < 0.1 as .
Source: Own construction

Table 8 Austrian long-run multipliers for the German and domestic tourism ratio

Parameter in model	Estimate	Std error	*p*-value
Intercept	1.885	2.454	0.4457
WSA	–0.011	0.017	0.5325
RPR	–11.541	6.056	0.0619
PRI	2.137	0.769	0.0075
CCI	0.007	0.020	0.7423

Source: Own construction

For the ratio of German to domestic visitors, sharing information and habit is not so significant, probably due to Austria being historically connected to Germany (see Table 7). Here significant relative prices are also in one lag, with a negative current effect revealed. Prices act without the lag positively and including the lag negatively, but both are less significant, and consumer confidence indicator as well. For the error correction model in the short run, the negative sharing of information and habit covers the first lag, again due to the typical destination to visit. This is also the case of the negative influence of relative prices without lag. Then, prices have a positive effect in the current period, with the small action of the consumer confidence indicator. The error correction term means returning to equilibrium for one period of 46.5%, approximately. For Table 8, decisive are prices with a positive relation in the long run.

CONCLUSION

Although the results depend partially on the frequency of the given data, time series length and type of processing, there have been many practical outcomes detected in this study. We perceive the importance of long-run relationships especially for policy-makers and planners, while short-run dynamics target business forecasting. Tourism modelling also enables government institutions to formulate and implement the right tourism policy strategies. This is related, e.g. to price regulation, the control of environmental quality and planning of suitable infrastructure. According to expectations, the *ect* parameter in the case of Austria achieves a lower value due to the long memory of the time series variable. The reason is the stable structure of visitors from Germany, which suppresses any response to changes in economic parameters.

For the Czech Republic and Austria in the case of modelling nights spent, a similar pattern of relationships is revealed, although we discuss some differences here. In the case of nights spent, the significant sharing of information and habit are evident in the first and second lag positive and then negative action. But in the short run, this relation is delayed in Austria, probably given by the historical connection of source and target countries. Current wages and salaries are decisive in both travel destinations, complemented in Austria by significant prices. This relationship pattern also holds for the short run. Moreover, the positive influence of the consumer confidence indicator is delayed opposite to the Czech Republic. While in both target destinations, for long-run relationships wages and salaries are important and positively related to nights spent; in the case of the Czech Republic, relative prices are decisive, and in Austria, prices are the most important. It seems that the Czech Republic is perceived in the long run as a destination with alternatives noticed to considerations. In Austria, both target and source countries are in close historical connection. So, a delay in the change of word-of-mouth effects and confidence is evident, supported by the inclination to price in short- and long-run actions, rather than to a mutual comparison of both territories. However, wages and salaries are significant in all the cases considered, a key parameter in the decision to travel.

In the case of studying the ratio of German visitors and residents, sharing information and habit is significant for the Czech Republic, whereas in Austria this is suppressed. The reasons are evident and mentioned above, as some destinations are complementary. But in Austria, the short-run influence is more significant. Wages and salaries are decisive in the Czech Republic, but in the case of Austria relative prices and prices are in play, although less significantly. This also holds in the case of short-run dependencies. For the long run, relative prices are important in the Czech Republic, whereas it is prices in Austria. In the short run, wages and salaries are decisive for the Czech Republic, but the comparison of source and target countries in price dominates the longer horizon. In Austria, prices seem decisive for the share of non-residents as well as nights spent.

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A Comparative Analysis of Business and Economics Researchers in the Visegrad Group of Countries, Austria and Romania Based on the Data Obtained from SciVal and Scopus

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Received 3.2.2023, **Accepted** (reviewed) 28.4.2023, **Published** 15.9.2023

Abstract

Research background: The aim of the paper is to compare the performance of economic researchers in Austria, Romania and the Visegrad 4 (Czech Republic, Hungary, Poland, and Slovakia) using performance indicators of researchers from the Scopus and SciVal databases. In the comparison of countries, Austria is included as a benchmark country, while the other five countries represent the countries of the former Eastern bloc. In the study, the definition of an economic researcher is based on indicators that can be obtained from databases. The study focuses first on the statistical properties of the indicators and then groups' researchers from countries using these indicators.

Purpose of the article: Paper pursued two goals. First, by presenting the relationships between the data obtained from the Scopus/SciVal databases, to present the most important key indicators, then to group the researchers with the help of the analyzed indicators, and to compare the publication performance of the chosen countries. A researcher is considered to be an economic researcher in the study whose at least thirty percent of the published articles in the SCImago database are in the subject areas of Business, Management, and Accounting and Economics, Econometrics, and Finance.

Methods: Three methods were used to perform the study. First, principal component analysis, multicollinearity analysis with variance inflation factor (VIF), and partial correlation analysis were performed using the correlation matrix. Second, using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranking

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procedure, researchers from each country were ranked using indicators. Finally, the distribution of ninths and tenths of ranked researchers was analyzed for each country. Three data sets were used for the analysis. A representative sample proportional to the population of a country, followed by the principle known in team sports that each country nominates the same number of athletes, and finally a dataset of all selected researchers.

Findings & value added: The first most important result can be stated that the stochastic linear relationships that can be described with the three data sets are very similar, the causal relationships are also the same. Based on the principal component analysis, the indicators can be divided into two groups: the component consisting of raw data and the component consisting of reference-based variables. In this case, too, the three datasets resulted in the same groups of variables. Of the eight indicators, two proved to be collinear: all references and the Hirsch index of all publications. A comparison of researchers from countries showed that economic researchers in Austria perform best, and researchers from other countries only follow in each dataset. The results are similar; it is difficult to rank between countries.

Keywords	***DOI***	***JEL code***
Science metrics, economics, management, multivariate statistics	*https://doi.org/10.54694/stat.2023.5*	*A11, C10, C12, I20*

INTRODUCTION

International competitiveness has become a top priority for countries in today's increasingly integrated political establishment, which is based on international relationships. Macilwain (2010) found that activities related to science, technology and innovation have a direct impact on social and economic well-being and also promote sustainable development. As for the Central European countries examined in the present study, the fullest possible transition to a knowledge-based economy is the key to their competitiveness as well as their positioning among the member states of the European Union. It can be achieved by investing in the modernization and development of higher education as well as research and development, in which respect the Visegrad Group of countries lag behind their western neighbours. According to a study by Bőgel et al. (2020), higher education in these countries is not moving in the right direction, and investment in R&D activities is low at both state and company levels. The transfer of new technologies, the ability to adapt to the changed environment is intended to avoid the middle-income trap in the studied countries, which ultimately threatens with the possibility of finding themselves in a stuck position if the Central European region is unable to renew and keep pace with the developed Western states. The biggest challenge for them in this regard is growth, in other words, their ability to achieve high productivity and create high value-added products, services and innovation in their own region. In their work, Nölke and Vliegenthart (2009) describe the Central European region as a region of dependent market economies where a strong hierarchy can be observed between the headquarters of multinational corporations and local corporations.

The present study examines six Central European countries. Four of these states also form a smaller entity within the European Union, which is based on their common political, cultural and historical ties (these states are the Czech Republic, Poland, Hungary and Slovakia). These member states are collectively referred to as the Visegrad Group of countries. What these states have in common is that they became communist satellite states of the Soviet Union after World War II. A kind of regime change and democratic transition as well as the creation of a market economy took place in these countries in the 1990s. By now these countries have become members of the North Atlantic Treaty Organization (NATO) and the European Union (EU), thus giving a significant contribution to the Europeanisation of their internal systems. Two other countries are added to the analysis as reference points, one of which is Austria as the leading state in the Central European region, with significant links to the Visegrad Group of countries. In addition to Austria, Romania is also included in the study as another reference country, which, as it happened in the case of the Visegrad Group of countries, came under the control of the Soviet Union, but the democratic transition did not take place there as peacefully as in the other four countries mentioned above. With regard to the EU, Austria and Romania are also good choices since Austria gained admission in 1995, much earlier than Romania, which joined the union twelve years later in 2007. The six studied countries differ in terms of the number of population, as Poland and Romania can be classified as larger countries, Austria, Hungary and the Czech Republic are medium-sized states, and Slovakia can be considered as a smaller country.

The paper aims to first analyze the statistical properties of indicators and data sets, then to analyze the performance of the selected countries in the discipline of Economics and Management based on the publication performance of researchers included in the data sets. The purpose of research is to compare the selected Central European countries based on three different data sets, one being a representative sample by the population of the countries, the second being a data set including the top 50 Economic researchers in each country, and the third data set consisting of every researcher satisfying the disciplinary requirements. These disciplinary – publication – requirements have been set in order to define who the Economic researcher in these countries is. In the paper, we first analyzed the relations between the indicators studied. We carried out the analyses for the three data sets simultaneously. These analyses included correlation analysis, principal component analysis, multicollinearity analysis, the linear regression estimation of the collinear indicators, and partial correlation analysis to determine the cause-and-effect relations. Then, the countries were ranked, Austria serving as a benchmark country.

The main research questions are how to define and who are the Economic researchers in the selected Central European countries. Secondly, what kind of correlations can be observed between the indicators describing the publication performance of the selected researchers? Thirdly, what are the principal components and what is cause-and-effect relation between these indicators, in order to define the best publication strategy leading to the highest publication performance of these researchers. Last but not least, what is the ranking of these countries based on the publication performance of their Economic researchers?

After the introduction, our study continues with the examination of the scientific performance of the selected countries, followed by the definition of the group of economic researchers and the issues surfaced during the compilation of the data set. In the next chapter, statistical analyses are carried out to explore the logical system of indicators characterizing the performance of the analyzed researchers. In following chapter, the TOPSIS ranking technique is used to determine the ranking of each country, our results are discussed then. Finally, conclusions are drawn from the research results.

1 EXAMINING THE SCIENTIFIC PERFORMANCE OF THE EAST CENTRAL EUROPEAN COUNTRIES: A SHORT LITERATURE REVIEW

The measurement of scientific performance can be performed at four levels: at the individual level of the researcher, at the level of scientific journals, at the level of research institutions (including universities and research centres), and at the level of countries (Gevers, 2014). Different bibliometric and scientometric performance indicators have been defined for each level, focusing primarily on the quality of scientific activity. Quality indicators are usually organized around an internationally accepted database and regulatory system, being used as reference points.

A ranking was found by Szuflita-Zurawska and Basinska (2021) in their study carried out among the Visegrad Group of countries. Based on their results, Poland has the highest productivity in terms of publication numbers, while the Czech Republic leads in terms of the number of publications per researcher in internationally indexed journals, and Hungary dominates in the number of ERC grants as well as publications written in international cooperation in general. A similar conclusion was reached by Dobos et al. (2021), whose results show that the Central European countries do not belong to the international scientific elite, a more conscious planning can be observed in only two of them, the Czech Republic and Poland, thus giving the leading role in the region to these two countries.

Few remarks should be taken regarding the selected Central European countries. On the one hand, it is important to mention that the studied countries are well comparable to one another because none of them belongs to the Anglo-Saxon countries so they may encounter language barriers in scientific publication (Jurajda et al., 2017). In addition, with regard to the post-Soviet states, a parallel can be drawn in their development in the field of social sciences and, more importantly, in the discipline of economics, which is a discipline that was neglected and pushed into the background during the Soviet period. In these countries, research in social sciences and economics could begin only in the 1990s and was significantly underfunded in comparison to natural and technical sciences (Vanecek, 2008).

Grančay et al. (2017) analyze the academic requirements defined regarding the economists of the Central European region between 2000 and 2015. They found that there was a dynamically increasing scholarly output of economists being a 317% increase regarding the Web of Science indexed publications and the impact of their publications achieve reputation interpreted in the increasing number of citations risen by 228%. They also found basic changes in the requirements by the implementation of newly defined science policies after the political transformation of these states. In their study and in Pajič's paper (2014) also, the most important pillars of national research evaluation measures are listed. Based on their results, national publication strategies can be drawn. While some of the countries – especially in the case of the Czech Republic – the local journals gained international indexing, Hungary has long been focusing on international collaborations and publishing in worldclass journals. Their findings show that from the absolute scholarly output, Poland and the Czech Republic are the leading countries of the region. On the other hand, Hungary thanks its traditionally strong scientometric evaluation system, publishes to a global audience extensively. Grančay and his co-authors' results point out that however these countries tend to become competitive actors in the international science community, they publish in their local and regional journals to a great extent, meaning that "only communication channels are internationalized, but not the communication itself". Economists from the region share similar risk to social scientists, that in order to publish to international journals, they tend to focus more on topics interesting for a wider global audience. This means in the long term that local or country-specific topics are abandoned (Löhkivi et al., 2012; Purkayastha at al., 2019).

2 WHO CAN BE CONSIDERED AN ECONOMIC RESEARCHER?

Due to the diversity and complexity of social and economic challenges, scientific research increasingly requires an inter- or multidisciplinary approach (Abramo et al., 2012). There is a clear consensus that there are no longer any field constraints or barriers in today's scientific work and that interdisciplinary research has become widely spread (Porter et al., 2009). Carrying out research in increasingly larger research groups is a general trend and the participants of these research groups tend to be professionals active in different disciplines. It occurs precisely because of these processes that the accurate definition and separation of certain disciplines are becoming increasingly difficult. Economics has long been separated from the social sciences and including several subfields. Such subfields include Finance, Economics and Organizational science or operations research (Truc et al., 2020). According to the classification of the Economic and Social Research Council (2021), Economics has two major disciplines, which are Economics and Management and Organizational science, respectively.

In their article (2021), Dobos et al. made an attempt to determine who could be considered an Economics Researcher. In their study, according to a preliminary definition, Economics Researchers were considered as such if a significant proportion of their publications appeared in an economic journal. Accordingly, their analysis was conducted in line with the subject areas listed in the SCImago Journal Ranking (SJR). In the SJR, journals are grouped at two levels, which are subject areas and subject categories. In their study, Economics Researchers were selected on the basis of subject areas, which are the following:

- Business, Management, and Accounting,
- Decision Sciences, and
- Economics, Econometrics, and Finance.

An additional filter condition during the compilation of the sample was that only those having already had publications in one of the listed disciplines were taken into account. This is also the group of researchers with an author ID in the Scopus citation database.

Then, in the second stage of the selection those having already published in at least three ranked journals in the subject areas mentioned in the field of Economics or in the field of social sciences were taken into account. This second selection step became necessary because if a researcher published only in the field of Decision Sciences, he could have gotten into the data set as a mathematician involved in operations research without having published in the other two areas of economic sciences. Due to the strong relations between Economics and social sciences, certain subject categories listed within the subject area of the social sciences are considered in our analysis. These include Development, Human Factors and Ergonomics, and Transportation.

Based on all these considerations, in this paper, those researchers are considered to be Economic researchers who published at least 30 percent of their papers in the subject areas of Business, Management, and Accounting, and Economics, Econometrics, and Finance. It is important to note, however, that a journal can be indexed in several subject areas and subject categories, as well as it can cover a diverse research profile. However, the discipline classification of the SJR can provide a good indication of the focus of a given paper. When setting the lower limit at 30 percent, a rule of thumb was applied so most researchers were included in our data set.

3 COMPILATION OF THE DATA SET

We started the data analysis by selecting the researchers of the monitored countries who satisfy the requirements mentioned in the last section. For the data compilation, we used the Scopus citation database and the SciVal research intelligence program based on the Scopus database. Following the disciplinary requirements detailed above, we narrowed the data set alongside the two mentioned sets of subject areas in the SJR:

- Business, Management and Accounting, and
- Economics, Econometrics and Finance.

We then determined the parameters to form the basis of our ranking. Apart from the subject areas, the total number of papers published in these two areas was chosen as a filter variable. While doing so, we relied on Scopus, which assigns to each researcher the subject areas where the researcher has already published. This function of the database is based on the scientific classification of journals in the SJR ranking. As SciVal can only highlight 150 researchers per country, we used this maximum number as a basis. Thus, 900 researchers active in the field of Economics from the six selected countries were added to the initial database. However, we were compelled to face the fact that this solution did not prove to be completely reliable, either.

We had to keep on narrowing down the initial database of 900 researchers as there were several problems with identifying whether the researchers were actually employed in a given country. The initial database we had compiled from Scopus also listed those researchers among the 150 professionals in a given country who were ever (even temporarily) employed in that country, so when their affiliation was geographically identified, that country was included in their publications. In order to eliminate this problem, we had to examine the profiles of the researchers in the database one by one and find their actual institutions.

In summary, the final dataset includes researchers per country who, at the time of the data compilation, were employed in that country according to Scopus and had already had publications in the two chosen subject areas. Therefore, after the narrowing phase, our initial data set of 900 researchers was narrowed down to 658 in the distribution shown in Table 1. The database of Dobos et al.'s paper (2021) was also selected on this principle, therefore the representativeness remained questionable, so the results can be up for a debate. The table also contains two additional datasets. One dataset, which contains 278 researchers, is a representative sample. The basis of representativeness was the number of populations per country. The other dataset contains 300 data items, which includes the same number of researchers from each country, selected according to a similar principle as seen in team competitions. There, too, each national team takes part with an equal number of competitors, regardless of the size of the country.

Table 1 Distribution of researchers in the dataset by countries

Country	Number of researchers in the datasets by countries					
	278 persons		300 persons		658 persons	
	person	%	person	%	person	%
Austria	27	9.712	50	16.667	106	16.109
Czech Republic	32	11.511	50	16.667	110	16.717
Poland	114	41.007	50	16.667	114	17.325
Hungary	29	10.432	50	16.667	82	12.462
Romania	60	21.583	50	16.667	133	20.213
Slovakia	16	5.755	50	16.667	113	17.173
Total	**278**	**100.000**	**300**	**100.000**	**658**	**100.000**

Source: Own editing based on the Scopus database

The researchers selected for the 278-person and 300-person datasets were identified by using a ranking technique per country, i.e., the best professionals from each country were included in the datasets. Among the available methods, researchers from six countries were ranked using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. An essential feature of TOPSIS method is that the available data set is normalised in terms of the variables. There are several options for normalisation, including Euclidean distance, transforming data to [0,1] interval. After normalisation, the already normalised data are weighted by the method, which can be done with two approaches: subjective and objective. In the case of subjective weighting, the weights of the aspects are predetermined, while in the case of objective weighting, they start from the statistical properties of the data set and weighting is built on them. Two methods are known for the latter approach. One is the entropy-based method (Zou et al., 2006), while the other is the standard deviation-based Criteria Through Intercriteria Correlation (CRITIC) method (Diakoulaki et al., 1995). TOPSIS performs further calculations on the weighted normalised data matrix. For each aspect, the method determines the ideal and negative ideal, i.e., the preferred and rejected values.

In the next step, for each observation – in the present study, for each researcher – we determine the distance from the ideal and negative ideal points. A quotient is then formed, which is between the values of 0 and 1 and the distance from the ideal point is proportional to the sum of the distances measured from the two preferred points. This value is 1 if observation (researcher) is preferred in everything, and 0 if observation is the least good in everything. The geometric approach to this is to examine the distance from two privileged points in the normalised space of the variables, which is based on the triangular inequality well-known in geometry.

Based on Scopus and SciVal, we measured performance through eight variables freely available on the researchers' datasheets. The variables also included publication, citation, and co-author indicators. The variables used for the analysis are as follows (with abbreviations in brackets):

- number of total publications (DOC),
- total number of citations (TOT-CIT),
- the Hirsch index (H-I),
- number of co-authors (C-A),
- number of publications between 2010 and 2019 (SO),
- number of citations to publications published between 2010 and 2019 (CIT),
- the five-year Hirsch index between 2015 and 2019 (H5-I), and
- the Field-Weighted Citation Impact (FWCI).

The first four of the variables include achievements over the entire research career, while the last four considers the activity of the last ten years between 2010 and 2019 before the date of data collection (June 25, 2020). Of the variables, the FWCI certainly needs further explanation, while the others, including the Hirsch index, are well-known. The FWCI basically shows how referential the author's publications are. If the value of FWCI is greater than one, more citations are expected from the publication compared to other publications in similar subject areas. The calculation algorithm of the FWCI index can be found in Elsevier (2019) and Purkayastha el al. (2019).

