STATISTIKA

STATISTICS AND ECONOMY JOURNAL

VOL. **104** (4) 2024

CZECH STATISTICAL OFFICE

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Changes in the Economic Behaviour of Czech Households in the Years of Economic Crisis and Pandemic

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Received 12.8.2024, **Accepted** (reviewed) 30.9.2024, **Published** 13.12.2024

Abstract

In the period following 2000, the Czech economy went through two crises, which were different in their causes, durations and consequences. The 2009–2013 crisis resulted from the global financial and fiscal crisis. Its causes were external and purely economic, and its impact on households' economic behaviour was 'standard' – a gradual and moderate reduction in consumption and investment with high unemployment and low inflation rates. The advent of the COVID-19 pandemic in 2020 meant a sudden and unexpected change in economic conditions – the closure of shops and services, restricted population movements, and household consumption limited to only the most essential products. A reduction in household consumption generally means an increase in household savings if all other circumstances are equal. The aim of the present paper is to show, using the methods of time series analysis, the effects of these two crisis periods in terms of data for the household sector or to show whether the fall in the propensity to consume and the rise in the propensity to save in 2020–2021 can be considered statistically significant compared to the crisis period of 2009–2013. Publicly available data from the Czech Statistical Office have been used for our analysis.

Keywords	***DOI***	***JEL code***
National accounts, households, final consumption expenditure, gross saving, time series analysis, time series stability tests	*https://doi.org/10.54694/stat.2024.41*	*E21, C82*

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INTRODUCTION

Households represent an important economic entity; they influence the national economy's performance through their economic behaviour. In analyses based on macroeconomic data (national accounts data), households are represented by the institutional sector, whose primary economic function is consumption (or production in the case of minor-scale entrepreneurs included in the household sector); the main sources for financing their activities are derived from labour income (or the sale of the results of their own activity). In the national accounts, household consumption is expressed by two indices: final consumption expenditure, which is (in simplified terms) what households spend, and actual final consumption, which is the sum of final consumption expenditure and social transfers in kind. It expresses what households consume regardless of who pays for this consumption. Final consumption is generally covered by disposable income. What is left is saving. Thus, in analyses of household economic behaviour, three indices are of primary interest: disposable income, final consumption expenditure and saving.

In general, it is typical for household spending on final consumption and investment to rise in years of economic growth. This behaviour results in decreases in their saving and financial saving rates. Households then find it difficult to fulfil their role as creators of spare funds to finance any deficits of other sectors, in particular, the general government. Households that do not generate sufficient financial resources for their consumption and investment cover the difference with the aid of credit. Years of recession or even crisis following after years of economic growth bring about a reversal in household behaviour, manifested by a cautious approach to consumption (and possibly consumption smoothing) and little interest in investment and, consequently, in long-term credit. At the same time, in years of crisis, it should be a prevailing behaviour for households to reduce their non-financial and financial investments or try to save their spare funds in less risky assets.

The economic behaviour of Czech households in the post-2000 period broadly conformed to this outline. Consumption and indebtedness increased in the years of economic growth, and consumption and investment were reduced in the years of recession and crisis. However, the crises that affected Czech (and not only Czech) households after 2000 differed in their causes, durations, and consequences. The period 2009–2013 was that of reversals in the Czech economy: a decline in economic activity in 2009, a recovery in 2010 and 2011, followed by the return of the crisis in 2012 and 2013, and growth from 2014 onwards (see Hronová and Hindls, 2013). This period is also characterised by a general decline in investment activity, low inflation, falling interest rates on deposits and loans, and a controlled depreciation of the Czech currency. The causes of this global crisis were economic factors originating from the mortgage and fiscal crisis in the US, which quickly spread to Europe and other parts of the world.

The period since 2014 was a period of prosperity in Czechia. The key sectors (industry, construction, services, and foreign trade) prospered, growth was supported by investment from both the businesses and the state, general government debt was falling in relation to GDP, and real wages were rising. The inflation rate and the unemployment rate were below 3%. But then an unexpected external stimulus intervened. The advent of the COVID-19 pandemic caused a sharp decline in economic activity in all spheres of activity, with production cutbacks in many large industrial enterprises, closure of shops and services, restricted population movements, and the resulting losses in transport and tourism, reduction of household consumption to only essential products, etc. The state mitigated the impact of the pandemic on enterprises and households through a system of massive subsidies and compensations. These measures prevented a sharp rise in unemployment and business failures but at the cost of increasing the general government deficit and debt. The root causes of this crisis were neither domestic nor economic. The pandemic situation froze the entire world economy. In addition to economic uncertainty and the inability to 'spend', household behaviour and motivation were paralysed by life and health insecurity. Consequently, the decrease in household final consumption expenditure was higher than that of GDP. As a result of the inability to travel and with the existence of unrealised purchasing power in the market for consumer goods, demand for real estate (including holiday housing) increased significantly in Czechia, which triggered a significant rise in property prices (see Hronová et al., 2022).

With the gradual easing of the healthcare restrictions, 2022 marked the beginning of a return to normal conditions for households. However, the pandemic period undoubtedly caused lasting changes in the economic behaviour of households that have not fully recovered their consumption habits even now. High inflation rates, particularly the rise in energy and food prices in 2023, forced households to once again curb their consumption and adopt a cautious investment behaviour. Restrictions in consumption generally imply an increase in savings if all other circumstances are equal. This general rule is regularly reflected in household behaviour. But was the growth in savings (meaning gross savings of the household sector) in the COVID-19 period really extraordinary? Can the fall in the propensity to consume and the rise in the propensity to save in 2020–2021 be considered statistically significant compared to the crisis period 2009–2013? How did these crisis periods differ in terms of data for the household sector?

We will seek an answer to this question by analysing the corresponding time series. However, we will also try to identify the intensity of these changes in the individual time series by analysing the data hidden in the indices. That is to say, to answer not only whether the changes in household behaviour trends have been confirmed but also how strong these trends are and for which indices they have been stronger or weaker. Moreover, to determine whether these differences were not only evident for each of the indices but also whether there were significant differences over time, as we examined qualitatively different periods (the downturn in economic activity in 2009, the recovery in 2010 and 2011, the growth difficulties in 2012 and 2013, the growth from 2014 onwards, and finally the impact of COVID-19 and events after 2019 – see above).

For such data analysis, we will first use techniques that formulate a model for each period. We will then subject these models to stability analysis. In other words, we will compare the levels of breaks (decline/growth). That is, the models' different (i.e., unstable) structures for both individual indices and individual time phases. Due to the specific features of economic development in different countries during the COVID-19 pandemic (see below), our analysis will focus on the case of Czechia, using publicly available data from the Czech Statistical Office (*www.czso.cz*).

1 LITERATURE REVIEW

The arrival of the COVID-19 pandemic was sudden and unexpected, quickly affecting the whole world. National governments reacted speedily and in the only way possible in such a situation: isolation of the infected, strict hygiene measures, and restrictions on movement and assembly. This approach logically brought a reduction in economic activity; most shops and services were closed, transport and travel were severely restricted, and schools were closed. All of this meant a fundamental change in households' economic and social behaviour and significantly affected firms' economic performance. In an attempt to prevent losses to businesses, especially small-scale producers, which in many cases (restaurants, hotels and other services) had to stop their activities altogether, national governments introduced several measures in the form of exceptional subsidies and compensations. These were intended, among other things, to maintain employment and, together with a system of extraordinary social benefits, to stabilise household incomes. These measures, together with limited shopping opportunities in shops and the impossibility of travelling, meant (despite the significant development of online shopping) a substantial reduction in household consumption. A decline in the propensity to consume generally implies an increase in the propensity to save. Therefore, many studies have looked not only at the decrease in household final consumption expenditure but also at the growth in household savings.

Studies on the impact of restrictive measures during the pandemic were already appearing in 2020 and 2021, and quite logically they were primarily based on high-frequency data, as only this could provide a practically up-to-date picture of changes in household economic behaviour. The anti-epidemic and social measures taken by governments were not the same for each country, and by analogy, household responses to the effects of the pandemic varied among countries. The specific nature of the data (from payment transactions) and the difficulties in internationally comparing the conditions were the reasons why studies of the impact of the pandemic on household behaviour were always focused on one particular country.

The Review of the Economics of Households Journal published over a dozen articles in 2020 and 2021 on various aspects of household economic and social behaviour in the context of the COVID-19 pandemic. The rationale for such an initiative was the fact that 'the pandemic and all its direct and indirect effects are mediated mainly through individuals making decisions within households' (Davis, 2021: 281).

The most common type of the data used for analysis already in 2020 was that of payment card records. Bounie et al. (2020) tracked changes in the economic behaviour of French households using card payment data. They found that households spent less because they earned less, and their purchases were concentrated in fewer outlets, but the average amount spent per purchase was higher than before COVID-19. Sheridan et al. (2020) examined the situation in Denmark and Sweden. Based on data from Danske Bank, they concluded that the decline in final consumption expenditure by Danish households was mainly a response to the threat of the pandemic; they considered the restrictions and closures of shops and establishments as well as restrictions on population movements to be less important in terms of the decline in consumption. The situation of Danish households (the source was again Danske Bank data) was also discussed by Anders et al. (2022). Their study reported that the most significant declines in final consumption expenditure occurred among pensioner and single-person households. However, the large initial decrease in consumption expenditure (by almost 30%) was offset by an increase in household savings and net worth. The differential response of different household types to pandemic-related measures was also demonstrated by Christelis et al. (2020). Using financial uncertainty models on data from six selected EU countries, they showed that the decline in consumption was most pronounced among low-income households, households in regions with high unemployment, and households of young persons. They also pointed out that these household groups should be targeted for state support in times of crisis. In contrast to Sheridan et al. (2020), they concluded that health concerns had not been shown to be an underlying factor in reducing consumption expenditure.

Data on card payments in Spain were used by Carvalho et al. (2021), who looked not only at the value of transactions made but also at the locations of the transactions concerning the economic level of the respective area. They concluded that the decline in consumption expenditure was more significant in areas with a wealthier population, in line with a significant reduction in mobility. Campos-Vazquez and Esquivel (2021) analysed point-of-sale payment transactions and mobile operator data during a pandemic shutdown in Mexico. During the first three months of the shutdown, household consumption expenditures fell by a quarter, but this decline was not uniform across the country. Logically, tourism-dependent areas were hit the hardest.

The situation in China, the country from where the COVID-19 epidemic started to spread, was, for example, studied by Li et al. (2020) and Chen et al. (2021). Li et al. compiled responses from two monthly China Household Finance Surveys (February and May 2020) and showed a drastic reduction in consumption due to income constraints. Chen et al. analysed daily payment transaction data from the UnionPay payment service provider. They showed that consumption spending fell by one-third in the three months following the outbreak.

The situation in Czechia during the COVID-19 pandemic was, for example, discussed by Botlíková et al. (2021), and Zubíková and Smolák (2022). The former authors focused on the analysis of the evolution of Czech households' final consumption expenditure and savings during the pandemic. They showed that the growth in savings was caused not only by a decrease in expenditure but also by an increase in income. The growth in household indebtedness was more pronounced during the economic crisis years 2009–2013 than during the pandemic period (2020–2021). In their study, Zubíková and Smolák (2022) examined the macroeconomic, primarily monetary and fiscal, effects of the pandemic in the Czech Republic. Analysing data for the pre-pandemic year 2019 and the pandemic years (2020–2021), they concluded that developments in Czechia were consistent with the partial hypotheses of the Mundell-Fleming model and the modified Phillips curve hypothesis.

Studies published between 2022 and 2024 already focused more on the broader context of the pandemic impact on household behaviour using data from regular surveys and partly on the change in the economic environment with the advent of high price increases. However, such analyses again focused (for the reasons outlined above) on the situation in one country.

The financial situation of French households (and businesses) during the two years of the pandemic was analysed by Fize et al. (2022) using bank account data from Credit Mutuel Alliance Fédérale. In particular, they focused on the evolution of gross household savings, expressed as the sum of current and savings account balances, securities accounts, and life insurance. The decline in final consumption expenditure, together with government support during 2020, meant a continuous (albeit slow) increase in gross savings. The end of 2021 then meant a decline in gross savings in all but the wealthiest household groups. For the poorest households, gross savings have returned to their pre-crisis levels. The study by De Pommerol et al. (2024) also looked at the evolution of gross savings by French households. The authors found that the pandemic period led to an unprecedented increase in gross savings, thanks to the stability of income (in the category of employees) and the decline in consumption. The savings rate of French households reached a record high of 26.6% of gross disposable income in the second quarter of 2020, falling to 17.5% of gross disposable income in 2023. However, the average post-COVID-19 (2022 and 2023) savings rate (18.8%) was still about four percentage points higher than the long-term pre-COVID-19 savings rate (14.6%). High inflation rates[3] caused the real value of financial assets to fall and eliminated revaluation gains.

Ridhwan et al. (2024) analysed the impact of restrictions during a pandemic on household income and consumption in Indonesia. They used high-frequency data from Bank Indonesia's monthly consumer survey, which had more than 176.000 respondents. They found that households struggled to smooth their consumption when their incomes fell, which led to an increase in the proportion of income devoted to consumption while reducing the proportion of debt repayments and savings. However, the impact of government restrictions on households varied by type of expenditure, by region, and by the attained education level.

A summary of the findings from the pandemic period was the study by Parker et al. (2022), in which the authors mainly focused on the comparison between the 2008–2009 and the COVID-19 crises. According to the authors, the key difference was that the pandemic measures reduced households' access to a range of goods and especially services; in other words, there was nothing to spend money on. On the other hand, there were extraordinary support and compensations from the state, support programmes for small entrepreneurs and compensations of employers' wage costs to maintain employment, which managed to keep income levels stable. Together with the inability to spend, that development led to an increase in savings, especially by low-income households. These subsidies and compensations were a different 'type of cure' for the crisis; in 2008–2009, when the economic recovery was particularly strong, the main 'type of cure' was a system of tax reliefs.

The periods of the pandemic crisis (2020) and the subsequent recession and recovery were the focus of a study by Chen et al. (2024). Using panel regression methods, the authors attempted to model the fall in consumption during the pandemic and its recovery in 2022, taking into account the nature of the cities where households live. They showed that spending on non-durable items returned very

[3] In France, the inflation rate was 5.2% in 2022 and 4.9% in 2023.

quickly to pre-pandemic levels; the recovery rate in leisure-related expenditures was significantly slower. The largest decline in consumption in the aftermath of the pandemic was observed in cities where the service sector dominated. A milder decline and faster recovery in consumption were observed in cities with a predominant secondary sector.

MacGee et al. (2022) analysed the effects of the pandemic on Canadian household debt and savings. Using income distribution models, they showed that while low-income households faced the highest risk of unemployment, their losses were offset by social transfers. In contrast, middle-income households experienced a significant increase in debt when they lost their jobs, as social transfers were insufficient to cover the decline in labour income. The increase in savings was particularly marked among high-income households, which were virtually free of unemployment and whose consumption expenditure was most decreased due to mobility constraints.

Marangoz and Ozkoc (2023) examined changes in household spending over a longer time period (2015–2022) in Turkey based on central bank data on card payments. They used the method of structural break tests, which allowed them to demonstrate that the drop in household consumption expenditures at the beginning of the pandemic was significantly smaller than the growth of these expenditures after the relaxation of restrictions at the end of the pandemic.

Most of the studies analysing household economic behaviour during the COVID-19 pandemic were focused on the immediate period of the pandemic in an attempt to capture the effects of the restrictions and the decline in household consumption. In other words, they attempted to capture the fundamental change in household consumption behaviour brought about by a completely exceptional situation. Therefore, trying to quickly provide information on changes in household economic behaviour, the first studies focused on the analysis of high-frequency data. Crises triggered by economic factors or by the behaviour of economic agents (financial institutions or political decisions) can differ fundamentally from the impact of a pandemic. Nevertheless, time-series analyses of short-term data are rare in the presented studies (see, in part, Parker et al., 2022; or Botlíková et al., 2021) that would provide a comparison between the significance of the change in household economic behaviour induced by the impact of the 2009 economic crisis on the one hand and the impact of the 2020–2021 pandemic on the other hand. It is this gap that we would like to fill by analysing the economic behaviour of Czech households based on data from the Czech Statistical Office. The aim of the present article is, therefore, to compare the intensity of the break that occurred in the economic behaviour of Czech households in the years of the economic crisis 2009–2013 and in the years of the pandemic crisis 2020–2021.

2 DATA AND METHODS USED

The distinct national-specific features of the economic crises during the pandemic (see above) led us to focus on the data of only one country, i.e., Czechia. The data source was the National Accounts database of the Czech Statistical Office.[4] Our analysis has been based on quarterly national accounts data for the period 2000 to 2023, not only for the household sector but also for the general government sector. We used both absolute indices (GDP, final consumption expenditure of households, final consumption expenditure of general government, and social transfers in kind) when their values were expressed in comparable prices; and relative indices (savings rate, financial savings rate, proportion of social benefits collected by households in their gross disposable income) when the selected absolute indices were available only in current prices.

In order to answer our research questions posed in the Introduction, i.e., to compare the intensity of breaks, it is suggested to use Chow's test of the stability of different data sections in a given time series (see, e.g., Cipra, 2003). We made a reasonable substantive assumption (see the description of the

[4] Cf. <*https://apl.czso.cz/pll/rocenka/rocenka.indexnu*>.

economic context above) that this would be a model with one 'qualitative' change between two consecutive time periods. And because we want to compare not only the evolution within the time series but also two different critical turning points in the economy (the crisis starting in 2009 on the one hand, and the onset of COVID-19 and related events in 2020 on the other hand), we split the time sub-periods in the quarterly time series data, which are for the period 2000–2023, as follows:

Table 1 Breakdown of time periods into sub-periods for the analysis of developmental changes

Period	Sub-period
2000–2013	2000–2008
	2009–2013
2014–2023	2014–2019
	2020–2023

The division into these periods corresponds to the definition of two qualitatively different phases in the development of the Czech economy, as described above. The divisions into sub-periods within these periods then correspond to two completely different causes of the breaks (so-called break dates): the economic crisis starting in 2009 and the crisis associated with the COVID-19 attack at the beginning of 2020. Both of these intervention breaks correspond to Chow's established methodology.

The basic idea divides a time series with T observations into two sub-periods of lengths T_1 and T_2, where $T_1 + T_2 = T$. For each sub-period, we then formulate two models:

$$y_t = \beta_1 + \beta_2 x_{t2} + \ldots + \beta_k x_{tk} + \varepsilon_t, \qquad t = 1, 2, \ldots, T_1, \tag{1}$$

and

$$y_t = (\beta_1 + \beta_{k+1}) + (\beta_2 + \beta_{k+2}) x_{t2} + \ldots + (\beta_k + \beta_{2k}) x_{tk} + \varepsilon_t, \qquad t = T_1{+}1, T_1{+}2, \ldots, T_1{+}T_2{=}T, \tag{2}$$

where x_t are the explanatory variables, i.e., independent variables (including the time variable); β are the model parameters. In principle, we are interested in stability if the model slopes, which may be tested, for example, with the aid of the F-test; the alternative hypothesis here is a statistically significant change in the slope.

We must also formulate the 'overall' model for the entire (i.e., undivided) time series:

$$y_t = \beta_1 + \beta_2 x_{t2} + \ldots + \beta_k x_{tk} + \varepsilon_t, \qquad t = 1, 2, \ldots, T. \tag{3}$$

The procedure can be applied as a test of the significance of changes in the time series evolution, i.e., a test of the evolution-instability verification, which must be followed by a detailed substantive analysis; mere statistical interpretation is probably not sufficient regarding the seriousness of this issue.

However, for our purpose of substantive analysis of the economic series behaviour, it will be more important to calculate the test statistic (4) for all of the different sub-periods (see Table 1) and then compare these calculated values of the statistic (4) with each other. In other words, a comparative analysis of the values of statistic (4) is employed to express the sensitiveness of the data in each time series with respect to the various qualitative economic stimuli and interventions affecting economic development.

The already mentioned Chow's statistic takes on the following form (cf. Cipra, 2003):

$$F = \frac{T-2k}{k}\frac{RSS-(RSS_1+RSS_2)}{RSS_1+RSS_2} \sim F(k;T-2k)\,, \tag{4}$$

where RSS is the estimated residual sum of squares in the 'undivided' model (3); that is, $RSS = \sum_{t=1}^{T} \hat{\varepsilon}_t^2$,

and F (4) has the distribution F (k; T – 2k), where 2k is the number of independent variables in model (1) or (2). Chow's test of stability thus consists of estimating three classical linear regression models (1), (2), and (3), subsequently determining, in the standard way, the estimated residual sums of squares RSS, RSS_1, and RSS_2.

The long time series thus allow us to compare the intensity of the impact of the 2009–2013 crisis on (mainly) household behaviour with that of the 2020–2023 pandemic.

3 RESULTS AND DISCUSSION

Naturally, the first step of our analysis is focused on separately examining the evolution of the Czech GDP in the two periods as defined in Table 1. We have thus applied Chow's stability test twice: first for the period 2000–2013 with a breakout sub-period at the boundary of 2008–2009 (the global economic crisis triggered by the collapse of Lehman Brothers Holdings and other US financial houses); second, analogously for the period 2014–2023 with a breakout sub-period at the break of the years 2019 and 2020 (the onset of the COVID-19 pandemic).

We have applied Formulas (1), (2), and (3) in estimating the following parameter values for the period 2000–2013:

b_0 = 719,033.594 and b_1 = 10,418.439 for the first sub-period, i.e. the years 2000–2008 according to Formula (1);

b_0 = 971,798.214 and b_1 = 2,014.171 for the second sub-period, i.e. the years 2009–2013 according to Formula (2); and

b_0 = 777,426.106 and b_1 = 6,639.831 for the entire undivided time series of 2000–2013 according to Formula (3).

Figure 1 shows the evolution of the GDP time series for both sub-periods in the 2000–2013 period (the divided (1) and (2) models in light grey and the undivided model in full colour).

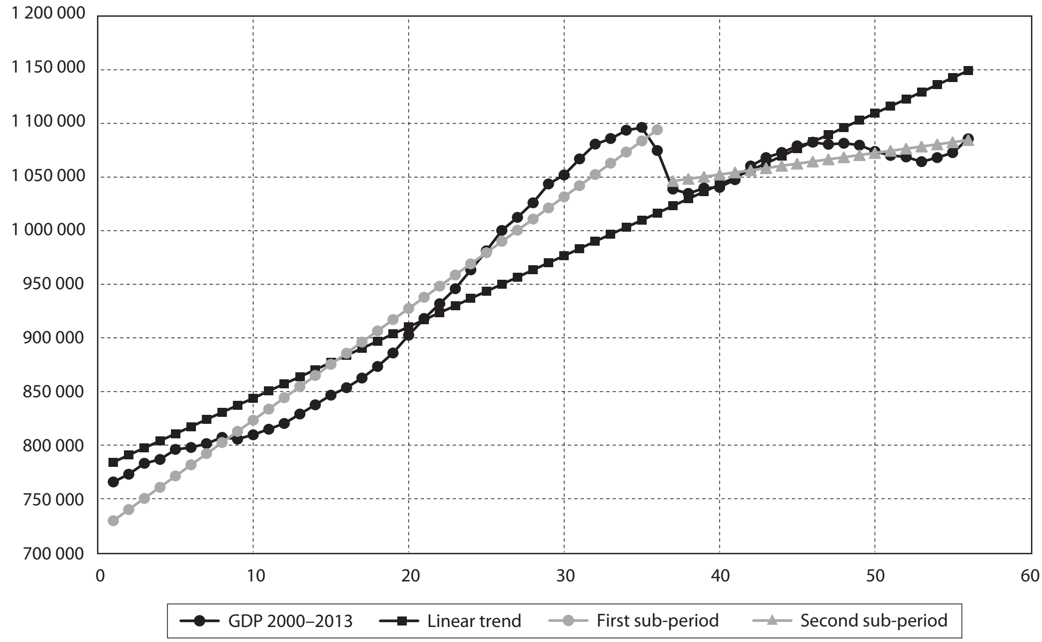
Analogically, we have applied Formulas (1), (2), and (3) in estimating the following parameter values for the period 2014–2023:

b_0 = 1,073,735.772 and b_1 = 11,473.348 for the first sub-period, i.e. the years 2014–2019 according to Formula (1);

b_0 = 1,104,314.287 and b_1 = 6,055.166 for the second sub-period, i.e. the years 2020–2023 according to Formula (2); and

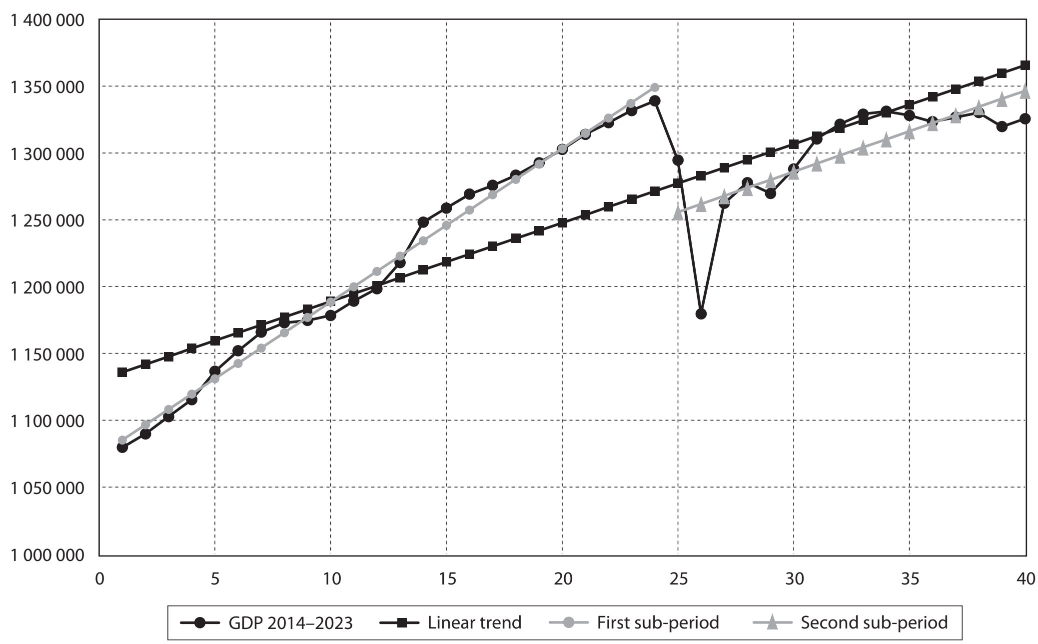
b_0 = 1,130,071.438 and b_1 = 5,886,001 for the entire undivided time series of 2014–2023 according to Formula (3).

Figure 1 Time evolution of the undivided and divided 2000–2013 GDP time series in Czechia



Source: <*www.czso.cz*>, the authors' own calculations

Figure 2 Time evolution of the undivided and divided 2014–2023 GDP time series in Czechia



Source: <*www.czso.cz*>, the authors' own calculations

Table 2 below shows the F-statistic values for both periods and their sub-periods from Formula (4), namely, $F_{2000–2013}$ = 214 311, $F_{2014–2023}$ = 137 569. Both of these values are statistically significant (at a level of 1-α = 0.90, the F-distribution quantiles are $F_{0.90}$ (1; 54) = 2 801 for 2000–2013 and $F_{0.90}$ (1; 38) = 2 842 for 2014–2023). What we interpret as more important is, however, the fact that the break rates (expressed via the F-statistic values) of the GDP evolution are similar to each other for both periods. It means that the break effect (i.e., the quantitative change) for the GDP evolution in the crisis that began in 2008 was about the same as that of the COVID-19 crisis.

This partial conclusion only shows that the economic downturn phenomena in the periods under review had different causes but were quantitatively similar in nature. GDP fell twice in each period under review, and the decline rates were comparable. The annual decline in GDP was recorded in 2009 (by 4.7%) and in 2012 (by 0.8%); and in the COVID-19 sub-period in 2020 (by 5.5%) and in 2023 (by 0.3%). The pattern of quarterly data evolution[5] was also similar: the decline in the first two of the consecutive quarters was followed by a period with slight quarter-on-quarter changes (up and down). When comparing the first post-crisis value with the last pre-crisis value, we again find only insignificant differences (+0.4% when comparing Q1 2014 and Q4 2008; and –0.7% when comparing Q1 2022 and Q4 2019).

Figures 1 and 2 prove this assertion at a glance. In the first sub-periods of both periods, i.e., in the sub-periods 2000-2008 and 2014–2019, the trends were positive, and the positives were similar (the respective trend guidelines b_1 = 10 418 439 for the sub-period of 2000–2008, and b_1 = 11 473 348 for the sub-period of 2014–2019 were also numerically close). However, a completely different situation then occurred after the dramatic breaks that came in 2009, and in 2020, i.e., always in the second sub-periods Here, the trend values' evolution curves started to differ visibly because the qualitative causes of their breaks were also different. This divergence needs to be explained. Below we will therefore try to analyse why this was the case and what actually happened. It turns out that the primary driver of the qualitative differences between the two periods, i.e., between the 2000–2013 and 2014–2023 periods, was mainly household final consumption expenditure. It will now be all the more interesting to see how the breaks in the development were distributed among the indices related to the household sector and, by extension, partly also to the general government sector. The F statistic values for our selected absolute and relative indices are summarised in Table 2.