4 STATISTICAL ANALYSIS OF THE DATA SET

During the examination of the three datasets (278 persons; 300 persons; 658 persons), we performed six analyses on eight variables to examine the relationship between the variables. We first mapped out the stochastic relationship between the variables by analysing the correlation matrix. Then, by using principal component analysis, we reduced the number of variables. In the third analysis, we analysed the multicollinearity between the variables by using the variance inflation factor (VIF). In the fourth stage of our analysis, collinear variables filtered with the help of VIF were estimated using linear regression. The fifth analysis explored the causal relationship between the variables using partial correlation. Statistical analyses were performed in parallel on the three datasets in order to compare their results. Our results show that for the parallel analysis, some comparability of the obtained results can also be performed, because the results obtained for the three data sets show only minor differences.

4.1 Correlation analysis

Table 2 summarizes the results of the correlation calculation. It stands out that the correlation between the selected variables is very high except for the FWCI index, while the FWCI shows a very weak linear relationship with the other six variables. By their nature, H-I and CIT show a weakly moderate relationship with FWCI, as both are citation-linked variables. There is a strong and very strong linear relationship between the other seven variables.

Another interesting feature of the correlations is that H-I shows a relatively strong correlation with all of the variables. The correlation matrix suggests that the variables can be divided into two groups. It can be observed that there is a strong correlation between the number of publications and the publications of the last 10 years, between all citations and publications of the last 10 years, and between the two Hirsch indices, as shown by the results marked in grey. The analysis also points out that the correlation coefficients of the three datasets differ insignificantly from each other, i.e. they reinforce each other's effect and direction. Each of the correlation coefficients is significant at level of .000 in Table 2. Due to lack of space, we have therefore not indicated the significance levels with the usual stars in SPSS.

Table 2 Correlations between the variables

Variables	Number of items	DOC	TOT-CIT	H-I	SO	CIT	H5-I	FWCI
C-A	278	–0.580	–0.379	–0.494	–0.466	–0.512	–0.476	–0.330
	300	–0.613	–0.409	–0.536	–0.494	–0.542	–0.519	–0.381
	658	–0.417	–0.254	–0.313	–0.339	–0.337	–0.315	–0.222
DOC	278		0.543	0.690	0.629	0.491	0.373	0.042
	300		0.582	0.741	0.680	0.526	0.474	0.147
	658		0.555	0.696	0.653	0.500	0.423	0.150
TOT-CIT	278			0.876	0.389	0.804	0.409	0.370
	300			0.855	0.428	0.796	0.448	0.427
	658			0.838	0.410	0.792	0.438	0.407
H-I	278				0.519	0.838	0.585	0.451
	300				0.572	0.823	0.660	0.549
	658				0.533	0.798	0.621	0.527
SO	278					0.433	0.522	0.145
	300					0.462	0.555	0.199
	658					0.492	0.582	0.238
CIT	278						0.707	0.612
	300						0.736	0.680
	658						0.725	0.651
H5-I	278							0.584
	300							0.638
	658							0.633

Source: Own editing based on the Scopus database

4.2 Principal component analysis

Table 3 shows the components of the variables. In the principal component analysis of the eight variables, we obtained two components for all three datasets that accounted for more than 70 percent of the variance. The fit of the model according to the Kaiser-Meyer-Olkin test was between 0.788 and 0.790, which values represent a mean model according to the accepted categorization.

In all three principal component analyses, we obtained two components each, which explain almost the same variance as rotation. It is also interesting that in each analysis the same variables were included in each component, but the variable H-I can be assigned to both components in each case. Since the majority of correlations are high, i.e. greater than 0.4 in absolute value, we can expect high collinearity between them, so examining multicollinearity was the next step to be taken.

4.3 Examination of multicollinearity with VIF index

There is no uniform rule in the literature as to which VIF values above which variables can be considered collinear. Although there are some empirically tested VIF thresholds that range from 2.5 to 10, in the case

Table 3 Variable components

Size of dataset	278 persons		300 persons		658 persons	
Variance explained	73.510 %		75.906 %		71.307 %	
KMO test	.789		.790		.788	
Variable	Component		Component		Component	
	1	2	1	2	1	2
Variance (%)	37.889	35.621	38.080	37.826	39.031	32.276
DOC	**0.925**	0.076	**0.922**	0.158	0.203	**0.888**
SO	**0.787**	0.139	**0.827**	0.153	0.272	**0.761**
H-I	**0.679**	**0.617**	**0.659**	**0.653**	**0.704**	**0.575**
C-A	**−0.632**	−0.329	**−0.644**	−0.356	−0.113	**−0.610**
FWCI	−0.084	**0.910**	−0.026	**0.926**	**0.891**	−0.063
CIT	0.478	**0.809**	0.441	**0.831**	**0.848**	0.394
H5-I	0.367	**0.720**	0.416	**0.719**	**0.751**	0.342
TOT-CIT	**0.571**	**0.577**	**0.542**	**0.599**	**0.649**	**0.485**

Note: Methods used: principal component analysis and Varimax rotation with Kaiser normalisation. Values in bold indicate values in the matrix greater than 0.5 to help assign components to variables.
Source: Own editing based on the Scopus database

of filtering redundancy out, there is no set of theoretical or logical rules by which they can be reliably determined. For this reason, accepting the recommendations of several studies (Lafi et al., 1992; Liao et al., 2012; O'Brien, 2007), 5 was chosen as a threshold. A similar analysis was performed in paper Dobos et al. (2021).

In the initial step, we used the inverse of the correlation matrix from principal component analysis, because the diagonal of the inverse matrix contains the VIF values with the inclusion of the other remaining variables. In the next step, the operation of calculating the diagonal of the inverse matrix was repeated, but only after the variable with the highest VIF value was dropped from the analysis. These steps were carried out until the VIF values fell below the predefined limit, in our case below 5.

The evolution of VIF values and the sequential screening of the variables are summarized in Table 4. It is worth noting here that there is no deterministic algorithm for filtering out collinear variables. As a first step, it is recommended in the literature to filter out the variable with the highest VIF value but any variable above the threshold is also suitable for the first step. In the next step, there are again two options: either the element with the highest VIF value is selected again or the variable with the largest decrease in the value of VIF. In our case, the first option was chosen – i.e. the element with the highest VIF value. The decision is justified by the fact that in the first step the VIF value of the variable H-I was the highest. This was followed by the CIT variable, while the collinear values for the other six variables were not very high.

The examination of the initial VIF values immediately revealed that the total number of publications, the number of co-authors, the publications of the last 10 years, the Hirsch index of the last 5 years, and the initial value of the FWCI index are less than 5, that is the threshold, meaning that these variables could not be included in the collinear variables to be eliminated due to the stepwise decrease of the VIF value. As a result, it can be concluded that the Hirsch index and the citations to the publications of the last 10 years had a linear dependence on the other variables. If we consider the content of the variables, the latter become evident. It is worth emphasizing, however, that in this case, too, the results of the three datasets move together.

Table 4 The evolution of VIF values

Variables	Number of items	1. phase	2. phase	3. phase
DOC	**278**	3.547	2.659	2.651
	300	4.418	3.034	3.033
	658	3.138	2.354	2.354
TOT-CIT	**278**	6.200	3.820	1.722
	300	6.048	3.792	1.865
	658	5.183	3.470	1.714
H-I	**278**	8.773		
	300	9.418		
	658	6.523		
C-A	**278**	1.876	1.853	1.816
	300	2.001	1.961	1.906
	658	1.287	1.273	1.261
SO	**278**	2.023	2.022	2.005
	300	2.195	2.195	2.186
	658	2.227	2.220	2.220
FWCI	**278**	2.255	2.149	1.937
	300	2.854	2.491	2.214
	658	2.359	2.178	1.937
CIT	**278**	6.674	6.497	
	300	6.576	6.572	
	658	5.864	5.859	
H5-I	**278**	3.117	3.010	2.227
	300	3.591	3.374	2.610
	658	3.351	3.187	2.515

Source: Own editing based on the Scopus database

4.4 Linear regression estimation of collinear variables

In the linear regression estimation of the collinear variables, the filtered two variables are estimated with the remaining six variables, the parameters and significance levels of which are illustrated in Table 5. Linear regression was performed by stepwise regression using the SPSS statistical analysis program instead of the usual enter method. Because we had two dependent variables for all of the three datasets, we performed six stepwise linear regressions. As it can be seen in the table, the R2 values of the six linear models are all very high, being above 0.8. The parameters of the variables and the constant are significant in each model, indicating the goodness of the models.

In estimating the Hirsch index, publications from the last 10 years did not participate in any of the model types. In addition, the number of co-authors was not included in the 278-person sample. In the citations of the last 10 years, however, neither the total number of publications nor the number of publications in the last 10 years participated in any of the regressions. The latter phenomenon can be attributed to the fact that the citation variable can be explained by variables derived from other citations.

Table 5 The parameters and significance levels of the equations

H–I	Const.	DOC	TOT–CIT	C–A	SO	FWCI	H5–I	R^2
278 persons	2.862	0.061	0.003	–	–	0.674	0.331	**0.882**
Significance	*.000*	*.000*	*.000*	–	–	*.000*	*.000*	–
300 persons	1.589	0.084	0.003	0.010	–	1.239	0.373	**0.894**
Significance	*.000*	*.000*	*.000*	*.017*	–	*.000*	*.000*	–
658 persons	1.904	0.072	0.004	0.005	–	1.012	0.342	**0.846**
Significance	*.000*	*.000*	*.000*	*.008*	–	*.000*	*.000*	–
CIT	**Const.**	**DOC**	**TOT–CIT**	**C–A**	**SO**	**FWCI**	**H5–I**	R^2
278 persons	–141.125	–	0.205	–0.712	–	61.312	44.802	**0.845**
Significance	*.000*	–	*.000*	*.006*	–	*.000*	*.000*	–
300 persons	–129.974	–	0.193	–0.699	–	79.459	43.090	**0.847**
Significance	*.000*	–	*.000*	*.005*	–	*.000*	*.000*	–
658 persons	–100.354	–	0.206	–0.262	–	62.023	41.211	**0.829**
Significance	*.000*	–	*.000*	*.009*	–	*.000*	*.000*	–

Source: Own editing based on the Scopus database

4.5 Analysis of partial correlations: cause-and-effect

Partial correlation is suitable for filtering out the effect of other variables when determining the correlation between two variables in a linear model. This can also be interpreted by mapping out the causal relationship between the two variables. Table 6 shows the partial correlations used to describe the causal relationships.

There are three types of causality, which are summarized in Pearl (2009):

- temporal priority,
- relationship, and
- non-spurious relationship.

In our case, temporal causality can be applied, for which we can build two causal chains. The first chain consists of the variables **C-A → DOC → TOT-CIT → H-I**, which means that the author must first build a network of co-authors and collaborate with other authors, if it is done successfully, the communication will be completed. The paper, which provides meaningful and significant results, is given a citation, and then the Hirsch index is calculated from the publications published by the author and the citations given to them. Acting similarly, we can form a logical chain about the last 10 years with the following causal sequence: **SO → CIT → H5-I → FWCI**. Of course, the two chains show temporality but it is worth noting that temporality does not necessarily mean an existing linear relationship, that is, correlation.

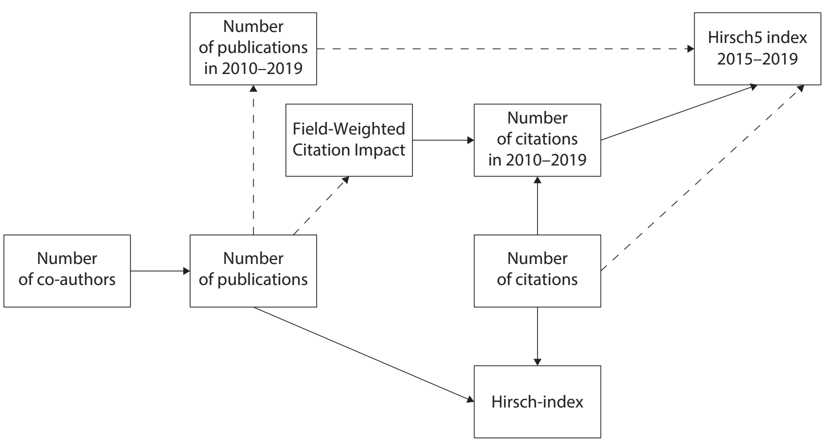
When exploring causal relationships, partial correlation values above 0.3 in absolute value are considered. There are five values between 0.40 and 0.62, while four more values are found between 0.30 and 0.40. If a value is entered in the two ranges for at least two datasets, it is assigned to the higher value. In Table 6, the examined partial correlations are indicated by colour. In this case, too, our results obtained in the three data sets prove to be very similar.

Table 6 Partial correlations

Variables	Number of items	DOC	TOT-CIT	H-I	SO	CIT	H5-I	FWCI
C-A	278	–0.417	0.054	0.111	–0.070	–0.157	–0.053	–0.199
	300	–0.426	0.055	0.141	–0.059	–0.169	–0.036	–0.204
	658	–0.281	0.021	0.104	–0.030	–0.097	–0.025	–0.094
DOC	278		–0.132	0.500	0.337	–0.036	–0.082	–0.389
	300		–0.121	0.560	0.334	–0.030	–0.034	–0.438
	658		–0.068	0.500	0.424	–0.017	–0.067	–0.310
TOT-CIT	278			0.620	0.052	0.473	–0.396	–0.149
	300			0.611	0.046	0.549	–0.432	–0.212
	658			0.575	0.020	0.565	–0.372	–0.190
H-I	278				0.009	0.163	0.185	0.217
	300				0.001	0.025	0.246	0.357
	658				–0.057	0.029	0.221	0.277
SO	278					–0.093	0.363	–0.093
	300					–0.063	0.330	–0.107
	658					0.015	0.377	–0.109
CIT	278						0.464	0.267
	300						0.455	0.302
	658						0.441	0.312
H5-I	278							0.214
	300							0.207
	658							0.252

Source: Own editing based on the Scopus database

Figure 1 Causal relationships between the variables



Source: Own editing based on the Scopus database

Figure 1 shows the causal relationships between the variables. Relationships between 0.40 and 0.62 are indicated in continuous and correlations between 0.30 and 0.40 in dashed lines. The figure shows that the block related to citations – including all citations, citations from the last ten years, the H-index, H5-I, and FWCI index – depends on the total number of publications, the number of publications in the last ten years, and on the number of co-authors. This suggests that the number of publications shows a strong correlation with the evolution of citations, while the number of co-authors is positively related to publication indices, i.e., to the total number of publications.

Based on the results, we can conclude that according to the causal system to be drawn, an increase in the number of co-authors increases the number of publications for a given author, and then the number of publications can increase the number of citations and thus the Hirsch indices.

5 RANKING OF RESEARCHERS USING TOPSIS RANKING TECHNIQUE

The TOPSIS method has already been used for compiling the data set. In the normalisation phase, we used the transformation of the variables to the interval [0,1], while the entropy-based method was used to determine the weights. This means that the rankings were not based on the rankings within each country, but on all the researchers in the data set.

5.1 The population-based sample including 278 researchers

First of all, it is worth examining the representative data set in proportion of its population with the TOPSIS method. The total number of researchers was 278, who were divided into ninths after the ranking. Thus, only 30 researchers were placed in the last ninth and 31 in the others. The means and standard deviations for each country are summarized in Table 7.

Table 7 shows that researchers in Austria have the highest average efficiency according to TOPSIS, followed by researchers from the Czech Republic and Slovakia, Hungary, Poland and finally Romania with the same values. It can be observed in the table that the average of the positions also shows this order. The relative standard deviations for the Slovak and Romanian researchers show that these countries have the largest deviation from their national average, while the most balanced data are seen in the case of the Polish professionals.

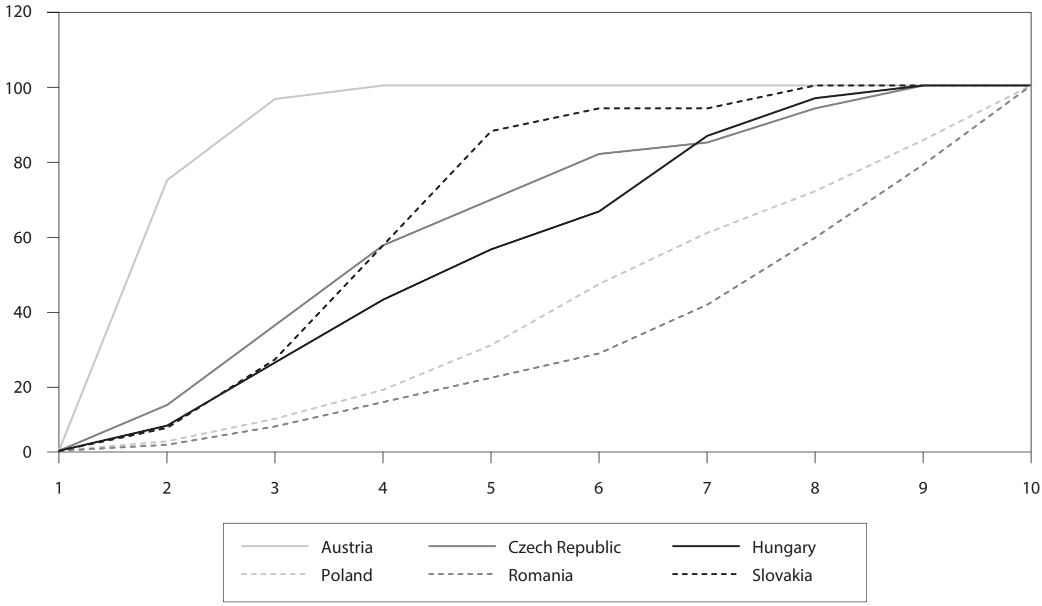
Data in Figure 2 is divided into ninths, which illustrates the extent to which researchers from each country are ahead in the rankings if their proportion is expressed in percentage. Thus, we examine how the distribution changes with the accumulation of each ninth by country. It can be seen from the figure that Austrian researchers give the best performance in total, followed by researchers from the Czech Republic and Poland. Hungary is found in the fourth place, ahead of Slovakia and Romania.

Table 7 The TOPSIS and ranking average, deviation and relative deviation of the 278-person data set

Countries	TOPSIS			Position		
	Average	Deviation	Relative deviation	Average	Deviation	Relative deviation
Austria	0.56	0.04	0.079	20.65	17.54	0.849
Czech Republic	0.48	0.03	0.066	100.16	61.93	0.618
Poland	0.45	0.03	0.059	165.18	70.33	0.426
Hungary	0.47	0.03	0.061	117.93	59.93	0.508
Romania	0.45	0.12	0.273	188.58	187.38	0.994
Slovakia	0.48	0.07	0.147	88.06	130.81	1.485

Source: Own editing based on the Scopus database

Figure 2 The ninths of the 278-person data set by countries



Source: Own editing based on the Scopus database

5.2 Same number of researchers per country, 300 researchers

After the population-based data set, the database containing the same number of researchers per country – a total of 300 people – is examined using the TOPSIS method. After sequencing, the researchers were divided into tenths so that each tenth would contain the same number of researchers, 30-30 persons. The means and standard deviations for each country are shown in Table 8.

The table shows that Austrian researchers have the highest average efficiencies according to TOPSIS, followed by their Czech counterparts. They are followed by Polish and Hungarian researchers, while Slovak and Romanian experts close the list with almost the same values. The average of the rankings also follows this order, while in terms of relative standard deviations, the Slovak and Romanian researchers

Table 8 The TOPSIS and ranking average, deviation and relative deviation of the 300-person data set

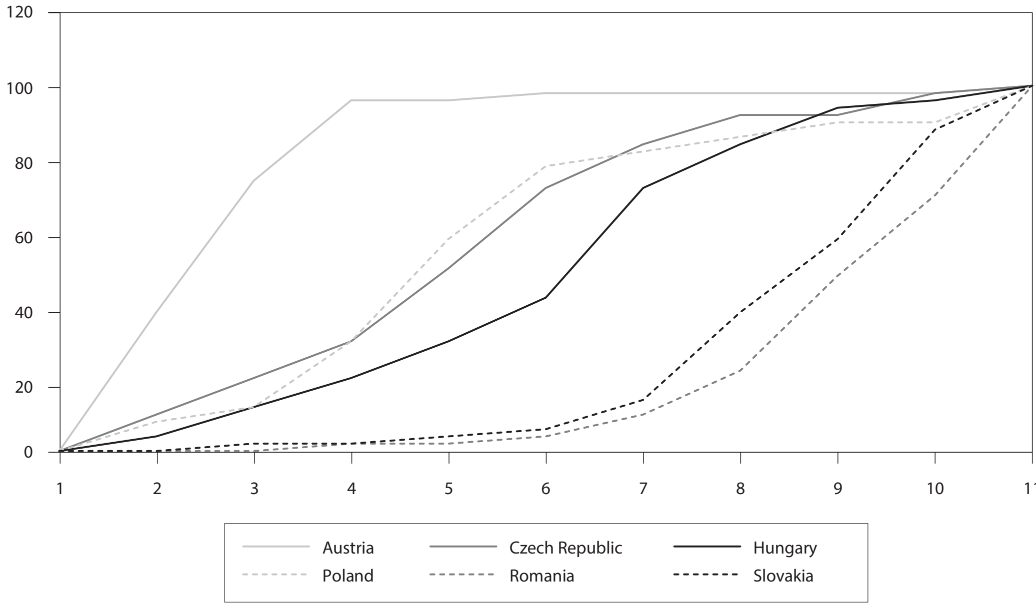
Countries	TOPSIS			Position		
	Average	Deviation	Relative deviation	Average	Deviation	Relative deviation
Austria	0.37	0.08	0.204	45.32	45.12	0.996
Czech Republic	0.31	0.04	0.126	123.60	66.13	0.535
Hungary	0.30	0.03	0.088	149.90	65.44	0.437
Poland	0.30	0.03	0.110	125.46	72.30	0.576
Romania	0.27	0.01	0.044	237.02	47.52	0.200
Slovakia	0.28	0.01	0.039	221.70	47.56	0.215

Source: Own editing based on the Scopus database

show the largest difference from their national average again. In this case, too, the Polish professionals have the most balanced data.

Figure 3 shows a similar picture to Figure 2. It can be observed that the Austrian researchers provide the best overall performance in this dataset as well. They are followed by the Czech Republic and Poland, while the Hungarian researchers are in the fourth place, followed by the Slovak and Romanian professionals.

Figure 3 The tenths of the 300-person data set by countries



Source: Own editing based on the Scopus database

5.3 Database of all available researchers, including 658 persons

Finally, the third data set was also examined using the TOPSIS method. This database consists of the profiles of all available researchers, including a total of 658 persons. Just as seen above, the researchers were divided into tenths. Table 9 shows the means and standard deviations for each country.

Table 9 The TOPSIS and ranking average, deviation and relative deviation of the 658-person data set

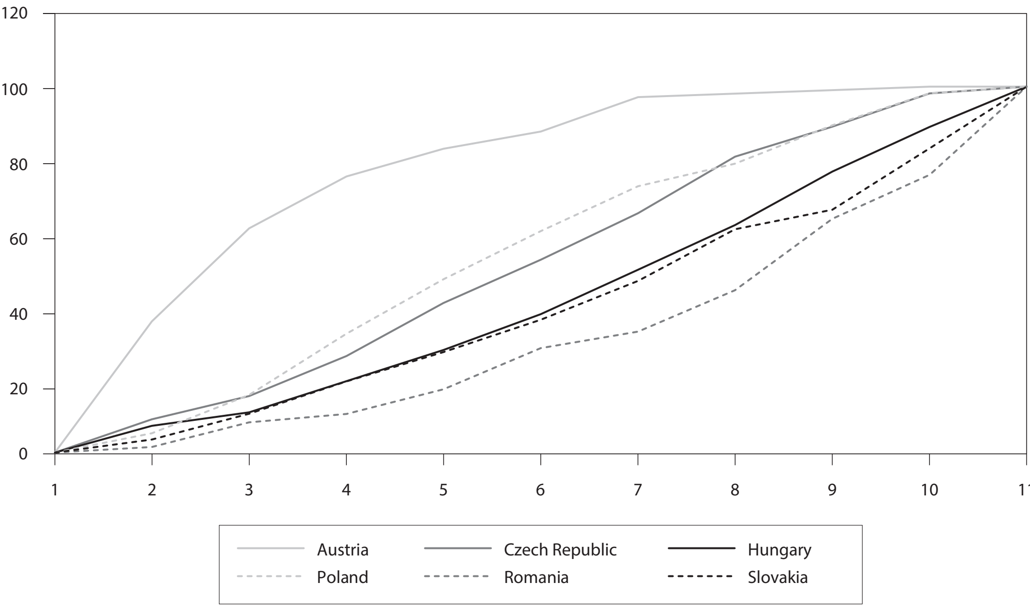
Countries	TOPSIS			Position		
	Average	Deviation	Relative deviation	Average	Deviation	Relative deviation
Austria	0.53	0.07	0.138	137.59	123.76	0.899
Czech Republic	0.47	0.05	0.096	310.95	161.81	0.520
Hungary	0.46	0.04	0.089	177.10	375.87	2.122
Poland	0.47	0.04	0.086	299.15	158.11	0.529
Romania	0.45	0.04	0.083	440.78	169.73	0.385
Slovakia	0.46	0.03	0.076	393.58	183.64	0.467

Source: Own editing based on the Scopus database

As in the previous two cases, researchers from Austria have the highest average efficiency according to TOPSIS, followed by the Czech Republic and Poland. Hungary and Slovakia closely follow each-other, and finally Romania closes the list. The average of the rankings also follows this order.

Figure 4 shows a similar result to those of Figures 2 and 3. It can be seen that the Austrian researchers provide the best performance in this data set as well. They are followed by the Czech Republic and Poland, while Hungary is ranked in the fourth place, ahead of Slovakia and Romania.

Figure 4 The tenths of the 658-person data set by countries



Source: Own editing based on the Scopus database

6 DISCUSSION

The analyses were two-ways in the paper. On the one hand, we analyzed the statistical properties of three compiled data sets to evaluate whether they differ substantially. Results show that the statistical properties are similar in all three data sets. This result shows that the correlations are similar in the data sets studied between the variables. Furthermore, the correlations are average and strong correlations. A weaker correlation can be found only in the case of the co-author and FWCI indicators. These results point out that the three data sets are correlated.

The relationship between the variables was then examined by principal component analysis. With principal component analysis, we obtained those two components explaining nearly three-quarters of the variance for all three datasets. This only confirms that the eight variables are linearly highly related. Therefore, it is worth examining the multicollinearity between the variables.

Multicollinearity was tested using the variance inflation factor (VIF). We obtained the result that the same two variables in each database, including the Hirsch index and the number of references received in the last ten years between 2010 to 2019, depend linearly on the other variables. This suggests that all the variables being duplicated in view of the two altered periods studied are eliminated from the analysis. This also means that the results of the analyses do not change significantly even after leaving these two variables. The two variables, as dependent variables were then linearly estimated with the remaining six variables, as independent variables in search of the answer to how we could recover the two variables from the databases with the other variables.

With partial correlation coefficients regarding the temporal causality, we then tested the causal relationships between our statistical variables (criteria). We obtained the result using the partial correlation that the number of co-authors is considered to be the most important input variable, while the output variable of the causal network is the five-year Hirsch index. Of course, the causality study also confirmed that Hirsch indices depend primarily on the number of publications and citations.

The other question stated at the beginning of the research was to compare and rank the countries based on the publication performance of the Economic researchers. From this aspect, we obtained the ranking of countries. This ranking shows the outstanding publication performance of Austrian Economic researchers, followed by the Czech and Polish researchers. Hungarian researchers are ranked in the middle based on all three databases, while Romania is considered to be the least successful compared to other countries. Hungarian researchers are generally stronger than their Slovak counterparts. These results suggest there we can observe still the economic and political effects long-lasting in the selected Central European countries, as we see leading position of Austrian researchers.

CONCLUSIONS

Higher education institutions in Central European countries are not at the forefront of the international scientific vanguard, they can rarely be found in the mainstream, and in terms of courses in Economics having worldwide popularity, they tend to be in the last third. Their fallback within the European Union member states can be explained by the publication performance, which is at a distance from the average publication performance of the Western European countries. To achieve a higher number of publications in internationally indexed journals by the authors of these countries, a change of attitude and culture within the academic community seems to be essential. However, an examination of the otherwise rather redundant Scopus database shows that the elite committed to economics research in Central Europe has a well-elaborated publishing strategy: they focus on increasing the number of publications, publishing them in the form of co-authorship, while intending to expand the volume of their citations on the basis of these factors, which will also have a positive effect on the changes in their Hirsch index. Based on their publication performance, typical groups cannot be described in terms of leading Economics Researchers in Central Europe, examining the dissemination of the results, they rather form a relatively homogeneous community. In the rankings of researchers made on the basis of quantitative results, the Polish and Czech economists are at the forefront, their Hungarian colleagues are found in the second line, while their Slovak and Romanian counterparts are observed to be lagging behind.

In the course of the future development of the survey methodology, it is definitely worth taking the population of each country into consideration, as it seems likely that the number of higher education institutions (academic research facilities) is related to the population (GDP volume, number of university and college students). In the future, the qualitative weighting of the quantitative indicators extracted from the Scopus database can also be performed, due to which it is worth considering the classification of a publication or citation (for example Q1/Q4 classifications in the SJR list).

ACKNOWLEDGMENTS

The authors thank Anna Urbanovics for her help in preparing the paper.

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Forecasting Analysis of Stock Prices on European Markets Using the ARIMA-GARCH Model

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Received 20.1.2023, **Accepted** (reviewed) 25.5.2023, **Published** 15.9.2023

Abstract

The achievement of profits when trading on the stock markets is conditioned by a quality analytical forecast of the development of stock prices in the coming period.

This research attempts to compare the results of the ARIMA model and the ARIMA-GARCH model to forecast the development of stock prices on a sample of selected stocks from the Czech, German, Austrian, Polish and British markets. The 4 most liquid titles from each of the above-mentioned markets were selected for the sample of analyzed stocks. Available daily closing stock price data, mostly from the period 2000–2022, were used for the analysis.

Research has shown that for most of the analyzed titles, it is more appropriate to use the ARIMA-GARCH model, which better captures variability for this data than just the ARIMA model. The quality of the selected model is evaluated by autocorrelation, heteroskedasticity tests, and Theil´s inequality coefficient.[3]

Keywords	*DOI*	*JEL code*
ARIMA, GARCH, stock price prediction, time series	*https://doi.org/10.54694/stat.2023.4*	*C22, C52, C58, G17*

INTRODUCTION

A functioning stock capital market enables the appreciation of invested capital, thus creating investment opportunities and, at the same time, offering opportunities for obtaining temporarily free capital to finance prospective projects that can support the development of businesses, sectors, and the entire economy. The development of stock prices is therefore an important information for investors who have invested their capital in stocks, or for subjects who are only considering their investment in certain stocks. Investing in stocks is one of the most sought-after investment options, which is characterized by easy access to investment and the possibility of achieving high returns, however, with a certain considerable level of risk. However, every investor must realize that the key to successful investing in stocks is the ability

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3 Article based on the *AMSE 2022 Conference* presentation.

to estimate the future development of stock prices, because based on this estimate it is necessary to take either a long position in anticipation of an increase in stock prices or a short position in anticipation of a fall in stock prices. The development of stock prices is very variable, in recent years quite volatile. Stock prices are affected by a large number of fundamental factors that are studied by fundamental analysts, but also by technical factors that are at the forefront of the interest of technical analysts. The influence of both one and the other group of factors on stock prices must be carefully analyzed to make a high-quality prediction of the further development of stock prices and to take an adequate investment position based on this prediction.

However, making a high-quality prediction of the development of stock prices is quite complicated, as financial time series of stock prices are usually characterized by non-stationarity, heteroskedasticity, and non-linear development. To successfully predict the development of stock prices, it is, therefore, necessary to choose a statistical model that can take into account and treat the specific characteristics of the financial time series of stock prices. If the application of such a model to the financial time series of stock prices would produce a high-quality prediction of the future development of stock prices, the investor could buy or sell at an appropriate moment, thereby achieving above-average profits while limiting risk in inefficient market conditions.

ARIMA models are statistical models that can be used to predict the future development of stock prices. There are three parts of ARIMA models: AR – autoregressive model, I – integrated part, MA – moving-average model. The paper is based on the Box-Jenkins methodology (Box and Jenkins, 1976), which according to Cipra (2013): "There is not yet a better routine tool for analyzing time-dependent observations." ARIMA modeling is frequently used for the forecasting of not only financial time series.

The financial time series often show signs of heteroskedasticity therefore the paper focuses on its testing and application of the ARIMA-GARCH modeling. This paper aims to check the applicability of the ARIMA model and its extension ARIMA-GARCH model in predicting the development of stock prices. A discussion about the volatility modeling with ARIMA and ARIMA-GARCH models is conducted. The quality of forecasts is measured based on the holdout sample with MAPE and Theil´s inequality coefficient.

The 4 most liquid stock titles from the Czech, British, German, Polish, and Austrian markets were chosen for the research. If the predictions of stock price development produced by ARIMA or ARIMA-GARCH models correspond to the actual stock price development, ARIMA or ARIMA-GARCH models can be considered effective tools that could help the investor in the European markets under investigation to "beat the market".

1 LITERATURE SURVEY

The Box-Jenkins methodology was described by (Box and Jenkins, 1976) and they show the ways how to find the best fit of a time-series model to past values of a time series.

The first description of the ARCH (autoregressive conditional heteroskedasticity) was introduced by Engle (1982), 21 years before receiving the Nobel Prize in Economics. In his article Engle also introduced the original Lagrange multiplier (LM) test for ARCH which is very simple to compute, and relatively easy to derive (Bollerslev et al., 1994).

Bollerslev et al. (1992) provided an extensive ARCH literature review that aimed to support further research in this area.

In the year 1986 independently Bollerslev (1986) and Taylor (1986) independently introduced GARCH (generalized ARCH), which proposed a natural generalization of the ARCH process introduced in the paper by Engle (1982).

Financial decisions are usually based on the tradeoff between risk and return. The paper by Engle (2001) presented an example of risk measurement which could be the input to a variety of economic decisions.

In his paper, Engle (2002) describes two frontiers in detail: the application of the ARCH models to the broad class of non-negative processes, and the use of Least Monte Carlo to examine the non-linear properties of any model that can be simulated. Using this methodology, he analyses more general types of the ARCH models, stochastic volatility models, and long-memory models breaking volatility models.

Poon and Granger (2003) mention 93 studies to date about volatility forecasting in financial markets. This study confirms that financial market volatility is forecastable but they also pose a question of how far ahead one could accurately forecast and to what extent can volatility changes be predicted. Among other conclusions, they state that GARCH (1,1) is the most popular structure for many financial time series

The article of Poon and Granger (2005) compared models with tests of volatility-forecasting methods on a wide range of financial asset returns and produced some practical suggestions for volatility forecasting. The authors induce that the financial market volatility is forecastable.

40 years after his first paper about ARCH Engle et al. (2012) declared that the ARCH/GARCH framework proved to be very successful in predicting volatility changes. They also stated that volatility clustering was most easily understood as news clustering. Trades convey the news to the market and the macroeconomy can moderate the importance of the news. These can all be thought of as important determinants of the volatility that is picked up by ARCH/GARCH. In the same paper, the authors conclude that the original modeling of conditional heteroskedasticity proposed by Engle (1982) has developed into a full-fledged econometric theory of the time behavior of the errors of a large class of univariate and multivariate models.

Hameed et al. (2006) focused on the Pakistani stock market, where they tried to model and forecast stock return volatility and test for weak efficiencies using the GARCH model and daily data for December 1998–March 2006.

One of the current applications of ARCH and GARCH models can be found in (Veselá, 2019) where she applies the ARCH and GARCH models to the prices of the PX index (Prague stock exchange index).

Challa et al. (2020) discuss the opinion of many researchers that GARCH and EGARCH models cannot provide the best results compared with ARIMA models. In their study, they conclude that ARIMA and ARIMA-GARCH models produce the same results over time, and volatility does not change.

2 METHODS AND METHODOLOGY

Methods applied in this paper combine typical steps for the ARIMA modeling – assumptions testing for stationarity and autocorrelation, ARIMA model application with a test of residual autocorrelation, and homoscedasticity. In the case of the homoscedasticity hypothesis rejection, the ARIMA-GARCH model is applied and forecast quality is evaluated.

2.1 Assumptions testing

The assumption of the use of ARIMA is stationarity. In the literature, it is mostly assumed that financial time series are at least weakly stationary, therefore it is possible to apply Box-Jenkinson procedures. In the case of non-stationarity, under certain conditions, it is possible to make the time series stationary, especially through differentiation.

The stationarity is verified by the ADF (Augmented Dickey-Fuller) unit root test and by the test of linear dependence, the Ljung-Box test. The lag length for the ADF is chosen on the base of AIC.

The Ljung-Box test needs to have set the lag m due to the fact, that different lags may affect the performance of the test statistic. Simulation studies suggest that the choice of $m \approx \ln(T)$ provides better power performance (Tsay, 2002).

2.2 ARIMA

The ARIMA models contain three parts – AR (autoregressive process), I (integrated process), and MA (moving average process). In particular, financial data such as return on investment show serial dependence, which can be modeled using an autoregressive process of order p – AR(p). The MA(q) process is the simplest model in this methodology and has the form of a linear combination of white noise processes, so the value of the time series depends only on the current and past values of this process.

This paper applies the Box-Jenkins methodology of ARIMA models that contains three steps:

1. Model identification,
2. Parameter estimation,
3. Model diagnostics.

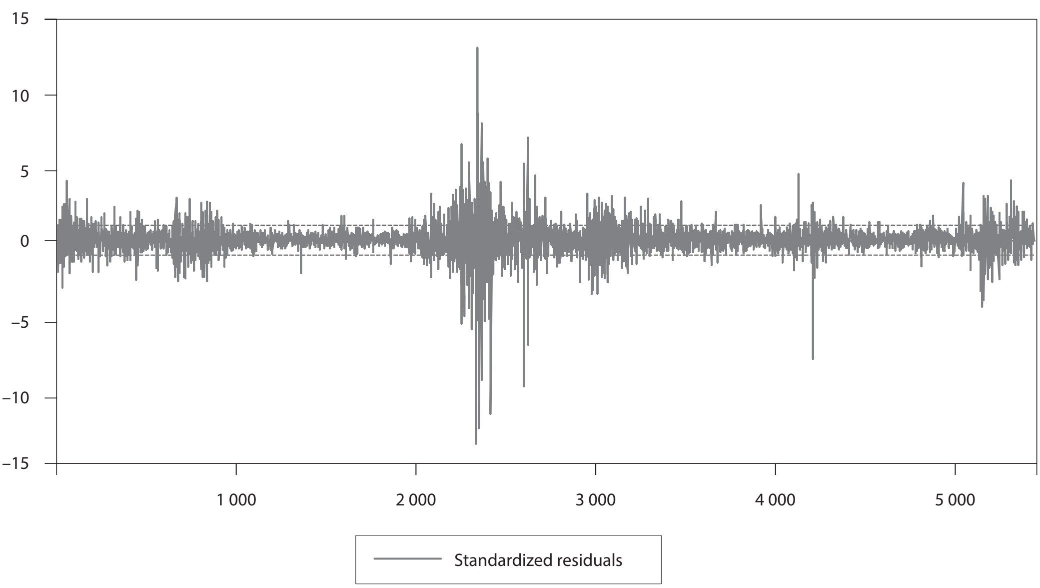
The model estimation is made with the automatic ARIMA modeling within the Eviews based on the AIC (Akaike information criterion). The model with statistically significant parameters that is reasonably simple and has a low value of AIC is chosen. For the parameter estimation, the maximum likelihood method was employed.

A fitted model must be examined carefully to check for possible model inadequacy. If the model is adequate, then the residual series should behave as white noise (Tsay, 2002: 39). The model diagnostic checks for the properties of residuals. In the case of a correct model, the residual should behave like white noise, it should not show serial correlation. In case of rejection of the hypothesis of the Ljung-Box test, the closest possible model to the former that does not lead to the rejection of this hypothesis was chosen.