Table 2 Values of the F-statistic for the individual time series

Period	*F* statistic values for absolute indices				
	GDP	**FCEh**	**STKh**	**ICEg**	**CCEg**
2000–2013	214.311	54.016	16.736	9.434	173.997
2014–2023	137.569	123.030	20.980	22.201	5.195
Period	***F* statistic values for relative indices**				
	FCEh/GDIh	**GSh/GDIh**	**SBh/GDIh**	**STKh/GDIh**	**NLh/GDIh**
2000–2013	16.432	9.969	25.466	0.661	4.942
2014–2023	50.157	56.717	94.557	68.894	46.106

Notes: GDP – gross domestic product; FCEh – final consumption expenditure of households; STKh – social transfers in kind in favour of households; ICEg – individual consumption expenditure of general government; CCEg – collective consumption expenditure of general government; GDIh – gross disposable income of households; GSh – gross saving of households; SBh – social benefits received by households; NLh – net lending of households.
Source: <*www.czso.cz*>, the authors' own calculations

[5] Data in average 2015 prices, seasonally adjusted.

Let us, therefore, first look at household final consumption expenditure, representing about 50% of GDP. Here, we again determine the values of Chow's statistic from Formula (4) for both time periods: $F_{2000–2013}$ = 54 016 and $F_{2014–2023}$ = 123 030. These two values perceptibly differ from each other. In other words, in the second period, the break was statistically more significant than in the first period; this observation complies with the assumption that the restrictions on consumption during the COVID-19 pandemic were drastic.

From the households' perspective, a characteristic feature of the COVID-19 years was a significant decline in final consumption expenditure in both the first and second quarters of 2020 (overall by 12.5%) and subsequent quarter-on-quarter fluctuations (measured by the development of this index in comparable prices, seasonally adjusted). Spending on intermediate consumption items (mainly footwear and clothes) declined the most, by 15.0% in Q2 2020, and by 37.6% in Q1 2021 vs. the pre-COVID-19 level (Q4 2019).

A similar pattern (initial decline and subsequent fluctuations) in household final consumption expenditure could be observed in the years 2009–2013. The decrease in total household consumption expenditure lasted for three consecutive quarters in 2009, but was less significant (a decline of 2.4%) than during the COVID-19 crisis. Expenditure on non-durable consumption items was the most affected by the crisis, with total expenditure value falling throughout the sub-period 2009–2013 (overall by 2.5%). In contrast, expenditure on durable consumption items rose and expenditure on services and medium-term consumption items was rather stagnant.

The consumption behaviour of households after each crisis was different. While in the first quarter of 2022, household final consumption expenditure fell by 1.3% compared to the last crisis quarter of 2021 and by 3.8% compared to the last pre-crisis quarter (Q4 2019), in the case of the 2009–2013 crisis, we can speak of stagnation in both comparisons (Q1 2014 vs. Q4 2013, and Q1 2014 vs. Q4 2008). In 2022 and 2023, household final consumption expenditure values continued to decline quarter-on-quarter, and in the last quarter of 2023, they reached a level corresponding (in comparable prices) to the first quarter of 2017. The reason for this continuous decline was the reluctance of households to spend because of high inflation rates.[6] In contrast, since the start of the recovery in 2014, household final consumption expenditure was rising continuously quarter-on-quarter until the end of 2019. Household spending was not constrained by either high inflation or concerns about the future after 2013, as it was after the COVID-19 crisis.

In terms of the distribution of final consumption expenditure by durability, expenditure on non-durables (especially food, due to the uncontrolled increase in inflation rate) declined the most after the COVID-19 crisis, and its level (at comparable prices) returned to the level of Q2 2006 as late as in the last quarter of 2023! At the same time, the proportion of such expenditures in total household final consumption expenditure fell from 47% in 2000 to 37% in 2023 (while the proportion of expenditures on services changed only insignificantly during the whole period under review, oscillating around 45%).

In terms of relative indices, the periods under comparison were also different; the years of the COVID-19 crisis (see the *F*-statistics values in Table 2) clearly appear to be the period with the most significant break, especially in the case of the savings rate, the financial savings rate, and the proportion of social transfers in kind in household gross disposable income.

A characteristic feature of the first crisis period (2009–2013) includes the proportion of the high values of the household final consumption expenditure (FCEh) in their gross disposable income (GDIh), which ranged from 85 to 90%,[7] and the low savings rate (GSh/GDIh) in the interval between 10 and 15%.[8]

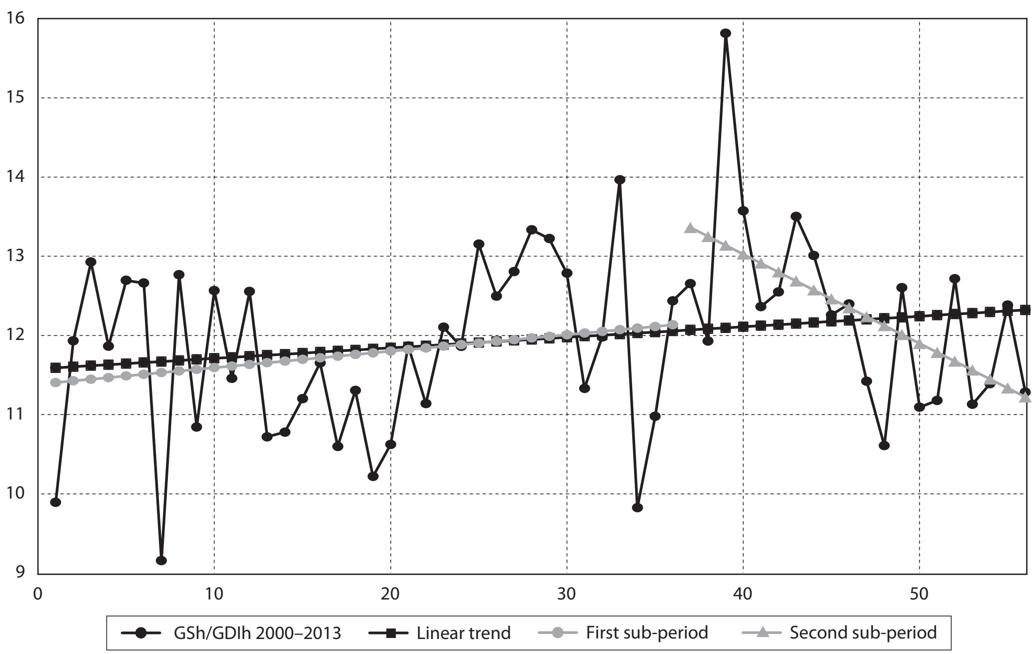
[6] The average inflation rate was 15.1% in 2022 and 10.7% in 2023.
[7] The average quarterly value of the propensity to consume in the 2000–2023 period was 87.3%.
[8] The average quarterly value of the savings rate in the 2000–2023 period was 13.7%.

In contrast, during the COVID-19 crisis, the FCEh to GDIh ratio fell to 78.2% in the last quarter of 2020 despite the temporary opening of many stores before the Christmas holidays. The savings rate thus reached an all-time high of 23.0%. This high value was related to the very different levels of the financial savings rate (NLh/GDIh), which averaged only 3.1% in the first crisis period. They averaged at 11.2% in the COVID-19 years. With such a high surplus, households were able to 'cover' the government financing deficit in 2020 and 2021, which was not the case in the 2009–2013 crisis (except in 2013).

The low and declining (from 86.0% in Q1 2022 to 80.4% in Q4 2023) proportion of FCEh in GDIh is also characteristic of the post-crisis years 2022–2023 (a period of high inflation). This phenomenon is, of course, reflected in the above-average savings rate and financial savings rate, which reached 19.3% and 12.8% in the last quarter of 2023.

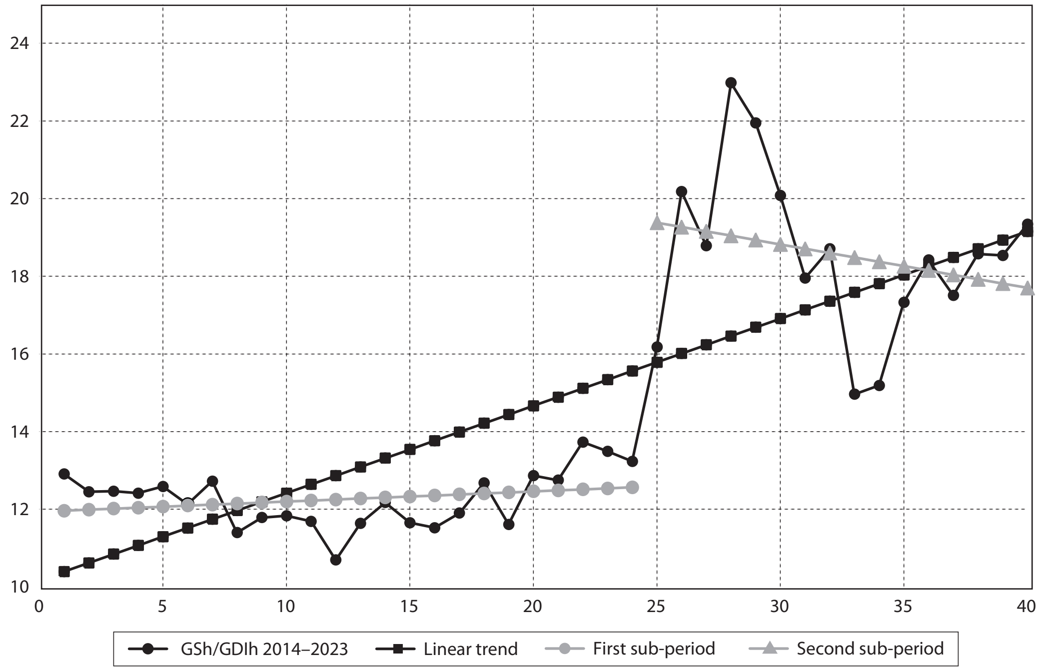
Figures 3 and 4 show that in the first sub-periods of both periods, i.e., 2000–2008 and 2014–2019, the trend was slightly positive and stable, and these two sub-periods were similar (the respective trend guidelines $b_1 = 0.021$ for the sub-period of 2000–2008, and $b_1 = 0.026$ for the sub-period of 2014–2019 are also numerically close to each other). However, a different situation then occurred after the dramatic breaks in the trend of the monitored indices that came after 2008 and after 2019, i.e., in the seconds sub-periods. Here, the trend values were completely reversed; both slopes were negative, and quantitative as well as qualitative breaks occurred. The high savings rate in the crisis years subsequently started to decline with significant quarter-on-quarter fluctuations (which is always a very unfavourable sign for the development in the economy) and demonstrates households' uncertainty and lack of confidence towards increased demand, i.e., a kind of 'fear' of spending. This was particularly evident in the 2014–2023 period and signalled households' great concern about future developments. It shows that the significance of the break was thus much higher in COVID-19 crisis than in the crisis years 2009–2013; this difference is, in fact, also evidenced by the value of the F-statistic shown in Table 2.

Figure 3 Time evolution of the undivided and divided 2000–2013 GSh/GDIh time series in Czechia



Source: <*www.czso.cz*>, the authors' own calculations

Figure 4 Time evolution of the undivided and divided 2014–2023 GSh/GDIh time series in Czechia



Source: <*www.czso.cz*>, the authors' own calculations

From the households' perspective, the two crisis sub-periods should also differ in the proportions of social benefits in GDIh and of social transfers in kind in GDIh, the largest part of which was spent on health care. The average level of social benefits proportion in GDIh was 25.7% in the 2009–2013 crisis, and this proportion had only insignificantly been changing over the 20 quarters under review. During the COVID-19 crisis , the average value of this proportion was 2.3 percentage points higher; it peaked (29.9%) in Q4 2020. The growth in the volume and proportion of social benefits during the COVID-19 years was mainly driven by increased payments on health care and on household-nursing care. In the case of in-kind social transfers proportion in favour of households in their GDIh, the difference was even higher, with an average of 20.4% in 2009–2013 and 24.5% in 2020–2021. This was due not only to increased spending on health care, but also to the spa support programme, where the state paid to households a substantial part of spa-resort care.[9] The values of *F*-statistics show that the break in the case of social transfers in kind proportion in GDIh cannot even be assessed as statistically significant in the first period. Even this formal conclusion is logical, since in the years of the first crisis there was no real impetus to break even in the volume of social transfers in kind, of which health and education expenditure values constitute a substantial part.

To illustrate, let us look at the two crisis sub-periods from the perspective of the entity that tried to counteract the crisis in both of these sub-periods, i.e., the data for the general government sector. Government individual final consumption expenditure (ICEg)[10] is equivalent to social transfers in kind

[9] The reason for these transfers was to keep the Czech spa resorts open during the pandemic.
[10] Mainly represented by non-investment expenditures on health, education and culture.

to households. It is therefore logical that, when considering their evolution, we reach similar conclusions as in the case of social transfers in kind 'received' by households[11] (see Table 2).

In the case of government collective final consumption expenditure[12] (CCEg), the difference in its evolution in the two crisis sub-periods can be attributed to different economic policies rather than to the different nature of the crises. CCEg declined continuously throughout the 2009–2013 period[13] as a result of restrictive fiscal policy, while during the COVID-19 crisis this spending rose through 2020 and declined through 2021, reaching the pre-crisis levels in Q4 2021 (all in comparable prices). Consistent with this, the *F*-statistic values (see Table 2) clearly rate the break in the years of the first crisis as statistically significant. However, in the COVID-19 crisis years, the CCEg proportion in total government spending was higher (26.6% on average) compared to the first crisis sub-period (24.1% on average).

To summarise, we can say that the formal method of testing the stability of the time series has allowed us to demonstrate what can intuitively be sensed but is not obvious at first glance from the data, i.e., the fact that the COVID-19 pandemic fundamentally affected (not only) the economic life of households and that its impact on the Czech economy was quantitatively and qualitatively different from that of the global crisis occurring after 2008. Formally, this change manifested itself as a statistically significant break in the evolution of basic indices' values related to the household sector.

However, from the perspective of the developments in the economic behaviour of the household sector, the COVID-19 years cannot be assessed only in purely negative terms. The drastic reduction in consumption led to a quite extraordinary increase in households' savings rate and financial savings rate, which made this period fundamentally different from the pure economic crisis, an example of which was the 2009–2013 sub-period. With high government deficits in the COVID-19 (but also post- COVID-19) years, households' high gross savings and high positive economic balance were positive factors reducing, among other things, the dependence of the Czech economy on foreign resources.

CONCLUSIONS

The nature of the business cycle is highly variable and, in a certain sense, historically unrepeatable. The causes of cyclical development are manifold and their manifestations perhaps even more so. The present paper has aimed to show how profound the differences can be in the manifestation of economic crises and to describe their effects using specific data. We have therefore compared two different (in terms of causes, consequences and lengths) crisis sub-periods. This allowed us to go into the depth of these processes in the analysis of the individual aggregates in the national accounts, and from these details to draw connections and differences in the behaviour of households in particular, which represent a key element of the economic processes and are, at the same time, the subjects that tend to be significantly affected by the recession. A valuable insight that we have gained from the analysis of the stability of developments is that the detailed responses to the economic crisis are very specific (although, for example, the evolution of the aggregate GDP values in two different crises may have been quite similar to each other in purely numerical terms), and are strongly influenced by behavioural elements and motivational preferences. Our results show these features quite convincingly and can thus point to future directions in which the behaviour of households, in particular under economic pressure, may go.

A way to analyse how the global problem is distributed in detail was to examine the evolution stability of different national accounts aggregates. Among several options, we have opted for Chow's stability tests, which we have preferred to other options, such as CUSUM analysis, which is also used to track change

[11] Natural social transfers are provided to households by government institutions and non-profit institutions serving households. Natural social transfers from the government accounted for more than 90% of their total value.
[12] This includes expenditure on administration, defence, security, science and research, etc.
[13] A decrease of 5.3% in Q4 2013 as compared to Q4 2008.

detection but would not allow us to model the primary trend of the relevant time series to such an explicit extent. In fact, it was the estimation of the underlying trend that has allowed us to show that, although the trend may be similar in different periods of crisis development per se, its detailed decomposition into causal relationships shows where the real roots and manifestations of the crisis are.

The choice of indices is also important, namely, in terms of their substantive meaning, the methodology of their construction and their basic statistical properties. The choice is between absolute and relative indices: in the case of absolute indices, it was possible to work with only a limited number of indices at comparable prices. Therefore, we have also analysed relative indices, where it is possible to better trace the qualitative aspect of the problem being solved. Such relative indices include, in particular, household final consumption expenditure in relation to household gross disposable income, the proportion of household gross savings in household gross disposable income, social benefits received by households in relation to their gross disposable income, and others (see above). To some extent, this approach has allowed us to gain insight into the behavioural aspects of household motivations and thus better understand how households react 'under economic pressure'.

Understandably, not all indices had the same degree of instability, shown in the rate of the break; it may even not be statistically and substantively significant for some indices. Among the absolute ones, we observed significant breaks between sub-periods (see Table 2 for details) mainly for gross domestic product (GDP, which is a quite logical choice given its degree of aggregation and the severity and extent of the recession), but also for household final consumption expenditure or, for example, for the index of government collective final consumption expenditure, especially in the period 2000–2013.

For relative indices, there were also a number of very significant breaks in the development sub-periods. This was the case, for example, for household final consumption expenditure relative to their gross disposable income (FCEh/GDIh), for the savings rate (GSh/GDIh) or for the financial savings rate (NLh/GDIh). In contrast, we have observed insignificant breaks of stability in sub-periods, especially between 2000 and 2013, for social transfers in kind in favour of households proportion in relation to their gross disposable income (STKh/GDIh). This conclusion logically points to the exceptional situation during the COVID-19 pandemic (with the increased health spending) versus the years of a 'standard' economic crisis, when the volume of social transfers in kind, and their proportions in GDIh, remained virtually unchanged. In line with standard analyses of household economic behaviour, we have used gross disposable income, which is the most important index in the household sector account, in the denominator of all relative indices.

The results obtained for the questions we set out to answer show that any significant break in the development of the national economy requires careful analysis in the structures of the indices that form the substantive hierarchy and that are affected by the critical development. Thus, a verbal description of the problem is not enough, but a combination of quantitative and qualitative analysis is also needed.

References

BOTLÍKOVÁ, M., BOTLÍK, J., STUCHLÍKOVÁ, J. (2021). Development of household savings and debts in small open economies during the global pandemic COVID 19 [online]. SHS Web of Conferences, 129: 01005, *The 21st International Scientific Conference Globalization and its Socio-Economic Consequences*. <https://doi.org/10.1051/shsconf/202112901005>.

BOUNIE, D., CAMARA, Y., GALBRAITH J. (2020). Consumers' mobility, expenditure and online-offline substitution response to COVID-19: evidence from French transaction data [online]. *HAL Working Paper*, 02566443. <https://telecom-paris.hal.science/hal-02566443/document>.

CAMPOS-VAZQUEZ, R. M., ESQUIVEL, G. (2021). Consumption and geographic mobility in pandemic times. Evidence from Mexico [online]. *Review Economics of the Household*, 19: 353–371. <https://doi.org/10.1007/s11150-020-09539-2>.

CARVALHO, V. M., GARCIA, J. R., HANSEN, S., ORTIZ, A., RODRIGO, T, et al. (2021). Tracking the COVID-19 crisis with high-resolution transaction data [online]. *Royal Society Open Science Journal*, 8(8): article 210218. <https://doi.org/10.1098/rsos.210218>.

CHEN, H., QIAN, W., WEN, Q. (2021). The impact of the COVID-19 pandemic on consumption: learning from high-frequency transaction data [online]. *AEA Papers and Proceedings*, 111: 307–11. <https://doi.org/10.1257/pandp.20211003>.

CHEN, R., LI, T., LI, Y. (2024). Analysing the impact of COVID-19 on consumption behaviors through recession and recovery patterns [online]. *Scientific Repports,* 14: article 1678. <https://doi.org/10.1038/s41598-024-51215-3>.

CHRISTELIS, D., GEORGARAKOS, D., JAPPELLI, T., KENNY, G. (2020). The COVID-19 crisis and consumption: survey evidence from six EU countries [online]. *Working Paper Series,* 2507, European Central Bank. <https://EconPapers.repec.org/RePEc:ecb:ecbwps:20202507>.

CIPRA, T. (2003). *Finanční ekonometrie*. 2nd Ed. Prague: Ekopress. ISBN 978-80-86929-93-4

DAVIS, G. (2021). The many ways COVID-19 affects households: consumption, time, and health outcomes [online]. *Review Economics of the Household*, 19: 281–289. <https://doi.org/10.1007/s11150-021-09563-w>.

DE POMMEROL, O. J., MADEC, P., PLANE, M., SAMPOGNARO, R. (2024). De la crise Covid au choc inflationniste: une analyse macro/micro du pouvoir d'achat en France [online]. *OFCE Policy brief,* 124, 15 février 2024. <https://www.ofce.sciences-po.fr/pdf/pbrief/2024/OFCEpbrief124.pdf>.

FIZE, E., PARIS, H., RAULT, M. (2022). Quelle situation financière des entreprises et des ménages deux ans après le début de la crise Covid? [online]. *Focus du CAE*, 83. <https://www.cae-eco.fr/quelle-situation-financiere-des-entreprises-et-des-menages-deux-ans-apres-le-debut-de-la-crise-covid>.

HRONOVÁ, S., HINDLS, R. (2013). Czech Households in the Years of Crises [online]. *Statistika: Statistics and Economy Journal*, 93(4): 4–23. <https://csu.gov.cz/docs/107516/a6931f2e-6b43-a1f8-70f7-876d824bd646/180213q4004.pdf?version=1.0>.

HRONOVÁ, S., MAREK, L., HINDLS, R. (2022). The Impact of Consumption Smoothing on the Development of the Czech Economy in the Most Recent 30 Years [online]. *Statistika: Statistics and Economy Journal*, 102(1): 5–19. <https://doi.org/10.54694/stat.2021.40>.

CHOW, G. (1960). Test of equality between sets of coefficients in two linear regressins [online]. *Econometrica*, 28(3): 591–605. <https://doi.org/10.2307/1910133>.

LI, J., SONG, Q., PENG, C., WU, Y. (2020). COVID-19 pandemic and household liquidity constraints: evidence from micro data [online]. *Emerging Markets Finance and Trade* 56(15): 3626–34. <https://doi.org/10.1080/1540496X.2020.1854721>.

MACGEE, J., PUGH, T., M., SEE, K. (2022). The heterogeneous effects of COVID-19 on Canadian household consumption, debt and savings [online]. *Canadian Journal of Economics*, 55(S1): 54–87. <https://doi.org/10.1111/caje.12546>.

MARANGOZ, M., OZKOC, H. H. (2023). Evaluation of the Impact of the COVID-19 Pandemic on Consumer Spending in Turkey by Structural Break Analysis [online]. *Statistika: Statistics and Economy Journal*, 103(1): 46–61. <https://doi.org/10.54694/stat.2022.21>.

PARKER, J. A., SCHILD, J., ERHARD, L., JOHNSON, D. (2022). Household spending responses to the economic impact payments of 2020: evidence from the consumer expenditure survey [online]. *NBER Working Paper Series*, 29648. <https://www.nber.org/system/files/working_papers/w29648/w29648.pdf>.

RIDHWAN, M. M., REZKI, J. F., SURYAHADI, A., RAMAYANDI, A., ISMAIL, A. (2024). The Impact of COVID-19 Lockdowns on Household Income, Consumption and Expectations: Evidence from High-frequency Data in Indonesia [online]. *Bulletin of Indonesian Economic Studies*, 60(1): 67–94. <https://doi.org/10.1080/00074918.2023.2167930>.

SHERIDAN, A., ANDERSEN, A. L., HANSEN, E. T., JOHANNESEN, N. (2020). Social distancing laws cause only small losses of economic activity during the COVID-19 pandemic in Scandinavia [online]. *PNAS,* 117(34): 20468–73. <https://doi.org/10.1073/pnas.2010068117>.

ZUBÍKOVÁ, A., SMOLÁK, P. (2022). Macroeconomic impacts of the COVID-19 pandemic in the Czech Republic in the period of 2020–2021 [online]. *International Journal of Economic Sciences*, XI(1): 117–145. <https://doi.org/10.52950/ES.2022.11.1.008>.

Is Job Preservation too Expensive? An Estimate of the Effects of the Covid Pandemic and the Economic Policy Response on the Labour Market

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Received 30.9.2024, **Accepted** (reviewed) 24.10.2024, **Published** 13.12.2024

Abstract

The Covid-19 pandemic triggered a massive economic policy response in all developed countries. There were various approaches that governments adopted with a variety of possible aims and outcomes. In our research we focus on estimating the effects of Covid-19 on the Czech Republic, a small open economy, which was typical in that it had high mortality, a long lockdown and a focus on job preservation. Using three different methods – input-output, CGE and ADL, we estimate the industry-level impact of the pandemic, taking induced effects into account. We show that, besides industries that were explicitly harmed like accommodation or transportation, some industries like construction seem to be implicitly vulnerable as well. This is an important finding especially for any future policy responses. Regarding the economic policy itself, we conclude that it was successful in terms of preserving jobs, but the expenditures were probably too high to call it an efficient policy response.

Keywords	***DOI***	***JEL code***
Labor market, economic policy, Covid pandemic, CGE model, econometrics	*https://doi.org/10.54694/stat.2024.53*	*E17, E24, E65*

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INTRODUCTION – LITERATURE REVIEW

The Covid-19 pandemic is still having serious effects on the global and local economies and society. A sharp economic downturn was witnessed in many developed countries in 2020 (Lucchese and Pianta, 2020; Coibion et al., 2020) and some researchers believe that the economic crisis can be even longer and worse than the GFC (Global Financial Crisis) that struck between 2007–2009 (Baker et al., 2020; Brown and Rocha, 2020). In June 2020, the World Bank anticipated the global GDP to shrink by 5.2%, which would be among the worst results since the Second World War (World Bank, 2020). The severity of the Covid-fueled crisis has also been demonstrated in a sharp decrease in new business startups, a fast increase in actual and expected firm dissolutions (Bartik et al., 2020; Bosio et al., 2020; Fairlie, 2020), high liquidity risks (Brown et al., 2020) and a rapid decline in world-wide trade (CCSA, 2020). This situation is further reinforced by a limited access to bank finance (Demirgüc-Kunt et al., 2020) and other sources of finance such as venture capital (Howell et al., 2020). EU member states were of course no exception – the EU witnessed a sharp –5.9% drop in GDP in 2020, accompanied by a decrease of employment by 1.7% (Eurostat, 2020). Nevertheless, the data show quite an asymmetric impact of the Covid-19 on economies around the world including the EU. Spain, Portugal, Greece and Italy were hit hard in comparison to other member states, while Ireland even had a positive GDP growth. The Czech Republic with its –5.8% GDP growth rate and –1.1% fall of employment was rather around the average among the EU countries. Such an asymmetric impact on national economies was of course inevitable for many reasons. Some of them are even out of the economic area (social, cultural or demographic conditions). From the economic reasons, contemporary studies mainly point at the structure of the economy, the openness of the economy and the extent of lockdowns and regulations along with fiscal stimuli. These factors probably played (and are still playing) key roles in the impact of Covid-19 on the economy.

Not surprisingly, the estimation of the economic impacts of Covid-19 has become a priority for many governments and scholars alike. Various methodological approaches have been used so far, with a clear dominance of input-output based models and CGE models. The main advantage of these models is their structural orientation that considers supply chains and demand linkages. As Covid-19 impacts the economy asymmetrically regarding the industries (some are under lockdown, some are not) the economic structure plays a crucial role in modelling the crisis' impact. Moreover, the Covid-19 crisis is a supply-demand crisis, therefore both sides must be considered.

So far published input-output and CGE based studies differ mainly in their purpose – the spectrum ranges from worldwide large macroeconomic studies to nationally oriented and specifically industry-oriented analyses. For example, Mandel and Veetil (2020) used input-output data on 56 industries in 44 countries concluding that the reduction of the world GDP was about 7% at the early stage of the crisis.

Walmsley et al. (2020) focused on the macroeconomic impact of mandatory business closures in the U.S. and other countries as well. They utilized modified GTAP model, dealing with the impact without countermeasures being accounted for (which is, however, typical even for most of other similar studies). They estimated that without supportive policies the impact of lockdowns and other Covid regulations would result in a huge 20.3% decrease in GDP and a 22.4% decrease in employment in the U.S. They only calculated the length of closures to 3 months, while doubling the length would also more than double the economic losses. They stressed that the impact on employment was so strong because services that are labor-intensive were more negatively impacted by the closures than was industry.

Richiardi et al. (2020) used dynamic input-output model with parametrization based on survey among 250 UK economists. They concluded that almost one quarter of all jobs in UK were at risk, with the Accommodation & Food industry contracting by over 80%, Transport & storage by over 40%, and Manufacturing by almost 30%.

Giammetti et al. (2020) identified key "sectors" in the Italian economy´s supply chain. Their results suggest that closing down those key sectors led to a loss of 52% of the total value added of the Italian economy, out of which 30% has been indirect. Havrlant et al (2021) used input-output framework with three possible scenarios, in which the middle scenario estimated that the GDP decreased by 7.2 % due to the economic lockdown in Saudi Arabia.