Another white noise property is homoscedasticity. If the errors are heteroscedastic then the standard error estimates are not correct. In the area of financial time series, the constant variance of errors is very rare. One of the reasons is volatility clustering where large changes are usually followed by other large changes as well as small changes (Brooks, 2019).

The volatility clustering can be seen in Figure 1, where large returns follow large returns, and small returns follow small returns.

Figure 1 Standardized residuals (model ARIMA, LLOY.L)



Source: Own construction

The presence of heteroscedasticity of residuals is tested by the ARCH-LM test proposed by Engle (1982). The Engle test for ARCH effects in the residuals of an estimated model was computed to assure that this class of models is appropriate for the data. The number of lags to include was 5 according to common practice. After the rejection of the hypothesis of homoscedasticity, the ARIMA-GARCH model was applied.

2.3 ARIMA-GARCH

The volatility can be modeled using the autoregressive process (AR), where after considering the volatility, we get the ARCH (autoregressive conditional heteroskedasticity) model, which was first introduced by Engle (1982). ARCH(1) – 'autocorrelation in volatility' is modeled by allowing the conditional variance of the error term, σ_t^2, to depend on the immediately previous value of the squared error, e_{t-1}^2.

The conclusions of the applications of the ARCH model in the literature confirm the predominance of its generalized model – GARCH (generalized ARCH), which was proposed by Bollerslev (1986). Compared to ARCH models, GARCH is a very popular tool for modeling conditional heteroskedasticity, and its modifications are constantly appearing in the literature (Veselá, 2019). GARCH(1, 1) – conditional variance σ_t^2 can also be modeled by its own lagged values of lag = 1.

This model can describe the behavior of volatility (not only) in financial data, where there is a larger fluctuation of data in more observations in a row.

Poon and Granger (2003) claim that: "Empirical findings suggest that GARCH is a more parsimonious model than ARCH and GARCH(1,1) is the most popular structure for many financial time series." This paper, therefore, uses the GARCH(1,1) model.

There are two conditions for estimates:

1. Non-negative GARCH coefficients.
1. Sum of GARCH coefficients (except constant) < 1 for the process to be stationary.

2.4 Model quality assessment

For the model quality assessment, the last 250 observations are not used for the parameter estimation and are used for the model quality assessment (holdout sample). The dynamic and static forecasts are calculated, where the dynamic forecast is a multi-step forecast starting from the first period in the forecast sample and the static forecast is a sequence of one-step-ahead forecasts, rolling the sample forward one observation after each forecast.

The two criteria are applied – the MAPE (mean absolute percentage error) and Theil's inequality coefficient U (Brooks, 2019). Theil's inequality coefficient (U) measures the prediction accuracy of a model. Theil's U is calculated in the Eviews and it always lies between zero and one, where zero indicates a perfect fit. The forecasts from the benchmark model (the random walk) is calculated and they are compared to the forecasts from the chosen model. A U-statistic equal to one implies that the model under consideration and the benchmark model are equally (in)accurate, while a value of less than one implies that the model is superior to the benchmark, and vice versa.

2.5 Data

The four most liquid stock titles from the Czech, British, German, Polish, and Austrian markets were chosen for the research in the period 1/2000–4/2022. The data of most of the titles are since 1/2000, 9 of them are traded for a shorter period, and the shortest is VIG.PR (since 2008). For each series, there are 3 566 to 5 711 observations. The closing prices were obtained from Finance Yahoo (2022). The logarithmic returns were used according to other studies. The calculations were made in the Eviews, ver. 12.

3 RESULTS

Twenty time series were tested for stationarity by the ADF test and autocorrelation by the Ljung-Box test. After confirming the suitability, the ARIMA model was applied and results together with the test of the ARCH effect are shown. After the rejection of the residual homoscedasticity hypothesis, the ARIMA-GARCH model was employed and the residual homoscedasticity hypothesis was tested. Then the quality of forecasts of the holdout sample was assessed.

3.1 ADF (augmented Dickey-Fuller) unit root test

The augmented Dickey-Fuller (ADF) test hypothesis says that the series contains the unit root, against the hypothesis that the series is stationary.

Table 1 ADF unit root test results

Series	p-value at level		p-value at 1st difference	
	Constant	Constant & Trend	Constant	Constant & Trend
CEZ.PR	0.6251	0.8674	0.0001*	0.0000*
ERBAG.PR	0.1329	0.3376	0.0001*	0.0000*
KOMB.PR	0.1630	0.3677	0.0000*	0.0000*
VIG.PR**	0.0272**	0.0640	0.0000*	0.0000*
BOIL.L	0.1532	0.0006**	0.0000*	0.0000*
LLOY.L	0.6284	0.7916	0.0000*	0.0000*
OEX.L	0.5890	0.4426	0.0000*	0.0000*
VOD.L**	0.0015**	0.0154**	0.0000*	0.0000*
CBK.DE	0.2206	0.5876	0.0000*	0.0000*
DBK.DE	0.5572	0.2284	0.0000*	0.0000*
DTE.DE**	0.0000**	0.0000**	0.0000*	0.0000*
LHA.DE	0.1105	0.3117	0.0001*	0.0001*
GNB.WA**	0.0001**	0.0006**	0.0000*	0.0000*
LBW.WA	0.0959	0.2238	0.0000*	0.0000*
PGN.WA	0.1044	0.0470**	0.0001*	0.0000*
PKO.WA**	0.0170**	0.0731	0.0000*	0.0000*
OMV.VI	0.2808	0.2929	0.0000*	0.0000*
RBI.VI	0.5464	0.4752	0.0000*	0.0000*
UQA.VI	0.5424	0.7446	0.0000*	0.0000*
VOE.VI	0.2131	0.4839	0.0000*	0.0000*

Notes: ** 5 series stationary (no unit root) on 5% level of sig. * after the 1st differencing all series stationary.
Source: Own construction

The most of time series is not stationary at level but after differencing this assumption of the ARIMA models is met.

3.2 Ljung-Box test

For all series, the lag of 9 was chosen because the number of observations in the studied time series T is between 3 566 and 5 711 therefore m as ln(T) is between 8.2 and 8.7. Results are not shown and for all series, the hypothesis of no linear dependence in the data is rejected so the use of ARIMA is appropriate.

3.3 ARIMA results

The parameter estimation is made with the automatic ARIMA modeling based on the AIC (Akaike information criterion). All series residuals show no autocorrelation (according to the Ljung-Box test, not shown).

Table 2 ARIMA results

Series	Model	Max. p-value of max AR/MA coefficient(s)	Series	Model	Max. p-value of max AR/MA coefficient(s)
CEZ.PR	(2,0)	0.0000	DTE.DE	(3,3)	0.0000
ERBAG.PR	(2,3)	0.0000	LHA.DE	(2,2)	0.0105
KOMB.PR	(4,4)	0.0000	GNB.WA	(4,3)	0.0021
VIG.PR	(3,1)	0.0053	LBW.WA	(2,4)	0.0000
BOIL.L	(4,2)	0.0000	PGN.WA	(2,4)	0.0001
LLOY.L	(4,4)	0.0000	PKO.WA	(2,2)	0.0000
OEX.L	(0,2)	0.0000	OMV.VI	(0,1)	0.0000
VOD.L	(3,3)	0.0077	RBI.VI	(2,2)	0.0000
CBK.DE	(3,4)	0.0000	UQA.VI	(1,3)	0.0000
DBK.DE	(3,0)	0.0000	VOE.VI	(2,2)	0.0000

Source: Own construction

For all models, the model estimation is statistically significant on the 5% level of significance. The next important step is to test the homoscedasticity assumption for residuals by the ARCH-LM test.

3.4 Test for ARCH effects – ARIMA model

Two heteroscedasticity tests for ARCH effects – ARCH-LM test of the residuals of the ARIMA model are calculated.

Table 3 Test for ARCH effects – ARIMA model

Series	Prob. F	Prob. Chi-square	Series	Prob. F	Prob. Chi-square
CEZ.PR	0.0000	0.0000	DTE.DE	0.0000	0.0000
ERBAG.PR	1.0000*	1.0000*	LHA.DE	0.0000	0.0000
KOMB.PR	0.0000	0.0000	GNB.WA	0.2248*	0.2246*
VIG.PR	0.0000	0.0000	LBW.WA	0.0000	0.0000
BOIL.L	0.0000	0.0000	PGN.WA	0.0000	0.0000
LLOY.L	0.0000	0.0000	PKO.WA	0.0000	0.0000
OEX.L	0.0000	0.0000	OMV.VI	0.0000	0.0000
VOD.L	0.0000	0.0000	RBI.VI	0.0000	0.0000
CBK.DE	0.0000	0.0000	UQA.VI	0.0000	0.0000
DBK.DE	0.0000	0.0000	VOE.VI	0.0000	0.0000

Note: * hypothesis of the homoscedasticity assumption not rejected.
Source: Own construction

Almost all tests reject the hypothesis of the homoscedasticity assumption (except ERBAG.PR and GNB.WA). ARIMA model residuals of 18 time series show the heteroscedasticity, the GARCH model needs to be applied for these series.

3.5 ARIMA-GARCH results

The model with statistically significant parameters is used. All series residuals show no autocorrelation (Ljung-Box test, not shown). All GARCH coefficients meet the conditions of nonnegativity and sum up to 1.

Table 4 ARIMA-GARCH results

Series	Model	Max. p-value of ARMA coefficient(s)	Max. p-value of ARCH GARCH coefficients
CEZ.PR	(2,0)	0.0034	0.0000
KOMB.PR	(3,0)	0.0287	0.0000
VIG.PR	(1,0)	0.0033	0.0000
BOIL.L	(1,1)	0.0000	0.0000
LLOY.L	(4,4)	0.0033	0.0000
OEX.L	(1,2)	0.0481	0.0000
VOD.L	(2,2)	0.0014	0.0000
CBK.DE	(1,0)	0.0000	0.0000
DBK.DE	(3,0)	0.0429	0.0000
DTE.DE	(2,2)	0.0000	0.0000
LHA.DE	(0,0)	NA	0.0000
LBW.WA	(2,4)	0.0378	0.0000
PGN.WA	(1,2)	0.0047	0.0000
PKO.WA	(1,2)	0.0047	0.0000
OMV.VI	(0,1)	0.0007	0.0000
RBI.VI	(2,2)	0.0000	0.0000
UQA.VI	(1,3)	0.0125	0.0000
VOE.VI	(2,2)	0.0260	0.0000

Source: Own construction

The parameters of the ARIMA model and GARCH model are statistically significant at the 5% level of significance for all time series, except for the LHA series where the data can be modeled only by the GARCH model.

3.6 Test for ARCH effects – ARIMA-GARCH model

To test the ARCH effects 2 tests are calculated for the ARIMA-GARCH model residuals.

Both tests do not reject the residuals' homoscedasticity hypothesis. It can be argued that in all models the variability is captured using the ARIMA-GARCH model.

For the illustration of the domination of the ARIMA-GARCH concerning homoscedasticity, the two charts of a chosen time series of CEZ are drawn.

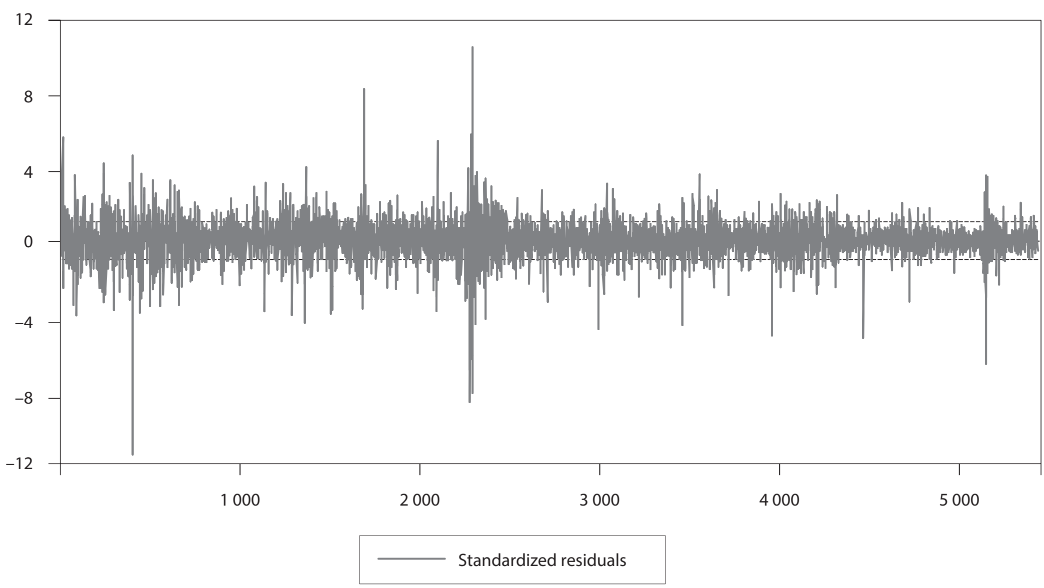
The volatility clustering after the ARIMA-GARCH model application has disappeared and residuals show a white noise behavior.

Table 5 Test for ARCH effects – ARIMA-GARCH model

Series	Prob. F	Prob. Chi-square	Series	Prob. F	Prob. Chi-square
CEZ.PR	0.9322	0.9321	DTE.DE	0.9631	0.9630
KOMB.PR	0.1834	0.1833	LHA.DE	0.7726	0.7723
VIG.PR	0.1317	0.1317	LBW.WA	0.3251	0.3250
BOIL.L	0.6106	0.6103	PGN.WA	0.6587	0.6586
LLOY.L	0.1018	0.1018	PKO.WA	0.2377	0.2376
OEX.L	0.9998	0.9998	OMV.VI	0.0584	0.0585
VOD.L	0.5685	0.5682	RBI.VI	0.6410	0.6460
CBK.DE	0.1406	0.1405	UQA.VI	0.6960	0.6958
DBK.DE	0.1269	0.1269	VOE.VI	0.1708	0.1708

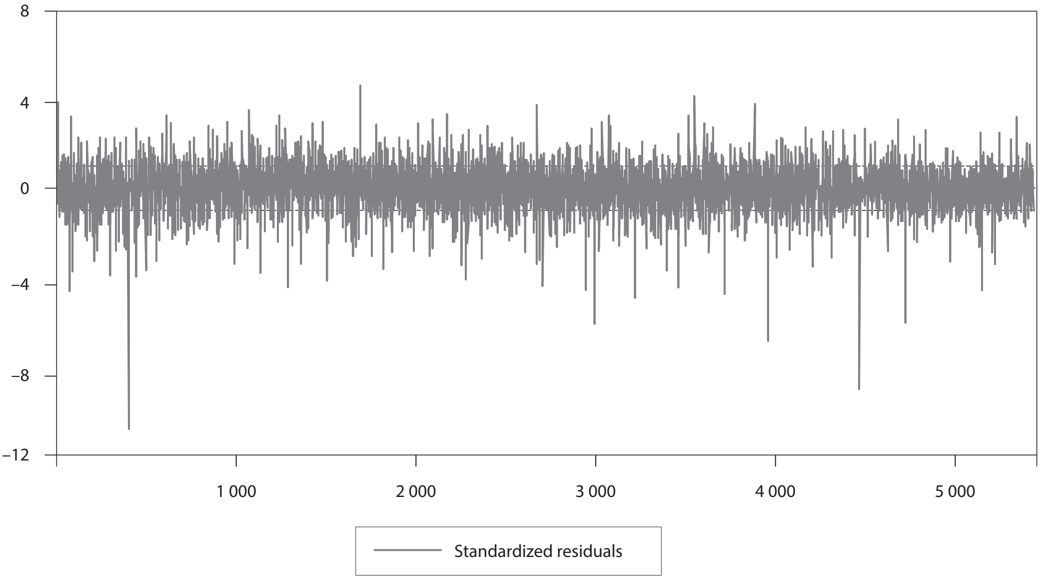
Source: Own construction

Figure 2 Standardized residuals (model ARIMA, CEZ.PR)



Source: Own construction

Figure 3 Standardized residuals (model ARIMA-GARCH, CEZ.PR)



Source: Own construction

3.7. Model quality assessment

Comparison of the dynamic and static forecast for holdout sample of the best model (ARIMA or ARIMA-GARCH).

Table 6 Dynamic and static forecast, Theil's U and MAPE

	Dynamic forecast		Static forecast	
	Theil's U	MAPE	Theil's U	MAPE
CEZ.PR	0.9616	178.3696	0.9295	175.6769
ERBAG.PR*	0.9758	184.4739	0.9460	177.7338
KOMB.PR	0.9832	186.8737	0.9463	180.6889
VIG.PR	0.9865	192.3616	0.9456	186.2756
BOIL.L	0.9804	196.5349	0.8812	186.8690
LLOY.L	0.9916	194.2859	0.9474	183.5451
OEX.L	0.9810	194.8318	0.9276	188.6082
VOD.L	0.9880	192.8578	0.9417	180.0431
CBK.DE	0.9891	196.9308	0.9451	185.6313
DBK.DE	0.9956	195.6509	0.9662	185.4271
DTE.DE	0.9930	194.9442	0.9781	188.5170
LHA.DE	0.9946	194.0667	0.9946	194.0667
GNB.WA*	0.9759	176.3603	0.9176	167.2431

Table 6				(continuation)
	Dynamic forecast		Static forecast	
	Theil's U	MAPE	Theil's U	MAPE
LBW.WA	0.9969	193.6844	0.9519	182.2170
PGN.WA	0.9879	188.7835	0.9242	173.6151
PKO.WA	0.9840	192.5113	0.9317	178.8812
OMV.VI	0.9724	183.1172	0.9498	178.2660
RBI.VI	0.9865	186.2470	0.9851	186.1770
UQA.VI	0.9804	188.6330	0.9584	185.5723
VOE.VI	0.9633	181.0152	0.9472	181.0183

Note: *ARIMA model.
Source: Own construction

The MAPE for the dynamic and static forecasts exceeds 100% for both forecasts for all time series. The model forecasts are unable to account for much of the variability of the out-of-sample part of the data. This is expected because forecasting changes in financial data is difficult.

Theil's inequality coefficient (Theil's U) is below 1 for both forecasts for all time series. The forecasts of the ARIMA-GARCH model outperform the forecasts of the benchmark.

CONCLUSION

This article focused on comparing the capture of variability by the often-used ARIMA model with the ARIMA-GARCH heteroskedasticity model. Volatility clustering was detected in the selected financial time series, therefore, after applying homoscedasticity tests, it proved to be a better ARIMA-GARCH model. The homoscedasticity test leads to no rejection of the equal variances hypothesis after the ARIMA-GARCH model application.

It follows from the performed calculations that the ARIMA model cannot be applied to the financial series of stock prices for the vast majority of stocks from the monitored sample. On the contrary, the ARIMA-GARCH model could be applied to all analyzed stocks from the Czech, British, German, Polish, and Austrian markets. However, the ARIMA-GARCH model was not so successful in predicting the development of stock prices on the monitored markets. In our opinion, the low success of the ARIMA-GARCH model is due to the high volatility of stock prices, but also of financial markets, which is characteristic of both the first decades of the new century. This increased volatility of financial markets was fueled by the ongoing and increasing internationalization and globalization of the world's financial markets, and further essentially continuously fueled by a whole series of factors and events taking place in the new millennium in rapid successions, such as the bursting of the Technology Bubble, the attack on the WTC, accounting scandals, the bursting of real estate bubbles that resulted in a financial crisis, global world imbalances, the COVID-19 pandemic, ongoing war conflicts, etc.

The financial markets of the new millennium are very volatile, turbulent, and changeable, which does not contribute to the successful use of statistical models that are exclusively based on historical data. New major, often global, events that cannot be predicted deviate stock prices from common, normal values. It seems that in such an economic environment, the ARIMA and ARIMA-GARCH statistical models cannot be used as useful tools for predicting the development of stock prices, and therefore as a tool for taking an appropriate investment position leading to excessive profits.

We believe that in further research, it would be appropriate to investigate the usability of asymmetric GARCH and EGARCH models in predicting the development of stock prices. At the same time, we believe that it would be beneficial from the point of view of comparing the results to apply the ARIMA and ARIMA-GARCH models used by us to older historical series of stock prices from the 80s-90s of the last century when stock markets were not yet recognized as having excessive volatility like today. and then compare the success of the mentioned models in periods of less and greater volatility.