Guan et al. (2020) used enhanced regional input-output model concluding that even those countries that are not directly affected by Covid-19 and lockdowns will suffer great losses due to global supply chains. Such cascading impacts will often take place in low- and middle-income countries. Open and highly specialized economies will probably suffer large losses according to their study, too.

Mariolis et al. (2020) focused solely on Greek tourism, which has been severely hampered during the Covid-19 crises, and its impact on the total economy. They estimated the impact to be about a 2.0% to 6.0% decrease in GDP followed by the decrease in the levels of employment of about 2.1% to 6.4%.

Of course, structural analysis makes sense not only for assessing the pure economic impact but also regarding the spread of the virus and the health working population itself. Osotimehin and Popov (2020) divide the U.S. economy into "essential" and "non-essential" sectors showing that the "cascading effects" that are actually based on supply chain and demand linkages increase the health but also economic risks substantially in both groups, but mainly in certain industries (like retail, textile or transportation). Keogh-Brown et al. (2020) used a CGE model to estimate the economic burden of Covid-19 including the cost caused by school closures, that alone could reach 7.3 % of the United Kingdom's GDP even after pandemic suppression.

Besides the input-output based estimates and CGE, several different approaches have occurred as well, mainly based on standard prediction VAR, ADL or ARIMA models. An interesting contribution in this area comes from Fezzi and Fanghella (2020) who use high frequency data from the Italian power market to quickly assess the impact of Covid measures (lockdowns). Similarly, Pragyan et al. (2022) used high frequency data about Nitrogen Dioxide emissions and found a 10 percent decrease of industrial production following the containment measures.

Microeconomic based models are still very scarce as the microeconomic data availability is still quite limited. An interesting study based partly on microeconomic data comes from Cakmakli et al. (2021). They quantified the Covid-19 macroeconomic effects using a combination of a virus spreading model and sectoral linkages, and they pinned down the magnitude of demand shocks by real time credit card purchases. In line with findings of Guan et al. (2020) they estimate the economic costs of Covid-19 to be much larger for an open economy because of the low external demand that amplifies the loss by international input-output linkages.

As described above, usually input-output framework or CGE models are being used for assessing the impact of external shocks like Covid-19 on the economy. Nevertheless, both these methods have their strengths and weaknesses. I-O models are quite straightforward, easy to interpret and able to analyze the impact in deep detail, regarding the industries or products. However, the input-output method is based on fixed proportions of intermediate use to production, meaning that it does not allow for an analysis of the changes in the production function's structure, and it does not allow for any substitution. Moreover, lack of supply side constraints along with the absence of household and government budget constraints and fixed prices are usually put forward as other critical issues (Gretton, 2013). Therefore, CGE models are often treated as superior to I-O for impact evaluation purposes. CGE models allow for substitution in functions (being often of CES nature) and are also generally presented as more reasonable abstractions with higher flexibility in comparison to standard I-O (Partridge and Rickman, 2010). On the other hand, CGE models are difficult to handle, especially in the case of a detailed economy breakdown where researchers face missing data or elasticity estimation problems. Such situations often yield inaccurate results, and a need for systematic ex post evaluations of CGE simulations arises (Kehoe et al., 2017; Kehoe, 2003). From this point of view, it seems reasonable to employ both methods to assess the impact of Covid-19, with emphasis on industrial breakdown and international trade. However, as both methods are rather static, it seems reasonable to employ at least one dynamic estimate to cross validate the results. As stated above, VAR, ARIMA or ADL models are typical examples of such a dynamic approach that could bring the missing dynamic piece into our estimation puzzle.

The purpose of this study is to estimate the effects of the Covid-19 pandemic on the economy of the Czech Republic using input-output framework along with the CGE estimation. The Czech Republic is quite a specialized (dominantly in the automotive industry) small and open economy, therefore it could have been in quite a risky situation according to previous findings of Guam (2020) or Cakmakli (2020). Moreover, the Czech Republic did not do well in Covid-19 mitigation – on the contrary, it was one of the worst countries regarding deaths per 100 000 or new cases per 100 000 in the world, consequently resulting in a long-lasting regulation policy (the Czech Republic was among the top 5 countries with the longest lockdowns in the world). The negative effects of lockdown on the economy can be even more severe due to such prolongation, as Walsmley et al. (2020) suggest.

From this point of view the analysis is quite unique. We are dealing with a small open economy with a high degree of specialization and a long and tight lockdown. That needs a detailed structured analysis on industry level as the pandemic and mitigation policy is likely to have an asymmetrical effect on the economy. For this purpose, we use three methods. The input output framework and modified CGE model should help us to uncover the effects of Covid-19 and subsequent mitigation policy on aggregate production and labor market, reflecting the Czech economy's structural specifics. To cross validate our findings we also estimate the effect by a rather traditional ADL estimate that focuses on the long term relationship between unemployment and production, allowing for a more dynamic approach in comparison to previous estimations. After that, we estimate the policy effects of government subsidy programs on the labor market.

1 DATA AND METHOD

In line with the studies outlined above, we use three different methods to assess the impact of Covid-19 on the Czech economy along with estimating the policy response effect – Input-Output analysis, modified CGE model and the autoregressive distributed lag (ADL) model.

Regarding the output variables we focus on general unemployment rate, jobs preserved and growth rate of the Gross Value added (GVA) in 2020. As the shock is assumed to be asymmetric, negatively affecting some parts of the economy more severely than others, we split the impact further among NACE Rev 2.1. industries (with partly aggregated services). An important task is to assess the impact of fiscal stimuli that have been undertaken during the Covid-19 pandemic. Their main purpose in the Czech Republic was to preserve employment. While the hours worked along with the GVA dropped down dramatically during the pandemic, because of closures and other pandemic measures, jobs/employment remained preserved by government policy. The difference between the real (official) change in unemployment and jobs and the estimated values should then yield the estimated policy effect.

At first, we use the standard multinational Input-Output model (based on world Input-Output tables; Timmer et al., 2015). It allows us to estimate the multiplicative effects of Final use changes on the economy by assuming the production structure (ratios of intermediate use to production on the level of each industry) is fixed over time. The model is calibrated onto the change of GVA from the reference figure. The reference figure is obtained from the prediction for the year 2020 at the end of 2019 by Czech National Bank (Czech National Bank, 2019), and the validation benchmark here is the officially published GDP growth rate (Czech Statistical Office, 2022). The gap between the growth estimate and real growth was 3.2 p.p. on the year-on-year rate. We assume that the effect of lockdowns and economic restrictions was similar all over the NACEs I-N (private services). We did the sensitive analysis of production (proportional decrease in output in I-N NACE) to fit the change of GVA to this value. Then, we analyze the effects on the final use, employment (and indirectly to unemployment) and structure of GVA.

Another advantage of this approach is that it will enable us to estimate the effects on GVA and employment for each industry. It takes into account the spillover/indirect and multiplier effects. Our model's primary data source are the official Input-Output tables estimated by the Czech Statistical Office for 2015 (Czech Statistical Office, 2022) and previously mentioned WIOT tables.

While more recent Input-Output tables for 2020 are available, we deliberately use the 2015 tables as our baseline. The 2020 tables already reflect the structural changes caused by Covid-19 and subsequent containment measures, which would distort our analysis. Using pre-Covid tables from 2015 allows us to capture the true impact of the pandemic by comparing the original economic structure with the Covid-induced changes.

As we said, the Input-Output models are based on fixed relationships. The key figure in this scheme are the technical coefficients. These coefficients can be calculated as the ratio of intermediate flow(x) from i-th industry to another one (j-th) to the production of j-th industry (z):

$$a_{ij} = \frac{x_{ij}}{z_j}. \tag{1}$$

These coefficients define the production functions of each industry. The matrix of these coefficients:

$$\mathbf{A}_{(\boldsymbol{nxn})} = a_{ij}. \tag{2}$$

The Input-Output system is closed, and there are two other essential relationships that help us define the relationship between GVA/production and final use. The closeness of the model to the production approach is:

$$\sum_{i=1}^{n} x_{ij} + \sum_{p=1}^{P} w_{pj} + imp_j = z_j, \tag{3}$$

where the w_{pj} items of GVA (p = 1, 2,… P, and it defines the level of detail of the GVA, e.g. the wages) and the imp_j is the import of j-th good. The closeness of expenditure approach:

$$\sum_{j=1}^{n} x_{ij} + \sum_{q=1}^{Q} f_{iq} + exp_i = \mathrm{z_i}, \tag{4}$$

where the f_{iq} is the items of final use (q = 1, 2, …Q, and it defines the level of detail of the final use, e.g. government consumption, household consumption…). From these equations, we can finally obtain the Leontief matrix:

$$L = (\boldsymbol{I} - \boldsymbol{A})^{-1}, \tag{5}$$

where $\boldsymbol{I}$ is the diagonal unit matrix (eye) and L is the Leontief matrix (column sums of this matrix are Leontief multipliers). This matrix defines the relationship between final use and production. When this matrix is multiplied by the proportion of GVA to production, it can determine the relationship between the final use and GVA.

We use the modified CGE model (Hosoe et al., 2015). This model is based on several agents, like the maximization of utility of households, government, firms, foreign and other components. It should be mentioned that the core of the domestically produced goods is based similarly on I-O tables – the technical coefficients (Leontief production function is there used) and the structure of the intermediate goods for domestic production is fixed. But another part of this is flexible (to calibrated coefficients) – for example, the relationship to capital, employment or the transfer from domestic goods to imported ones. We calibrate this model to relevant data from the Czech Statistical office (Czech Statistical Office, 2022). The CGE model is used in a very similar way. We did a sensitive analysis of its restrictions to analyze NACEs which fit the drop of GVA. It should be mentioned that the CGE model is more flexible, and we expect to obtain a milder effect than from the I-O model with a strictly fixed relationship. We use this model in a slightly untraditional way – we are looking for the size of the shock (restrictions into production which simulates the lockdown) that corresponds to the measured (real) shock into GVA. From this we calculate the effect on unemployment.

The crucial role in CGE models is the maximization of utility. Our model is the Standard CGE model by Hosoe et al. (2015). This model is a simultaneous system of 24 types of equations multiplied by a count of input factors and a count of industries, for eq. The model with two factors and ten industries leads to 296 equations to be solved. This model is based on the maximization of utility. Maximization of utility is quite a problematic concept from a practical point of view. This task is transformed into the maximization of consumption. One of the most used consumption functions is the Cobb-Douglas function; then, the utility maximization can be expressed as:

$$U = \prod_{i=1}^{n} f_{iH}^{\alpha_i} . \tag{6}$$

The f_{iH} is the consumption of i-th good of households, and α_i is the coefficient which defines the weight of each good in consumption functions and its equilibrium can be easily estimated as the ratio of that good to the total sum of consumption. Household consumption is limited by their income and savings minus taxes. In our set of equations, these results in demand:

$$f_{iH} = \frac{\alpha_i}{p_i} * INC_H , \tag{7}$$

where p_i is the price of i-th good and H is income of households (Income from wages, capital income, savings minus taxes).[4] We assume that the households are owners of companies (that's why their income is from capital).

The government and the investment is often based on the following fixed structure of consumption, which is ultimately the same as the maximization of utility of households:

$$f_{iG} = \frac{\mu_i}{p_i} * INC_G . \tag{8}$$

The INC_G is a government income. The INC_G represents government income which consists of tax revenues from multiple sources: import taxes, factor taxes (taxes on labor and capital income), production

[4] The household income (INC_H) in our model corresponds to the disposable income as defined in the System of National Accounts. It includes all household income sources (wages, mixed income, property income, social benefits) minus obligatory payments (taxes, social contributions). This definition ensures consistency with national accounting standards and provides a comprehensive measure of households' spending capacity and its aligned to our data.

taxes (including VAT and excise taxes), minus government savings. This comprehensive definition captures all main tax revenue streams in line with the standard CGE model structure. The savings in both (private and public) are defined as a fixed ratio of income.

The domestic production of goods is calculated in several steps (stages). In the first stage is solved the problem of GVA inputs (factors). This is the maximization of profit subject to the C-D function. In the second stage is solved the maximization of profit subject to the Leontief production function (fix relationships), and in the third phase is solved the mixture of domestic and foreign goods in the final mix of goods. In the first stage is the firms' production functions used as constraints in profit maximization:

$$\max_{y_j, W_{qj}} \pi_j^y ;\, where\, \pi_j^y = p_j^y y_j - \sum_{q=1}^{Q} p_q^f w_{qj}, \tag{9}$$

subject to:

$$Y_j = b_j \prod_{q=1}^{1} w_{qj}^{\beta_{qj}}. \tag{10}$$

The β_{qj} is share coefficient of the q-th good in the production function of i-th goods. The second stage of the product is just a Leontief production function – proportionally mixes the goods from the first stage with fix ratio (by technical coefficients eq.) with intermediate input. Armington functions will solve the foreign entities. These functions introduce small differences between domestic and foreign goods by "cost" of transport/taxes. It's assumed that foreign goods are imperfectly substitutable with domestic.

The autoregressive distributed lag (ADL) models use the lagged dependent and independent variables to explain the dependent one. ADL models are one of the most used models for estimating the long term and short term relationship between the economic variables. For a final comparison we fit the ADL (5, 1) model of the relationship between unemployment and GVA. This model is based on seasonally adjusted rates. The model has a wide distribution of the error term (not typical) but without prevalent autocorrelation. Both variables (GVA and unemployment) have a unit root of 1 (we did the ADF test), and the residuals were stationary. According to the results, we can state a long-term relationship (Granger, 1969). This all was also proved by the standardised Granger test and ADF test in the t-series library (Trapletti and Hornik, 2022). The standard ADL(p, q) model can be written as:

$$Y_t = \beta_o + \beta_1 \mathrm{Y}_{\mathrm{t}-1} + \beta_2 Y_{t-2} + \cdots \cdots + \beta_p Y_{t-p} + \theta_1 X_{\mathrm{t}-1} + \theta_2 X_{t-2} + \cdots \cdots + \theta_q X_{t-\mathrm{Q}}$$

The Y_t (rate of unemployment) depended on the variable used as a lagged explanatory variable, and X_{t-1} independent explanatory variable – GVA growth rate (lagged). We used seasonally adjusted y-o-y rates published by the Czech Statistical Office (Czech Statistical Office, 2022).

2 RESULTS

Using three different methods to assess the impact of Covid-19 on the Czech economy including the estimation of policy effects yields heterogenous results. That is not very surprising. While I-O analysis is static with no allowance for input substitution, the CGE model is more complex and flexible based on agent's optimization, and it can be viewed as a corrected I-O model in a way. The ADL model is then not structured but dynamic, allowing us to capture the short term and long term relationship between production and labor. Table 1 illustrates the results.

Table 1 Share of positive answers to job search questions and item-response probabilities

	Input–Output	CGE	ADL
	% change of employment	**% change of employment**	**% change of employment**
Agriculture, forestry, fishing	–1.860	–0.202	–
Mining, manufacturing	–1.589	–0.422	–
Automotive industry	–1.582	–0.418	
Electricity, gas, water, waste	–1.092	–0.184	–
Construction	–1.013	–5.671	–
Trade	–1.107	–0.005	–
Transport	–1.400	–0.965	–
Accommodation	–10.575	–8.258	–
Services (private)	–6.356	–9.375	–
Services (public)	–0.125	–1.445	–
Other activities	–0.507	–0.006	**–**
Total estimated change of employment	**–2.270**	**–1.360**	**–**
Estimated unemployment rate	**4.02**	**3.49**	**3.16**
Official unemployment rate	**2.55**	**2.55**	**2.55**
Policy effect on unemployment	**–1.47**	**–0.94**	**–0.61**
Policy effect on jobs preservation	**19 527**	**14 387**	**10 308**

Source: Authors

Our results suggest that the Covid-19 pandemic and subsequent mitigation measures had expectedly asymmetric impacts on the economy. Obviously, the Accommodation and private service sector have been struck most severely. However, that is quite predictable as these industries have been locked down and heavily regulated. This holds true regardless of the method we use. Nevertheless, several results differ quite substantially depending on the method. We can see that the input-output model splits the impacts more evenly among industries that were indirectly affected in comparison to CGE, also with a higher estimated total effect on employment. The CGE model predicts a higher impact of the pandemic on Construction and Public services, but considerably lower on other industries including Automotive. As the Czech Republic is largely dependent on the automotive industry, this seems like good (and a bit surprising) news. Taking a look at the ADL model estimate, we may also assume that the CGE model probably offers more realistic results. The total effect on unemployment and employment alike is close for the ADL and CGE estimates. Employing the ADL as a sort of cross validation tool seems interesting even from the methodological point of view. We then may assume that the total effect but also the industry-level effects of CGE are likely to represent the impact of Covid-19 better in comparison to simple input-output analysis.

Regarding the policy effects we can see that there was a positive effect of government policy on preserving jobs and thus lowering possible unemployment. The effect varies according to the method we use from decreasing the unemployment rate by 1.47% to 0.61%. Focusing on the CGE model as a modest estimate, we may conclude that the government policy successfully preserved approximately 14 000 FTE jobs with its policy.

Considering the total cost for Programs Antivirus A and B, that have been major channels for preserving jobs in affected firms, we may at least approximately estimate the cost of one job that has been saved by this policy. Both programs spent 23.7 billion CZK (almost 1 billion EUR) on employee wage compensations, meaning that the average cost of one job preserved was almost 1.7 million CZK (71 thousand EUR). Knowing that the GDP per capita in 2020 was 532 180 CZK (21 thousand EUR) means that the cost of preserving the job was three times more expensive than the job's production. Such a situation is vastly inefficient and the policy measures undertaken in the Czech Republic should definitely be questioned.

The CGE model appears to provide more realistic results for several reasons. Unlike the I-O model, it captures price adjustments and allows for substitution between production factors, which is crucial during supply-side shocks like Covid-19 lockdowns. The CGE model also incorporates behavioral responses of economic agents to changing market conditions. This flexibility, combined with better alignment with ADL estimates, suggests that the CGE framework better reflects the actual adjustment mechanisms in the economy, particularly evident in sectors like Construction and Automotive.

It should be noted that our estimates for public services might overstate the employment effects, as these jobs would likely have been preserved through alternative government funding mechanisms in the absence of the Antivirus program. Therefore, the estimated impact on public services should be interpreted with caution as it represents more of a reallocation of government support rather than actual job losses.

CONCLUSION

The Covid-19 pandemic and the subsequent series of lockdowns and other containment regulations imposed by the Czech Republic and all developed countries worldwide started an inevitable economic downturn. In comparison to the crisis that struck a decade ago this one is not of an economic nature and is not purely demand-driven but more likely supply-demand driven. This makes the crisis unique as the solution does not depend on economic measures but on the ability to contain the virus and put the economies back into a normal situation. Governments on one hand were forced to impose various restrictions to contain the spread of the virus, on the other hand they used various fiscal stimuli to "soften the landing" and protect workplaces and companies from dissolution. Of course, governments but also other stakeholders are therefore highly interested in estimations of Covid-19 pandemic impact on the economy. Many various studies emerged since 2020 dealing with such estimates from different perspectives. In our contribution we combine three rather standard approaches. To deal with the structural nature of the Covid-19 shock, we employ input-output framework and then the CGE model, that is in fact an extension of input-output analysis. Truly, the shock is supply-demand led which needs to take both demand and supply linkages into account. Moreover, the shock is asymmetric, affecting some industries more than others (even due to specific nature of lockdowns themselves). To add some more dynamic perspective into our estimate we add an autoregressive distributed lag model (ADL) to estimate the relation between the unemployment rate and the gross value added. Such an addition also serves as a benchmark for our input-output and CGE estimates, which are rather static. On this ground we may conclude that the CGE model brings probably better results than the simple input-output estimate.

Our estimates suggest that the impact of the Covid-19 pandemic and its mitigation truly had asymmetric impacts on the Czech economy. While we naturally see the most severe negative effects on Accommodation, Transportation and Services, which have been directly hit by the mitigation policy, we may also anticipate quite substantial negative effects on Construction, while the Automotive industry may suffer less than has been expected.

From the policy impact point of view, we can say that the policy itself has been at least partially successful in preserving jobs in the economy. The unemployment rate could have reached 3.49 % but officially it was only 2.55 %. We may assume that the difference could be counted towards the government policy, that has been aimed mainly on job preservation after all (neglecting the estimation error). That means approximately 14 000 jobs have been saved by the government. Of course, the question of efficiency arises here as the fiscal stimuli have been enormous. Programs Antivirus A and B, which have been major channels for preserving the jobs in affected firms, spent 23.7 billions CZK (almost 1 billion EUR) on employee wage compensations, meaning that one average job place preserved cost 1.7 million CZK – three times more, that is the GDP per capita. Such a finding suggests a huge inefficiency in the economic measures that have been undertaken in the case of the Czech Republic. Moreover, as the domestic labor market has been probably above its potential with very low unemployment rates, we must ask if the jobs´ protection is not only temporary and if the financial aid has not been only postponing the labor market reversal to its natural rates. This problem opens space for further research.

Several limitations of our analysis should be acknowledged. First, our CGE model assumes household consumption is primarily constrained by disposable income, while during lockdowns, the main constraint was actually the inability to spend due to closed establishments, leading to forced savings. This might affect our estimates of consumption patterns and their subsequent effects. Second, the static nature of both I-O and CGE models limits our ability to capture dynamic adjustments in economic behavior, particularly the post-lockdown consumption rebounds. Third, while our ADL model adds some dynamic perspective, it cannot fully capture the structural breaks in economic relationships caused by unprecedented policy interventions. Additionally, our analysis focuses primarily on employment effects, while other important aspects like price level changes, long-term structural shifts, or the efficiency of alternative policy measures remain outside the scope of this study. These limitations suggest potential directions for future research, particularly regarding the dynamics of household consumption patterns during forced lockdowns and the long-term structural changes in the economy.

ACKNOWLEDGEMENT

This result was financially supported by institutional support for the long-term conceptual development of the research organization for the years 2023–2027 and is part of the research task “Impacts of the Targeted Employment Support Program Antivirus (70210)” (Dopady cíleného programu podpory zaměstnanosti Antivirus, 70210) solved by the Research Institute for Labour and Social Affairs (Výzkumný ústave práce a sociálních věcí, v. v. i.,) in the years 2024–2025.

References

BAKER, S. R., BLOOM, N., DAVIS, S. J., TERRY, S. J. (2020). *Covid-induced economic uncertainty*. NBER Working Paper 26983.

BARTIK, A. W., BERTRAND, M., CULLEN, Z. B., GLAESER, E. L., LUCA, M., STANTON, C. T. (2020). *How are small businesses adjusting to COVID-19? Early evidence from a survey*. NBER Working Paper w26989.

BOSIO, E., JOLEVSKI, F., LEMOINE, J., RAMALHO, R. (2020). Survival of Firms in Developing Economies during Economic Crisis. In: DJANKOV, S. PANIZZA, U. (eds.) *COVID-19 in Developing Economies*, London: Centre for Economic Policy Research, 157–174.

BROWN, R., ROCHA, A. (2020). Entrepreneurial Uncertainty during the Covid-19 Crisis: Mapping the Temporal Dynamics of Entrepreneurial Finance [online]. *Journal of Business Venturing Insights*, Vol. 14. <https://doi.org/10.1016/j.jbvi.2020.e00174>.

BROWN, R. ROCHA, A., COWLING, M. (2020). Financing entrepreneurship in times of crisis: Exploring the impact of COVID-19 on the market for entrepreneurial finance in the United Kingdom [online]. *International Small Business Journal*, online first. <https://doi.org/10.1177/0266242620937464>.

ÇAKMAKLI, C., DEMIRALP, S, KALEMLI-ÖZCAN, S., YESILTAS, S., YILDIRIM, M. A. (2020). *COVID-19 and Emerging Markets: a SIR Model, Demand Shocks and Capital Flows*. NBER Working Papers 27191, National Bureau of Economic Research, Inc.

CCSA. (2020). *How COVID-19 is Changing the World: a Statistical Perspective*. Committee for the Coordination of Statistical Activities.

COIBION, O., GORODNICHENKO, Y., WEBER, M. (2020). *The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending*. NBER Working Paper 27141.

CZECH NATIONAL BANK. (2019). *CNB forecast – archive: CNB forecast – November 2019* [online]. <https://www.cnb.cz/en/monetary-policy/forecast/cnb-forecast-archive>.

CZECH STATISTICAL OFFICE. (2022). *GDP, National Accounts: Database of National accounts, Czech Republic* [online]. <https://apl.czso.cz/pll/rocenka/rocenka.index>.

DEMIRGÜÇ-KUNT, A., PERIA, M. S. M., TRESSEL, T. (2020). The global financial crisis and the capital structure of firms: Was the impact more severe among SMEs and non-listed firms? *Journal of Corporate Finance*, 60: 101514.

FAIRLIE, R. (2020). The Impact of COVID-19 on Small Business Owners: Evidence from the First 3 Months after Widespread Social-Distancing Restrictions. *Journal of Economics and Management Strategy*, 1: 1–14.

FEZZI, C., FANGHELLA, V. (2020). Real-Time Estimation of the Short-Run Impact of COVID-19 on Economic Activity Using Electricity Market Data. *Environmental and Resource Economics*, 76: 885–900

GIAMMETTI, R., PAPI, L., TEOBALDELLI, D., TICCHI, D. (2020) The Italian value chain in the pandemic: the input–output impact of Covid-19 lockdown [published online ahead of print, 6.6.2020]. *Journal of Industrial and Business Economics*, 1–15. <https://doi.org/10.1007/s40812-020-00164-9>.

GRANGER, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37(3): 424–38.

GRETTON, P. (2013). *On input–output tables: uses and abuses*. Productivity Commission, staff research note.

GUAN, D., WANG, D., HALLEGATTE, S. et al. (2020). Global supply-chain effects of COVID-19 control measures. *Nat Hum Behav*, 4: 577–587.

HAVRLANT, D., DARANDARY, A., MUHSEN, A. (2021). Early estimates of the impact of the COVID-19 pandemic on GDP: a case study of Saudi Arabia [online]. *Applied Economics*, 53(12): 1317–1325. <https://doi.org/10.1080/00036846.2020.1828809>.

HOSOE, N., GASAWA, K., HASHIMOTO, H. (2015). *Textbook of computable general equilibrium modeling – programming and simulations*. Palgrave Macmillan, UK.

HOWELL, S., LERNER, J., NANDA, R., TOWNSEND, R. (2020). Financial Distancing: How Venture Capital Follows the Economy Down and Curtails Innovation. *Harvard Business School Working Paper*, 20–115.

KEHOE, T. J., PUJOLAS, P. S., ROSSBACH, J. (2017). Quantitative trade models: Developents and challenges. *Annual Review of Economics*, 9: 295–325.

KEOGH-BROWN, M. R., TARP JENSEN, H., EDMUNDS, W. J., SMITH, R. D. (2020). The impact of Covid-19, associated behaviours and policies on the UK economy: a computable general equilibrium model. *SSM – Population Health*, Vol. 12.

LUCCHESE, M., PIANTA, M. (2020). The Coming Coronavirus Crisis: What Can We Learn? [online]. *Intereconomics*, 55: 98–104. <https://doi.org/10.1007/s10272-020-0878-0>.

MANDEL, A., VEETIL, V. (2020). The Economic Cost of COVID Lockdowns: an Out-of-Equilibrium Analysis [online]. *Econ. Disaster Clim. Chang*, 19: 1–21. Epub. ahead of print: PMID 32838118, PMCID PMC7304379. <https://doi.org/10.1007/s41885-020-00066-z>.

MARIOLIS, T., RODOUSAKIS, N., SOKLIS, G. (2020). The COVID-19 multiplier effects of tourism on the Greek economy [online]. *Tourism Economics*, 27(8). <https://doi.org/10.1177/1354816620946547>.

PARTRIDGE, M., RICKMAN, D. (2010). Computable General Equilibrium (CGE) Modelling for Regional Economic Development Analysis. *Regional Studies, Taylor & Francis Journals*, 44(10): 1311–1328.

PRAGYAN, D., FURCERI, D., OSTRY, J. D., TAWK, N. (2022). The Economic Effects of COVID-19 Containment Measures. *Open Economies Review*, 33: 1–32.

OSOTIMEHIN, S., POPOV, L. (2020). *Sectoral Impact of COVID-19: Cascading Risks*. WP 30, May 2020, Opportunity and Inclusive Growth Institute.

RICHIARDI, M., BRONKA, P., COLLADO, D. (2020). *The Economic Consequences of COVID-19 lock-down in the UK. An Input-Output Analysis Using Consensus Scenarios*. WP: ISER, University of Essex.

TIMMER, M. P., DIETZENBACHER, E., LOS, B., STEHRER, R., DE VRIES, G. J. (2015). An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. *Review of International Economics*, 23: 575–605.

TRAPLETTI, A., HORNIK, K. (2022). *Tseries: Time Series Analysis and Computational Finance* [online]. R package version 0.10-51. <https://CRAN.R-project.org/package=tseries>.

WALMSLEY, T., ROSE A., WEI, D. (2020). Impacts on the U.S. Macroeconomy of Mandatory Business Closures in Response to the COVID-19 Pandemic [online]. *SSRN*. <https://ssrn.com/abstract=3570117 or http://dx.doi.org/10.2139/ssrn.3570117>.

WORLD BANK. (2020). *COVID-19 to Plunge Global Economy into Worst Recession since World War II*. Press Release, 8th June, Washington DC.

Digitalization in the Public Sector: Unravelling (Un)Conditional Effects of E-Government on the Absorption of European Cohesion Policy

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Received 6.3.2024 (revision received 20.5.2024), **Accepted** (reviewed) 10.8.2024, **Published** 13.12.2024

Abstract

This paper contributes to the recent empirical literature on the absorption determinants of the European Cohesion Policy (ECP). In particular, it attempts to verify the effect of the digitalization of the public sector in the form of e-government services on the ECP absorption rates during the period 2007–2016. Using the fixed effects panel models, we confirm that increased usage of e-government services is associated with higher absorption rates of the beneficiaries. Moreover, we reveal its conditional effects in connection with government quality, human capital, and recessionary periods. While its positive effect is neutralized in the recession, the benefits of the e-government use towards ECP absorption are more pronounced at a higher level of government quality and a share of skilled labor. The results therefore suggest that the promotion of digitalization and training can not only promote economic growth and innovation as commonly known but, as the analysis shows, can also be valuable in terms of ECP absorption rates.

Keywords	***DOI***	***JEL code***
Digitalization, European Cohesion Policy, e-government, absorption	*https://doi.org/10.54694/stat.2024.11*	*E22, H50, I25, O38*

INTRODUCTION

In the current era characterized by technological breakthroughs, digitalization has become one of the key elements in driving social progress and economic growth (Ding et al., 2021; Rong, 2022; Zhang et al., 2021). Previous research points to its ability to improve entrepreneurial performance by lowering

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operational costs and higher efficiency of supply chains which turns into increased revenues, market expansion, and finally accelerates the GDP growth rates (see, e.g., Endres et al., 2022; Gomes et al., 2022; Kreiterling, 2023).

Digital technologies can not only support innovation in private companies, but similar effects can be observed in the public sector as well (Dos Santos et al., 2022; Fischer et al., 2021). In this regard, *e-government* has been acknowledged to boost labor productivity in the public sector, its efficiency, and economic growth (Corsi et al., 2006). It can also increase transparency and make government services more accessible to citizens (Castro and Lopes, 2022).

Such benefits prevail in many European countries that stand out globally for their resilient digital government strategies and efficient online services (see, United Nations, 2022). Moreover, the European Union (EU) is proactively shaping the digital landscape of Europe by advancing e-government, ensuring transparency, and prioritizing citizen-centric services. In this respect, the European Commission acts, among other things, in building European interoperable platforms, such as a common framework for the management of citizens' electronic identity (European Commission, 2022).

The EU acknowledges the significant transformative potential of e-government not only in streamlining public services but also in promoting cohesion. In this respect, the e-government should represent an important catalyst with regard to the EU's main investment policy, the European Cohesion Policy (ECP). The projects financed by the ECP may contribute to the fulfillment of the EU's digital strategy, "*A Europe fit for the digital age*", but also the e-government should play a pivotal role in the active engagement of the citizens, transparent management, and efficient absorption of the ECP funds, i.e., the ability to efficiently use the ECP payments (European Commission, 2024a; Tiganasu and Lupu, 2023).

Although the theoretical assumptions point to the relevance of e-government in the ECP absorption, it must be said that there has been published only one paper that attempts to quantitatively evaluate the effect of e-government on ECP absorption (Tiganasu and Lupu, 2023) those findings are restricted to the Central and Eastern European (CEE) region.

Given that above, we formulate the research question as follows: *is the increased use of e-government services in all EU beneficiary countries contributing to the ECP absorption directly or are there any conditionalities?* Since most of the previous empirical research on the determinants of the ECP absorption capacity has been done in the form of qualitative studies lacking answers to this question (see, e.g., Milio, 2007; Moreno, 2020; Tosun, 2014; Surubaru, 2017), this paper aims to contribute to this strand of research by providing a quantitative analysis of absorption capacity determinants for all EU recipient countries in the period 2007–2016, with a focus on the e-government and its effects.

Our results suggest that e-government seemed to boost the ECP absorption rates in the selected period directly, but it had also a conditional dimension. While its positive effect diminished during the recessionary periods, the beneficial effect of increased e-government usage on the ECP absorption rates became more noticeable with a higher share of skilled labor and government quality.

The remainder of this article is structured as follows. The next section reviews empirical studies focusing on the driving forces of the ECP absorption and their expected outcomes. In the second section, we explain our choice of model specification, including the selected variables under investigation. The third section is devoted to the empirical results and discussion. The last part summarizes our findings and offers recommendations regarding e-government intending to support the ECP absorption rates in the EU beneficiary countries.

1 LITERATURE REVIEW

So far, empirical research on the ECP absorption rate has been predominantly carried out in the form of case studies or comparative analyses (see, e.g., Milio, 2007; Moreno, 2020; Terracciano and Graziano, 2016; Tosun, 2014; Surubaru, 2017). In this context, the authors evaluate the absorption levels across countries, regions, and individual programming periods, but also attempt to clarify which determinants drive the ECP absorption.

Overall, the absorption levels tend to be relatively low initially for many recipient countries, followed by accelerated spending at the end of program periods. This pattern in expenditure is debatable as it can distort the expected effects of the ECP due to a possible "*absorption-for-all*" approach (Stiblarova, 2022; Surubaru, 2017).

Significant differences regarding absorption may, however, emerge between countries or regions. Some studies point out that, compared to the old EU member states, newer members tend to absorb a higher proportion of the ECP funding because of their greater need for investments in key areas, such as infrastructure or institutional capacity-building (see, e.g., Ciffolilli et al., 2023; Tosun, 2014). Moreover, Moreno (2020) investigates the regional absorption capacity in the programming period 2007–2013, which is not so much of interest compared to absorption at the national level. The author finds significantly heterogeneous evidence not only between countries but also within the regions of one country, which in a certain way alleviates the effect of cultural factors on the absorption capacity.

The majority of empirical studies on the ECP absorption, although, acknowledge that sound institutional, political, and legal conditions are the primary drivers of absorption (see, e.g., Bachtler et al., 2014; Ciffolilli et al., 2023; Incaltarau et al., 2020; Surubaru, 2017). Since good government quality is a prerequisite for development (Incaltarau et al., 2020), it can mediate not only the effect of the Cohesion Policy but also its implementation (Rodriguez-Pose and Garcilazo, 2015).

In this regard, good government quality should ensure higher transparency and accountability in the ECP allocation and implementation, which should be in turn reflected in the higher absorption rate of the funds (Ciffolilli et al., 2023; Surubaru, 2017). Mendez and Bachtler (2024) confirm this assumption for 173 European regions in the period 2007–2013. The authors acknowledge the government quality to be the fundamental determinant of timely spending and outcomes of the ECP. Based on the results, Mendez and Bachtler (2024) also call for capacity-building in regions that suffer from low government quality to boost ECP implementation.

Tosun (2014) provides the analysis of the European Regional Development Fund (ERDF) absorption capacity of 25 recipients in the 2000–2006 programming period. In line with expectations, the author observes a positive relationship between government effectiveness and ERDF absorption. Similar evidence is provided by Incaltarau et al. (2020) who investigated the absorption capacity in the period 2007–2015. The authors confirm that government effectiveness and control of corruption strongly support the ECP absorption, and this holds especially for the newer member states, i.e., countries that joined the EU in 2004 and 2007. Such results could explain why some of these countries still face difficulties regarding efficient ECP funding compared to the old member states.

The absorption of the ECP funds can be accelerated or slowed down by the way the country is able to manage the disbursement of funds from the ECP. Thus, political support can help build institutional structures needed for ECP administration (Ciffolilli et al., 2023). In this context, Surubaru (2017) focuses on the ECP absorption in two recipient countries–Bulgaria and Romania during the period 2007–2013. Based on the questionnaire, the author stresses that greater Bulgarian absorption could be attributed to the simplification of processes regarding the drawing of funds by the political agency. Although both countries had less experience with managing funds, it seems that they significantly improved in terms of establishing the institutional structure and procedures needed to manage the ECP funds.

In addition to the government quality, administrative capacity has been approved to be one of the strongest predictors of ECP absorption (see, e.g., Ciffolilli et al., 2014; OECD, 2020; Terracciano and Graziano, 2016; Tosun, 2014). Here, the focus is placed on the human resource-related infrastructure (both quantity and quality) in public administration responsible for the processing of the ECP funding.

A high administrative capacity enables better implementation of EU policies and thus promotes the absorption of the ECP funds (see, e.g., Bachtler et al., 2014; Incaltarau et al., 2020). For this reason, Incaltarau et al. (2020) suggest aiming at administrative capacity-building and control of corruption in regions with low administrative capacity. Dimitrova and Toshkov (2009) and Incaltarau et al. (2020) claim that the weakness regarding administrative capacity has been mainly observed in newer EU member, both before and after their accession. The elimination of unfair practices in the form of corruption or rent-seeking could therefore assist countries to reach their growth potential through more efficient ECP.

The socio-economic conditions of recipient countries/regions have been also considered relevant in absorption research in previous empirical studies (see, e.g., Ciffolilli et al., 2014; Kersan-Skabic and Tijanic, 2017; Mendez and Bachtler, 2024). Ciffolilli et al. (2014) observe that low-income countries tend to spend the ECP rapidly to boost their economic growth. The absorption of the ECP also positively correlates with the ECP allocation itself; here, the authors find that higher allocation is associated with a higher absorption rate (Incaltarau et al., 2020; Mendez and Bachtler, 2024). This is related to the fact that with a higher allocated amount of the ECP, the implementing agencies can expand their capacities, but also do scalable projects (Ciffolilli et al., 2014).

Except for that, successful project implementation requires skilled labor. Taking this into consideration, a sufficient level of human capital may allow to implement the ECP projects more effectively and in turn, contribute to the higher absorption. A similar relationship may be expected for the infrastructure as well (see, e.g., Kersan-Skabic and Tijanic, 2017).

On the contrary, the effect of some absorption drivers has not been clearly confirmed yet. Such a case is, for example, fiscal decentralization. Kersan-Skabic and Tijanic (2017) find a positive effect of fiscal decentralization on the absorption of the ECP in the period 2000–2011. While according to Tosun (2014), it seems that fiscal decentralization decelerates the absorption performance, which may be the result of the need for greater coordination across multiple entities and subsequent delays in drawing funds. However, the results do not seem to be robust. A similar, insignificant evidence on the effect of political decentralization has been brought by Incaltarau et al. (2020) while investigating absorption capacity in the period 2007–2015.

The absorption level can be additionally related to exogenous factors, such as economic crises. In this regard, the recession can lead to lower absorption, as during the crisis it can be more difficult to co-finance projects from the ECP due to fiscal consolidation (European Commission, 2013; Surubaru, 2017).

Difficulties in terms of the ECP may also arise due to the lack of digitalization, although, it has not been extensively explored in quantitative studies with connection to the ECP absorption. A rare econometric analysis is provided by Tiganasu and Lupu (2023) who examine the trilateral relationship between regional governance, digitalization, and the ECP payments for 56 regions from the CEE countries. The authors confirm a positive effect of digitalization on the ECP payments in the observed period 2007–2018. Tiganasu and Lupu (2023) also state that in the CEE regions with weak governance, the possibility of carrying out massive digitalization decreases, and so does the subsequent access to the ECP funding.

Since the evidence on this matter is limited, the aim of this paper is to investigate how the digitalization of government services, i.e., the e-government activities of individuals are related to the absorption of the Cohesion Policy. In contrast to Tiganasu and Lupu (2023), we provide evidence for all recipients of the ECP in the programming period 2007–2013, including the n + 3 allocation rule at the national level, by which we contribute to this strand of literature. Not only direct effect of e-government is the subject of investigation. We assume that there might be some conditionalities regarding e-government. While in general, the recessionary period may be associated with lower absorption rates, the effect of e-government during the crisis period has not been investigated. Additionally, the effectiveness may also depend on the governance quality and the human capital, i.e., the ability of citizens to use such services. Although in the majority of professions digital skills are considered crucial, according to the European Commission (2024b), more than a third of working Europeans still lack basic digital skills which could diminish the e-government benefits. The obtained results will be used for the formulation of recommendations with the aim of ensuring effective and faster absorption of the ECP funds.

2 METHODOLOGY AND DATA

Since the aim of this paper is to examine the main drivers of the ECP absorption, with an emphasis placed on the effect of e-government, we estimate the fixed effects panel model (Baltagi, 2021) in the following way:

$$Absorption_{it} = \beta\, Egov_{it-1} + \sum_{c=1}^{C} \gamma_c \log CV_{cit-1} + \alpha_i + \varepsilon_{it}\,. \tag{1}$$

Our dependent variable $Absorption_{it}$ presents the ECP absorption rate (%) in the particular recipient country i in period t. The set of explanatory variables consists of $Egov_{it-1}$, the proxy for digitalization in the public sector, and several control variables (CV_{cit-1}). Among them, frequently mentioned are absorption determinants, such as human capital, ECP expenditure, and government quality. These continuous explanatory variables are considered lagged by one year ($t - 1$) to control for possible endogeneity problem. We also control for the crisis period (2008–2009) and the effect of the membership in the euro area. Finally, the term α_i denotes fixed effects, and ε_{it} is the random term.

As for defining the dependent variable, the ECP absorption rate is calculated in a standard way as a percentage share of total spent ECP funds on the total allocated sum of ECP funds (see, e.g., Ciffolilli et al., 2023; Surubaru, 2017; or Tosun, 2014):[2]

$$Absorption_{it} = \frac{ECP\ payments_{it}}{ECP\ allocation_{it}}\,. \tag{2}$$

It follows from this that the absorption rate of the ECP is restricted in its range, i.e., it varies from 0 to 100 percent (see Table 1).

Table 1 Descriptive statistics

	Obs.	Mean	Std. dev.	Min	Max
Absorption	280	44.667	33.612	0.000	100.000
E-gov	223	42.893	18.178	4.930	88.080
ECP	251	0.997	1.230	0.009	4.990
Human cap	245	30.879	8.735	14.700	49.200
Govern	252	6.763	1.084	4.592	8.878

Source: Author's calculations based on data from the European Commission, Eurostat, and the World Bank

Regarding the proxy variable for digitalization, our main independent variable of interest $Egov_{it-1}$ represents the proportion of residents who have communicated with public bodies through websites

[2] As for the definition of the variable, to prevent non-stationarity and consequent spurious regression, we express most variables as ratio indicators (i.e., % of population, GDP).

in the past year.[3] Here, we anticipate that the use of e-government initiatives will reduce administrative burdens and expedite procedures related to project implementation, and, among other things, will thus be linked to a higher rate of ECP fund absorption.

Furthermore, it is probable that the effect of e-government will depend on some other variables. Because of this, we also look at the possibility of how the e-government interacts with crisis prevalence ($E\text{-}gov_{t-1}$ x $Crisis_t$), human capital ($E\text{-}gov_{t-1}$ x $Human\ cap_{t-1}$), and government quality ($E\text{-}gov_{t-1}$ x $Govern_{t-1}$).

Firstly, the effect of e-government in times of crisis has not been closely investigated yet. The e-government could potentially play a positive mediating role through the improvement of the ECP management and selection processes, which could be later translated into faster ECP absorption. However, we expect that the progress of e-government has likely been moderated in the crisis of 2008–2009 as a result of fiscal consolidation.

For the government quality and human capital, we posit that they may play a mediator role in delivering a positive effect of the e-government activities on the ECP absorption. While the positive effect regarding government quality has been confirmed by Tiganasu and Lupu (2023), the empirical literature lacks evidence on the interaction of human capital and e-government. In this regard, we expect that the synergy between e-government and human capital can boost the absorption of the European Cohesion Policy funds by promoting efficiency, transparency, and stakeholder engagement.

The mentioned explanatory variables are listed in the model also as the linear terms, i.e., the control variables. The choice of our control variables has been made based on previous empirical studies concerning the ECP absorption rate. Concerning this, we include the total ECP expenditure (as a share of GDP) to the recipient countries (ECP_{it-1}) as it has been shown that larger amounts are associated with faster absorption (see, e.g., Mendez and Bachtler, 2024).

We also consider human capital ($Human\ cap_{it-1}$), proxied by a share of employed people with tertiary education. We expect that highly skilled labor can contribute to more effective implementation and faster absorption of the ECP funds as in Ciffolilli et al. (2023).

Similarly, a higher-level government quality ($Govern_{it-1}$) has been acknowledged to promote the ECP absorption rates (Bachtler et al., 2014; Surubaru, 2017; Terracciano and Graziano, 2016). To construct this variable, we follow the study of Incaltarau et al. (2020); we define government quality as the equally weighted composite measure of control of corruption and political stability indicators. The used indicators have been retrieved from the World Governance Indicators database provided by the World Bank.

Finally, we consider two dummy explanatory variables. One for controlling the crisis period 2008–2009 ($Crisis_{it}$) and the other for controlling the membership in the euro area ($Euro_{it}$). While in the case of the crisis, past studies point to a lower absorption (Surubaru, 2017), in the second case, we expect that member countries may experience higher ECP absorption due to policy alignment and enhanced coordination.

The model is estimated based on 28 recipient countries in 2007–2016.[4] We chose this period since it fully covers the programming period 2007–2013, including the n + 3 allocation rule. The descriptive statistics for considered variables are provided in Table 1. We also provide the correlation matrix in Table A1 in the Appendix.

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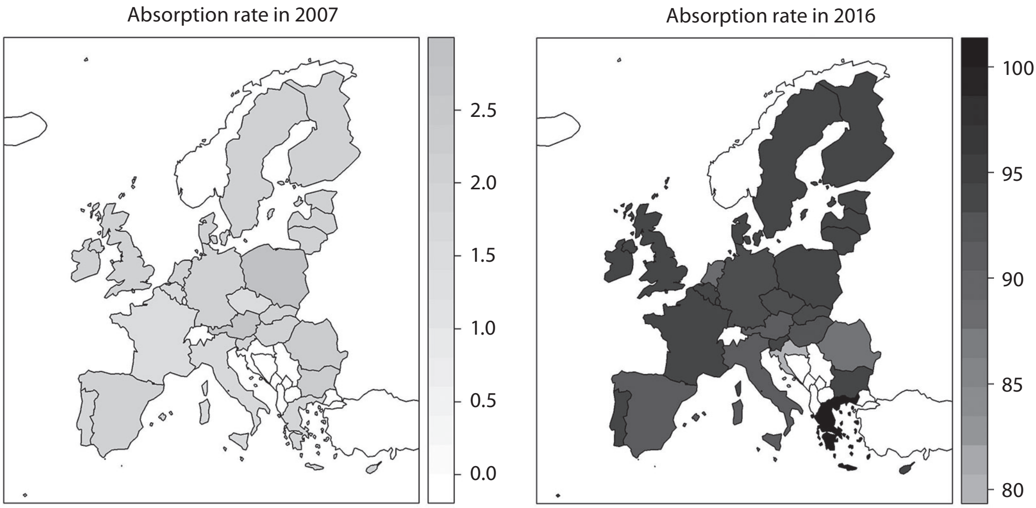
[3] To the best of our knowledge, there is not a more suitable indicator that directly captures communication between legal entities and public institutions. While we acknowledge that the ECP recipients include both individuals and legal entities, the rationale for using this indicator stems from the fact that the level of interaction of individuals with public institutions should be highly correlated with the interaction of legal entities with public institutions. Notably, countries like Denmark, Finland, and Sweden exhibit the highest values in our e-government proxy. These countries also lead in more complex e-government rankings, such as the United Nations' E-Government Development Index (EGDI), validating our assumption.

[4] The newer observations have not been included since we would not be able to capture the absorption rate for the entire programming period 2014–2020. That is, we would not be able to capture a significant use of funds which occurs mostly after the end of the programming period.

3 EMPIRICAL RESULTS AND DISCUSSION

Firstly, we provide empirical evidence on the ECP absorption rate across the recipient countries. The comparison of the start (year 2007) and the end of drawing on ECP (year 2016) within a given programming period is depicted in Figure 1.

Figure 1 Absorption rate of the ECP in the EU countries (year 2007 and 2016)



Source: Author's elaboration based on data from the European Commission © EuroGeographics for the administrative boundaries

As can be seen, the difference over time is significant. The absorption rate in the first year of the programming period 2007–2013 reached a deficient level in all beneficiary countries, while in 2016 it ranged between 80–100 percent. The obtained evidence thus confirms the slow start of ECP funding, with the minimum absorption rate achieved by Luxembourg, at 1%.

On the other hand, Poland has been a leader with the absorption of 2.8%. It must also be said that Poland has been the largest recipient of the ECP in this programming period, with a budget of over 67 billion EUR which may indicate that a higher budget is associated with faster absorption as in Mendez and Bachtler (2024).

Similar to the Polish economy, many CEE countries have benefited from higher ECP funding and shown above-average absorption rates, such as Estonia, Lithuania, or Slovenia. The results, therefore, do not necessarily imply that more developed countries with better digitization are also more adept at securing funding and meeting monitoring criteria, leading to a higher absorption rate. However, some differences in the dynamics of the absorption of financial resources can be observed in the CEE countries over time compared to the average absorption rate in the EU as well (see Figure A1 in the Appendix). For instance, Romania and Croatia have absorbed significantly lower ECP funding throughout the whole programming period (see also Figure 1 on the right). Such evidence can be explained by the fact that these countries lacked sufficient administrative capacity and institutional quality, needed for efficient management and implementation of the ECP projects.

It should also be noted that Croatia became the EU member state only in 2013 and before that, it only received pre-accession funding to build administrative capacity and improve the quality of institutions devoted to the EU funds' management. Despite this effort, many authors point out that an "*absorption shock*" occurred in the next program period as well (see, e.g., Puljiz et al., 2019).

Table 2 Direct effect of the absorption drivers (fixed-effects panel model)

	Absorption rate of the ECP (in %)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
$E\text{-gov}_{t-1}$	2.786***	2.630***	1.023***	0.955***	0.976***	0.975***
	(0.230)	(0.230)	(0.256)	(0.246)	(0.217)	(0.215)
ECP_{t-1}		9.919***	3.877*	3.741*	3.962**	4.024**
		(2.552)	(2.017)	(2.004)	(1.872)	(1.882)
Human cap_{t-1}			6.910***	6.886***	6.942***	6.945***
			(1.103)	(1.088)	(1.199)	(1.193)
Euro_t				12.269	12.647	12.472*
				(7.688)	(7.636)	(7.236)
Crisis_t					1.738	1.559
					(4.511)	(4.607)
Govern_{t-1}						2.711
						(7.010)
No. of observations	223	223	217	217	217	217
No. of countries	28	28	28	28	28	28
R-squared	0.498	0.546	0.804	0.809	0.809	0.809
Log likelihood	–987.640	–976.533	–858.103	–855.391	–855.264	–855.160
AIC	1 977.280	1 957.067	1 722.205	1 718.781	1 720.529	1 722.320

Note: Standard errors are in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.
Source: Author's calculations based on data from the European Commission, Eurostat, and the World Bank

However, such a scenario did not occur in all recipient countries. To provide a bigger picture of the effects of the absorption driving forces, we present the estimation results from fixed-effects panel models in Table 2. To address potential issues of heteroskedasticity and autocorrelation, robust standard errors of estimated regression coefficients are reported in parentheses. Several model variants are considered (columns (I)–(VI)) altering a set of regressors to check the robustness of the results, while we focus solely on the direct effects of considered determinants.

Firstly, we focus on our main variable of interest, e-government (*E-gov*). In line with our assumptions, we confirm that the more citizens use e-government services, the higher the absorption rate is observed in the recipient countries (columns (I)–(VI)). We therefore validate the scarce evidence on the CEE countries provided by Tiganasu and Lupu (2023) according to which digitalization seems to remove certain administrative obstacles and facilitate communication and partnership with governing bodies in the ECP implementation, leading to higher ECP absorption rates. As for the e-government services, their higher rates of usage are not typical simply for the countries of Western or Northern Europe–for instance, Estonia made great progress in digitalization after gaining independence in the 1990s, thanks to which today it excels in digital public services. Along with Denmark, Finland, and Sweden, it has been also ranked by the United Nations as one of the most digitally advanced economies in the world (see, United Nations, 2022). At the same time, their ECP absorption rate was also above average.

Similarly, we find a positive and statistically significant effect of the total ECP expenditure (*ECP*) on the ECP absorption rate in 2007–2016 (columns (II)–(VI)). The results therefore point to the fact that countries with a higher budget achieve a higher absorption on average, of which the aforementioned

Poland was a perfect example. Additionally, a larger proportion of skilled labor (*Human cap*) is associated with increased ECP absorption rates, aligning with the research by Kersan-Skabic and Tijanic (2017).

Regarding our binary explanatory variables, *Euro* and *Crisis*, we observe that countries that use the common currency, the Euro, have adopted on average more ECP funding (columns (IV)–(VI)). The same applies to the crisis period 2008–2009 (columns (V)–(VI)) which does not confirm the claims about the worsened possibility of drawing the ECP funds in the recessionary periods. We must add, however, that the significance of the estimated coefficients related to the *Euro* and *Crisis* has not been proved in all considered model specifications, so we cannot draw clear conclusions based on these models. Similar insignificant evidence is provided for government quality (*Govern*, column, VI).[5]

Table 3 Conditional effects of the e-government (fixed-effects panel model)

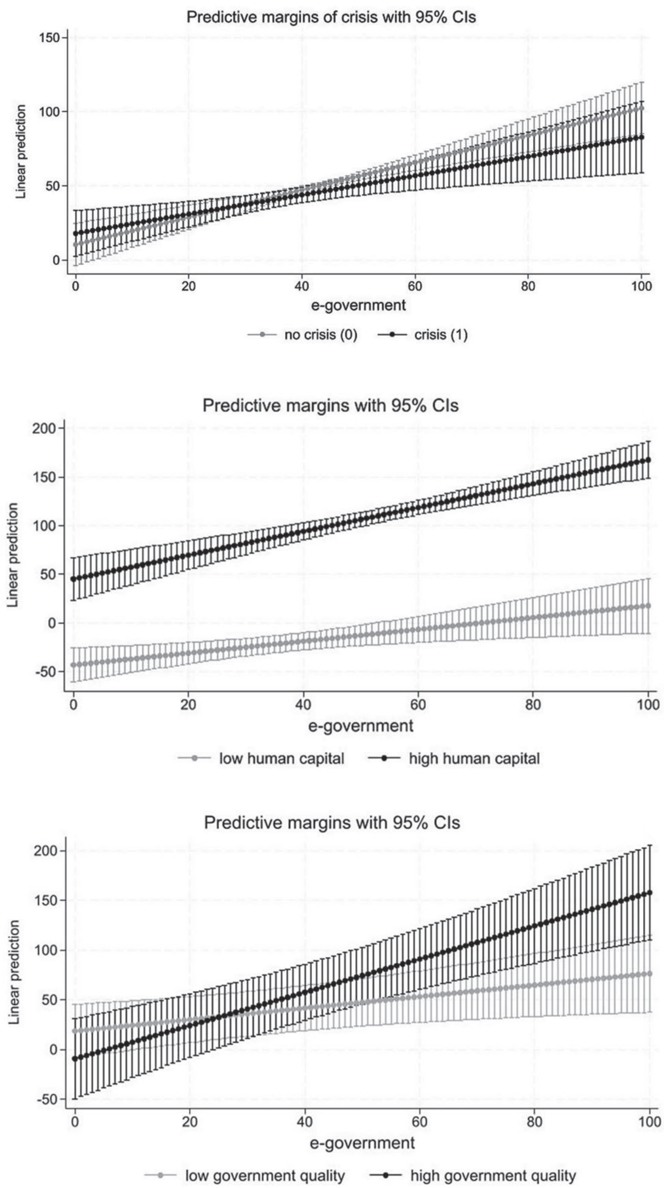
	Absorption rate of the ECP (in %)		
	(I)	(II)	(III)
E-gov_{t-1}	0.919***	–0.143	–0.789
	(0.160)	(0.450)	(0.767)
ECP_{t-1}	3.989***	5.276***	4.876***
	(1.509)	(1.648)	(1.598)
Human cap_{t-1}	6.677***	4.907***	6.955***
	(0.425)	(0.783)	(0.446)
Euro_{t}	8.959*	6.355	12.215**
	(4.874)	(5.181)	(5.699)
Crisis_{t}	7.507	–4.619	3.435
	(6.294)	(3.505)	(3.825)
E-gov_{t-1} x Crisis_{t}	–0.271**		
	(0.137)		
E-gov_{t-1} x Human cap_{t-1}		0.034***	
		(0.013)	
Govern_{t-1}			-6.963
			(7.593)
E-gov_{t-1} x Govern_{t-1}			0.273**
			(0.116)
No. of observations	217	217	217
No. of countries	28	28	28
R-squared	0.833	0.810	0.815
Log likelihood	–962.788	–981.958	–851.9001
AIC	1 939.575	1 977.916	1 719.802

Note: Standard errors are in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.
Source: Author's calculations based on data from the European Commission, Eurostat, and the World Bank

[5] Since the main goal of this study is to focus on the effect of e-government on the ECP absorption rate, we opted for the model specifications in which this main explanatory variable is always represented. This brings the disadvantage of a higher correlation of the E-gov variable with government quality (see correlation matrix in Table A1 in the Appendix). To address multicollinearity, we explore various model specifications by sequentially incorporating individual explanatory variables, ensuring the E-gov variable is included last. Moreover, the effect of government quality is not key from the point of view of this analysis, and its insignificance is, through the lens of higher correlation, rather taken with caution.