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ANNEX – STOCKS

	Symbol	Name
Czech	ERBAG.PR	Erste Group Bank AG
	KOMB.PR	Komercní banka, a.s.
	CEZ.PR	CEZ, a. s.
	VIG.PR	Vienna Insurance Group AG
British	BOIL.L	Baron Oil Plc
	OEX.L	Oilex Ltd
	LLOY.L	Lloyds Banking Group plc
	VOD.L	Vodafone Group Public Limited Company
German	LHA.DE	Deutsche Lufthansa AG
	DBK.DE	Deutsche Bank Aktiengesellschaft
	CBK.DE	Commerzbank AG
	DTE.DE	Deutsche Telekom AG
Polish	GNB.WA	Getin Noble Bank S.A.
	PKO.WA	Powszechna Kasa Oszczednosci Bank Polski Spólka Akcyjna
	PGN.WA	Polskie Górnictwo Naftowe i Gazownictwo S.A.
	LBW.WA	Lubawa S.A.
Austrian	RBI.VI	Raiffeisen Bank International AG
	OMV.VI	OMV Aktiengesellschaft
	VOE.VI	Voestalpine AG
	UQA.VI	UNIQA Insurance Group AG

Source: Finance Yahoo (2022)

Evaluation of Digital Development Based on the International Digital Economy and Society Index 2020 Data

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Received 18.5.2023 (revision received 21.7.2023), **Accepted** (reviewed) 26.7.2023, **Published** 15.9.2023

Abstract

Digitalization and technological advances develop together with our society. The European Commission intends to monitor this development using the International Digital and Society Index (I-DESI) and provide an objective comparison of the participating countries. This comparison of the counties can be an important part of the roadmap of digital transformation for companies and other participants in the market. The aim of this study is to further analyze the 2020 data of I-DESI using multivariate statistical methods not included in the official report. Our objective is to show whether there are differences between the EU and non-EU countries (discriminant analysis, variance analysis), whether the dimensions of the I-DESI index are overlapping (correlation analysis, factor analysis), and whether different country groups can be formed (cluster analysis). Answering these questions, we can give a useful tool to companies for a more successful digital transformation.

Keywords	***DOI***	***JEL code***
International Digital Economy and Society Index (I-DESI), digital transformation, Information and Communication Technology (ICT), analytics, Multivariate Statistical Analysis	*https://doi.org/10.54694/stat.2023.21*	*C3, H83, L86, L96*

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INTRODUCTION

Monitoring the digital and related social changes in different countries can provide steady and controlled development of our society. The European Commission uses a complex indicator, the International Digital Economy and Society Index (I-DESI), to monitor the digital development of EU countries and provide comparisons with the rest of the world (European Commission, 2021a). This monitoring activity of technological progress became a key responsibility of the European Commission, as it gives valuable waypoints for the individual countries regarding their potential improvements, and it ensures the EU's competitiveness against other countries such as the US, Japan and South Korea.

The I-DESI indicator consists of five main dimensions. These are *Connectivity*, which represents the high-speed internet access and the mobile network coverage, *Human Capital*, which represents the ability of the population to consume online content and to take part in online activities, *Use of Internet* and *Integration of Digital Technology*, which illustrates the internet usage of citizens and businesses, and *Public Services*, which shows the demand and supply for online services in the public administration field. The main dimensions are interpreted and measured through 24 subdimensions. The data is therefore a continuous multivariate data set measured on an interval scale, where several samples (countries) on each unit are measured with several variables. I-DESI uses a similar weighting system as used for DESI, another index for only EU Member States. The reasons for the differences are that ultrafast broadband and e-healthcare data are not available from certain non-EU countries, so these sub-indicators have been omitted from the I-DESI indicator. According to the report of the European Commission (2021c), the correlation between the main dimensions and subdimensions of DESI and I-DESI is strong with a value of 0.89 between the scores for 2015–2018 data and the country ranking thus a comparison of the two indicators is reliable.

The European Commission's official report (European Commission, 2021a) for 2020 is based on a trend analysis of data collected since 2015 for the 27 EU Member States and 18 non-EU participants (Australia, Brazil, Canada, Chile, China, Iceland, Israel, Japan, Mexico, New Zealand, Norway, Russia, Serbia, South Korea, Switzerland, Turkey, the United Kingdom and the United States) According to the trend analysis, Finland leads the ranking, and the most advanced non-EU country is the United States.

In this study, we analyze the I-DESI 2020 data set using multivariate statistical methods not included in the official report. The aim is to compare the results of EU Member States with those of non-EU participants. For successful digital transformation, it is important to know for the businesses how well the different regions are performing in digitalization. Furthermore, analytics is one of the most important tools of digitalization, so it seems to be implicit in analyzing all data about digital intensity (as a dimension of digital maturity) of different regions.

Accordingly, we thoroughly analyze I-DESI data, and the structure of our study is as follows. In the literature review, we provide a brief overview of the latest publications on measuring digitization and analyzing international indicators. Next, we summarize our research questions and the statistical methods used. Analyses and results include the following statistical analyses: discriminant analysis, comparison of means, correlation analysis, principal component analysis, partial correlation analysis, and cluster analysis. Finally, we summarize our Conclusion.

1 LITERATURE REVIEW

There are only a few publications in the international literature examining the I-DESI indicator. Sources typically compare the DESI system with other measurement methods and ranking procedures, look for a link between DESI and other indicators, or present results in a national or regional analysis. The I-DESI is rarely in the centre of attention.

A detailed summary was prepared of the measurement methods of the digitalized economy (Kokh and Kokh, 2019). Besides the DESI and I-DESI, the authors included the ICT (Information and Communication

Technology) Development Index, the Huawei Global Network Index, the eGovernment Development Index, the Boston Consulting Group Economic Digitization Index, the Global Digital Competitiveness Index, the Digital Evolution Index, and the Ivanov Digital Index. After analyzing and comparing the calculation methodology of the indices, the authors concluded that all listed indices are global and suitable to characterize the countries in terms of digital development. The authors further explain that there are no indicators that measure the level of digitization of individual industries and services that could be used for sector-specific analysis.

The relationship between the DESI and other indices was also examined. The impact of consumption index growth, purchasing power parity and unemployment on the DESI between 2013 and 2018 were investigated in a study (Stavytskyy et al., 2019). Their results confirm that 98% of DESI values are determined by previous years' data and that a 1% increase in unemployment is a 0.2% decrease in DESI, a 1% increase in the consumption index comes with a 0.2% increase in DESI, so is an increase in the market index is accompanied by an increase in the DESI value. DESI dimensions were also used to assess the impact of financial markets and institutions on digital development (Ha, 2022). Among the DESI dimensions, the role of Human Capital was highlighted as the main factor and digitalization was found to have a significant effect on financialization. The relationship between DESI and GDP was also confirmed (Turuk, 2021) and the current situation of digital enterprises in Central and Eastern Europe using the DESI indicator and the GDP was examined. Using data collected from 2015 to 2019, it showed the relationship between countries' GDP per capita and the DESI. According to his calculations, among the DESI dimensions, the Use of Internet, the Integration of Digital Technologies and Public Services have a positive effect on the development of GDP per capita. The study did not show a significant relationship between the impact of internet access and human capital on GDP per capita.

The relationship between the dimensions of DESI and labour market indicators were also investigated (Başol and Yalçin, 2020). In this, the authors compared 2018 DESI data dimensions with positive employment indicators (personal earnings, employment rate) and negative employment indicators (labour market insecurity, long-term unemployment rate) with correlation analysis and regression calculation. They concluded that with the increase in DESI, both the employment rate and personal earnings would increase, as well as the long-term unemployment rate and labour market insecurity, so digital development will improve positive employment indicators. Others studied the relationship between digitalization and labour productivity and the global competitiveness index using cluster analysis (Polozova et al., 2021). The analysis identified four clusters, leaders, prospective countries, followers, and transition countries. The Nordic countries are also at the forefront of this analysis. They managed to prove the relationship between DESI and labour productivity, while the relationship between DESI and the competitiveness index was not clear. The relationship between unemployment and digital development was also proved (Mirzaei and Soleimani, 2021). These indicators have a saddle-shaped connection. With digital development unemployment increased in this study to a certain maximum, but this effect is said to be possible to prevent with cautious digital expansion. The effect of digitalization on public health was also studied using DESI dimensions and the Eurobarometer survey (Moreno-Llamas et al., 2020). Sedentary behaviour, such as the number of hours a person sits, was found to be in a positive linear relationship with the indices of digital development and e-device ownership at the country level.

The relationship between sustainability and digitization in the data of the Visegrád countries was analyzed in another regional study (Esses et al., 2021). In their study, the authors proved correlations between the dimensions of DESI, countries' GDP, Human Development Index (HDI) and Social Progress Index (SPI). Their results cover the effects of Covid-19, which led to a leap forward in the digitization of countries in 2020 compared to the previous years. Another example of a regional analysis proposed to rebuild the technological development monitoring framework of the region in Abruzzo, Italy, following the European guidelines for the DESI index (Russo, 2020). In his study, he maps the digital economy of Abruzzo, describes the course of digitization over time and creates a unique data collection system to track the progress. An analysis of the state of digitization was also prepared in Romania (Gurău, 2021).

Earlier the 2019 DESI results were studied with multivariate statistical methods (Bánhidi et al., 2020; Bánhidi et al., 2021). Similar to the present study, the authors examined linear relationships between dimensions using correlation analysis as well as principal component analysis, and a causal chain is also established by partial correlation analysis. This study only included the data of EU Member States. These countries were grouped by cluster analysis. In our study, we supplement this series of studies by discriminating the data of the EU member states and non-EU countries and comparing their results. An alternative ranking method was presented based on the statistical properties of the DESI composite index data sets (Bánhidi et al., 2021). They used Data Envelopment Analysis (DEA) and composite indices (CI), and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Based on the results, the Nordic countries (Finland, Sweden, Denmark) lead the ranking just as the original DESI ranking.

From different data and from the I-DESI index, it is clear that most countries are ready for digital transformation. There are differences but digital transformation is well-researched in different countries (e.g., Russia (Nissen et al., 2018), Greece (Bousdekis and Kardaras, 2020), Slovenia and Hungary (Erjavec et al., 2018), or Denmark (Scupola, 2018)) and different fields (e.g., education (Teixeira et al., 2021), health care (Burton-Johnres et al., 2020), management consultancy (Tarjáni et al., 2021) or banking (Cuesta et al., 2015)). This really short overview of studies shows that there are big differences in the depth and advances of digital transformation in the different regions of the world. Making it necessary to analyze the data on digital characteristics as thoroughly as possible.

2 STATISTICAL METHODS

In this paper, we analyzed the data of the International Digital Economy and Society Index published in December 2020 (European Commission, 2021c) using multivariate statistical methods. The data set is shown in the Appendix (Table A1). We selected the methods based on an analysis of the previous year (Bánhidi et al., 2020), in order to compare the results from 2019 and 2020. Our research questions and selected methods are:

Q1. Is it possible to separate the dataset into groups of EU and non-EU countries?
(discriminant analysis)
Q2. Is there a difference between EU and non-EU averages?
(analysis of variance, ANOVA)
Q3. What linear relationships can be detected between the dimensions of the indicator system?
(correlation analysis)
Q4. How can we reduce the number of model variables?
(principal component analysis)
Q5. What causal relationships can be considered between the model variables?
(partial correlation analysis)
Q6. How can we group the studied countries?
(cluster analysis)

We began the data analysis with graphical studies. Then we used Wilks's λ and canonical correlation in the discriminant analysis. To compare the means, the conditions of the analysis of variance were checked with the QQ plot, Shaphiro-Wilk, Kolmogorov-Smirnov, and Box test. Pearson correlation coefficients were used for the correlation test. Outliers were evaluated based on Mahalanobis distances. Due to the strong correlation revealed between the dimensions (0.35–0.82), the number of variables was reduced by principal component analysis without rotation and with Varimax rotation. The suitability of the sample was checked with a Kaiser-Meyer-Olkin measure (0.804), and the model was evaluated with Bartlett's test.

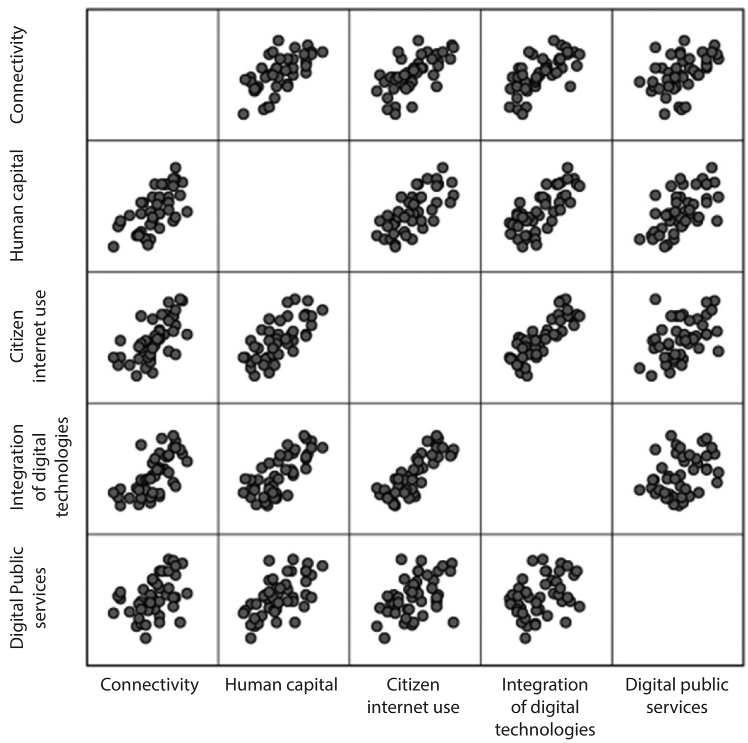
The presumed causal chain between the variables was established by a partial correlation test performed at a 15 percent significance level. Hierarchical cluster analysis was used to group the countries. The basis of group formation was the relationship within the group. The squared Euclidean distance was used to generate the distances. The result was plotted on a dendrogram. For the calculations, we used the IBM Statistics Package for Social Sciences (SPSS) statistical software.

3 ANALYSES AND RESULTS

Graphical examinations help to form an overall impression of the data set, whether there are outliers, differences between groups, or other anomalies. To illustrate multivariate data sets, Rencher (2002) suggests profiles, cobweb diagrams, characteristic signs, and boxes. The statistical software package only supports profiles (bar charts) among these. Figure A1 shows the I-DESI data of the studied countries.

Visual inspection of the data reveals that there are countries with low I-DESI values among both the EU Member States (such as Greece and Poland) and non-EU countries (such as Brazil and Mexico). High values are also present in EU countries (such as Finland and the Netherlands) and non-EU countries (such as Korea and the United States). Some countries have a balanced profile with all I-DESI components close to each other. Examples of such balanced EU countries are Austria, Ireland, Luxembourg and Sweden. Similar examples of the non-EU group are the United Kingdom and the United States. In contrast, there are countries where the value of one component is twice as high as that of the other. In Greece, the value

Figure 1 Bivariate scatter plots



Source: Calculation on the European Commission data (EC, 2021b)

of Connectivity and Public Services are three times the value of Human Capital and twice the value of the Use of Internet and the Integration of Digital Technologies. A similar phenomenon can be observed in Brazil and China. The value of Connectivity is typically high in EU countries, but in some cases, the value of Public Services or the Integration of Digital Technologies is the highest among the dimensions (e.g. Finland, Germany, the Netherlands and Sweden). According to Figure A1 the values of Public Services are generally high in non-EU countries, in four cases Connectivity has the highest value. The Integration of Digital Technologies ranks first in Israel and Switzerland, and the Use of Internet in Iceland is the highest of the five indicators.

Possible outliers are Denmark and the USA based on graphical analysis, as they are outside of the +1.5 interquartile range. If these two data are proved to be outliers, it is better to exclude them from further analyses. To prove the case of outliers, graphical and numerical tests are used. The graphical test is based on the bivariate scatter plots in Figure 1. The plots show possible correlations of the variables, probably because they are all related to digitalization. These correlations are not investigated further in this paper. The most scattered relationship is between citizen internet use and public services and between business technology and public services. Possible outliers are only present in the plot between citizen internet use and public services, but these data points do not belong to Denmark or the USA. Based on the bivariate scatter plots, the cases of outliers for Denmark and the USA are not proved.

Numerical analysis of the outliers is based on the Mahalanobis distances. Mahalanobis distances are calculated for all data points, and the highest values are present in Table 1. These distances are compared with a $\chi 2$ distribution of the same degrees of freedom to provide a p-value in the table. Even the highest values of the Mahalanobis distances are not significant, which confirms the result of the graphical analysis with no outliers presumed.

Table 1 Mahalanobis distances

	Mahalanobis distance	Sig.
Iceland	12.17295	0.0325
Korea	10.24161	0.0687
France	8.20925	0.1451
Lithuania	8.18205	0.1465
Israel	7.92057	0.1607

Source: Calculation on the European Commission data (EC, 2021b)

3.1 Separation of the dataset (discriminant analysis)

After the graphical evaluation, we examined whether the data of the EU member states differ from the results of the non-EU participants by discriminant analysis. Since the two samples did not have the same number of items, we corrected the data for the size of the groups. The eigenvalue was 0.208, and the canonical correlation was 0.415. For two groups, the canonical correlation is the most useful measure in the table and coincides with the Pearson correlation coefficient between scores and groups. The value of the canonical correlation is weak, below 0.5, thus, it is not possible to separate the two data sets based on the data. Wilks's λ value was 0.828 with a significance of 0.177. The high value of Wilks's λ and the low significance score shows that there is no difference between the averages of EU and non-EU countries according to the classification with the grouping variable, and the groups cannot be separated based on the data set alone. The related χ^2 test examines the hypothesis that data from EU and non-EU countries come from the same population. As the result is not significant, this grouping of the EU and non-EU countries could even be random.

3.2 Comparison of country groups (analysis of variance)

Analysis of variance (ANOVA) examines the difference between means. The assumptions required for the reliability of the analysis are the independence of the samples, the multivariate normality, and the equality of the covariance matrices (homogeneity of variance). The independence of the samples can be assumed in our case because the different samples come from different countries. Multivariate normality and equality of variance were checked from graphical and numerical studies.

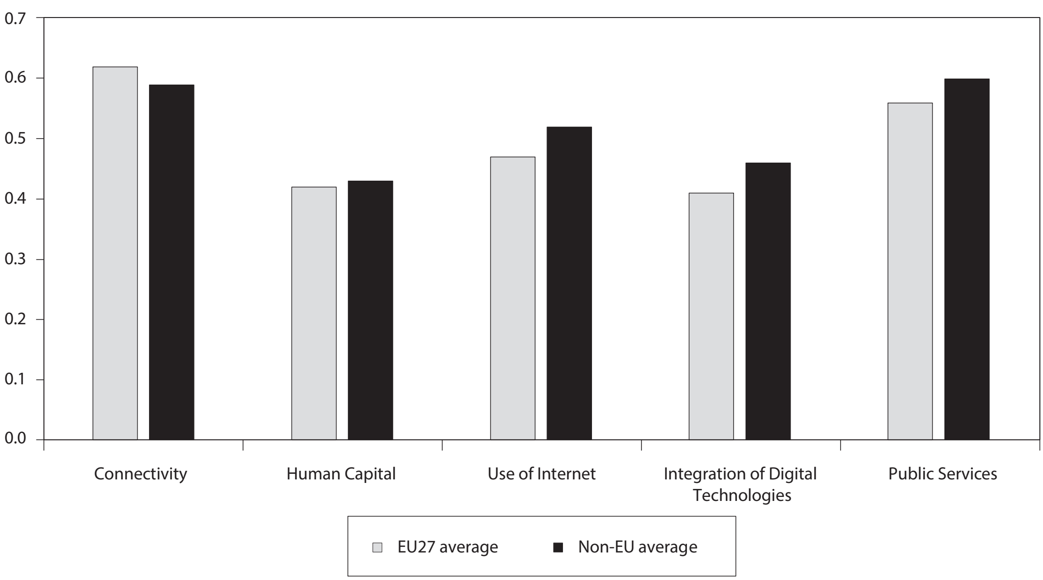
To assess multivariate normality, Rencher (2002) suggests checking each variable separately. If normality can be assumed for all variables, then the multivariate distribution is also considered normal. Univariate normality testing is usually done by graphical analysis as it is a fast and reliable method to diagnose abnormalities. Based on QQ plots, we have no reason to assume a deviation from normality. The Kolmogorov-Smirnov test was not significant for any of the variables, and the Shapiro-Wilk test showed a weakly significant result for the Integration of Digital Technologies at 0.05. This test is for small

Table 2 Tests for normality

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Connectivity	0.077	45	0.200*	0.973	45	0.366
Human capital	0.093	45	0.200*	0.970	45	0.291
Citizen internet use	0.078	45	0.200*	0.975	45	0.436
Integration of digital technologies	0.120	45	0.105	0.945	45	0.034
Public services	0.080	45	0.200*	0.979	45	0.584

Notes: * this is a lower bound of true significance. a Lilliefors significance correction.
Source: Calculation on the European Commission data (EC, 2021b)

Figure 2 Differences between the means



Source: Own design based on the data of the National Bank of Hungary sample sizes and has higher statistical power than the Kolmogorov-Smirnov test. For this reason, normality is assumed for the univariate and multivariate cases. Test results are shown in Table 2.

Homogeneity of variance was examined by comparing the standard deviations of the variables and using the Box test. The standard deviation of the five variables is similar in the two groups, suggesting homogeneity of variance. The most significant difference between the groups was in Internet access, where the variance of the EU group is half (0.05101) of the variance of the non-EU group (0.10427). The results of the Box test to verify multivariate variance homogeneity were not significant, so we assumed equality of covariance matrices. With this, we checked the conditions of the multivariate analysis of variance, the results can be considered authentic. The averages are illustrated in Figure 2.

The value of Connectivity is generally higher in the EU Member States, while the Use of Internet services, the Integration of Digital Technologies and Public Services are higher in non-EU countries. There is no significant difference in Human Capital between the two groups. In MANOVA, the null hypothesis is tested that the values of the five dimensions, measured in the EU and in non-EU countries, can be derived from the same population using F tests. None of the five dimensions were significant at the 0.05 level, thus we have no reason to assume that there is a significant difference between the two groups. The maximum value of $\eta 2$ for internet services was 0.031, so this dimension alone only explains 3.1% of the difference between the EU and non-EU countries. Therefore, the data set can be examined together.

3.3 Relation of the index's dimensions (correlation test)

After proving no difference between EU and non-EU data, the correlation analysis was performed on the entire data set. The result is shown in Table 3. The correlation between the variables is positive in all cases, so they move together. This is also apparent from the context of the data, as all five dimensions are meant to represent an aspect of digital development (European Commission, 2021c). In nine of the ten cases examined, the correlation between the Integration of Digital Technologies and Public Services is significant at only a 0.05 level. In the case of the 2019 data set (Bánhidi et al., 2020), the correlation was significant at a 0.01 level in all cases. Examining the data of the EU member states only, the p-value is 0.467, which is also not significant at the level of 0.01. Looking only at data from non-EU countries, Public Services do not show a significant correlation with any of the other DESI dimensions, suggesting that the Public Services is less related to the other four indicators.

The multicollinearity between the variables were also examined. The variance inflation factors (VIF) of all dimensions have a value of less than 5, the variables are not multicollinear, and the linear relationships

Table 3 Matrix of the Pearson correlation coefficients

Dimensions	Human capital	Use of internet	Integration of digital technologies	Public services
Connectivity	0.626** 0.000	0.641** 0.000	0.656** 0.000	0.433** 0.003
Human capital		0.705** 0.000	0.730** 0.000	0.602** 0.000
Use of internet			0.823** 0.000	0.444** 0.002
Integration of digital technologies				0.355* 0.017

Notes: ** correlation is significant at the 0.01 level (two-way). * correlation is significant at the 0.05 level (two-way).
Source: Based on calculation of Tarjáni et al. (2022)

between them are not significant. For the sake of brevity, we will not go into details. The application of the VIF method is described in Vörösmarty and Dobos (2020).

3.4 Reduction of dimensions as model variables (principal component analysis)

Due to strong correlations between the I-DESI dimensions, we performed principal component analysis to simplify the model and explore latent variables. The Kaiser-Meyer-Olkin (KMO) score was 0.804, indicating the adequacy of the sampling and suggesting the existence of latent variables. The result of the Bartlett test was significant, which proves the relationship between the variables, which makes the data set suitable for principal component analysis. The communalities ranged from 0.6 to 0.9, thus, the principal components explain most of the variance. According to our calculations without rotation, the first factor explains 68.8 percent of the variance. Factor weights were above 0.810 with four variables indicating strong correlation, but with Public Services, the value of the factor weight was only 0.653. Two principal components explained 83.4 percent of the variance. With the second factor, Public Services showed the highest correlation with a value of 0.737.

To confirm the results, we used the Varimax rotation method, which explained 83.4 percent of the variance in the same way for the two main components but resulted in different factor weights. The factor weights obtained after rotation are summarized in Table 4. The rotation converged after three iterations.

Table 4 Factor weights after rotation

Dimensions	Factors	
	Digital capability	**Digital applications**
Integration of digital technologies	0.932	0.136
Use of internet	0.881	0.240
Connectivity	0.767	0.295
Human capital	0.718	0.539
Public services	0.210	0.962

Source: Based on calculation of Tarjáni et al. (2022)

The first main component is strongly correlated with the Integration of Digital Technologies, the Use of Internet, and Connectivity, the impact of Human Capital is moderate, and Public Services have a weak correlation with this component. In the analysis of the previous year's data (Bánhidi et al., 2020), the Integration of Digital Technologies was more correlated with the second main component. In our opinion, the change shows the impact of the Covid-19 pandemic on digitalization, as the digital applications of businesses have begun to mix with the characteristics of residential use. Assuming the transient nature of the effect, the previous names of the components were retained.

3.5 Relationships between dimensions as model variables (partial correlation analysis)

We examined the causal relationships between I-DESI dimensions by partial correlation analysis. Of the ten coefficients, six were found to be significant at the less strict 0.15 significance level, which is listed in Table 5. The values of the significant coefficients ranged from 0.2 to 0.6, thus, the system is characterized by weak and moderate causal relationships.

Based on the partial correlation coefficients, we set up the causal chain between the variables shown in Figure 3.

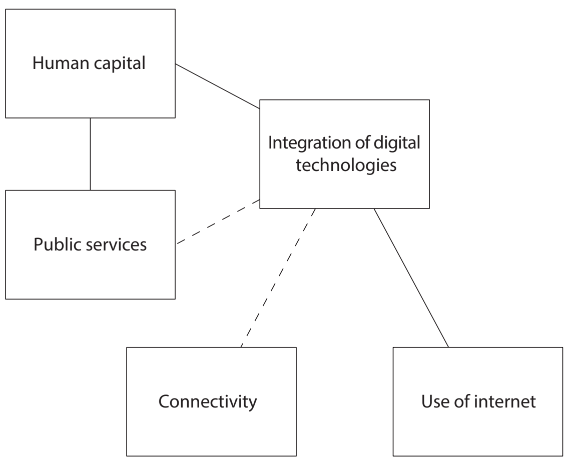
Compared to the figure based on the previous year's data (Bánhidi et al., 2020), it is apparent that Connectivity can still be considered an independent variable but is no longer related to the Use of Internet,

Table 5 Partial correlation coefficients matrix

Dimensions	Human capital	Use of internet	Integration of digital technologies	Public services
Connectivity	0.143 0.365	0.147 0.353	0.228 0.147*	0.136 0.390
Human capital		0.119 0.425	0.380 0.013*	0.469 0.002**
Use of internet			0.519 0.000**	0.150 0.342
Integration of digital technologies				– 0.252 0.107*

Notes: ** correlation is significant at the 0.01 level (two-way). * correlation is significant at the 0.15 level (two-way).
Source: Based on calculation of Tarjáni et al. (2022)

Figure 3 Causal relations between the variables



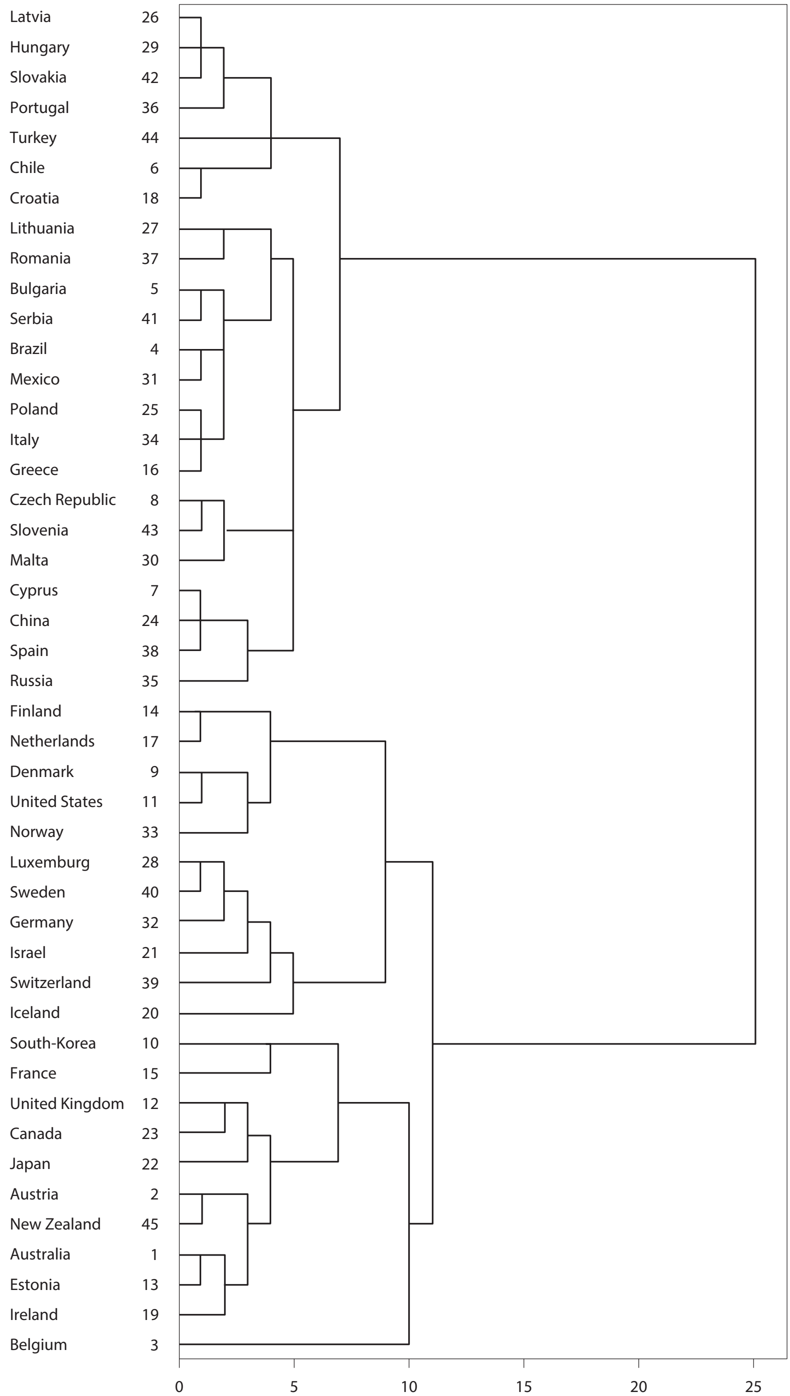
Source: Based on calculation of Tarjáni et al. (2022)

but it is directly related to the Integration of Digital Technologies. In the case of Human Capital, it is no longer a clearly independent variable and is no longer linked to the Use of Internet. However, the Use of Internet is also linked to the Integration of Digital Technologies based on the 2020 data set, as are the other three variables. Data from 2020 show that the Integration of Digital Technologies has shifted closer to the private sector than in the previous year, presumably as a result of the COVID-19 pandemic. The Public Services dimension is no longer strongly linked neither to the Integration of Digital Technologies nor to Human Capital.

3.6 Categorization of the data set (cluster analysis)

For grouping the surveyed countries, we used hierarchical cluster analysis with a square Euclidean distance measure and between-groups linakge, where the group formation was based on the relationship between the groups. The results are on a dendrogram in Figure 4. Based on the results, the countries participating in the survey can be divided into two major groups, the 22 countries that perform better in digitalization

Figure 4 Dendrogram of the cluster analysis



Source: Calculation on the European Commission data (EC, 2021b)

(EU member states: Finland, the Netherlands, Denmark, Luxembourg, Sweden, Germany, France, Austria, Estonia, Ireland, Belgium), and the 23 less digitalized countries (EU Member States: Latvia, Hungary, Slovakia, Portugal, Croatia, Lithuania, Romania, Bulgaria, Poland, Italy, Greece, the Czech Republic, Slovenia, Malta, Cyprus, Spain). For three clusters, the 11 best-performing countries stand out from the more advanced block, including the northern EU member states (Finland, the Netherlands, Denmark, Luxembourg, Sweden, and Germany) and the United States, Norway, Israel, Switzerland and Iceland.

Cluster analysis was also performed with fixed cluster numbers, and the results of this study are shown in Table 6. Dividing the countries into three clusters, the 11 best-performing countries are separated from the other 11 countries in the middle field and the 23 least less digitalized countries. By defining four clusters, only Belgium's ranking changes, sticking out of the midfield. For five clusters, the 11 best-performing countries split into the top five (Denmark, the United States, Finland, the Netherlands, Norway) and the six better-performing countries (Iceland, Israel, Luxembourg, Germany, Switzerland, Sweden).

Table 6 Result of the cluster analysis for three, four and five clusters

Countries	3 clusters	4 clusters	5 clusters
Australia	1	1	1
Austria	1	1	1
South Korea	1	1	1
United Kingdom	1	1	1
Estonia	1	1	1
France	1	1	1
Ireland	1	1	1
Japan	1	1	1
Canada	1	1	1
New Zealand	1	1	1
Belgium	1	2	2
Brazil	2	3	3
Bulgaria	2	3	3
Chile	2	3	3
Cyprus	2	3	3
Czech Republic	2	3	3
Greece	2	3	3
Croatia	2	3	3
China	2	3	3
Poland	2	3	3
Latvia	2	3	3
Lithuania	2	3	3
Hungary	2	3	3
Malta	2	3	3
Mexico	2	3	3
Italy	2	3	3

Table 6 (continuation)

Countries	3 clusters	4 clusters	5 clusters
Russia	2	3	3
Portugal	2	3	3
Romania	2	3	3
Spain	2	3	3
Serbia	2	3	3
Slovakia	2	3	3
Slovenia	2	3	3
Turkey	2	3	3
Denmark	3	4	4
United States	3	4	4
Finland	3	4	4
Netherlands	3	4	4
Norway	3	4	4
Iceland	3	4	5
Israel	3	4	5
Luxembourg	3	4	5
Germany	3	4	5
Switzerland	3	4	5
Sweden	3	4	5

Source: Calculation on the European Commission data (EC, 2021b)

Some discrepancies were noted in Figure 4. For example, China ended up in the same group as Spain, which we found interesting. To ensure the results further, we performed a k-means cluster analysis using the five clusters result as an initial. The number of replications was 10, and the Minkowski distance parameter was 2. The results are shown in Table 7.

Table 7 Result of the k-means cluster analysis for five clusters using the five clusters' initial

Countries	5 clusters initial	k-means clusters
Australia	1	1
Austria	1	1
Canada	1	1
Estonia	1	1
France	1	1
Ireland	1	1
Japan	1	1
New Zealand	1	1
South Korea	1	1
Belgium	2	2

Table 7 (continuation)

Countries	5 clusters initial	k-means clusters
Chile	3	2
Croatia	3	2
Czech Republic	3	2
Hungary	3	2
Latvia	3	2
Lithuania	3	2
Portugal	3	2
Slovakia	3	2
Slovenia	3	2
Brazil	3	3
Bulgaria	3	3
China	3	3
Cyprus	3	3
Greece	3	3
Italy	3	3
Malta	3	3
Mexico	3	3
Poland	3	3
Romania	3	3
Russia	3	3
Serbia	3	3
Spain	3	3
Turkey	3	3
Denmark	4	4
Finland	4	4
Netherlands	4	4
Norway	4	4
United States	4	4
Germany	5	5
Iceland	5	5
Israel	5	5
Luxembourg	5	5
Sweden	5	5
Switzerland	5	5
United Kingdom	1	5

Source: Calculation on the European Commission data (EC, 2021b)

China maintained its place with Spain in this analysis, and mainly the second cluster expanded with countries from the third, not leaving Belgium alone anymore. The United Kingdom also changed its place and joined the fifth cluster the other members of the Commonwealth countries back in cluster one.

CONCLUSION

In our study, we examined the five dimensions of the I-DESI index using multivariate statistical methods. We found answers to our research questions:

Q1. *We found that it is possible to separate the dataset into groups of EU and non-EU countries.* Based on the graphical analysis of the data, we found that Connectivity is typically high in the EU member states, while the values of Public Services are generally higher in the non-EU countries.

Q2. *We found that there is no difference between EU and non-EU averages.* Based on the discriminant analysis, we found that the data series for EU member states and non-EU countries did not differ from each other, and when comparing the averages, there was no significant difference between the two groups, thus, we analyzed the two data sets together.

Q3. *We found some linear relationships between the dimensions of the indicator system.* In the correlation analysis, we found that there are strong correlations between the variables, the strongest is between the Use of Internet and the Integration of Digital Technologies, which makes the data suitable for principal component analysis.

Q4. *We found that the number of model variables cannot be reduced.* In the principal component analysis, two principal components were separated. The Integration of Digital Technologies, the Use of Internet, and Connectivity are strongly correlated with the first principal component, and the impact of Public Services is of marginal importance in the case of the second factor. Human Capital is almost equally involved in both factors.

Q5. *We found some relationships between the model variables.* Based on the partial correlation analysis, we set up the causal chain between the variables and found that the Integration of Digital Technologies has shifted closer to the factors of the private sector compared to the previous year's data, presumably due to the COVID-19 pandemic.

Q6. *We could categorize the analyzed countries.* During the cluster analysis, we formed groups from the participating countries. In the case of three clusters, the 11 best-performing countries are separated from 11 of the mid-range countries and the 23 least digitalized countries. For four clusters, Belgium stood out in the middle, and for five clusters, the best-performing countries split from the leading and high-performing countries. The k-means cluster analysis reinforced these results, expanding the fourth cluster and specifying the place of the United Kingdom between clusters one and five.

These results form an important basis for further research related to digitalization. Not only the regional differences and the changes over time are visible, but we can see that EU states are great areas for digitized operations and related research too. To examine the aftermath of the COVID-19 epidemic and to assess the temporary approach of the private sector to the digitization of businesses, it is worth carrying out similar analyses in the upcoming years. In this way, long-term conclusions can be drawn about the relationship between pandemics and digitalization.