When examining the driving forces behind the ECP absorption rate, it is also plausible that certain conditional effects may arise. Since we focus on the role of e-government, we provide the estimation results where we consider several interaction terms. In particular, interaction terms of the e-government with the *Crisis* variable, human capital (*Human cap*), and government quality (*Govern*). The results on the conditional effects of the e-government are available in Table 3.

Figure 2 Interaction plots



Note: We depict the interaction plots for statistically significant interaction terms.
Source: Author's calculations based on data from the European Commission, Eurostat, and the World Bank

Firstly, we focus on the interaction between e-government and the crisis. Although the difference in slopes is relatively modest (as indicated by the upper interaction plot in Figure 2), our results show that the positive effect of greater e-government use is neutralized during the examined recessionary period. Given that the 2008–2009 recession was characterized by fiscal austerity, our findings suggest that modernization and innovation were deprioritized due to fiscal consolidation and austerity measures during this crisis. During challenging fiscal periods, the advancement of e-government can be particularly arduous, especially in countries lacking a robust internet infrastructure. This was notably the case in many (especially Central and Eastern) European countries at the time, which validates such findings.

On the other hand, we find a positive and statistically significant coefficient related to the interaction term of the e-government and human capital. This suggests that the benefits of the increased use of e-government towards ECP absorption rate are more pronounced in the case that there is a higher proportion of highly skilled labor in the recipient countries (as indicated by the middle interaction plot in Figure 2). The results can be explained in the sense that higher-skilled labor will more likely have the necessary digital skills, which present a prerequisite for the efficient use of e-government. For digital literacy, it needs to say that it has been increasing in the EU countries, however, in some countries, the share of people with these skills is still relatively low–for example in Bulgaria or Romania (see, European Commission, 2024b; Tarjani et al., 2023). The promotion of these skills can therefore not only foster economic growth and innovation but also, as the analysis shows, be valuable from the point of the ECP absorption rate.

We also find a positive and statistically significant interaction term of the e-government and government quality, suggesting that sound institutions go hand in hand with e-government activities facilitating the ECP absorption. The findings imply that superior government quality, coupled with increased utilization of e-government services, leads to a greater ECP absorption rate. Our evidence of the conditional effect of e-government on government quality also validates the regional evidence of Tiganasu and Lupu (2023) and thus calls for an increase in the quality of the institution with the aim of delivering a higher absorption of the ECP funding.

CONCLUSIONS

Unlike the existing case studies and comparative analyses concerning the determinants of the ECP absorption, this paper aimed to quantitatively measure the effect of the e-government on the ECP absorption rates, which is still not the subject of extensive research. Based on the fixed-effects panel estimation, our results confirm that e-government matters for the absorption of the ECP payments. In particular, the more these services are used, the higher absorption rates are observed in the period 2007–2016, which validates the scarce evidence on the CEE region by Tiganasu and Lupu (2023).

The main contribution of this paper, however, lies in revealing its conditional effects. We find that the positive effect of e-government diminishes in times of crisis, and thus does not deliver the expected outcome on the EU absorption rates. To overcome such problems, it would be advisable to strengthen the e-government systems to assure their resilience during the recessionary periods. Not only robust digital infrastructure but also ensuring training and capacity building for responsible ECP authorities and coordinators could increase their ability to cope with difficult crisis periods and mitigate the consequences of crisis on the ECP absorption rates in the next programming periods.

For the human capital and government quality, we discover the opposite–higher skilled labor and government quality seem to enhance the benefits of e-government on the ECP absorption. While the improvement of government quality has already been proven to contribute to the effectiveness of e-government concerning ECP absorption, the positive interaction of human capital with e-government presents a novel finding. This suggests that the use of the expertise of highly qualified workers is important for optimizing the benefits of e-government. To enhance the ECP absorption, the effort could be thus directed to facilitate the establishment of digital innovation hubs, and strengthen cooperation between universities and research institutions, which can boost innovations and transfer of knowledge, but also provide highly skilled graduates. The policies should be also targeted at training and promoting digital literacy. In this respect, the EU's initiative "A Europe fit for the digital age" with a budget of 250 billion from NewGenerationEU could bring desired effects, as it aims to ensure that 80 percent of the EU citizens have basic digital skills by 2030.

Although, it must be added that some challenges in applying digital technologies in the public sector include, for instance, high deployment costs, privacy and ethical concerns, legal frameworks, and data security (for more, see, e.g., Dos Santos et al., 2022). By addressing them, building robust infrastructure, and focusing on training and cooperation of the responsible authorities, the beneficiary countries could, therefore, promote their ECP absorption rates.

ACKNOWLEDGMENT

This work was supported by the Scientific Grant Agency VEGA under Grant No. 1/0154/24.

References

BACHTLER, J., MENDEZ, C. ORAZE, H. (2014). From Conditionality to Europeanization in Central and Eastern Europe: Administrative Performance and Capacity in Cohesion Policy [online]. *European Planning Studies*, 22(4): 735–757. <https://doi.org/10.1080/09654313. 2013.772744>.

BALTAGI, B. (2021). *Econometric Analysis of Panel Data*. 6th Ed. Springer International Publishing.

CASTRO, C., LOPES, C. (2022). Digital Government and Sustainable Development [online]. *Journal of Knowledge Economy*, 13: 880–903. <https://doi.org/10.1007/s13132-021-00749-2>.

CIFFOLILLI, A. et al. (2014). *Expert Evaluation Network on the Performance of Cohesion Policy 2007–2013. Synthesis of National Reports 2013* [online]. <http://aei.pitt.edu/102005/1/2013_synth.pdf>.

CIFFOLILLI, A. et al. (2023). *Absorption Rates of Cohesion Policy Funds: Preliminary Study Results* [online]. Brussels: Policy Department for Structural and Cohesion Policies. <https://www.adcoesao.pt/wp-content/uploads/absorption_rates_of_cohesion.pdf>.

CORSI, L. et al. (2006). *EGovernment Economics Project (eGEP)* [online]. European Commission: eGovernment Unit, DG Information Society and Media. <https://www.researchgate.net/profile/Marcella-Corsi/publication/241765626_eGEP_E conomic_Model_Final_Report_on_the_Benefits_Costs_and_Financing_of_eGovernment/links/02e7e531d0604cfd84000000/eGEP-Economic-Model-Final-Report-on-the-Ben efits-Costs-and-Financing-of-eGovernment.pdf>.

DIMITROVA, A., TOSHKOV, D. (2009). Post-accession Compliance between Administrative Coordination and Political Bargaining [online]. *European Integration Online Papers*, 13(2): 1–18. <https://doi.org/10.1695/2009019>.

DING, Y., ZHANG, H., TANG, S. (2021). How Does the Digital Economy Affect the Domestic Value-Added Rate of Chinese Exports? [online]. *Journal of Global Information Management*, 29(5): 71–85. <https://doi.org/10.4018/JGIM.20210901.oa5>.

DOS SANTOS, S. B. et al. (2022). Digital Transformation in the Public Sector: Enabling Technologies and Their Impacts. In: LOPEZ SANCHEZ, V. M. et al. (eds.) *Industrial Engineering and Operations Management* [online]. Springer International Publishing. <https://doi.org/10.1007/978-3-031-14763-0_9>.

ENDRES, H., HUESIG, S., PESCH, R. (2022). Digital Innovation Management for Entrepreneurial Ecosystems: Services and Functionalities as Drivers of Innovation Management Software Adoption [online]. *Review of Managerial Science*, 16: 135–156. <https://doi.org/10.1007/s11846-021-00441-4>.

EUROPEAN COMMISSION (2013). *Cohesion Policy: Strategic Report 2013 on Programme Implementation 2007–2013* (COM(2013) 210 final) [online]. <https://ec.europa.eu/regional_policy/sources/policy/how/programming-and-implementation/strategic-report/2013/strat_report_2013_en.pdf>.

EUROPEAN COMMISSION (2022). *EGovernment and Digital Public Services* [online]. <https://digital-strategy.ec.europa.eu/en/policies/egovernment>.

EUROPEAN COMMISSION (2024a). *Cohesion Policy Helps Europe Take the Lead in the Digital Age* [online]. <https://ec.europa.eu/regional_policy/whats-new/panorama/2024/02/14-02-2024-cohesion-policy-helps-europe-take-the-lead-in-the-digital-age_en>.

EUROPEAN COMMISSION (2024b). *Digital skills* [online]. <https://digital-strategy.ec.europa.eu/en/policies/digital-skills>.

FISCHER, C., HEUBERGER, M., HEINE, M. (2021). The Impact of Digitalization in the Public Sector: A Systematic Literature Review [online]. *Der Moderne Staat – Dms: Zeitschrift für Public Policy, Recht und Management*, 14(1): 3–23. <https://doi.org/10.3224/dms.v14i1.13>.

GOMES, S., LOPES, J. M., FERREIRA, L. (2022). The Impact of the Digital Economy on Economic Growth: The Case of OECD Countries [online]. RAM, *Revista De Administração Mackenzie*, 23(6): 1–31. <https://doi.org/10.1590/1678-6971/eramd220029.en>.

INCALTARAU, C., PASCARIU, G. C., SURUBARU, N.-C. (2020). Evaluating the Determinants of EU Funds Absorption across Old and New Member States – the Role of Administrative Capacity and Political Governance [online]. *JCMS: Journal of Common Market Studies*, 58(4): 941–961. <https://doi.org/10.1111/jcms.12995>.

KERSAN-SKABIC, I., TIJANIC, L. (2017). Regional Absorption Capacity of EU Funds [online]. *Economic Research*, 30(1): 1191–1208. <https://doi.org/10.1080/1331677X.2017.1340174>.

KREITERLING, C. (2023). Digital Innovation and Entrepreneurship: A Review of Challenges in Competitive Markets [online]. *Journal of Innovation and Entrepreneurship*, 12. <https://doi.org/10.1186/s13731-023-00320-0>.

MENDEZ, C., BACHTLER, J. (2024). The Quality of Government and Administrative Performance: Explaining Cohesion Policy Compliance, Absorption and Achievements across EU Regions [online]. *Regional Studies*, 58(4): 690–703. <https://doi.org/10.1080/00343404.2022.2083593>.

MILIO, S. (2007). Can Administrative Capacity Explain Differences in Regional Performances? Evidence from Structural Funds Implementation in Southern Italy [online]. *Regional Studies*, 41(4): 429–442. <https://doi.org/10.1080/00343400601120213>.

MORENO, R. (2020). EU Cohesion Policy Performance: Regional Variation in the Effectiveness of the management of the Structural Funds. *Investigaciones Regionales – Journal of Regional Research*, 46(1): 27–50.

OECD (2020). *Strengthening Governance of EU Funds under Cohesion Policy: Administrative Capacity Building Roadmaps* [online]. Paris: OECD Multi-level Governance Studies, OECD Publishing. <https://doi.org/10.1787/9b71c8d8-en>.

PULJIZ, J., MALEKOVIC, S., KESER, I. (2019). Cohesion Policy in Croatia: What Have We Accomplished so Far? In: PETAK, Z., KOTARSKI, K. (eds.) *Policy-Making at the European Periphery. New Perspectives on South-East Europe* [online]. Cham: Palgrave Macmillan. <https://doi.org/10.1007/978-3-319-73582-5_15>.

RODRIGUEZ-POSE, A., GARCILAZO, E. (2015). Quality of Government and the Returns of Investment: Examining the Impact of Cohesion Expenditure in European Regions [online]. *Regional Studies*, 49(8): 1274–90. <https://doi.org/10.1080/00343404.2015.1007933>.

RONG, K. (2022). Research Agenda for the Digital Economy [online]. *Journal of Digital Economy*, 1(1): 20–31. <https://doi.org/10.1016/j.jdec.2022.08.004>.

STIBLAROVA, L. (2022). European Cohesion Policy to the Rescue? Revising (Counter)-Cyclical Effects in the EU-28 Recipient Countries [online]. *Ekonomicky casopis*, 70(9–10): 681–702. <https://doi.org/10.31577/ekoncas.2022.09-10.01>.

SURUBARU, N.-C. (2017). Administrative Capacity or Quality of Political Governance? EU Cohesion Policy in the New Europe, 2007–13 [online]. *Regional Studies*, 51(6): 844–856. <https://doi.org/10.1080/00343404.2016.1246798>.

TARJANI, J. A., KALLO, N., DOBOS, I. (2023). Evaluation of Digital Development Based on the International Digital Economy and Society Index 2020 Data [online]. *Statistika: Statistics and Economy Journal*, 103(3): 355–373. <https://doi.org/10.54694/stat.2023.21>.

TERRACCIANO, B., GRAZIANO, P. R. (2016). EU Cohesion Policy Implementation and Administrative Capacities: Insights from Italian Regions [online]. *Regional & Federal Studies*, 26(3): 293–320. <https://doi.org/10.1080/13597566.2016.1200033>.

TIGANASU, R., LUPU, D. (2023). Institutional Quality and Digitalization: Drivers in Accessing European Funds at Regional Level? [online]. *Socio-Economic Planning Sciences*, 90: 101738. <https://doi.org/10.1016/j.seps.2023.101738>.

TOSUN, J. (2014). Absorption of Regional Funds: A Comparative Analysis [online]. *JCMS: Journal of Common Market Studies*, 52(2): 371–387. <https://doi.org/10.1111/jcms.12088>.

UNITED NATIONS. (2022). *UN E-Government Survey 2022* [online]. <https://publicadministration.un.org/egovkb/en-us/Reports/UN-E-Government-Survey-2022.

ZHANG, W. et al. (2021). Study on the Effect of Digital Economy on High-Quality Economic Development in China [online]. *PLoS One*, 16(9): e0257365. <https://doi.org/10.1371/journal.pone.0257365>.

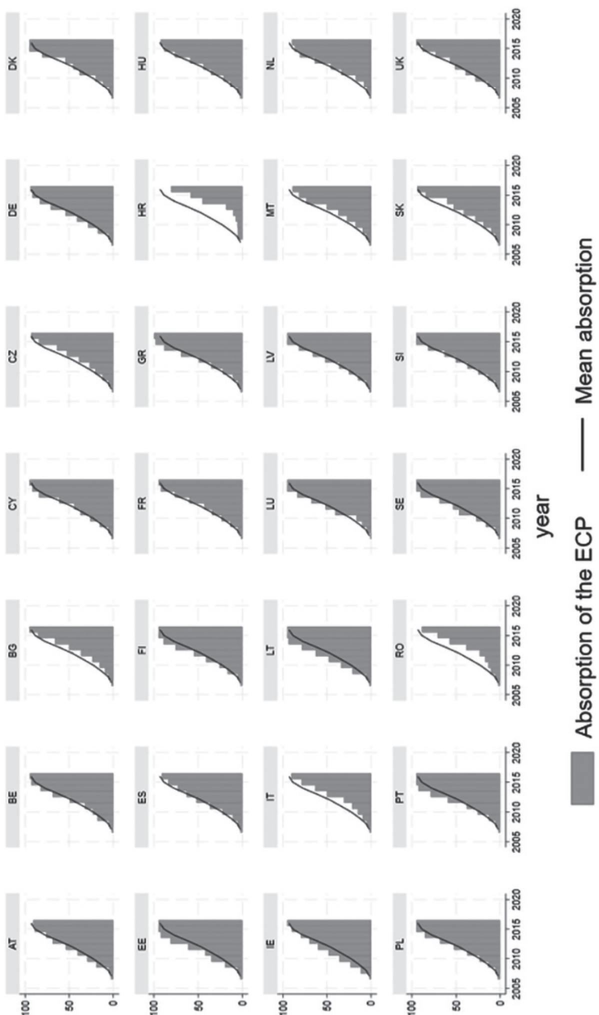
APPENDIX

Table A1 Correlation matrix of considered variables

	Absorption	E-gov	ECP	Human cap	Govern
Absorption					
E-gov	0.385				
ECP	0.190	–0.323			
Human cap	0.422	0.506	–0.175		
Govern	0.099	0.781	–0.496	0.424	

Source: Author's calculations based on data from the European Commission, Eurostat, and the World Bank

Figure A1 Absorption of the ECP by EU countries and years



Source: Author's elaboration based on data from the European Commission

Comparison of Claim Reserves Methods Using Insurance Portfolio Generators

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Received 22.4.2024 (revision received 29.7.2024), **Accepted** (reviewed) 26.8.2024, **Published** 13.12.2024

Abstract

Different reserving methods can be used to predict claim values in non-life insurance. This article compares two different methodological approaches to reserving methods, namely, Chain-ladder (the traditional approach to reserving in non-life insurance) and state-space modeling (the modern approach based on recursive Kalman filtering). Moreover, the paper compares both methods with the involvement of clustering which divides claims into several groups according to their similarity and ensures greater homogeneity of data. To be able to compare the accuracy of reserve predictions numerically one suggests three types of generators of large insurance portfolios that represent well the behavior of the given methods in practice (one of them is derived directly from a real Czech non-life insurance claims portfolio). The obtained results may serve as a hint to improve the state-space methodology in order to give comparable results with classical approaches to reserving since in future the state-space modeling will be important for micro reserving where the "clustering" gains nearly a form of individual policy contracts.

Keywords	***DOI***	***JEL code***
Chain-ladder, claims portfolio generators, clustering, loss reserving, non-life insurance, state-space model	*https://doi.org/10.54694/stat.2024.22*	*C32, C53, G22*

INTRODUCTION

Loss reserving is crucial for each insurance company since it is used to estimate funds for future claim payments and obtained results serve to ensure the financial stability of the insurer. In this paper, we deal with the estimation of reserves in non-life insurance. The article aims to provide a description of loss reserving and focuses on the comparison of two reserving methods and their application to insurance

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claims portfolios. The Chain-ladder method, usually considered as a benchmark method in loss reserving and known for its effectiveness across diverse insurance scenarios, is compared to the log-normal model, which is a representative of state-space modeling and modern reserving methods. These reserving methods are supplemented by clustering method CLARA, introduced in Kaufman and Rousseeuw (1990), to assess the benefit of clustering for reserve accuracy (according to our experience, the method CLARA seems to be the most suitable in the context of reserving).

In order to dispose of a sufficient number of portfolios to which we could apply the considered methods and consequently compare particular approaches, we propose three different types of non-life insurance claims portfolio generators. For each generator and an adequately large sample of generated portfolios, the accuracy of the claims and reserve estimates is compared using different techniques, namely, comparing boxplots and further verifying the improvement of prediction accuracy using the paired sign test for equality of medians of reserves deviations. The section concerning the construction of insurance portfolio generators can be also useful for actuarial practice generally (not only for reserving).

This paper is structured as follows. Section 1 serves as a brief literature review. Section 2 provides an overview of the importance of loss reserving in non-life insurance, discusses two different approaches to reserving, explains the concept of clustering in the context of loss reserving and surveys the references in literature. Section 3 provides an overview of two distinct regulatory frameworks used in the insurance industry, Solvency II and IFRS 17, and introduces the concept of Claims Development Results (CDR). In Section 4, we present the generators used to create the insurance claims portfolios used for the numerical study. Section 5 presents the results of the numerical study and discusses the accuracy of estimates. Finally, the last section summarizes the conclusions achieved in this paper and suggests further research possibility.

1 LITERATURE REVIEW

As mentioned above, actuarial science is a field that has undergone significant evolution. This also includes reserving as its important part. Thus, there are many publications dealing with this field. The development of the reserving methods has progressed from basic deterministic approaches to sophisticated statistical and machine-learning techniques.

As examples of the deterministic methods that are based on the extrapolation of historical data, we can mention the Chain-Ladder method, see, e.g., Wüthrich and Merz (2008) including its stochastic model by Mack (1993), and Bornhuetter-Ferguson method presented in Bornhuetter and Ferguson (1972).

Due to the gradually increasing computational power and increased data availability, researchers could use more complex statistical methods. One of the representatives from this group is the generalized linear model that allowed to robustly model the relationship between claims data and influencing factors, see, e.g., England and Verrall (2002).

A different approach, based on state-space modeling, enables dynamic modeling of claims processes by incorporating both observed data and latent variables. Verall (1989) was a pioneering article introducing state-space models for claims reserving, presenting their ability to capture the complexity of claims development over time. Later articles, such as De Jong (2005) or Atherino et al. (2010), and recent advancements by, e.g., Costa and Pizzinga (2020) or Hendrych and Cipra (2021) further enhance the flexibility and predictive power of this approach.

The advent of machine learning has further transformed reserving methodologies. Techniques such as random forests and neural networks, presented, for example, in Wüthrich (2018), provide non-linear modeling capabilities. Recent studies by, e.g., Duval and Pigeon (2019), De Felice and Moriconi (2019) or Delong et al. (2020) can be used as an additional source of knowledge in the area of reserving.

Since there is an enormous volume of literature including internet reports dealing with reserving, in addition to the publications we have presented so far, we only list several other references dealing with this topic from various points of view: Balona and Richman (2020), Cipra (2010), England et al. (2018), Kaas et al. (2004), Munroe et al. (2018), Wüthrich and Merz (2008), The Actuarial Community (2022), Zhang (2010). Some of them will be referred later in the text to explain specific problems of reserving.

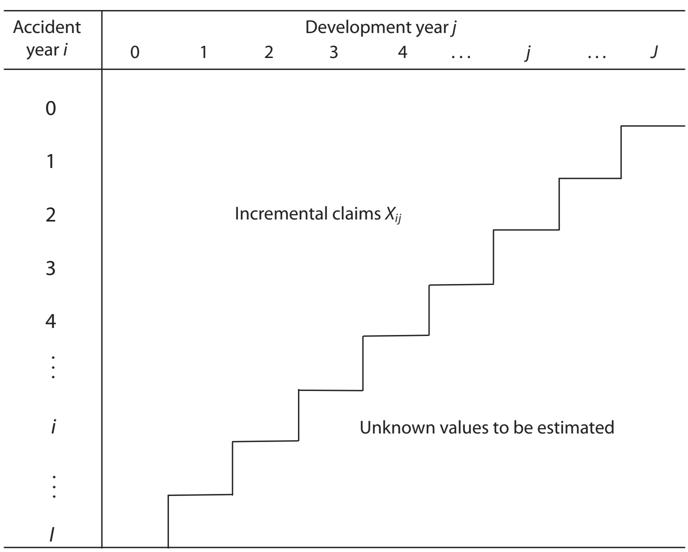
2 LOSS RESERVES IN NON-LIFE INSURANCE

Loss reserving is an important aspect of non-life insurance, which serves as a financial tool to estimate funds for future claim payments. Insurance companies may consider various methods to predict the ultimate value of claims that have been reported, but still not settled, and those that have not yet been reported. The main purpose of reserving is to ensure that insurance companies have appropriate funds to cover claim settlements, which is connected to the maintenance of financial stability and fulfilment of insurers' obligations to policyholders. One must steadily monitor and adjust the loss reserves because of the development of insurance portfolios caused by the reporting new information.

In practice, one can encounter different reserving methods, but these methods can be divided into two main groups of the so-called micro and macro reserving. The difference between these two types of reserving lies in the form of data, one is working with. The micro approach involves a detailed investigation of individual claims, with detailed information about each claim. On the other hand, the macro approach takes a broader perspective and individual claims are considered in an aggregated form. Nevertheless, both approaches are complementary and can be mutually combined.

In the case of macro reserving, one of the most used data representations is a run-off triangle, also called a development triangle. This triangle is a tabular representation of historical claims data over multiple periods. Typically, the claims are organized by accident years, which are represented by rows ($i = 0, ..., I$), and delays in reporting or payments captured in columns ($j = 0, ..., J$). Finally, the diagonals of the triangle represent particular calendar years. Based on the values appearing in the triangle, we can divide these triangles into incremental and cumulative ones. An illustration of a run-off triangle can be found in Figure 1. The actuaries can use diverse statistical techniques and mathematical models to analyze the patterns within the run-off triangle in order to complete the triangle into the rectangle by estimating the unknown future payments, the ultimate losses and the appropriate reserves.

Figure 1 Illustration of a run-off triangle



Source: Own construction based on Wüthrich and Merz (2008)

2.1 Classical approaches to loss reserving

In this article, we apply two different approaches to reserving. One of them, called Chain-ladder, can be classified as a classical approach to loss reserving, since it is a time-tested methodology proving its effectiveness across diverse insurance scenarios. Such classical methods are popular for their balance between simplicity and efficiency.

The Chain-ladder method, see e.g. Mack (1993), is one of the fundamental deterministic approaches utilized in non-life insurance reserving. It gained its success mainly due to its simplicity and easy applicability. It operates on the assumption that historical development patterns will persist into the future. Let $C_{i,j}$ represent the cumulative amount of claims occurred during accident year and paid till development year delay j. The chain-ladder estimates the unknown values with the use of so-called development factors $f_0, ..., f_{J-1}$, that connect cumulative values in the j-th and $j + 1$-th column and which are estimated as the ratios $\hat{f}_j = \frac{\sum_{i=0}^{I-j-1} C_{i,j+1}}{\sum_{i=0}^{I-j-1} C_{i,j}}$. By extrapolating these development factors, one can estimate ultimate losses $\hat{C}_{i,J}$ for each accident year i as $C_{i,J-i} \cdot \hat{f}_{J-i} \cdot \ldots \cdot \hat{f}_{J-1}$. While the Chain-ladder method provides a practical and intuitive framework, its simplicity may cause inaccuracies of estimates in more complex insurance cases. For further details about the Chain-ladder, see Wüthrich and Merz (2008) or Cipra (2010).

The univariate Chain-ladder can be generalized to its multivariate version, where several run-off triangles are considered at once. Considering claims from more triangles allows for a detailed analysis of the impact of various covariates on the development patterns of claims. This approach can lead to improving the precision of loss reserving.

The multivariate Chain-ladder can be expressed within the SUR (Seemingly Unrelated Regression) framework, which is beneficial for the robustness of parameter estimates in situations when there are correlations in the error terms across equations. This model was introduced in Zhang (2010). When considering N development triangles, one works with vectors of cumulative claims $\boldsymbol{C}_{i,k} = \left(C_{i,k}^{(1)}, \ldots, C_{i,k}^{(N)}\right)$ in the model $\boldsymbol{C}_{i,k+1} = \boldsymbol{B}_k \cdot \boldsymbol{C}_{i,k} + \boldsymbol{\varepsilon}_{i,k}$, where $\boldsymbol{B}_k$ is a development matrix of type $N \times N$ in development period k and $\boldsymbol{\varepsilon}_{i,k}$ is an N-dimensional random vector with several assumptions imposed on it. For these assumptions and more details on the multivariate Chain-ladder see Zhang (2010).

In addition to the models based on the Chain-ladder approach, there is also a number of similar models that work with development triangles, e.g., Bornhuetter–Ferguson, Benktander–Hovinen or Cape–Cod model (see, e.g., Wüthrich and Merz, 2008).

2.2 State-space models in loss reserving

A different approach to loss reserving that is considered in this article is so-called state-space modeling, where a linear state-space model plays a significant role in non-life insurance loss reserving. In this framework, one still works with aggregated claims ordered primarily to run-off triangles, but these triangles are transformed into the time series that are then modeled. The linear state-space models assume that the unobservable states and their observations follow linear relationships over time. Generally, such a model is given by the following system of equations:

$$\boldsymbol{y}_t = \boldsymbol{Z}_t \boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \tag{1}$$

$$\boldsymbol{\alpha}_{t+1} = \boldsymbol{T}_t \boldsymbol{\alpha}_t + \boldsymbol{R}_t \boldsymbol{\eta}_t, \tag{2}$$

where $\boldsymbol{y}_t$ is a p-dimensional observation vector at time t, $\boldsymbol{\alpha}_t$ is an m-dimensional state vector at time t, $\boldsymbol{Z}_t$, $\boldsymbol{T}_t$, and $\boldsymbol{R}_t$ are matrices of parameters of types $(p \times m)$, $(m \times m)$ and $(m \times k)$, respectively. Random vectors $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\eta}_t$ are assumed to be normally distributed, where $\boldsymbol{\varepsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{H}_t)$ is a p-dimensional random vector and $\boldsymbol{\eta}_t$~$N(\mathbf{0},\boldsymbol{Q}_t)$ is a k-dimensional random vector with covariance matrices $\boldsymbol{H}_t$ and $\boldsymbol{Q}_t$, respectively. Moreover, $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\eta}_t$ are assumed to be independent. Since the state vectors are estimated by a recursive algorithm in time, it is also necessary to set an initial state $\boldsymbol{\alpha}_1$, fulfilling $\boldsymbol{\alpha}_1$~$N(\boldsymbol{a}_1,\boldsymbol{P}_1)$, which is independent to $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\eta}_t$ ($\boldsymbol{a}_1$ and $\boldsymbol{P}_1$ are some initial estimates).

This linear framework offers mathematical tractability and flexibility, allowing for efficient estimation and prediction using the Kalman filter (see Brockwell and Davis, 1991). The practical implementation can be realized by means of a selected software, e.g., using *KFAS* package available in software R and introduced in Helske (2017).

As mentioned above, run-off triangles need to be transformed to the form of time series. Then, they can enter the model as the observation vector $\boldsymbol{y}_t$. There are several ways how to order claims occurring in the development triangle. A row-wise ordering, resulting in time series with missing observations, was introduced in Atherino et al. (2010). Supposing normality of data is in this particular task vastly simplistic, thus, in order to meet the assumption of normality in the state-space model, Hendrych and Cipra (2021) introduced a log-normal model, assuming log-normal distribution of incremental claims. Hence, when working with logarithmically transformed incremental claims, one obtains the normal data.

The considered log-normal model is given by the following equations:

$$y_t(n) - y_t^0(n) = \alpha_t(n) + \varepsilon_t(n), \tag{3}$$

$$\alpha_{t+1}(n) = \alpha_{t-s+1}(n) + \eta_t(n), \tag{4}$$

where $y_t(n)$ and $y_t^0(n)$ represent the logarithmized incremental claims with appropriately adjusted index after row-wise ordering in the n-th run-off triangle for $n = 1, \ldots, N$. The values $y_t^0(n)$ correspond to the logarithmized values from the first column of the n-th run-off triangle. Their subtraction in (3) is considered as a setting of initial levels in the observation equation. For random variables $\varepsilon_t(n)$ and $\eta_t(n)$, we suppose $\varepsilon_t(n) \sim N\left(0, \sigma_\varepsilon(n,n)\right)$ and $\eta_t(n) \sim N\left(0, \sigma_\eta(n,n)\right)$, respectively.

Formulas (3) and (4) need to be transformed into their matrix forms that correspond to Formulas (1) and (2). Then it is possible to use appropriate software to estimate the model and subsequently forecast the missing observations in vector .

Based on Hendrych and Cipra (2021), the matrix form of the log-normal model is:

$$\boldsymbol{y}_t - \boldsymbol{y}_t^0 = \begin{pmatrix} 1 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots & & \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & 1 & 0 & \cdots & 0 \end{pmatrix} \boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \tag{5}$$

$$\boldsymbol{\alpha}_{t+1} = \begin{pmatrix} \begin{matrix} 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{matrix} & & \\ & \ddots & \\ & & \begin{matrix} 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{matrix} \end{pmatrix} \boldsymbol{\alpha}_t + \begin{pmatrix} \begin{matrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \end{matrix} & & \\ & \ddots & \\ & & \begin{matrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \end{matrix} \end{pmatrix} \boldsymbol{\eta}_t, \tag{6}$$

where $\boldsymbol{y}_t = \left(y_t(1),\ldots,y_t(N)\right)'$, $\boldsymbol{y}_t^0 = \left(y_t^0(1),\ldots,y_t^0(1)\right)'$, $\boldsymbol{\varepsilon}_t = \left(\varepsilon_t(1),\ldots,\varepsilon_t(N)\right)'$,

$$\boldsymbol{\eta}_t = \left(\eta_t(1),0,\ldots,0,\ldots,\eta_t(N),0,\ldots,0\right)',$$

$$\boldsymbol{\alpha}_t = \left(\alpha_t(1),\ldots,\alpha_{t-s+1}(1),\ldots,\alpha_t(N),\ldots,\alpha_{t-s+1}(N)\right)'.$$

Moreover, residual vectors $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\eta}_t$ have covariance matrices $Var(\boldsymbol{\varepsilon}_t) = \boldsymbol{H}_t = \left(\sigma_\varepsilon(m,n)\right)_{m,n=1,\ldots,N}$ and $Var(\boldsymbol{\eta}_t) = \boldsymbol{Q}_t = \left(\sigma_\eta(m,n)\right)_{m,n=1,\ldots,N}$, respectively.

After using Kalman smoothing and obtaining smoothed time series, one can transform the obtained values back to their original scale and proceed to the reserve calculation.

2.3 Preliminary clustering of loss data

Since in many cases it can be advantageous to work with more run-off triangles, rather than with single one, as mentioned above, one can deal with the problem of optimal distribution of claims to several groups that are then represented by individual development triangles. In some situations, the run-off triangles are naturally separated but, in many cases, there is only one portfolio of insurance claims with a potential to group it into more than one subportfolios. For this purpose, one can use various clustering methods.

Clustering corresponds to the grouping of similar elements based on their characteristics and identifies patterns and relationships within the data. In the context of loss reserving, one can assume that policies with comparable risk factors and exposure may have similar claim development behavior. By categorizing these policies into clusters with similar risk characteristics, insurers can take such a clustering into account in their loss reserving models to better capture the unique dynamics within each group.

In literature, there are numerous methods of unsupervised clustering that can be used in the context of insurance claims. In Vejmělka (2023), several methods, that are implemented in software R, have been compared. Namely, the function called *balanced_clustering* from the package *anticlust*, see Papenberg and Klau (2021), the function *Kmeans* from the *stats* package, proposed in Hartigan and Wong (1979), the function *Mclust* in the package *mclust*, see Scrucca et al. (2016), and the function *Clara_Medoids* in package *ClusterR,* introduced in Kaufman and Rousseeuw (1990).

Since in Vejmělka (2023) the CLARA (Clustering Large Applications) method provided the best results among the clustering methods involved in the comparison study, it is also preferred in the numerical study which is a part of this article. CLARA is an algorithm that extends the PAM (Partitioning Around Medoids) algorithm. PAM itself is an effective clustering method, however, it can be numerically complex in the case of large datasets due to its quadratic time complexity. This can be considerably problematic in the context of insurance data that can be quite extensive. The aim of CLARA is to overcome this limitation by performing the clustering on a subset of the data, which results in more computationally acceptable situation for larger datasets.

CLARA can be described as a three-step process. In the first step, multiple randomly chosen subsamples of the dataset are selected. The PAM algorithm is then applied to each subsample, medoids are calculated and observations from the subsamples are assigned to the appropriate clusters. Secondly, the obtained clusters are evaluated based on their overall stability. Finally, the most stable medoids and clusters are selected.

A completely different approach involves machine learning algorithms using neural networks. They can identify complex patterns within large datasets and due to the automatic process of identifying clusters, the need of manual interventions is reduced which can speed up the analysis. Nevertheless, complex deep learning models usually operate as black boxes, which results in very difficult or even impossible interpretation of the underlying decision-making processes. This lack of transparency can be a significant problem, especially in insurance, where interpretability is crucial for regulatory compliance. Several examples and references may be found, e. g., in Du (2010) or Kauffmann et al. (2022).

3 REGULATORY FRAMEWORK: CLAIMS DEVELOPMENT RESULTS

Solvency II and IFRS 17 represent two distinct regulatory frameworks used in the insurance industry, each with its own set of objectives and requirements. Solvency II, which has been established by the European Union, focuses primarily on ensuring the financial stability and solvency of insurance companies operating within the EU. It requires thorough evaluation of risks and sufficient capitalization to protect policyholders and keep market credible. In contrast, IFRS 17, an accounting standard developed by the International Accounting Standards Board, deals mainly with financial reporting and accounting standards for insurance contracts. It aims to enhance transparency and comparability of financial statements by requiring insurers to provide more detailed information about their insurance contracts.

The fundamental difference between Solvency II and IFRS 17 from a computational point of view subsists mainly in the fact that Solvency II considers risk over a one-year time horizon, whereas IFRS 17 is based on the fulfilment cash flows over their lifetime, see England et al. (2018). Reserves estimated using appropriate reserving methods can be used as one of the inputs to estimate future claims liabilities when determining the Best Estimate under IFRS 17. However, the Best Estimate may also incorporate additional modifying considerations and extensions.

In the Solvency II framework, it is fundamental to assess the insurer's ability to meet its obligations over a one-year horizon, as outlined in Pillar 1 (Quantitative Requirements). The methodology denoted as Claims Development Results (CDR) plays an important role in this process. It offers an insight into the development of insurance claims over time, specifically enabling insurers to project claims liabilities for the forthcoming year. It can be used for estimation of Solvency Capital Requirement (SCR), which is a key component of Solvency II. To estimate the SCR, a log-normal distribution with the mean equal to the expected ultimate loss and the standard deviation corresponding to the standard deviation of the CDR, is often applied. Then the -th percentile of this distribution can be used as the estimate of the SCR. One can find a more detailed information, e.g., in England et al. (2018) or Munroe et al. (2018).

The observable CDR for accident year i and accounting year $I + 1$ has been defined in England et al. (2018) in the following way:

$$\widehat{CDR}_i\left(I+1\right)=\hat{R}_i^{D_I}-\left(X_{i,I-i+1}+\hat{R}_i^{D_{I+1}}\right)=\hat{C}_{i,J}^{I}-\hat{C}_{i,J}^{I+1}, \tag{7}$$

where $\hat{R}_i^{D_I}$ and $\hat{R}_i^{D_{I+1}}$ are the reserves for the claims occurred at year i estimated at time I and $I + 1$, respectively. Value $X_{i,I-i+1}$ is an appropriate incremental claim. Finally, $\hat{C}_{i,J}^{I}$ and $\hat{C}_{i,J}^{I+1}$ are the estimates of ultimate claims calculated at time I and $I + 1$, respectively (all for accident year i). The aggregated CDR is then defined as:

$$\widehat{CDR}\left(I+1\right)=\sum_{i=1}^{I}\widehat{CDR}_i\left(I+1\right). \tag{8}$$

Since one of the goals of the numerical study is to compare the considered reserving methods how accurately they can estimate the actual values of the reserves and CDRs, we have to use some aggregate metric for the CDR comparison. For this purpose, we use a little modified form of the so-called CDR score introduced in Balona and Richman (2020):

$$\widehat{CDR}_{SCORE}\left(I+1\right)=\sqrt{\frac{\sum_{i=1}^{I}\left(\left|X_{i,I-i+1}\right|\cdot\left|\widehat{CDR}_i\left(I+1\right)\right|\right)}{\sum_{i=1}^{I}\left|X_{i,I-i+1}\right|}}. \tag{9}$$

where the difference lies in the choice of the absolute value of $CDR_i(I + 1)$ instead of the square function considered in the mentioned article. The aim is to minimize the CDR score which means that one has stable reserves with a reasonable change in reserves between calendar years I and $I + 1$. Therefore, one should calculate this metric in addition to the reserve estimation.

4 CLAIMS PORTFOLIO GENERATORS

In order to effectively evaluate considered methods in practice, it is necessary to apply them across a large number of portfolios. Additionally, having the data about the future development of such claims, in the language of run-off triangles to know the values in the lower triangle as well, is crucial for comparison of the reserves against actual outcomes. Therefore, an ideal solution consists in application of an insurance claims generator, which addresses both of these requirements. However, it is important to construct and calibrate these generators consistently to reflect the characteristics of real portfolios as closely as possible. In the numerical study presented in this paper, we apply the aforementioned methods to portfolios generated by three distinct generators, which are described in the following three subsections.

4.1 Generator based on real Czech data

The first generator used for insurance claims portfolios creation is the one created by the authors that is based on a real insurance claims portfolio delivered by the Czech Insurers' Bureau. This particular portfolio consists of claims paid by the guarantee fund administered by the Czech Insurers' Bureau, which covers expenses arising from incidents caused by vehicles without third-party liability insurance or unidentified vehicles where the responsible party is unknown. Our data concerned exclusively the claims that occurred between years 2001 and 2010. Furthermore, we considered several adjustments of the underlying portfolio which, however, do not affect the credibility of the generated portfolios.

The generator has been constructed applying maximum likelihood and kernel density estimation. First, the corresponding volume of claims is generated and for each claim its type is determined. Furthermore, the year of the claim occurrence and, based on the type of claim, the number of payments, the time until settlement and the size of claim are simulated. Since the number of payments and their delays often influence the value of these payments, this is also considered during the simulation. A portfolio, generated in this way, should have similar properties as the original portfolio.

This generator was used to generate 500 portfolios consisting of approximately 65 000 claims. An illustration of these data can be found in Table 1.

Table 1 Illustration of data in Czech Insurers' Bureau portfolios

ID	Type	AM	PM	Payment	Ultimate
1	1	64	69	23 706	23 706
2	1	109	124	40 813	40 813
3	2	94	101	9 629	36 704
3	2	94	112	4 587	36 704
3	2	94	122	22 488	36 704

Source: Own construction

For each claim information on *ID*, which serves to distinguish different claims, its *Type* (two possible types), accident month *AM* and *Ultimate* value, is known. Additionally, each row corresponds to one payment of amount *Payment* paid in month *PM*.

4.2 Generator Gabrielli and Wüthrich (2018)

The second generator proposed in Gabrielli and Wüthrich (2018) is based on neural networks to incorporate individual claims feature information. This individual claims history simulation machine was constructed applying a neural network architecture which was calibrated to real insurance data that have occurred between 1994 and 2005. For each of these claims, there is available additional information, such as the line of business or age of the injured, together with 12 years of claims development.

The architecture of this individual claims simulation machine consists of eight steps. Firstly, reporting delays that correspond to the differences between accident and reporting years are simulated. This is followed by payment indicator simulation, whether there are any payments or not. In the third step a number of payments is simulated, followed by a total claim size simulation. The last four steps then serve for cash flows modeling. For a detailed description of the simulation machine see Gabrielli and Wüthrich (2018).

After some adjustments that are necessary before clustering, which mainly consisted in excluding redundant information from the data, 500 portfolios comprising approximately 320 000 claims were generated. A few examples of generated data can be found in Table 2.

Table 2 Illustration of data in Gabrielli and Wüthrich portfolios

ID	LoB	AY	AQ	Age	RepDel	Payment	PayDel
1	4	1994	4	25	0	97	1
2	1	1994	2	39	0	1 476	0
2	1	1994	2	39	0	705	1
3	1	1994	1	38	0	5 709	0
3	1	1994	1	38	0	2 358	2

Source: Own construction

In addition to *ID*, for each claim it is also known its accident year *AY*, accident quarter *AQ*, reporting delay *RepDel*, age of the injured *Age* and line of business *LoB* (four possible types). In this case, each row corresponds to one payment of amount *Payment* paid with delay *PayDel*.

4.3 Generator Wang and Wüthrich (2022)

The third individual claims generator introduced in Wang and Wüthrich (2022) is based on the R package *SynthETIC* of Avanzi et al. (2021). The *SynthETIC* simulator specifically allows for desirable data features typically occurring in practice. It has been structured in such a way that the generated portfolio of claims should resemble an auto liability portfolio. Moreover, its code has a modular form. The generator consists of eight modules such as, e.g., claim occurrence date, number of partial payments, sizes of partial payments without allowance for inflation, distribution of payments over time or claim inflation. Such an independent coding allows adjustments in each module, their possible replacements or removal according to a particular purpose.

This simulator has been modified by Wang and Wüthrich. They have complemented this simulation environment with additional claim features resulting with the enhanced generator. For more details see Wang and Wüthrich (2022).

Similarly, as in the previous generator, several adjustments in the generated portfolios have been considered. Again, 500 portfolios were generated, in this case each with approximately 50 000 claims. An illustration of the data follows (see Table 3).

Table 3 Illustration of data in Wang and Wüthrich portfolios

ID	Type	AY	Payment	PayDel	Ultimate
1	1	1	2 434	1	2 434
2	4	1	11 017	0	34 110
2	4	1	11 815	1	34 110
2	4	1	11 278	2	34 110
3	3	1	2 428	1	2 428

Source: Own construction

Variable *ID* has the same meaning as before. Each claim is described by its accident year *AY* and its *Type* (six possible classes). Again, each row corresponds to one payment of amount *Payment* paid with delay *PayDel*.

The clustering method CLARA described in Section 2.3 requires the feature matrix entering the clustering process in a numerical form, i.e., it is necessary to transform the categorical variables, such as *Type*, *LoB* or *AQ* into dummy variables. Moreover, variable *Age* is further considered in the form of three dummy variables , (≤ 30, ≥ 51 and the interval between).

5 COMPARISON OF NUMERICAL STUDY RESULTS

This section deals with the numerical study using data created by means of generators from Section 4. The generators create not only the data in the upper run-off triangle in Figure 1, that are used for claim reserves prediction, but also for the predicted lower triangle in Figure 1. Hence, one can evaluate for each generated portfolio the accuracy of particular reserve methods.

Given that the log-normal model assumes the log-normality of incremental claims, it is also important to verify that such an assumption holds for the considered data. There are several tests that can be used, both those that test directly the log-normality of incremental claims and also those that test the normality of the logarithmized values. In our case we have chosen the well-known Kolmogorov-Smirnov test that was used for random samples of claims of size 500, since the total number of generated incremental claims is too large. Repeated testing for various random samples has shown that the null hypothesis of log-normality of the data cannot be rejected.

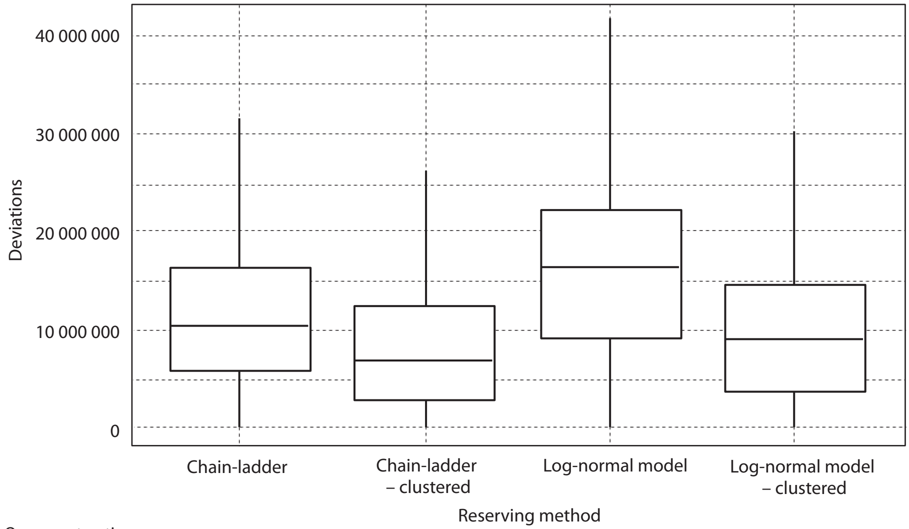
5.1 Results of numerical study

For each portfolio, introduced in Subsections 4.1–4.3, the main interest concerns comparing deviations of reserves from the actual values and modified CDR scores presented in Section 3 for the considered reserving method described in Section 2. This is achieved using graphs with boxplots. Results for the Czech portfolio presented in Section 4.1 follow.

Figure 2 presents deviations among estimated and actual reserves depicted graphically by means of boxplots over 500 portfolios generated by the Czech data generator from Section 4.1 for particular reserve methods (Chain-ladder, Chain-ladder clustered, log-normal model and log-normal model clustered). Figure 3 is analogous for modified CDR score.

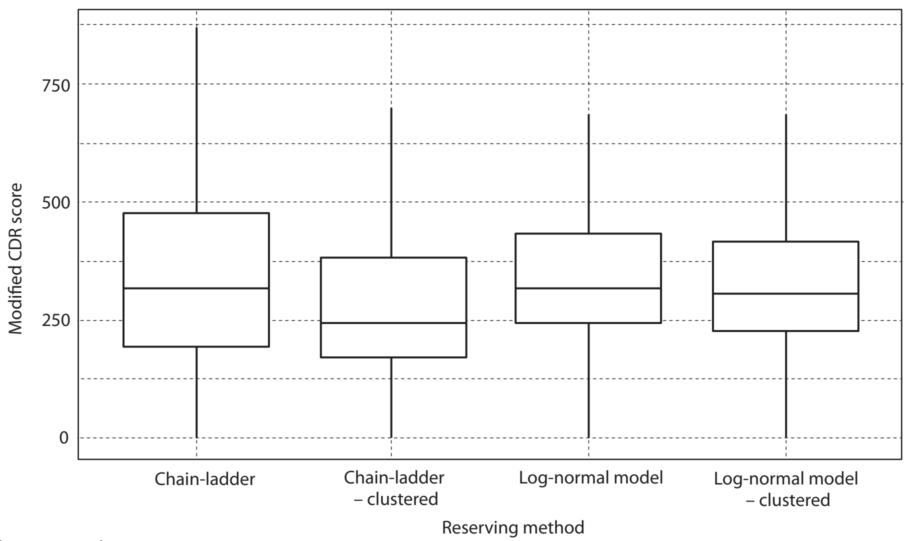
In addition to the boxplots presented in Figures 2 and 3, one can be interested in the accuracy of individual estimates, not only the aggregated reserve. For this purpose, we consider two approaches how to measure and compare the accuracy of considered reserving methods concerning individual estimates.

Figure 2 Deviations of reserves – Generator based on real Czech data



Source: Own construction

Figure 3 Modified CDR score – Generator based on real Czech data



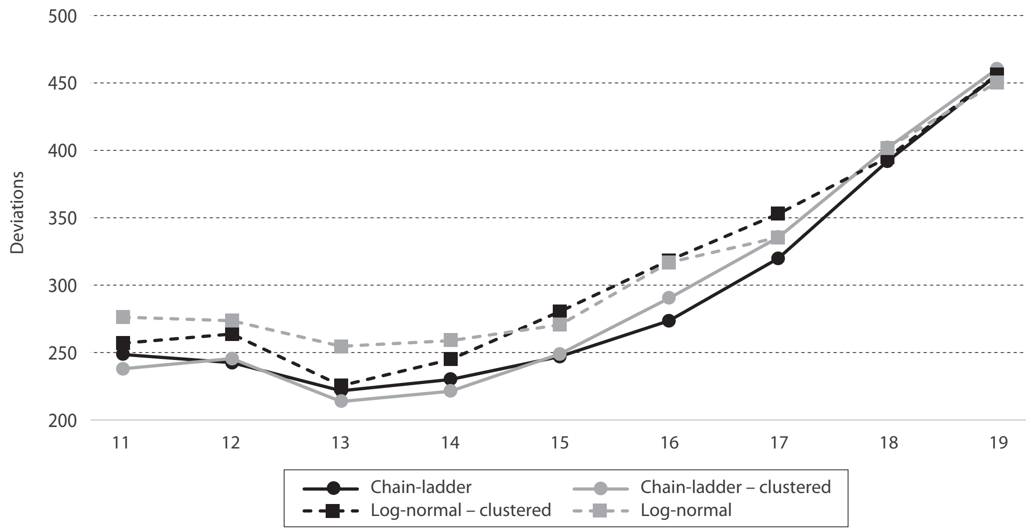
Source: Own construction

In the first case, the accuracy of estimates in individual calendar years following the last accounting year for which the claims are known is compared. Graphical results are presented only for the first portfolio to save space. For each subdiagonal in the lower run-off triangle, we calculate the following value:

$$D_k = \sqrt{\frac{\sum_{i=k-J}^{I}\left(\left|X_{i,k-i}\right| \cdot \left|X_{i,k-i} - \hat{X}_{i,k-i}\right|\right)}{\sum_{i=k-J}^{I}\left|X_{i,k-i}\right|}}, \tag{10}$$

where $k > I$. Values D_k for the considered reserving methods are shown by means of the graph in Figure 4.

Figure 4 Deviations development – Generator based on real Czech data

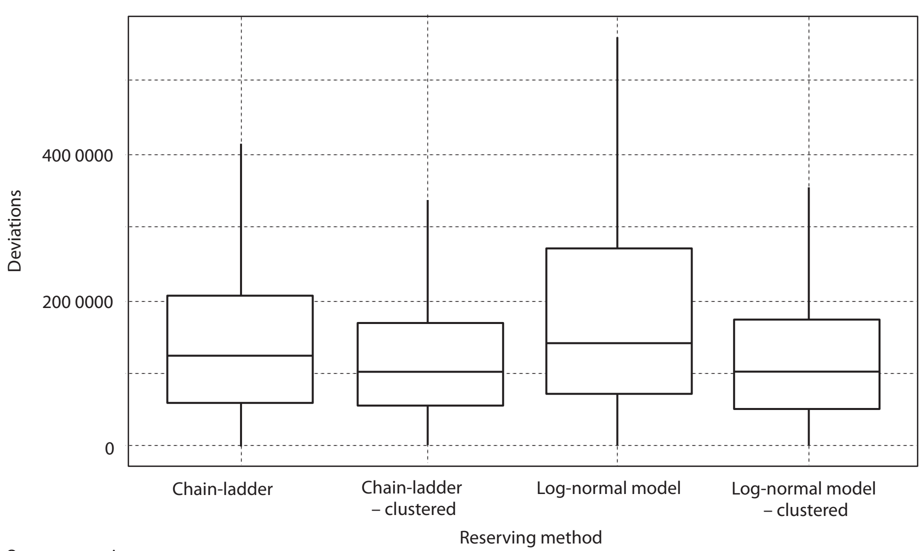


Source: Own construction

Since the second approach to the accuracy of individual estimates is applied to all three portfolios, it will be presented at the end of this subsection.

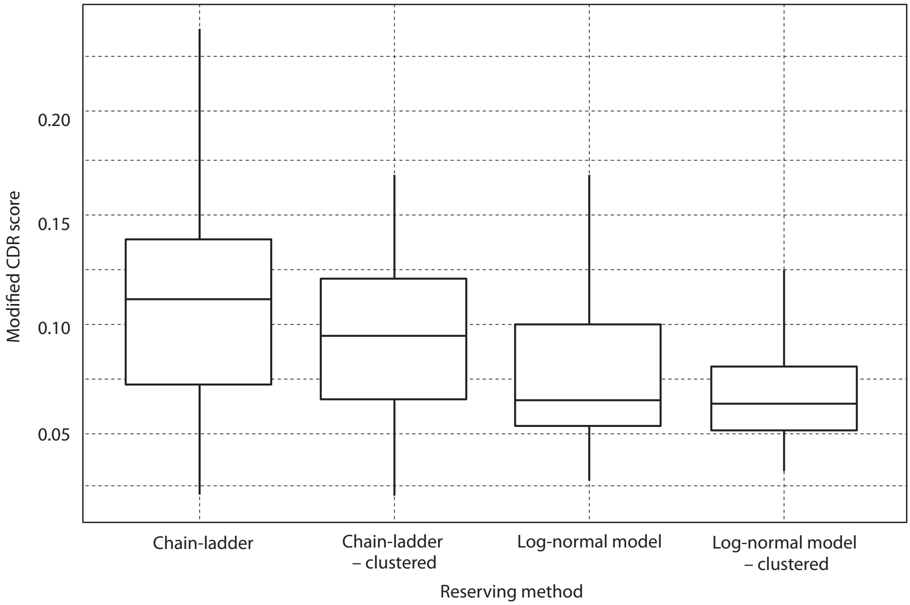
For the second portfolio from Section 4.2, we present the results corresponding to the deviations of reserves and modified CDR score in the same form as for the first portfolio, see Figures 5 and 6.

Figure 5 Deviations of reserves – Generator Gabrielli and Wüthrich (2018)



Source: Own construction

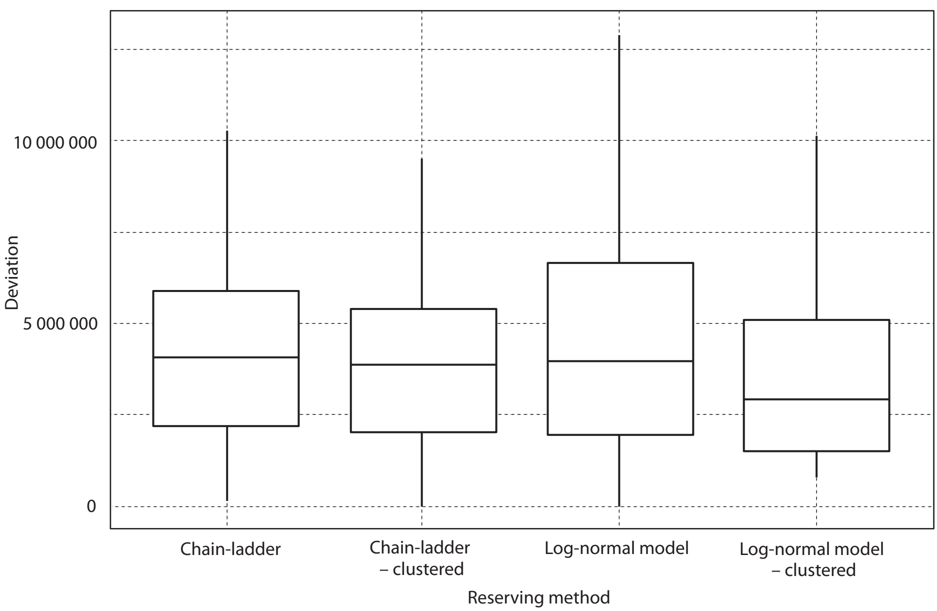
Figure 6 Modified CDR score – Generator Gabrielli and Wüthrich (2018)



Source: Own construction

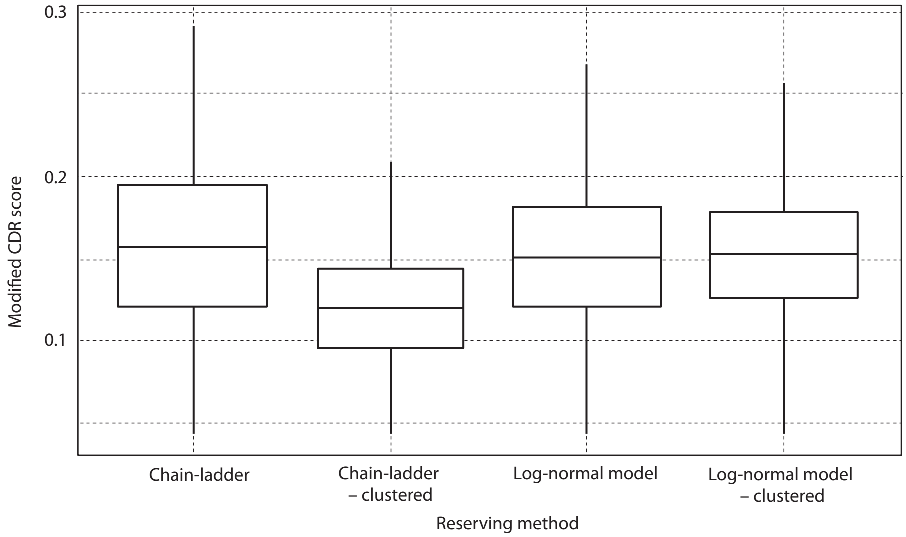
Finally, boxplots corresponding to the results obtained for the third portfolio from Section 4.3 are given in Figures 7 and 8.