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APPENDIX

Table A1 Basic data of our study

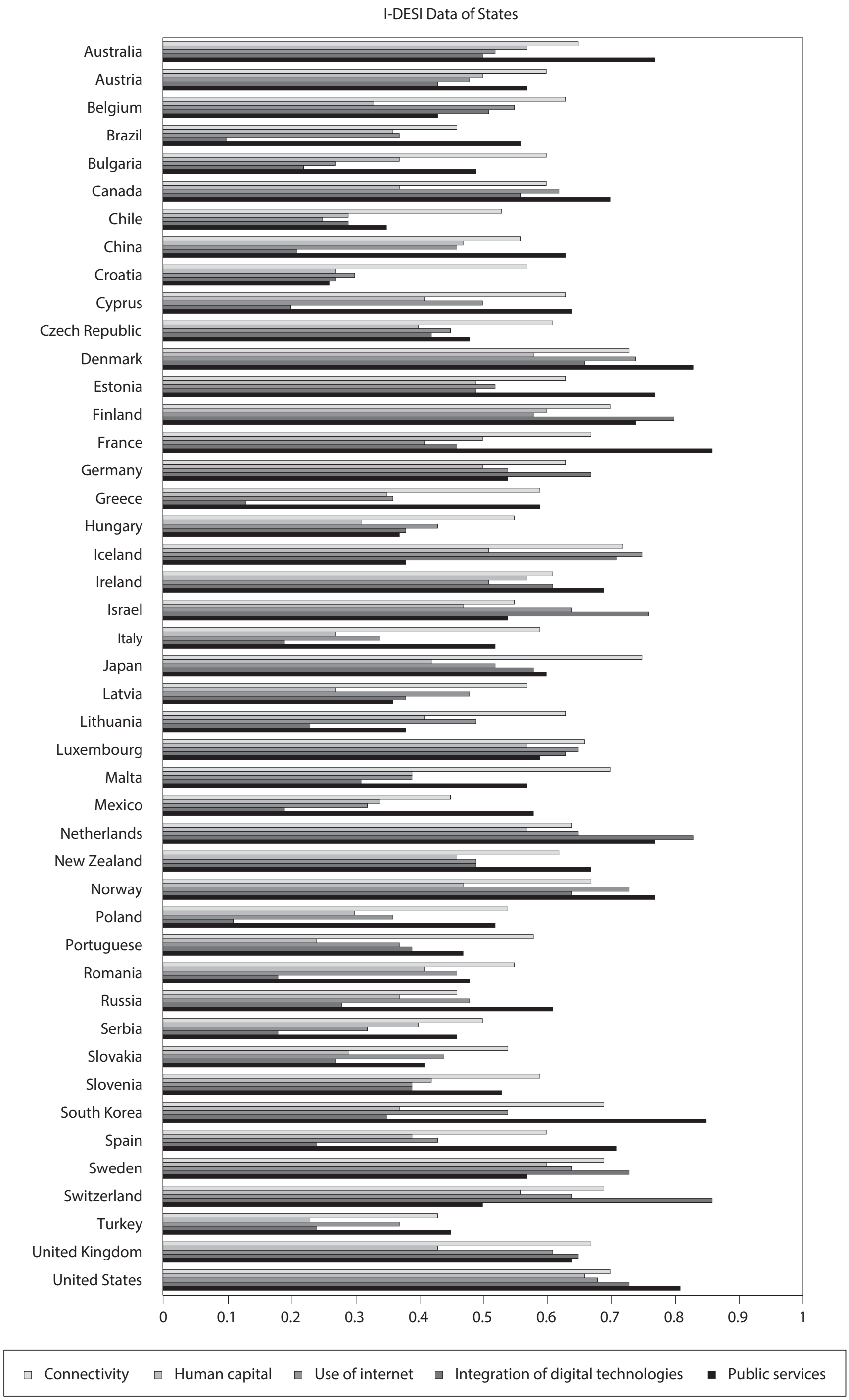
Countries	Dimensions					
	Connectivity	Human capital	Use of internet	Integration of digital technologies	Public services	I-DESI
Weights	0.25	0.25	0.15	0.20	0.15	
EU27 average	0.62	0.42	0.47	0.41	0.56	0.50
Austria	0.60	0.5	0.48	0.43	0.57	0.52
Belgium	0.63	0.33	0.55	0.51	0.43	0.49
Bulgaria	0.60	0.37	0.27	0.22	0.49	0.40
Croatia	0.57	0.27	0.30	0.27	0.26	0.35
Cyprus	0.63	0.41	0.5	0.2	0.64	0.47
Czech Republic	0.61	0.40	0.45	0.42	0.48	0.47
Denmark	0.73	0.58	0.74	0.66	0.83	0.7
Estonia	0.63	0.49	0.52	0.49	0.77	0.57
Finland	0.70	0.60	0.58	0.80	0.74	0.68
France	0.67	0.50	0.41	0.46	0.86	0.57
Germany	0.63	0.50	0.54	0.67	0.54	0.58
Greece	0.59	0.35	0.36	0.13	0.59	0.40
Hungary	0.55	0.31	0.43	0.38	0.37	0.41
Ireland	0.61	0.57	0.51	0.61	0.69	0.60
Italy	0.59	0.27	0.34	0.19	0.52	0.38
Latvia	0.57	0.27	0.48	0.38	0.36	0.41
Lithuania	0.63	0.41	0.49	0.23	0.38	0.44
Luxembourg	0.66	0.57	0.65	0.63	0.59	0.62
Malta	0.7	0.39	0.39	0.31	0.57	0.48
Netherlands	0.64	0.57	0.65	0.83	0.77	0.68
Poland	0.54	0.30	0.36	0.11	0.52	0.36
Portuguese	0.58	0.24	0.37	0.39	0.47	0.41
Romania	0.55	0.41	0.46	0.18	0.48	0.42
Slovakia	0.54	0.29	0.44	0.27	0.41	0.39
Slovenia	0.59	0.42	0.39	0.39	0.53	0.47
Spain	0.60	0.39	0.43	0.24	0.71	0.47

Table A1 (continuation)

Countries	Dimensions					
	Connectivity	Human capital	Use of internet	Integration of digital technologies	Public services	I-DESI
Sweden	0.69	0.60	0.64	0.73	0.57	0.65
Non-EU average	0.59	0.43	0.52	0.46	0.60	0.52
Australia	0.65	0.57	0.52	0.5	0.77	0.60
Brazil	0.46	0.36	0.37	0.1	0.56	0.37
Canada	0.60	0.37	0.62	0.56	0.70	0.55
Chile	0.53	0.29	0.25	0.29	0.35	0.35
China	0.56	0.47	0.46	0.21	0.63	0.46
Iceland	0.72	0.51	0.75	0.71	0.38	0.62
Israel	0.55	0.47	0.64	0.76	0.54	0.58
Japan	0.75	0.42	0.52	0.58	0.60	0.57
Mexico	0.45	0.34	0.32	0.19	0.58	0.37
New Zealand	0.62	0.46	0.49	0.49	0.67	0.54
Norway	0.67	0.47	0.73	0.64	0.77	0.64
Russia	0.46	0.37	0.48	0.28	0.61	0.43
Serbia	0.50	0.40	0.32	0.18	0.46	0.38
South Korea	0.69	0.37	0.54	0.35	0.85	0.54
Switzerland	0.69	0.56	0.64	0.86	0.50	0.66
Turkey	0.43	0.23	0.37	0.24	0.45	0.34
United Kingdom	0.67	0.43	0.61	0.65	0.64	0.59
United States	0.70	0.66	0.68	0.73	0.81	0.71

Source: Calculation on the European Commission data (EC, 2021b)

Figure A1 I-DESI data of the examined states



Source: Calculation on the European Commission data (EC, 2021b)

Rectifying Sampling Inspection by Variables or Attributes? Combined Inspection

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Received 13.2.2023 (revision received 7.4.2023), **Accepted** (reviewed) 2.5.2023, **Published** 15.9.2023

Abstract

Acceptance sampling, one of the techniques used in quality control, is analysed in present paper. We shall study sampling inspection plans when the remainder of a rejected lot is inspected, i.e. rectifying plans. These plans were introduced by Dodge and Romig for inspection by attributes (each inspected item is classified as either good or defective). Analogous rectifying plans for inspection by variables with one specification limit for the quality characteristic were introduced by the author of this contribution. In present article we shall consider combined inspection (all items from the sample are inspected by variables, but remainder of a rejected lot is inspected only by attributes). We shall show that the combined inspection is the best in many situations. Using plans for combined inspection we can often achieve significant savings of the inspection cost under the same protection of producer and consumer.

Keywords	***DOI***	***JEL code***
Acceptance sampling, rectifying LTPD and AOQL plans, inspection by attributes, inspection by variables, cost of inspection	*https://doi.org/10.54694/stat.2023.6*	*C40, L15, C83*

INTRODUCTION

The sampling inspection plans by attributes (each inspected item is classified as either good or defective) are acceptance plans (n, c), where n is the number of items in the sample (the sample size), c is the acceptance number. Using this acceptance plan we decide as follows – see e.g. Hald (1981): the lot is rejected when the number of defective items in the sample is greater than c. There are no assumptions for using these plans.

The rectifying plans by attributes were introduced in Dodge and Romig (1998). In this book are two types of inspection plans. For inspection of separate lots are used the LTPD plans (LTPD is the lot tolerance percent defective), for inspection of series lots from the same producer are used the AOQL plans (AOQL is average outgoing quality limit). The Dodge-Romig plans (n, c) minimize the mean number I_a of items inspected per lot of process average quality $\bar{p}$, assuming that the remainder of a rejected lot is inspected under one of following conditions that protect the customer against receiving low-quality lots:

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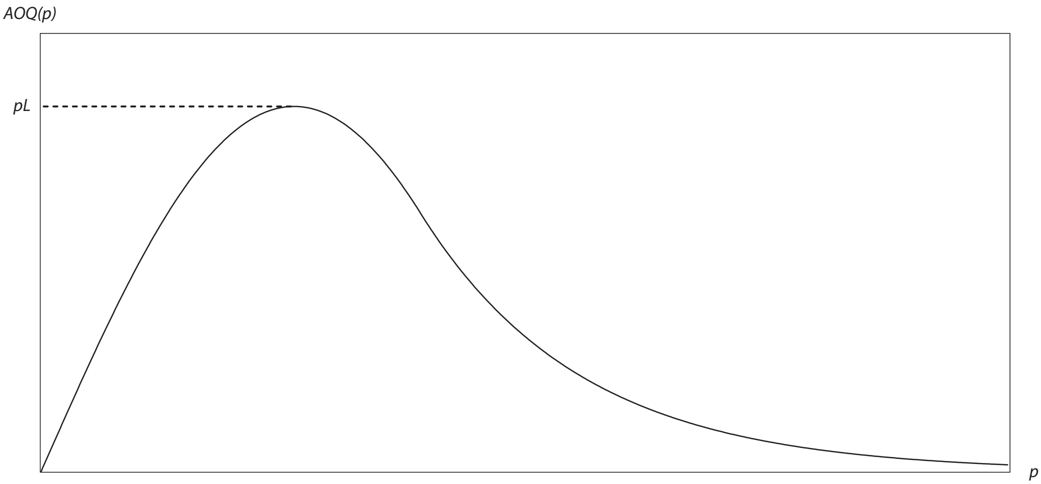
a) the average outgoing quality,[2] defined as the mean fraction defective after inspection when the fraction defective before inspection was p, is less or equal to p_L for all values of input quality p, where $100p_L$ is average outgoing quality limit AOQL (the chosen parameter) – *the AOQL plans by attributes*,
b) the lots with the fraction defective $p \geq p_t$ ($100p_t$ is the lot tolerance percent defective LTPD, the chosen parameter) are accepted with probability which is less or equal to β, where β is consumer's risk (commonly β = 0.10) – *the LTPD plans by attributes*.

Figure 1 Typical graph of the average outgoing quality *AOQ(p)*



Source: Own construction

The sampling inspection plans by variables are acceptance plans (n, k), where n is the number of items in the sample (the sample size), k is the acceptance constant. Assumptions: Measurements of a single quality characteristic X are independent, identically distributed normal random variables with unknown parameters μ and σ^2. For the quality characteristic X is given either an upper specification limit U (the item is defective if its measurement exceeds U), or a lower specification limit L (the item is defective if its measurement is smaller than L). It is further assumed that the unknown parameter σ is estimated from the sample standard deviation s. Under the assumptions the lot is accepted when (see e.g. Klůfa, 2015):

$$\frac{U-\bar{x}}{s} \geq k, \quad \text{or} \quad \frac{\bar{x}-L}{s} \geq k,$$

where:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \; s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2}\,.$$

[2] The average outgoing quality AOQ is a function of the fraction defective before inspection p – see Klůfa (2020). A typical graph of this function is in Figure 1.

Analogous rectifying plans by variables were introduced by the author of this contribution. These plans (n, k) for inspection by variables minimize the mean number I_v of items inspected per lot of process average quality $\bar{p}$, assuming that the remainder of a rejected lot is inspected under the same conditions which used Dodge-Romig for protection the consumer against receiving low-quality lots – see the condition a) and the condition b). In Klůfa (1994) are the rectifying LTPD plans by variables for inspection of separate lots. Calculation of these LTPD single sampling plans by variables using software Mathematica we can find in Klůfa (2010) using software R in Kasprikova and Klůfa (2011). In Klůfa (1997) are the rectifying AOQL plans by variables for inspection of series lots from the same producer. Calculation of the AOQL single sampling plans by variables we can find in Klůfa (2014).

Other papers concerning of Dodge-Romig rectifying plans are Chen and Chou (2001), Kasprikova and Klůfa (2015), Yazdi and Nezhad (2017), Klůfa (2018). Dodge-Romig LTPD sampling inspection plans by variables using EWMA statistics (the exponentially weighted moving average statistic) are in Kasprikova (2017). Dodge-Romig AOQL plans based on the EWMA statistic are in Kasprikova (2019). Other sampling inspection plans based on EWMA statics are in Wang (2016), Aslam, Azam and Jun (2015), Balamurali, Azam and Aslam (2014), Aslam, Azam and Jun (2018). Similar acceptance sampling plans we can find in Gogah and Al-Nnasser (2018), Yazdi, Nezhad., Shishebori and Mostafaeipour (2016), Wang and Lo (2016), Nezhad and Nesaee (2019). The AOQL plans for inspection by variables are also in Klůfa (2020), Chen (2016)

1 INSPECTION COSTS

Let us denote $L(p)$ the probability of accepting a submitted lot with fraction defective p. The function $L = L(p)$ is called the operating characteristic. The operating characteristic gives important information for producer and consumer. The function $L = L(p)$ is decreasing function of p for each acceptance plan.

The number of inspected items when the lot with fraction defective p is accepted (n is the sample size, N is the lot size) is:

n with probability $L(p)$,

and the number of inspected items when the lot with fraction defective p is rejected is:

N with probability $1 - L(p)$.

Therefore, the mean number of items inspected per lot of process average $\bar{p}$ (the given parameter) is:

$$I = nL(\bar{p}) + N(1 - L(\bar{p})) = N - (N - n)\, L(\bar{p}) = n + (N - n)(1 - L(\bar{p})). \tag{1}$$

1.1 Cost of inspection by attributes

For inspection by attributes the operating characteristic of acceptance plan (n, c) is (see e. g. Hald, 1981):

$$L(p; n, c) = \sum_{i=0}^{c} \frac{\binom{Np}{i}\binom{N-Np}{n-i}}{\binom{N}{n}}. \tag{2}$$

Therefore, according to (1) the mean number of items inspected per lot of process average quality $\bar{p}$ is $I_a = N - (N - n)\, L(\bar{p}; n, c) = n + (N - n)(1 - L(\bar{p}; n, c))$, i.e.:

$$I_a = N - (N-n)\sum_{i=0}^{c} \frac{\binom{N\bar{p}}{i}\binom{N-N\bar{p}}{n-i}}{\binom{N}{n}}. \tag{3}$$

Let us denote c_a the cost of inspection of one item by attributes, c_v the cost of inspection of the same item by variables. Usually is $c_v > c_a$ (when $c_v \le c_a$, the rectifying plans for inspection by variables are always more economical than the corresponding attribute sampling plans, since the sample size for inspection by variables is always less than the corresponding sample size for inspection by attributes). Under the notation:

$$I_a c_a = C_a, \tag{4}$$

is the mean cost of inspection by attributes per lot of process average quality $\bar{p}$, assuming that the remainder of a rejected lot is inspected.

1.2 Cost of inspection by variables

For inspection by variables the operating characteristic of acceptance plan (n, k) is (see e. g. Kaspříková and Klůfa, 2011):

$$L(p; n, k) = \int_{k\sqrt{n}}^{\infty} g(t; n-1, u_{1-p}\sqrt{n})\, dt, \tag{5}$$

where: $g(t; n-1, u_{1-p}\sqrt{n})$ is probability density function of noncentral Student t-distribution with $(n - 1)$ degrees of freedom and noncentrality parameter $\lambda = u_{1-p}\sqrt{n}$ (u_{1-p} is quantile of standard normal distribution of order $1 - p$). Therefore, according to (1) the mean number of items inspected per lot of process average quality $\bar{p}$ is $I_v = N - (N - n)\, L(\bar{p}; n, k) = n + (N - n)(1 - L(\bar{p}; n, k))$, i.e.:

$$I_v = N - (N-n).\int_{k\sqrt{n}}^{\infty} g(t; n-1, u_{1-\bar{p}}\sqrt{n})\, dt, \tag{6}$$

and

$$I_v c_v = C_v \tag{7}$$

is the mean cost of inspection by variables per lot of process average quality $\bar{p}$, assuming that the remainder of a rejected lot is inspected.

1.3 Cost of combined inspection by variables and attributes

For combined inspection by variables and attributes (all items from the sample are inspected by variables, but remainder of rejected lot is inspected only by attributes) the inspection cost, when the lot with fraction defective p is accepted, is:

nc_v with probability $L(p; n, k)$,

and the inspection cost, when the lot with fraction defective p is rejected, is:

$nc_v + (N - n)\, c_a$ with probability $1 - L(p; n, k)$.

Therefore, the mean cost of combined inspection per lot of process average quality $\bar{p}$ is:

$$C_{va} = nc_v\, L(\overline{p};\, n, k) + [nc_v + (N - n)\, c_a\,]\; [1 - L(\overline{p};\, n, k)],$$

i.e.:

$$C_{va} = nc_v + (N - n)\; c_a(1 - L(\overline{p};\, n, k)), \tag{8}$$

where the operating characteristic is in Formula (5). Instead of C_{va} we can minimize C_{va}/c_a, i.e.:

$$I_{va} = nc_r + (N - n)(1 - L(\overline{p};\, n, k)), \tag{9}$$

where:

$$c_r = \frac{c_v}{c_a}\,. \tag{10}$$

The new parameter c_r is a ratio of the cost of inspection of one item by variables and the cost of inspection of the same item by attributes. Usually $c_r > 1$ (when $c_r \leq 1$, the acceptance plans for inspection by variables are always more economical than the corresponding attribute sampling plans). For determination of acceptance plan by variables and attributes (combined inspection) we must first estimate in each situation parameter c_r from economical point of view.

2 COMPARISON OF THE INSPECTION COSTS

2.1 Inspection by variables versus inspection by attributes

For the comparison of the single sampling plans for inspection by variables with the corresponding Dodge-Romig plans for inspection by attributes from economical point of view we shall define the parameter S by formula:

$$S = 100\left(1 - \frac{C_v}{C_a}\right). \tag{11}$$

When $S > 0$, acceptance plan for inspection by variables is more economical than the corresponding Dodge-Romig plan for inspection by attributes, when $S < 0$, acceptance by attributes is preferable. The parameter S represents *the percentage of savings of inspection cost* when acceptance plan for inspection by variables is used instead of the corresponding plan for inspection by attributes. Using (10) the percentage of savings of inspection cost is:

$$S = 100\left(1 - \frac{I_v}{I_a}\, c_r\right). \tag{12}$$

2.2 Combined inspection versus inspection by attributes

For the comparison of the single sampling plans for combined inspection with the corresponding Dodge-Romig plans for inspection by attributes from economical point of view we shall similarly use the parameter:

$$S = 100\left(1 - \frac{C_{va}}{C_a}\right). \tag{13}$$

When $S > 0$, combined inspection is more economical than inspection by attributes, when $S < 0$, inspection by attributes is preferable. Since $C_{va} = I_{va}\; c_a$, the percentage of savings of inspection cost is:

$$S = 100\left(1 - \frac{I_{va}}{I_a}\right). \tag{14}$$

2.3 Combined inspection versus inspection by variables

If $c_r > 1$, the combined inspection is always more economical than the inspection by variables, as follows from the following mathematical theorem.

Theorem: Let us given N, $\bar{p}$ and $p_t(p_L)$. If $c_r > 1$, then the minimum mean cost of combined inspection per lot of process average quality $\bar{p}$ is less than the minimum mean cost of inspection by variables.