Figure 7 Deviations of reserves – Generator Wang and Wüthrich (2022)



Source: Own construction

Figure 8 Modified CDR score – Generator Wang and Wüthrich (2022)



Source: Own construction

The second approach mentioned above compares all the estimated values in the lower run-off triangle (see Figure 1). The corresponding metric is calculated as the sum of squared differences of estimated and actual values (we call it the modified Frobenius norm). Since for each generated portfolio one obtains one value for each reserving method, we present medians of these values in Table 4.

Table 4 Medians of modified Frobenius norm of estimated run-off triangles

Portfolio	Chain-ladder	Chain-ladder – clustered	Log-normal model	Log-normal model – clustered
Gen. based on real Czech data	6 832 916	6 828 086	7 497 782	7 269 261
Gen. Gabrielli and Wüthrich	130 800	126 495	144 577	126 337
Gen. Wang and Wüthrich	1 732 335	1 728 779	2 193 398	2 179 933

Source: Own construction

5.2 Discussion of results

The results obtained in Section 5.1 allow us to compare the considered reserving methods including the impact of clustering. Figure 2 shows that Chain-ladder achieves significantly better results when compared to the log-normal model. The Chain-ladder boxplot values are lower than in the case of the log-normal model and the median of deviations is notably lower as well. One can see that clustering considerably improves the estimates, since for both reserving methods the boxplots narrowed down. Applying the paired sign test for equality of medians, the null hypothesis is strongly rejected (with p-value less than 0.001) in both cases in favor of one-sided alternative. This confirms the significant improvement of the accuracy of reserve estimates after clustering. Without clustering, the Chain-ladder dominates the log-normal model, but after incorporating clustering, the difference almost disappears.

In Figure 3, where the modified CDR scores are compared, a slight improvement after clustering can be seen as well, however, it is nearly negligible for the log-normal model. When comparing the methods by means of a graph showing the deviations development over individual calendar years (Figure 4), one can see that the Chain-ladder achieves almost always lower values than the log-normal model. In the first half, the most accurate variant was the clustered version, in the second half the non-clustered one.

Similar results as in Figure 2 can be found in the remaining figures corresponding to the other considered portfolios. Again, the pairwise sign tests confirm clustering improvement. However, significantly lower values of the modified CDR score can be observed for the log-normal model.

All reserving methods are also compared with respect to the modified Frobenius norm introduced in Section 5.1. Table 4 contains medians of the calculated norm values for each generated portfolio and one can see that also according to this table, the clustering improves the estimates. However, the dominance of the Chain-ladder persists.

CONCLUSION

This article discussed the importance of loss reserving in non-life insurance and compared two different reserving methodological methods – the Chain-ladder method and the state-space modeling. It also confirmed the significance of clustering in the context of loss reserving. The concept of run-off triangles and how actuaries can use statistical techniques and mathematical models to analyze the patterns within the run-off triangles to estimate future payments and appropriate reserves were explained. Additionally, we provided an overview of two distinct regulatory frameworks used in insurance, Solvency II and IFRS 17, and introduced the CDR approach. In this context, the paper can be useful for actuaries dealing with reserve estimation in non-life insurance practice.

In the numerical study, we presented the comparison of deviations of reserves from actual values and modified CDR scores for different reserving methods using boxplots. We discussed the accuracy of estimates in individual calendar years and explored the overall accuracy of the estimates. The numerical study demonstrated the benefit of clustering when considered in loss reserving. The results show that the Chain-ladder achieved better results when compared to the log-normal model, and that clustering considerably improved the estimates for both reserving methods. We also discussed the accuracy of individual estimates and presented graphical results for the first portfolio.

The obtained results may serve as a hint to improve the state-space methodology in order to give comparable results with classical approaches to reserving. The reason is obvious: in future the so-called micro reserving will play a key role in non-life insurance reserving based on neural networks and deep learning where the classical methods of the type of Chain-ladder will be quite insufficient for the corresponding computational procedures (see, e.g., Avanzi et al., 2021; Balona and Richman, 2020; Gabrielli and Wűthrich, 2018; Wang and Wűthrich, 2022; Wűthrich and Merz, 2008). One can also try to extend the one step ahead CDR predictions to the ones for more steps ahead in multivariate run-off triangles including analytical formulas for prediction errors.

ACKNOWLEDGEMENT

The authors thank to Dr. Radek Hendrych for his efficient help when preparing this paper and to anonymous reviewers for helpful comments and improvements.

References

ATHERINO, R., PIZZINGA, A., FERNANDES, C. (2010). A row-wise stacking of the runoff triangle: State space alternatives for IBNR reserve prediction [online]. *ASTIN Bulletin*, 40(2): 917–946. <http://doi.org/10.2143/AST.40.2.2061141>.

AVANZI, B., TAYLOR, G., WANG, M., WONG, B. (2021). SynthETIC: an individual insurance claim simulator with feature control [online]. *Insurance: Mathematics and Economics*, 100: 296–308. <https://doi.org/10.1016/j.insmatheco.2021.06.004>.

BALONA, C., RICHMAN, R. (2020). The actuary and IBNR techniques: A machine learning approach [online]. *SSRN Electronic Journal*. <http://doi.org/10.2139/ssrn.3697256>.

BORNHUETTER, R. L., FERGUSON, R. E. (1972). The actuary and IBNR. *Proceedings of the Casualty Actuarial Society*, 59: 181–195.

BROCKWELL, P. J., DAVIS, R. A. (1991). *Time Series: Theory and Methods*. 2nd Ed. New York: Springer-Verlag. ISBN 978-0-387-97429-3

CIPRA, T. (2010). *Financial and Insurance Formulas.* Berlin, Heidelberg: Springer-Verlag. ISBN 978-3-7908-2592-3

COSTA, L., PIZZINGA, A. (2020). State-space models for predicting IBNR reserve in row-wise ordered runoff triangles: Calendar year IBNR reserves & tail effects [online]. *Journal of Forecasting*, 39: 438–48. <https://doi.org/10.1002/for.2638>.

DE FELICE, M., MORICONI, F. (2019). Claim Watching and Individual Claims Reserving Using Classification and Regression Trees [online]. *Risks*, 7(4): 1–36. <https://doi.org/10.3390/risks7040102>.

DE JONG, P. (2005). State Space Models in Actuarial Science. *Proceedings of the Second Brazilian Conference on Statistic*: 16–31.

DELONG, Ł., LINDHOLM, M., WÜTHRICH, M. V. (2021). Collective reserving using individual claims data [online]. *Scandinavian Actuarial Journal*, 1: 1–28. <https://doi.org/10.1080/03461238.2021.1921836>.

DU, K. L. (2010). Clustering: A neural network approach [online]. *Neural Networks*, 23: 89–107. <http://doi.org/10.1016/j.neunet.2009.08.007>.

DUVAL, F., PIGEON, M. (2019). Individual Loss Reserving Using a Gradient Boosting-Based Approach [online]. *Risks*, 7(3). <https://doi.org/10.3390/risks7030079>.

ENGLAND, P., VERRALL, R. J., (2002). Stochastic Claims Reserving in General Insurance [online]. *British Actuarial Journal*, 8(3): 443–518. <https://doi.org/10.1017/S1357321700003809>.

ENGLAND, P., VERRALL, R. J., WÜTHRICH, M. V. (2018). On the lifetime and one-year views of reserve risk, with application to IFRS 17 and Solvency II risk margins [online]. *SSRN Electronic Journal*. <http://doi.org/10.2139/ssrn.3141239>.

GABRIELLI, A. V., WÜTHRICH, M. (2018). An individual claims history simulation machine [online]. *Risks*, 6(2). <https://doi.org/10.3390/risks6020029>.

HARTIGAN, J. A., WONG, M. A. (1979). Algorithm AS 136: A K-means clustering algorithm [online]. *Applied Statistics*, 28: 100–108. <https://doi.org/10.2307/2346830>.

HELSKE, J. (2017). KFAS: Exponential family state space models in R [online]. *Journal of Statistical Software*, 78(10): 1–38. <https://doi.org/10.18637/jss.v078.i10>.

HENDRYCH, R., CIPRA, T. (2021). Applying state space models to stochastic claims reserving [online]. *ASTIN Bulletin*, 51(1): 267–301. <https://doi.org/10.1017/asb.2020.38>.

KAAS, R., GOOVAERTS, M., DHAENE, J., DENUIT, M. (2004). *Modern Actuarial Risk Theory*. Berlin, Heidelberg: Springer-Verlag. ISBN 978-3-540-70998-5

KAUFMAN, L., ROUSSEEUW, P. J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. New York: Wiley. ISBN 0-471-87876-6

KAUFFMANN, J., ESDERS, M., RUFF, L., MONTAVON, G., SAMEK, W., MÜLLER, K. R. (2022). From clustering to cluster explanations via neural networks [online]. *IEEE Transactions on Neural Networks and Learning Systems,* 35(2): 1926–1940. <https://doi.org/10.1109/tnnls.2022.3185901>.

MACK, T. (1993). Distribution-free calculation of the standard error of chain ladder reserve estimates [online]. *ASTIN Bulletin*, 23(2): 213–225. <https://doi.org/10.2143/AST.23.2.2005092>.

MUNROE, D., ZEHNWIRTH, B., GOLDENBERG, I. (2018). Solvency capital requirement and the claims development result [online]. *British Actuarial Journal*, 23(15). <https://doi.org/10.1017/S1357321718000041>.

PAPENBERG, M., KLAU, G. W. (2021). Using anticlustering to partition data sets into equivalent parts [online]. *Psychological Methods*, 26(2): 161–174. <https://doi.org/10.1037/met0000301>.

SCRUCCA, L., FOP, M., MURPHY, B., RAFTERY, A. E. (2016). Mclust 5: clustering, classification and density estimation using Gaussian finite mixture models [online]. *The R Journal*, 8(1): 289–317. <https://doi.org/10.32614/RJ-2016-021>.

THE ACTUARIAL COMMUNITY (2022). *Loss Data Analytics* [online]. [cit. 22.7.2024]. <https://openacttexts.github.io/Loss-Data-Analytics/ChapLossReserves.html#S:Data>.

VEJMĚLKA, P. (2023). Clustering methods usable in loss reserving in non-life insurance and their comparison. *Proceedings of the 41st International Conference on Mathematical Methods in Economics:* 421–426. ISBN 978-80-11-04132-8

VERRALL, R. J. (1989). A State Space Representation of the Chain Ladder Linear Model [online]. *Journal of the Institute of Actuaries*, 116(3): 589–610. <https://doi.org/10.1017/S0020268100036714>.

WANG, M., WÜTHRICH, M. (2022). Individual claims generator for claims reserving studies: Data Simulation R [online]. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4127073>.

WÜTHRICH, M. V. (2018). Machine learning in individual claims reserving [online]. *Scandinavian Actuarial Journal*, 2018(6): 465–480. <https://doi.org/10.1080/03461238.2018.1428681>.

WÜTHRICH, M. V., MERZ, M. (2008). *Stochastic Claims Reserving Methods in Insurance.* West Sussex: Wiley & Sons. ISBN 978-0-470-77272-0

ZHANG, Y. (2010). A general multivariate chain ladder model [online]. *Insurance: Mathematics and Economics*, 46(3): 588–599. <https://doi.org/10.1016/j.insmatheco.2010.03.002>.

Bankruptcy Prediction Using First-Order Autonomous Learning Multi-Model Classifier

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Received 3.6.2024, **Accepted** (reviewed) 15.7.2024, **Published** 13.12.2024

Abstract

Research background: Bankruptcy and financial distress prediction has always been an integral part of any financial management system. It gives an indication to stakeholders to take precautionary measures in order to avoid losses. The traditional approaches for prediction, including logistic regression and discriminant analysis, are constrained by their inability to deal with complex and high-dimensional data (Odom and Sharda, 1990; Min and Lee, 2005). Recent developments in the field of machine learning, and particularly autonomous learning classifiers, present a potential proposed alternative.
Purpose: The purpose of this paper is to propose a first-order autonomous learning classifier (F-O $ALMM_0$) for predicting bankruptcy of business entities and individuals.
Design/methodology/approach: The data file contained a total of 352 companies obtained from the Kaggle database and incorporating 83 financial ratios. Initially, the model's performance was assessed as a preliminary step, but the results were average, followed by the application of Principal Component Analysis (PCA) to enhance the quality of the input's variables. Afterwards, the number of independent variables was reduced to 26. Thus, the results were improved.

Keywords	***DOI***	***JEL code***
Bankruptcy prediction, first-order, autonomous learning, Multi-Model Classifier, Principal Components Analysis	*https://doi.org/10.54694/stat.2024.30*	*C45, C53, C67, G17, G33*

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INTRODUCTION

The need for an accurate bankruptcy prediction model has become more urgent in recent times. This is because financial markets have become so complex that even the failure of large corporate firms causes a huge impact on the economy. The conventional statistical models are satisfactory up to some extent but generally fail due to the dynamic and nonlinear nature of the financial data. The paper introduces a new first-order autonomous learning classifier, F-O $ALMM_0$, to predict bankruptcy. This model reduces the inefficiencies inherent in traditional models by employing the latest machine learning techniques.

Bankruptcy is one major issue that many companies in different industries and sectors face. It occasions a crumbling of the financial structure of a company, halt in its operation, and dislocates employees into unemployment (Štefko et al., 2020). Basically, it means the company cannot meet its obligations in terms of employees, distributors, suppliers, shareholders, and lenders (Horváthová and Mokrišová, 2018). Only the assets that are in the hands of the judicial authorities remain, and these will be sold to pay off the company's debts. Many things lead to bankruptcy, but the end result is the same. Of these, however, the most significant is neglect; that is, not heeding the signs of bankruptcy before it takes hold (Kanapickienė et al., 2023). Ignoring these signs and doing nothing to arrest them will definitely bring a company to bankruptcy (Zhang et al., 2021).

Bankruptcy prediction is considered to be one of the important solutions in developed countries, being one of the major dependencies of risk management in large corporations (Safi et al., 2022). At the outset, statistical models were devised by focusing on specific financial ratios which actually turned out to possess excellent predictive abilities pertaining to bankruptcy (Srebro et al., 2021).

Artificial intelligence is nowadays considered one of the most powerful contemporary tools in bankruptcy prediction. Previous studies have shown that classification capabilities of intelligent models were more accurate and better than earlier statistical models (Odom and Sharda, 1990; Wilson and Sharda, 1994; Cooper, 1999; Jo et al., 1997; Min and Lee, 2005; Zieba, Tomczak and Tomczak, 2016; Salehi and Pour, 2016; Karas and Reznakova, 2017; Belas et al., 2017). For this reason, research in this area has become very attractive since quality of the results can always be improved. The more advanced AI becomes, the more accurate bankruptcy prediction is.

The aim of this paper is to utilize the F-O $ALMM_0$ model for bankruptcy prediction, which is considered a very important activity not only for companies but also for individuals, as it will help them discover their financial health. This model is a hybrid intelligent multi-model classifier. To test this predictive ability, 83 financial ratios were depended on, and a sample consisting of 352 companies, totaling 2 661 financial instances. This sample will be divided into a training sample and a testing sample. Moreover, the process of financial input purification will be examined to determine its role in improving the quality of this model. The Principal Component Analysis (PCA) technique will be relied upon for this verification. Finally, the results of the model will be compared before and after the input processing. The main question addressed in this paper is: How accurate is the F-O $ALMM_0$ model in bankruptcy prediction, and how effective is the PCA technique in improving the quality of financial inputs and the model's accuracy?

Major contribution of this research is to develop and validate the F-O $ALMM_0$ model for bankruptcy prediction, enhanced by applying PCA in order to improve the quality of the input variables. This contribution comes in various ways:

In this paper, a novel integration of self-directed learning classifiers and dimensionality-reduction techniques are proposed to create an improved method of prediction that is more accurate and reliable.

The empirical results obtained in this study underline the effectiveness of the F-O $ALMM_0$ model in developing the body of knowledge with practical and theoretical implications. The tool works for the early warning of potential bankruptcies, thus helping financial analysts, policymakers, and investors in decision-making processes.

This research fills the gap in literature through different approaches to applying machine learning techniques to financial prediction and provides new insights and empirical evidence that can be used to support the effectiveness of these methods.

The various limitations of traditional models – revealing how F-O $ALMM_0$ overcomes such limitations – will give further depth to the research in the current discussion on improving the models of bankruptcy prediction.

In the following part of the contribution, an overview of the literature is given, focused primarily on specific studies dealing with the issue of predicting bankruptcy of business entities. This is followed by the Methods chapter, in which the used data, methods and selection of variables are described. In the chapter Case Study, the research outputs are presented and evaluated, respectively the ability of the F-O $ALMM_0$ model to predict bankruptcy is tested. The final chapter summarizes the achieved results and describes their application in practice as well as research limitations.

1 LITERATURE REVIEW

The inability of macroeconomic policies to sufficiently address systemic risks, as evidenced in the financial crisis of 2008, is regarded by many as part of the cause of the crisis (Aliu et al., 2022). Indeed, a significant number of analysts argue that the low interest rate policy adopted by the Federal Reserve was the main cause of the housing bubble in the US (Dufour and Orhangazi, 2014). This imperative of increasing lending led to a speculative attitude in lending, and risk management practices were sidetracked (Smaranda, 2014). In such endeavors, various methodologies starting from classical statistical approaches to some of the most promising emerging artificial intelligence techniques have been implemented (Zhou et al., 2012).

The realm of failure prediction literature has been predominantly influenced by the dominance of multiple discriminant analysis for an extended period (Bauer, 2012). Beaver (1966) pioneered the application of univariate discriminant analysis. Blum (1974) formulates the model for failing companies and demonstrates that incorporating periodic revisions into the model fails to enhance the precision of forecasting. Ohlson (1980) introduced conditional probability models as an alternative to the multiple discriminant analysis.

Machine Learning, a sub-domain of Artificial Intelligence, focuses on the development of methodologies and approaches that enable computers to learn (Krulický et al., 2020). Machine Learning can be formulated in various ways (Yu, 2013). The most popular computational intelligence methodologies are found to be very effective in solving nonlinear problems (Zvaríková et al., 2022). Furthermore, these methodologies have the high capability to extract meaningful information from imprecise data and discover complex patterns that cannot be perceived by humans or traditional systems (Cleofas-Sanchez et al., 2016). Notably, Wu and Wang (2000) pioneered the application of neural networks for the assessment of credit risk specifically pertaining to small and medium-sized enterprises (SMEs). Serrano-Cinca (1996) employed self-organizing maps as a methodological approach. Desai et al. (1996) determined that the modular neural network and Multi-Layer-Perceptron (MLP) exhibited particular efficacy in accurately forecasting non-performing loans. Final and Fatih Oglu (2002) developed a hybrid classifier incorporating associative memories and self-organizing maps (SOM) in their approach to speaker recognition. Min and Lee (2005) utilized support vector machines (SVMs) to address the issue of bankruptcy prediction. Hsieh (2005) devised a credit scoring model that used the K-means clustering algorithms and SOM in order to ascertain the optimal inputs for a feed-forward Multilayer Perceptron (MLP). Glezakos et al. (2010) propose an alternative assessment and assert that logistic regression models exhibit high efficacy. Chen et al. (2011) introduced an evolutionary method to concurrently optimize the complexity and weights of a learning vector quantization network, with a focus on symmetric cost preference. Lin and Yang (2012) developed a rolling-logit model that allows the forecasting of corporate bankruptcy in the Taiwan Security Exchange, using current information as well as past information. Cao (2012) introduced a new multiple classifier ensemble model called MCELCCh-FDP that combines different classifiers using firm life cycle and Choquet integral in addressing financial distress. Serrano-Cinca and Gutiérrez-Nieto (2013) used Partial Least Square Discriminant Analysis as a predictive tool for the 2008 banking crisis in the United States. Khashei et al. (2013) applied essential principles of the MLP neural networks and fuzzy logic to construct a hybrid binary credit risk prediction model. Tsai et al. (2014) undertook an extensive study that aimed to compare classifier ensembles using three commonly employed classification techniques, namely decision trees (DT), SVM, and MLP neural networks. Giordani et al. (2014) discussed how adding spline functions to a logistic bankruptcy model improves prediction accuracy by 70% to 90%. This approach identifies complex nonlinear relationships between firm distress and financial metrics of leverage, earnings, and liquidity. Kou et al. (2014) proposed a multi-criteria decision-making (MCDM) framework for prioritizing various clustering algorithms. Kim et al. (2015) proposed the GMBoost, which is a geometric mean-based boosting algorithm and is one of the potential remedies for the class imbalance problem. In the research by Barboza et al. (2017), with a view to predicting bankruptcy a year ahead, a number of machine learning models were fitted, including boosting, support vector machines, bagging, and random forest. Li et al. (2017) used a linear programming algorithm to calculate the efficiency of company stability. Traczynski (2017) introduced a Bayesian model averaging approach to predict bankruptcy, addressing uncertainty in identifying the correct model. Key findings are that only the ratio of total liabilities to total assets and the volatility of market returns consistently predict default across various industries. This new method, which combines information from multiple models or includes industry-specific factors, performs better than traditional single-model approaches.

Angelov and Gu (2017) introduced an innovative 0-order multi-model classifier named Autonomous Learning Multiple-Model ($ALMM_0$-0). Tang et al. (2019) introduced an evolutionary pruning neural network (EPNN) model to predict bankruptcy. Soares et al. (2020) used the zero-order Autonomous Learning Multiple-Model ($ALMM_0$-0*) neuro-fuzzy methodologies, with the primary aim of categorizing diverse cardiac ailments based on auditory signals. Santos et al. (2022) presented the First-Order Autonomous Learning Multi-Model ($ALMM_0$) system as a regressor, which demonstrated the potential for seamless adaptation into a binary classifier. Sabek and Saihi (2023) made a comparison of the results between logistic regression and artificial neural networks in the forecast of financial distress for Saudi Arabia and Algeria. Rainarli and Sabek (2023) applied many machine learning methods to train the prediction model and process missing values and imbalanced data. Sabek (2023) compared two varieties of Artificial Neural Networks (ANNs) to Logistic Regression (LR) in the prediction of financial distress. His conclusion was that the superiority of the networks over LR depends on factors such as the specific network's type and its suitability for the given issue. Sabek and Horak (2023) used Gaussian Process Regression (GPR) to predict financial distress, optimized its hyperparameters to extract the optimal model, and then compared it with other machine learning models. They found that GPR achieved very suitable results. Altman et al. (2023) presented and examined the Omega Score, a new metric designed to improve the prediction of defaults in small and medium-sized enterprises (SMEs). They reconsider the traditional models of default prediction and estimate the effectiveness of the Omega Score in identifying SMEs that are at risk. Valaskova et al. (2023) explored the issue of bankruptcy forecasting in the Visegrad Group countries after the outbreak of COVID-19. They showed how economic disturbances caused by the pandemic had changed bankruptcy risk factors and suggested implications for financial management and policy development in the post-pandemic period.

In summary, therefore, the 2008 financial crisis can be qualified as partial inability of macroeconomic policies to address systemic risks from the housing market. For instance, many analysts have pointed out the low-interest-rate policy by the Federal Reserve as key in the formation of the housing bubble. The speculative lending that followed took no heed of risk management and set base for the wide-scale financial instability.

In the field of failure prediction, traditional methodologies, mostly multiple discriminant analysis, have occupied center stage in this domain for quite a long time. Of late, there have been innovations such as the introduction of univariate discriminant analysis, conditional probability models, and a range of machine learning techniques. More specifically, machine learning methodologies, including neural networks, self-organized maps, and SVMs, have displayed prowess for handling nonlinear phenomena and extracting relevant information from imprecise data.

Key contributions in bankruptcy prediction and credit risk assessment include the use of neural networks for SMEs, modular neural networks and MLPs for non-performing loans, and hybrid classifiers based both on associative memories and on self-organizing maps, for speaker recognition. Other innovative approaches entail logistic regression models, evolutionary methods for the optimization of learning vector quantization networks, and rolling-logit models to predict corporate bankruptcy.

Other methodologies proposed for predicting financial distress and bankruptcy have been the multiple classifier ensemble models, boosting algorithms with geometric mean – based variants, and Bayesian model averaging approaches. They encompass information from various models or involve industry-specific factors, even if they generally outperform the single-model solutions.

Machine learning has been in focus of late which has been experimented upon boosting, bagging, and random forests to predict bankruptcy. Methods like Omega Score for SMEs, Gaussian Process Regression (GPR), and analysis of bankruptcy risk factors post-COVID-19 have also been highlighted for their significant contributions to the field.

Furthermore, Autonomous Learning has become more significant. Researchers have developed new age models that are programmed to learn and improve autonomously with the passage of time without human intervention. Most important ones include the zero-order Autonomous Learning Multiple-Model ($ALMM_0$) and the First-Order Autonomous Learning Multi-Model (ALMM1). The $ALMM_0$ model represents how complex data patterns like cardiac ailments based on auditory signals can be effectively categorized using neuro-fuzzy methodologies. As binary classifiers, it easily adapts. Similarly, the First-Order Autonomous Learning Multi-Model ($ALMM_0$) system points out significant potential as both a regressor and a classifier in relation to autonomous learning in financial risk management and more areas of business beyond this scope.

The field of bankruptcy prediction has undergone a transformation from traditional statistical methods to more advanced machine learning methods and autonomous learning models, providing more precise and dependable tools for managing financial risk.

The first author is a leading expert in the sphere of financial distress and bankruptcy prediction, having an impressive record of scholarly publications that unequivocally prove his in-depth knowledge of and further innovativeness in this domain. He definitely turns out to be outstanding in his collaborative work on how to cope with challenges of missing and imbalanced data in bankruptcy prediction using machine learning. Moreover, he has compared artificial neural networks to logistic regression, proving their models on differentiating financial distress. His research in the optimization of hyperparameters in Gaussian Process Regression further proves skill in predictive accuracy. This proves the adaptability and efficiency of the techniques within different economic contexts. Further, his comparative evaluation of CA Score, Kida, and Springate models for financial distress prediction in Algeria serves as evidence of his comprehensive analytical studies and dedication to advancing the field.

2 METHODS

In this paper, as a first step, the ability of F-O $ALMM_0$ to predict bankruptcy will be tested by training the model using a training sample consisting of 2 001 financial instances, and then testing it using a testing sample consisting of 660 financial instances. In the second phase, the PCA technique will be used to extract only those principal components which have the biggest influence on the dependent variable and hence reduce the input size and improve its quality. The model will then be tested again. The results of the model before and after using the PCA technique will be compared.

F-O $ALMM_0$ is a Multi-model developed by Gu and Angelov (2018), for binary classification purposes and this is basically consistent with the purpose of the current study.[5]

The initial version of the model, Zero-Order $ALMM_0$, was created by Angelov and Gu (2017), and it has been employed in numerous prior research investigations for the purpose of classification. The model has consistently demonstrated a remarkable proficiency in its classification capabilities (Angelov and Gu, 2017; Soares et al., 2020).

Angelov and Gu (2017) examine the $ALMM_0$ general applicability with data drawn from diverse sources without any geographic and temporal limitation. In contrast, Soares et al. (2020) are interested in heart sound classification, and their recorded data usually comes from publicly available medical databases. Their time ranges are not precisely stated but were generally of data up until about 2020.

This motivated us to test the second version of the model First-Order $ALMM_0$ for classification, mainly because, to the best of our knowledge, this version of the model has not been investigated and tested before. According to Angelov et al. (2018), $ALMM_0$ has been realized to form a generic system which can be easily applied for the purpose of multi-model systems connected to probabilistic or other local models. The system is completely data-driven; therefore, it lets its structure be defined by non-parametric data clouds generated from empirical observations and makes no assumption about the distribution or properties of data in any form. This makes the new system capable of acquiring meta-parameters directly from the data and recursively updated, making the efficiency of memory usage and computational calculations within the algorithm more enhanced.