Proof: We must prove inequality:

$$\min_M C_{va} < \min_M C_v ,$$

where: M is the set of plans (n, k) for which one of conditions a) or b) applies - see Introduction. Since $C_{va} = I_{va}c_a$ and $C_v = I_v c_v$, according to (10) we must prove:

$$\min_M I_{va} < \min_M c_r I_v , \tag{15}$$

because:

$$\min_M I_{va} = \min_M \{nc_r + (N-n)(1 - L(\bar{p}; n, k))\}$$

and

$$\min_M c_r I_v = \min_M \{c_r[n + (N-n)(1 - L(\bar{p}; n, k))]\} = \min_M \{nc_r + (N-n)(1 - L(\bar{p}; n, k)) + (c_r - 1)(N-n)(1 - L(\bar{p}; n, k))\} ,$$

inequality (15) is evident.

Illustration for the AOQL plans: The AOQL was chosen 0.1%, i.e. $p_L = 0.001$. The process average fraction defective is $\bar{p} = 0.0008$ and $c_r = 2$ (the cost of inspection of one item by variables is twice the cost of inspection of one item by attributes). For inspection a lot with $N = 500$ items we shall look for the AOQL plan for inspection by attributes, the AOQL plan for inspection by variables and AOQL plan for combined inspection. These AOQL plans we shall compare from economical point of view.

For input parameters of acceptance sampling $p_L = 0.001$, $N = 500$, $\bar{p} = 0.0008$ we find the AOQL plan for inspection by attributes in Dodge and Romig (1998). We have:

$$n = 210, c = 0.$$

Under the same input parameters of acceptance sampling we can compute the corresponding AOQL plan for inspection by variables (see Klůfa, 2014):

$$n = 75, k = 2.8265.$$

Moreover, for $c_r = 2$ we can calculate according to (12) the percentage of savings of inspection cost:

$$S = 8.$$

It means that under the same protection of consumer the AOQL plan for inspection by variables (75, 2.8265) is more economical than the corresponding Dodge-Romig AOQL attribute sampling plan (210, 0). Since $S = 8$, it can be expected approximately 8% saving of the inspection cost.

Under input parameters of acceptance sampling $p_L = 0.001$, $N = 500$, $\bar{p} = 0.0008$ and moreover $c_r = 2$ we can compute the corresponding AOQL plan for combined inspection (see Klůfa, 2014):

$n = 49$, $k = 2.8561$,

and according to (14) the percentage of savings of inspection cost:

$S = 30$.

It means that under the same protection of consumer the AOQL plan for combined inspection (49, 2.8561) is more economical than the corresponding Dodge-Romig AOQL attribute sampling plan (210, 0). Since $S = 30$, it can be expected approximately 30% saving of the inspection cost.

Combined inspection is clearly the best in this situation – see also Table 1.

Table 1 AOQL plans for inspection by attributes (upper row), variables (middle row) and combined inspection (lower row) and percentage of savings of inspection cost *S* (in %)

$p_L = 0.001$, $c_r = 2.0$

$\bar{p}/N$	500	1 000	4 000	10 000	50 000	100 000
0.0001	(210, 0)	(270, 0)	(340, 0)	(355, 0)	(830, 1)	(835, 1)
	(34, 2.8973) S = 60	(41, 2.8885) S = 64	(56, 2.8799) S = 70	(67 ,2.8776) S = 76	(88, 2.8778) S = 80	(97, 2.8788) S = 80
	(28, 2.9303) S = 66	(34, 2.9101) S = 70	(49, 2.8865) S = 74	(59, 2.8809) S = 79	(79, 2.8777) S = 81	(88, 2.8781) S = 83
0.0002	(210, 0)	(270, 0)	(340, 0)	(355, 0)	(830, 1)	(835, 1)
	(42, 2.8709) S = 50	(52, 2.8699) S = 56	(77, 2.8721) S = 66	(95, 2.8759) S = 76	(131, 2.8840) S = 78	(148, 2.8877) S = 84
	(33, 2.9012) S = 58	(43, 2.8841) S = 63	(65, 2.8751) S = 71	(82, 2.8756) S = 80	(115, 2.8811) S = 81	(131, 2.8844) S = 85
0.0003	(210, 0)	(270, 0)	(340, 0)	(775, 1)	(1 330, 2)	(1 350, 2)
	(48, 2.8579) S = 42	(63, 2.8600) S = 48	(98, 2.8715) S = 64	(125, 2.8798) S = 68	(180, 2.8934) S=74	(206, 2.8987) S = 78
	(37, 2.8857) S = 52	(49, 2.8738) S = 57	(80, 2.8718) S = 69	(105, 2.8769) S = 73	(156, 2.8888) S = 78	(181, 2.8941) S = 80
0.0004	(210, 0)	(270, 0)	(340, 0)	(775, 1)	(1 330, 2)	(1 350, 2)
	(54, 2.8482) S = 34	(72, 2.8549) S = 42	(119, 2.8732) S = 60	(158, 2.8853) S = 64	(240, 2.9038) S = 72	(280, 2.9107) S = 78
	(41, 2.8735) S = 47	(55, 2.8666) S = 53	(95, 2.8714) S = 67	(130, 2.8806) S = 69	(204,2.8978) S = 76	(241, 2.9047) S = 81
0.0006	(210, 0)	(270, 0)	(695, 1)	(775, 1)	(1 870, 3)	(2 480, 4)
	(65, 2.8353) S = 20	(91, 2.8486) S = 28	(170, 2.8794) S = 46	(244, 2.8986) S = 54	(417, 2.9262) S = 66	(512, 2.9361) S = 68
	(46, 2.8618) S = 38	(65, 2.8587) S= 44	(127, 2.8741) S = 57	(188, 2.8903) S = 63	(337, 2.9174) S = 7 1	(419, 2.9276) S = 74
0.0008	(210, 0)	(270, 0)	(695, 1)	(775, 1)	(2 420, 4)	(3 070, 5)
	(75, 2.8265) S = 8	(111, 2.8447) S = 14	(231, 2.8859) S = 30	(363, 2.9117) S = 42	(749, 2.9495) S = 52	(1 018, 2.9635) S = 58
	(49, 2.8561) S = 30	(73, 2.8545) S = 36	(159, 2.8780) S = 47	(258, 2.9004) S = 56	(562, 2.9383) S = 62	(749, 2.9517) S = 67
0.0010	(210, 0)	(270, 0)	(695, 1)	(775, 1)	(2 420, 4)	(3 070, 5)
	(75, 2.8265) S = 8	(111, 2.8447) S = 14	(231, 2.8859) S = 30	(363, 2.9117) S = 42	(749, 2.9495) S = 52	(1 018, 2.9635) S = 58
	(49, 2.8561) S = 30	(73, 2.8545) S = 36	(159, 2.8780) S = 47	(258, 2.9004) S = 56	(562, 2.9383) S = 62	(749, 2.9517) S = 67

Source: Own calculation, Dodge and Romig (1998) – upper row

Illustration for the LTPD plans: The LTPD was chosen 2%, i.e. $p_t = 0.02$. The process average fraction defective is $\bar{p} = 0.004$ and $c_r = 2$ (the cost of inspection of one item by variables is twice the cost of inspection of one item by attributes). For inspection a lot with $N = 1000$ items we shall look for the LTPD plan for inspection by attributes, the LTPD plan for inspection by variables and LTPD plan for combined inspection. These LTPD plans we shall compare from economical point of view.

For input parameters of acceptance sampling $p_t = 0.02$, $N = 1000$, $\bar{p} = 0.004$ we find the LTPD plan for inspection by attributes in Dodge and Romig (1998). We have:

$n = 185$, $c = 1$.

Under the same input parameters of acceptance sampling we can compute the corresponding LTPD plan for inspection by variables (see Klůfa, 2010):

$n = 104$, $k = 2.2940$.

Moreover, for $c_r = 2$ we can calculate according to (12) the percentage of savings of inspection cost:

$S = 20$.

It means that under the same protection of consumer the LTPD plan for inspection by variables (104, 2.2940) is more economical than the corresponding Dodge-Romig LTPD attribute sampling plan (185, 1). Since $S = 20$, it can be expected approximately 20% saving of the inspection cost.

Under input parameters of acceptance sampling $p_t = 0.02$, $N = 1000$, $\bar{p} = 0.004$ and moreover $c_r = 2$ we can compute the corresponding LTPD plan for combined inspection (see Klůfa, 2010):

$n = 85$, $k = 2.3221$,

and according to (14) the percentage of savings of inspection cost:

$S = 31$.

It means that under the same protection of consumer the LTPD plan for combined inspection (85, 2.3221) is more economical than the corresponding Dodge-Romig LTPD attribute sampling plan (185, 1). Since $S = 31$, it can be expected approximately 31% saving of the inspection cost.

Combined inspection is clearly the best in this situation – see also Table 2.

Table 2 LTPD plans for inspection by attributes (upper row), variables (middle row) and combined inspection (lower row) and percentage of savings of inspection cost S (in %)

$p_t = 0.02$, $c_r = 2.0$

$\bar{p}/N$	500	1 000	4 000	10 000	50 000	100 000
0.0001	(105, 0)	(115, 0)	(195, 1)	(265, 2)	(335, 3)	(335, 3)
	(43, 2.4478) S = 28	(49, 2.4192) S = 46	(62, 2.3736) S = 46	(70 ,2.3526) S = 46	(83, 2.3256) S = 48	(88, 2.3170) S = 48
	(36, 2.4909) S = 37	(43, 2.4478) S = 51	(56, 2.3925) S = 50	(64, 2.3679) S = 50	(77, 2.3371) S = 52	(83, 2.3256) S = 52
0.0002	(105, 0)	(115, 0)	(195, 1)	(265, 2)	(335, 3)	(335, 3)
	(57, 2.3891) S = 22	(68, 2.3574) S = 46	(87, 2.3186) S = 52	(100, 2.2992) S = 48	(120, 2.2760) S = 54	(129, 2.2675) S = 66

Table 2 (continuation)

$p_t = 0.02$, $c_r = 2.0$

$\bar{p}/N$	500	1 000	4 000	10 000	50 000	100 000
0.0002	(47, 2.4281) S = 32	(58, 2.3858) S = 52	(78, 2.3351) S = 56	(90, 2.3138) S = 52	(112, 2.2845) S = 57	(120, 2.2760) S = 68
0.0003	(105, 0)	(185, 1)	(330, 3)	(395, 4)	(520, 6)	(585, 7)
	(70, 2.3526) S = 16	(85, 2.3221) S = 24	(113, 2.2834) S=34	(131, 2.2657) S = 36	(160, 2.2441) S = 38	(172, 2.2369) S = 40
	(56, 2.3925) S = 28	(71, 2.3502) S = 33	(100, 2.2992) S = 40	(118, 2.2780) S = 41	(147, 2.2530) S = 43	(160, 2.2441) S = 44
0.0004	(105, 0)	(185, 1)	(330, 3)	(395, 4)	(520, 6)	(585, 7)
	(83, 2.3256) S = 10	(104, 2.2940) S = 20	(142, 2.2567) S = 32	(165, 2.2410) S = 38	(204, 2.2210) S = 42	(221, 2.2141) S = 44
	(64, 2.3679) S = 24	(85, 2.3221) S = 31	(124, 2.2721) S = 40	(148, 2.2523) S = 43	(188, 2.2284) S = 46	(204, 2.2210) S = 47
0.0005	(165, 1)	(245, 2)	(450, 5)	(520, 6)	(710, 9)	(770, 10)
	(97, 2.3033) S –12	(124, 2.2721) S = 8	(174, 2.2358) S = 24	(205, 2.2206) S = 30	(256, 2.2021) S = 36	(278, 2.1958) S = 36
	(72, 2.3479) S = 8	(99, 2.3005) S = 21	(150, 2.2508) S = 33	(182, 2.2315) S = 37	(234, 2.2093) S = 40	(256, 2.2021) S = 41
0.0006	(165, 1)	(245, 2)	(450, 5)	(520, 6)	(710, 9)	(770, 10)
	(110, 2.2868) S	(145, 2.2544) S = 2	(211, 2.2181) S = 22	(251, 2.2037) S = 34	(318, 2.1861) S = 44	(346, 2.1804) S = 50
	(78, 2.3351) S = 3	(114, 2.2823) S = 18	(180, 2.2325) S = 31	(221, 2.2141) S = 41	(290, 2.1927) S = 49	(318, 2.1861) S = 54
0.0007	(165, 1)	(305, 3)	(510, 6)	(760, 10)	(1 060, 15)	(1 180, 17)
	(124, 2.2721) S	(169, 2.2386) S	(254, 2.2027) S = 17	(306, 2.1888) S = 24	(393, 2.1723) S = 30	(429, 2.1670) S = 30
	(83, 2.3256) S	(128, 2.2684) S = 12	(215, 2.2164) S = 18	(268, 2.1986) S = 32	(356, 2.1785) S = 35	(393, 2.1723) S = 36

Source: Own calculation, Dodge and Romig (1998) – upper row

CONCLUSION

From the results of this paper (see Table 1 and Table 2) it follows that the combined inspection (all items from the sample are inspected by variables, but remainder of rejected lot is inspected only by attributes) is in many situations most economical. This conclusion is valid especially when we chose small values for the lot tolerance percent defective LTPD or the average outgoing quality limit AOQL and (see Table 1 and Table 2) the number of items in the lot N is large and the process average fraction defective $\bar{p}$ is small. In this case it makes sense to estimate from economical point of view the parameter c_r, i.e. the ratio of the cost of inspection of one item by variables and the cost of inspection of the same item by attributes (without c_r the acceptance plan for combined inspection cannot be determined). Using the acceptance plans for combined inspection instead of the corresponding acceptance plans for inspection by attributes or acceptance plans for inspection by variables we can achieve significant savings of the inspection cost (the combined inspection is always more economical than inspection by variables). Numerical investigations show that the percentage of savings of inspection cost is in many situations greater than 50%.

ACKNOWLEDGMENT

This paper was processed with contribution of long-term institutional support of research activities by Faculty of Informatics and Statistics, Prague University of Economics and Business (IP400040).

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Jiřina Moravová
(8.4.1932–20.8.2023)

Stanislava Hronová | *Prague University of Economics and Business, Prague, Czech Republic*

At the age of 91 years, our long-time colleague and excellent educator Ms Jiřina Moravová has passed away. She devoted her entire professional life to statistics – both in academia and in the area of the state statistics.

Jiřina Moravová was born in Pilsen where she also graduated from a secondary school. In 1954, she completed her studies of statistics at the then Faculty of Economics and Engineering of the Czech Technical University in Prague (*ČVUT*) and started to work at the Trade Research Institute and the State Statistical Office. In 1964, she was admitted to the Department of Statistics of the University of Economics, Prague (*now called the Prague University of Economics and Business; VŠE*). In 1990, she moved to a newly created Department of Economic Statistics to which she remained faithful until she retired in 2008. In 1992–1998, she served as Vice-Dean for Education of the Faculty of Informatics and Statistics of the University of Economics, Prague (*VŠE*). At the turn of 1994–1995, she was an acting dean (after the dean, Professor Likeš, died, until a new dean was elected). In 2006–2008, she was in charge of the Department of Economic Statistics.

Ms Moravová undoubtedly belonged to leading experts in the area of theory and practice of economic and social statistics. Throughout her tenure at the University of Economics, Prague (*VŠE*) she co-operated with the statistical office and its research institute where she was significantly involved in the design of household sample surveys, especially household budget statistics and social statistics (she prepared, inter alia, the first Czechoslovak micro-censuses, contributed significantly to the design and use of consumption units, worked in an advisory committee for price statistics, etc.). During her teaching career, she has supervised a number of Master's theses, published dozens of teaching texts for students of the University of Economics, Prague (*VŠE; e.g. 300 Examples for the Course of Statistics in Internal Trade*, 1970; *Basics of Social Statistics*, 1998; *Economic and Social Indicators: from Statistics to Knowledge*, with Jaroslav Jílek, 2007) and a huge number of professional articles and research reports.

After she retired, she devoted her time to her family and spent her free time at a beloved cottage in *Popelín* in the *Jindřichův Hradec* District.

Tribute to her memory!

Statistical Days 2023 (Tichá Orlice) Event of Statistical Conference by the Czech Statistical Society

Ondřej Vozár[1] | *Czech Statistical Office, Prague, Czech Republic*

The annual conference of the Czech Statistical Society, *Statistical Days 2023*, took place on the banks of the Tichá Orlice between Choceň and Brandýs nad Orlicí (Czech Republic) during 19–21 May 2023. It was organized by joint effort of the Department of Applied Mathematics of the Faculty of Electrical Engineering and Computer Science, Technical University of Ostrava; Department of Mathematical Analysis and Applications of Mathematics, Faculty of Science, Palacký University Olomouc; Faculty of Informatics and Statistics, Prague University of Economics and Business; Department of Probability and Mathematical Statistics of the Faculty of Mathematics and Physics, Charles University, Prague and the Czech Statistical Society. This event has a long tradition in bringing Czech statisticians together starting in Olomouc in the year 1994.

This conference consisted of three thematic blocks. The first, entitled *Echoes of Covid: Epidemiology, Immunology, and Statistics*, presented real-life experience with the dissemination and interpretation of Covid epidemiologic data from the point of view of statisticians, immunologists, and epidemiologists. The second one, entitled *Socioeconomic Echoes of Covid*, included discussion on changes in the structure of socioeconomic phenomena and processes, effects to long-term links between indicators, possibilities, limits of economic modeling in similar situations and challenges for official statistics producers. These two blocks were closely linked and included a broad discussion. In the more general blocks *Statistical Methods and Application Statistics*, an extensive scope of contributions was presented ranging from methodological issues like fitting models on discrete data, randomized response techniques; applications of statistics in aviation, sports, pedagogy research, hydrology, and use of Python in teaching of statistics and recreational mathematics.

During the conference, the Board of the Czech Statistical Society was established for a two-year term in 2023–2025. The participants were invited to publish their contributions in the Bulletin of the Czech Statistical Society and in *Statistika: Statistics and Economy Journal*.

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Statistika received an Impact Factor

Statistika: Statistics and Economy Journal, published by the Czech Statistical Office, has been included among periodicals with an Impact Factor in the newest edition of the *Journal Citation Reports 2023* of the Web of Science database, a clear proof of its high scientific quality.

Statistika has been indexed in the **Web of Science** database of scholarly literature since 2016, where it is included in the *Emerging Sources Citation Index.* Journals that are included in this database can receive an Impact Factor, which our scientific quarterly has now succeeded. The Impact Factor for *Statistika* is 0.2 (for 2022).

Only scholarly journals that demonstrate sufficient scientific quality, appropriate citation rate and fulfil the required standards for the peer review process and publication ethics can receive the Impact Factor (there are 8 periodicals focused on Economics in the Czech Republic having an IF now).

The Czech Statistical Office would like to thank everyone involved in the publication of our journal and especially the journals´ Editorial and Executive Boards, reviewers, and authors.

We believe we will be able to maintain and increase our IF during the upcoming years and that it will became an important stimulus for further development of our professional quarterly.

Conferences

The ***25th Applications of Mathematics and Statistics in Economics Conference (AMSE 2023)*** took place **from 30th August to 3rd September 2023 in Rájecké Teplice** (hotel Diplomat), **Slovakia**. This year organized by the Faculty of Economics, Matej Bel University in Banská Bystrica. More at: <*https://www.amse-conference.eu*>.

The ***31st Interdisciplinary Information Management Talks Conference (IDIMT 2023)*** on "New Challenges for ICT and Management" was held **during 6–8 September 2023 in Hradec Králové, Czechia**. More at: <*https://idimt.org*>.

The ***17th International Days of Statistics and Economics Conference (MSED 2023)*** took place **during 7–9 September 2023 at the Prague University of Economics and Business, Czechia**. The aim of the conference is to present and discuss current problems of Statistics, Demography, Economics and Management. More at: <*http://msed.vse.cz*>.

The ***41st International Conference on Mathematical Methods in Economics (MME 2023)*** was held **from 13th to 15th September 2023 in Prague, Czechia**. More at <*https://mme2023.vse.cz*>.

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Design: Toman Design
Layout: Ondřej Pazdera
Typesetting: Družstvo TISKOGRAF, David Hošek
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Published by the Czech Statistical Office
ISSN 1804-8765 (Online)
ISSN 0322-788X (Print)
Reg. MK CR E 4684