According to Angelov and Gu (2017) and Soares et al. (2020), adopting the self-learning method has several advantages:

- Adaptability: The model learns and updates itself in real-time based on new data, thus being relevant and accurate.
- Simplicity and Interpretability: Being simple and easy to understand makes this method useful in applications.
- Real-Time Processing: Data is processed fast; hence, it is best for scenarios necessiting immediate feedback.
- Robustness: Handles noise and outliers very well, boosting its performance on imperfect data. On the other side, this method is not without its deficiencies:
- Limited to Zero-Order: The zero-order model cannot deal with complex relationships in the data, thus crippling its overall efficiency.
- Scalability Issues: The model could be difficult to manage and scale with increasing data.
- Dependence on Initial Data Quality: It depends a lot on the quality of the first training data set.
- Complexity in Real-World Implementation: This can turn out to be complex in real-world scenarios due to integration and resource management problems in the implementation of the methodology.

2.1 Autonomous learning of Multi-Model systems

For several decades, multi-model systems have been in use in a rather wide spectrum of applications within adaptive control, observers, predictors, and classifiers, and have proven to be an effective tool in dealing with difficulties stemming from uncertainties related to measurements and motion. Actually, their operation is based on the ancient principle of «divide and rule,» where complex problems are broken down into a series of more feasible ones and then integrated together (Angelov et al., 2018).

[5] The model code and demo are publicly published at: <*https://www.researchgate.net/publication/322446053_FirstOrder_Autonomous_Learning_Multi-Model_System_source_code_Matlab_version*>.

Autonomous Learning Systems (ALSs) can be perceived as the physical embodiments of artificial intelligence. ALSs can be conceptualized as a convergence of sensor-equipped computational platforms (machines/devices) equipped with software algorithms, enabling these systems to acquire evolving intelligence through interaction with the self-monitoring and external environment. Some of the very basic properties of ALSs include the ability of self-adaptation and self-monitoring; therefore, self-learning or autonomous learning, learning of new knowledge, and update of existing knowledge are very crucial (Angelov, 2012).

The next section describes the learning process for the $ALMM_0$ system in some detail, structured around two major steps: structure identification and parameter identification: (Angelov and Gu, 2018)

For every recently acquired data sample, denoted as x_{K+1}, the global mean μ_K and the average scalar products X_K are updatedto μ_{K+1} and X_{K+1}.

The unimodal discrete density at the x_{K+1} and the central points of the existing data clouds $\mu_{K,i}$ (i = 1, 2 ,…, N_K) are computed using the following equation:

$$D\kappa(x) = \frac{1}{1+\frac{\|x-uk\|^2}{\sigma^2 k}} \quad . \tag{1}$$

Denoted by $D_{K+1}(x_{K+1})$ and $D_{K+1}(\mu_{K,i})$ (i = 1, 2 ,…, N_K). The following principle is examined to determine if x_{K+1} has the capability to generate a novel rule:

$$\text{Cond.1} \quad \text{IF } (D_{k+1}(x_{K+1}) > \max_{I = 1,2,\ldots,N_k} (D_{k+1}(\mu_{K,i}))) \; . \tag{2}$$

$$\text{Or } (D_{k+1}(x_{K+1}) < \min_{I = 1,2,\ldots,N_k} (D_{k+1}(\mu_{K,i}))) \; .$$

Then (X_{K+1} is a new focal point).

In case condition 1 is satisfied, a new rule is generated, depending on the value of X_{K+1}. A very important step would then be to check for a possible overlapping between the newly acquired data cloud and the previously existing data clusters. A principle of preventing overlap is utilized in view of the following:

$$\text{Cond.2} \quad \text{IF } (D_{k+1,i}(x_{K+1}) \geq \frac{1}{1+n^2} \quad .$$

Then the i^{th} facal point and the respective data could needs to be replaced by a new one. (3)

Where: $D_{k+1,i}(x_{K+1})$ is the unimodal discrete density computed per rule (data cluster) using the following equation:

$$D_{k+1,i}(x_{K+1}) = 1+\frac{\frac{1}{s_{ki}^2\left\|x_{k+1}-u_{k,i}\right\|^2}}{\left(s_{k,i}+1\right)\left(s_{k,i}X_{k,i}+\left\|x_{k+1}\right\|^2\right)-\left\|x_{k+1}+s_{k,i}u_{k,i}\right\|^2} \quad . \tag{4}$$

The logical basis for considering $D_{k+1,i}(x_{K+1}) \geq 1/(1 + n^2)$ arises from the well-known Chebyshev inequality, which elucidates the probability of a specific data sample, denoted as x to be n time standard deviation, away from the mean, μ:

$$P(\|x-u\|^2 \leq n^2\,\sigma^2) \geq 1-\tfrac{1}{n^2}\,. \tag{5a}$$

By employing the unimodal discrete density, the Chebyshev inequality can be restated in an elegant manner:

$$P(D_{k+1,i}(x_{K+1}) \geq -\frac{1}{1+n^2}) \geq 1-\tfrac{1}{n^2}\,. \tag{5b}$$

Here, n = 0.5 is used. That is, $(D_{k+1,i}(x_{K+1}) \geq 0.8$ for x_{K+1} is less than $\sigma/2$ away from the central point of the i^{th} data cloud. Put differently, x_{K+1} demonstrates a close proximity to all the points of the i^{th} data cloud. Consequently, x_{K+1} will be able to replace the focal point of the i^{th} data cloud.

In the event that Condition 1 is satisfied and Condition 2 is unfulfilled, a new rule termed «data cloud» with the focal point x_{K+1} is inserted.

$$N_{k+1} \leftarrow N_k + 1, \tag{6a}$$

$$S_{k+1,}N_{k+1} \leftarrow 1, \tag{6b}$$

$$u_{k+1,}N_{k+1} \leftarrow x_{k+1}, \tag{6c}$$

$$X_{k+1,}N_{k+1} \leftarrow \|x_{k+1}\|^2. \tag{6d}$$

In contrast, when Conditions 1 and 2 are concurrently met, the current overlapping data cluster (assuming the i^{th} data cloud) is substituted by a novel one with the central point x_{K+1}, denoted as $(N_{k+1} \leftarrow N_k)$.

$$S_{k+1,i} \leftarrow \left\lceil \frac{1-s_{K,i}}{2} \right\rceil, \tag{7a}$$

$$u_{k+1,i} \leftarrow \frac{x_{k+1}+u_{k,i}}{2}\,, \tag{7b}$$

$$X_{k+1,i} \leftarrow \frac{\|\,x_{k+1}\,\|^2+X_{k,i}}{2}\,. \tag{7c}$$

The aforementioned principle aims to prevent the discarding of previously gathered information within the ALMM0 system, because the novel data cloud may be initialized by an abnormal data sample.

In the event that Condition 1 fails to meet the required criteria, the value of x_{K+1} is allocated to the closest existing data cloud based on the utilization of the following equation:

$$\text{IF } (j^*) = \underset{i\,=\,1,2,\ldots,N}{\text{Arg min}} \; (\|x-u_i\|)) \text{ Then } (\text{Ꞓ}_{j^*} \leftarrow x). \tag{8}$$

The corresponding quantities are updated as follows $(N_{k+1} \leftarrow N_k)$:

$$S_{k+1,i} \leftarrow S_{k,i} + 1, \tag{9a}$$

$$u_{k+1,i} \leftarrow \frac{S_{k,i}}{S_{k+1,i}}u_{k,i} + \frac{1}{S_{k+1,i}}x_{k+i}\,, \tag{9b}$$

$$X_{k+1,i} \leftarrow \frac{S_{k,i}}{S_{k+1,i}} X_{k,i} + \frac{1}{S_{k+1,i}} \| x_{k+i} \|^2 . \tag{9c}$$

The descriptors (sample count, dot product, and average) of the remaining data clusters remain unchanged during the subsequent processing iteration. In $ALMM_0$, each data cloud serves as a foundation for constructing the antecedent (IF) part of the fuzzy rules.

2.2 The training algorithm of the First-Order Autonomous Multi-Model

The training algorithm starts by initializing the system and the first cloud as follows (Santos et al., 2022):

$$\begin{cases} K \leftarrow 1 \\ u \leftarrow x_1 \\ E(\|x\|^2) \leftarrow \|x_1\|^2 \\ N \leftarrow 1 \\ f_1 \leftarrow x_1 \\ X_1 \leftarrow \|x_1\|^2 \\ M_1 \leftarrow 1 \\ C_1 \leftarrow \Omega_0 I_{[(n+1)\times(n+1)]} \\ a_1 \leftarrow 0_{[(n+1)\times 1]} \\ B_1 \leftarrow 1 \\ P_1 \leftarrow 0 \end{cases} \tag{10}$$

In the aforementioned context, μ represents the overall mean value of the data points that have been analyzed. N denotes the total count of samples that have undergone analysis. F_k signifies the central point from cloud k. X_k represents the average scalar product of the data points scrutinized by the same cloud. Represents the total count of samples that utilized in generating the aforementioned cloud. Corresponds to the iteration number at which the cloud was formed, and denotes the sum of all previously normalized densities associated with the cloud. M_k denotes the total number of samples used in generating the above-mentioned cloud. B_k is the iteration number where this cloud was created and P_k refers to the summation of all previous normalized densities λ linked to this cloud.

After the initialization, the algorithm proceeds to analyze the following sample.

For the remaining samples, a tri-phase process is followed. The system undergoes each stage consecutively for every sample during the training process. The three stages encompass the ensuing procedures, such as cloud creation/ antecedents update, stale rule removal, the consequents update.

- Cloud creation/Antecedents update:

The initial phase commences with the incrementing of K while simultaneously updating the system's global parameters, namely μ and $E(X^2)$. Subsequently, the unimodal global density is computed for each focal point and the sample under examination:

$$D(x_j) < \min(D(f_i)) \text{ v } D(x_j) < \max(D(f_i)) . \tag{11}$$

If false, the nearest cloud is found, using Formula (12):

$$l = \underset{i=1,2,\dots,N}{\operatorname{Arg\,min}} (\|x_j - f_i\|) . \tag{12}$$

Then, the found cloud antecedents are updated, using Formula (13):

$$\begin{cases} M_l \leftarrow M_l + 1 \\ f_l \leftarrow \dfrac{M_l - 1}{M_l} f_l + \dfrac{1}{M_l} x_j \\ X_l \leftarrow \dfrac{M_l - 1}{M_l} X_l + \dfrac{1}{M_l} \| x_j \| \end{cases} . \tag{13}$$

Then, the algorithm proceeds to the next phase.

In the event that condition 1 is true, it becomes necessary to generate the antecedents for a novel rule. Nevertheless, there exists a possibility of sample x_j overlapping with the existing cloud antecedents. Therefore, it becomes imperative to check the position the sample compared to all clouds. In order to accomplish this objective, an update is applied to each cloud based on Formula (13). Subsequently, the unimodal local density of sample x_j is computed for each cloud utilizing their updated antecedents. The logical value of Formula (14) is then cheched:

$$\max(Di(xj) > 0.8. \tag{14}$$

If false, the absence of any identified overlap indicates the necessity for generating a novel cloud using Formula (15):

$$\begin{cases} N \leftarrow N + 1 \\ f_N \leftarrow x_j \\ M_N \leftarrow 1 \\ X_N \leftarrow \| x_j \| \\ B_N \leftarrow K \\ C_N \leftarrow C_1 \leftarrow \Omega_0 I_{[(n+1)\times(n+1)]} \\ A_N \leftarrow \sum_{i=1}^{N-1} \dfrac{A_t}{N-1} \end{cases} . \tag{15}$$

Then, the algorithm proceeds to the subsequent phase. If true, and an overlap is detected, the current existing cloud is determined based on the Formula (16):

$$L = \underset{i = 1,\ldots,N}{\arg\min} \; (D_i(x_j)) . \tag{16}$$

Afterwards, a novel cloud is generated over the existing on, using Formula (17):

$$\begin{cases} f_l \leftarrow \dfrac{x_j - f_l}{2} \\ M_l \leftarrow ceil\left(\dfrac{1 - M_l}{2}\right) \\ X_l \leftarrow \dfrac{\|x_j\|^2 + \mathrm{E}(\|x\|^2)_l}{2} \\ B_l \leftarrow K \\ P_l \leftarrow 0 \cdot \end{cases} \tag{17}$$

Then, the algorithm proceeds to the second phase.

- Removal of stale rules:

In the second step, the algorithm initiates updating the local density of x_j for all updated clouds. In the second step, the algorithm starts by updating the local density of x_j for all updated cloud.

They are subsequently normalised according to Formula (18):

$$\lambda_i = \frac{D_i\left(x_j\right)}{\sum_{i=1}^{N} D_i\left(x_j\right)} . \tag{18}$$

Upon acquiring the normalized densities, the utility of each rule, denoted as ηi, is computed based on its antecedent utilizing Formula (19):

$$P_i \leftarrow P_i + \lambda_i . \tag{19}$$

If B_i = K, Then:

$$\eta_i \leftarrow 1 . \tag{20}$$

Otherwise,

$$\eta_i \leftarrow \frac{1}{K - B_i} P_i . \tag{21}$$

Subsequently, the utility of each rule is subjected to a comparison with a minimum admissible value, η_0, through Formula (22) (condition 3):

$$\eta_i \leftarrow \eta_0 . \tag{22}$$

For every logical value that holds true, the corresponding rule is eliminated, leading to a decrement in the number of clouds. Irrespective of the logical value of condition 3 for each cloud, the algorithm proceeds to the next phase.

- Consequent parameters update:

In conclusion, the algorithm proceeds to update the consequent parameters utilizing the Formulas (23) and (24):

$$C_i \leftarrow C_i - \frac{\lambda_i C_i u_j u_j^T C_i}{1 + \lambda_i u_j^T C_i u_j} , \tag{23}$$

$$a_i \leftarrow a_i - \lambda_i C_i u_j (y_i - u_j^T a_i) . \tag{24}$$

3 DATA AND VARIABLES

In this section, a comprehensive explanation of the data used in the study is provided. Ready-made data extracted from Kaggle were relied upon for this purpose. It should be noted that not all the data was used; some of it was excluded in order to organize the training and testing samples appropriately, as depicted in Table 1.

Table 1 Data set description

Data set characteristics	Multivariate	Area	Business	Number of instances	2 661
Attribute characteristics	Real	Number of attributes	83	Bankrupt instances	1 247
Associated tasks	Classification	Number of companies	352	Normal instances	1 414

Note: This data is multivariate, as it includes 83 financial ratios. It is extracted from the financial statements of real, non-fictitious companies, prepared for classification purposes, and in the field of business. The data is extracted from the Kaggle database. It includes 3 672 financial instances for 422 companies, but this data was filtered and only 2 661 financial instances for 352 companies were used. Divided into 1 247 bankruptcy instances and 1 414 healthy instances.
Source: Own construction

Table 1 illustrates the characteristics of the data used, which are financial data associated with real companies, not fictional ones, specifically designed for the purpose of studying bankruptcy prediction. It is noteworthy that the number of predictors is 83 (financial ratios).

The selection process of the independent variables to be used for bankruptcy detection was beyond the authors. As explained above, these data were already existing and downloaded from the Kaggle website. The large number of 83 variables probably indicates the intention of the data creators to include all financial ratios that could be useful for predicting bankruptcy and which have been mainly used in previous relevant studies.

After data refinement, the analysis relied on data from 352 companies, with a total of 2 661 financial instances distributed as follows: 1 247 bankruptcy instances and 1 414 healthy instances. In Table 2, the total sample is divided into a training sample and a testing sample.

The training sample consisted of 187 companies and included a total of 2 001 financial instances, which were divided into 896 bankruptcy and 1 105 healthy instances. Regarding the test sample, there were data from 165 companies that provided a total of 660 financial instances: 351 cases of bankruptcy and 309 healthy instances.

Table 2 Data set divisions

Train	187 Companies	2 001 Instances	Bankrupt	896
			Normal	1 105
Test	165 Companies	660 Instances	Bankrupt	351
			Normal	309

Note: After examining and sorting the original data, the study sample was extracted, which pertains to the data of 352 companies, with a total of 2 661 financial instances. Since the model must undergo training and testing processes, the data was divided into a training sample that includes 2 001 instances, divided into 896 bankruptcy instances, 1 105 health instances. Secondly, a test sample, which includes 660 instances, divided into 351 bankruptcy instances, 309 health instances.
Source: Own construction

4 RESULTS

In this section, the ability of the F-O ALMM$_0$ model to predict bankruptcy will be tested. As explained in the previous section, the study sample is divided into a training sample and a testing sample. Using MATLAB, the samples were included. On the other hand, the model code was incorporated, and then the model instructions were applied. As a first step, the command to input the samples into the model was given, followed by training and verification. Lastly, the model's ability to predict bankruptcy was tested. Tabel 1 shows results of the classification accuracy.

Table 3 Confusion matrix

Observed		Predicted	
		Y	
		Bankrupt	Normal
Actual Y	Bankrupt	254	97
	Normal	119	190
Accuracy		67.27	

Note: The confusion matrix aids to identify several elements, firstly, the model's overall classification accuracy, in this case, was 67.27%, this rate is the result of dividing the total number of correctly classified instances by the total number of instances. The intersection of observed bankruptcy and predicted bankruptcy expresses instances that are correctly classified, and the intersection of observed bankruptcy with predicted normal expresses instances that are incorrectly classified. The intersection of observed normal and predicted bankruptcy expresses instances that are incorrectly classified, and the intersection of observed normal with predicted normal expresses instances that are correctly classified.
Source: Own construction

Table 3 shows the classification accuracy for the F-O $ALMM_0$ model after training and subsequent testing. From this table, one can see that the overall accuracy reached 67.27%, which is fairly reasonable for an intelligent model. It correctly classified 190 healthy instances and misclassified 119 instances. It successfully classified 254 bankruptcy instances and misclassified 97 instances, correspondingly. As such, it can be said that the model is considerably challenged during classification at the side of the classification of the healthy instances. Table 4: Accuracy prediction measures, Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE), evaluating the model on the ability to predict bankruptcy. Moreover, Recall – a sensitivity measure – was used to test the model for its ability to detect bankruptcy instances. Further on, True Negative Rate (TNR) was applied as a measure of the model's ability to recognize healthy instances.

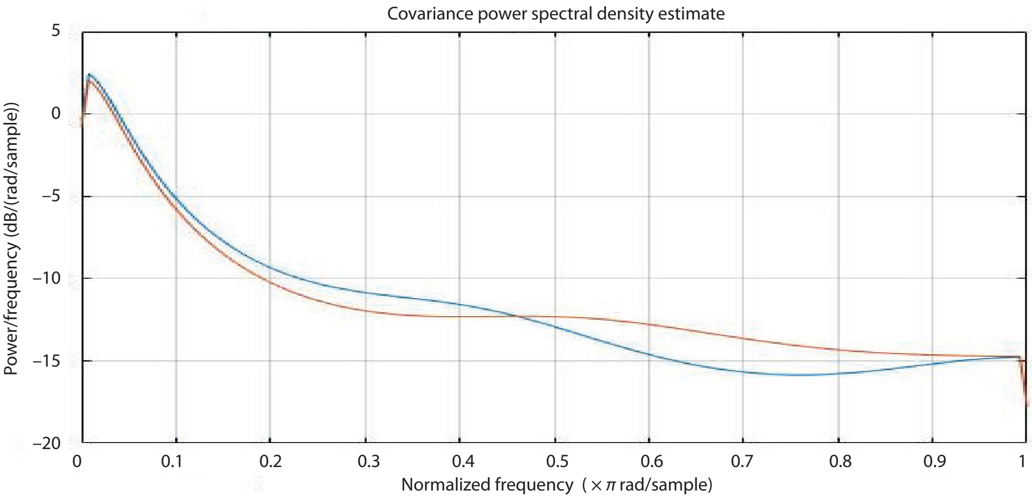
Table 4 Error values

Model	Type I	Type II	Type III	Recall	TNR
F-O $ALMM_0$	0.327	0.327	0.572	68.10	66.20

Note: To evaluate the classification accuracy more specifically, the most important measures that help in determining the model error were used, type I, Mean Absolute Error, type II, Mean Square Error, type III, Root Mean Square Error. Although Recall and TNR are elements of the confusion matrix, they are presented in this table for clarification purposes. Recall to assess the model's capacity in detecting instances of bankruptcy. TNR to evaluate the model's proficiency in identifying healthy instances.
Source: Own construction

Table 4 illustrates the values of the measures used to assess the model's error. These values exhibit relatively high levels, particularly RMSE. This indicates that the model encounters difficulties in accurately classifying bankruptcy. This is reflected in the overall accuracy of 67.27 %. Besides the Recall and TNR measures, moderate values are presented. Note that the TNR rate is lower than the Recall rate, indicating that the model has more difficulty classifying healthy instances compared to classifying instances of bankruptcy. This is also in line with our earlier observation from Table 3. Figure 1 further demonstrates a disparity between actual vs. predicted values.

Figure 1 Predicted vs actual plot



Note: A figure expressing the relationship between the actual values and the predicted values in the form of two curves, the first curve in blue represents the actual values, while the red curve represents the predicted values. The figure highlights the observed convergence between the two curves at some point, and the observed dissonance at some point.
Source: Own construction

The blue curve indicates the actual values, while the red shows the expected values. It can be noted that the two curves, at a point within the range of 0 to 0.1, came very close but this did not persist to result in divergence in other ranges. In order to improve the accuracy of the model in predicting bankruptcy, it was necessary to first improve the quality of the inputs. As mentioned earlier, the results of the model were not satisfactory, and this can be attributed to the presence of impurities that needs to be eliminated. That is in case it removes unneeded variables that confuse the learning of the model and retains only the variables which have a high impact on the dependent variable. It is important to note that 83 predictors are a very large number and should be reduced to a number that allows the model to be well trained. However, the number of predictors should not be reduced arbitrarily; rather a systematic method called principal component analysis, or PCA, ought to be followed. This is one such technique for extracting those independent variables which have most influence on the dependent variable. A prerequisite to the use of PCA is that there must be some multicollinearity between the predictors; if there is no multicollinearity, the inputs are all independent, and hence PCA would never be needed.

Table 5 illustrates the results of the test for detecting multicollinearity among the independent variables. It should be noted that the variables presented in the Table 5 are a random sample of the overall test results used for illustrative purposes only. Based on the results shown in Table 5, the presence of linear multicollinearity among the variables is inferred. This is attributed to the shrinkage of Tolerance values and the inflation of VIF values. Regarding the Tolerance measure, the more its values are inflated and approached 1, the more this indicates the fading of linear multicollinearity, and vice versa. As observed in Table 5, all Tolerance values are very small and close to zero. With respect to the VIF measure, the more its values shrink and do not exceed the threshold of 3, the more this indicates the fading of linear multicollinearity, and vice versa. Furthermore, it is noteworthy that all VIF values in the Table 5 confirm the presence of multicollinearity since their values exceeded 10 in all instances. Table 6 presents the initial and extracted values of the independent variables. As mentioned earlier, the variables presented in the Table 6 are a random sample of the overall test results used for illustrative purposes only.

Table 5 Multicollinearity test before PCA

Predictors	Collinearity statistics	
	Tolerance	VIF
X25	0.036	27.455
X33	0.039	25.357
X34	0.021	48.174
X38	0.011	93.841
X48	0.045	22.404
X51	0.023	43.290
X63	0.015	67.559
X64	0.012	84.181
X70	0.010	95.799
X73	0.007	148.365
X77	0.009	110.877
X81	0.033	30.697

Note: A statistical test using linear regression for the purpose of examining the selected data, and ascertaining whether there is an overlapping relationship between the independent variables or not. The test depends on two basic indicators, Tolerance and VIF, if the values of tolerance are small and do not approach 1, and the values of VIF are very inflated and exceed 3. This indicates the existence of multicollinearity between the variables.
Source: Own construction

Table 6 Communalities

Predictors	Initial	Extraction
X25	1	0.960
X33	1	0.917
X34	1	0.992
X38	1	0.970
X48	1	0.969
X51	1	0.851
X63	1	0.848
X64	1	0.931
X70	1	0.925
X73	1	0.847
X77	1	0.959
X81	1	0.976

Note: A statistical sub-test of the outputs of the Principal Components Analysis. This test is based on two basic indicators, the initial values, the extracted values. The second indicator is the most important, as it indicates the extent to which the data is well represented in the appropriate manner that aids in extracting suitable principal components. If the extracted values exceed 0.75, this indicates the success of the statistical test in extracting the suitable components.
Source: Own construction

Through Table 6, it is observed that the initial value remains constant at 1, which is favorable. However, our primary concern lies in the extracted value, as it indicates the extent to which the data is well represented in the appropriate manner that aids in extracting suitable principal components.

It is evident from Table 6 that the extracted value exceeds 0.75 in all instances, which is highly suitable and indicates the effectiveness of PCA in extracting the principal components. Table 7 illustrates the correlation between the financial ratios and the extracted principal components. It is worth noting once again that the variables and components presented in the Table 7 are a random sample from the overall test results, used for illustrative purposes only.

Table 7 Rotated components matrix

Financial ratios	Components							
	1	2	3	4	5	6	7	8
X25	0.031	**0.340**	0.032	–0.025	0.018	–0.002	0.018	0.907
X33	0.045	–0.003	0.200	0.002	0.165	–0.006	**0.916**	0.004
X34	0.022	0.002	–0.021	–0.026	–0.003	–0.002	0.006	–0.003
X38	0.022	–0.044	–0.030	–0.018	–0.007	**0.959**	–0.007	–0.002
X48	0.076	0.093	–0.038	–0.041	0.021	–0.005	0.004	**0.970**
X51	**0.381**	0.164	0.135	–0.061	–0.085	–0.285	0.102	0.134
X63	–0.178	–0.038	0.008	**0.850**	0.007	–0.035	0.017	–0.011
X64	–0.794	0.016	0.056	**0.343**	–0.006	–0.011	–0.021	–0.037
X70	**0.347**	0.048	–0.036	–0.840	0.032	0.012	–0.002	0.069
X73	–0.307	0.067	0.111	0.274	0.005	0.017	–0.019	–0.013
X77	**0.927**	–0.005	–0.018	–0.065	0.028	0.023	0.026	0.033
X81	0.105	0.121	–0.041	–0.060	0.034	–0.003	0.008	**0.966**

Note: A statistical sub-test of the outputs of the Principal Components Analysis. The test expresses the relationship between the extracted principal components and the financial ratios. Principal components that have relationships of values greater than 0.3 with three or more financial ratios are considered strong components. Principal components that have relationships of values greater than 0.3 with fewer than three components are considered weak components.
Source: Own construction

As a final result of the PCA test, 26 principal components were extracted. These components have the highest influence on the dependent variable. Table 7 illustrates the relationship between the extracted principal components and the financial ratios. It is worth noting that a component that does not have a high correlation with a value ≥ 0.3 with three or more financial ratios is considered a weak component and preferable to be excluded. 18 strong components were observed, alongside 8 components showing weak correlation. To verify the disappearance of multicollinearity among predictors, the new data will be subjected to the test of multicollinearity.

Table 8 demonstrates that multicollinearity has definitely disappeared, and the results presented above are contrary to the results of the multicollinearity test prior to PCA testing, as indicated in Table 5. It is noteworthy that the Tolerance has inflated and become constant at a value of 1, while the VIF value has decreased and does not exceed 3 in all instances. Now that the principal components have been extracted, the model can be tested again. But experimenting with 26 components relying was found to be more accurate than relying on 18 components only. That means the weak components also play a significant role in improving accuracy. Table 9 shows the accuracy of the model classification after applying the PCA and extracting the suitable principal components.

Table 8 Multicollinearity test after PCA

Independent variables	Collinearity statistics	
	Tolerance	VIF
1	1	1
2	1	1
3	1	1
4	1	1
5	1	1
6	1	1
7	1	1
8	1	1
9	1	1
10	1	1
11	1	1
12	1	1

Note: A statistical test using linear regression for the purpose of examining the selected data, and ascertaining whether there is an overlapping relationship between the independent variables or not. The test depends on two basic indicators, Tolerance and VIF, if the values of tolerance are small and do not approach 1, and the values of VIF are very inflated and exceed 3. This indicates the existence of multicollinearity between the variables.
Source: Own construction

Table 9 Confusion matrix after PCA

Observed		Predicted	
		Y	
		Bankrupt	Normal
Actual Y	Bankrupt	269	82
	Normal	67	242
Accuracy		77.42	

Note: The confusion matrix aids to identify several elements, firstly, the model's overall classification accuracy, in this case, was 77.42%, this rate is the result of dividing the total number of correctly classified instances by the total number of instances. The intersection of observed bankruptcy and predicted bankruptcy expresses instances that are correctly classified, and the intersection of observed bankruptcy with predicted normal expresses instances that are incorrectly classified. The intersection of observed normal and predicted bankruptcy expresses instances that are incorrectly classified, and the intersection of observed normal with predicted normal expresses instances that are correctly classified.
Source: Own construction

Table 9 presents the accuracy of classification from F-O $ALMM_0$ model after training and testing. As noted, the overall accuracy was 77.42%, which is satisfactory in its totality. Improvement in the model is highly significant because it managed to classify correctly 269 bankruptcy instances; whereas, it misclassified 82 instances. It also classified 242 healthy instances correctly and misclassified 67. Notice that the misclassification rate of the model concerning the healthy instances has decreased, and the classification ability has increased after applying the PCA technique. Table 10 focuses on the model's ability to predict bankruptcy by measures of prediction accuracy.

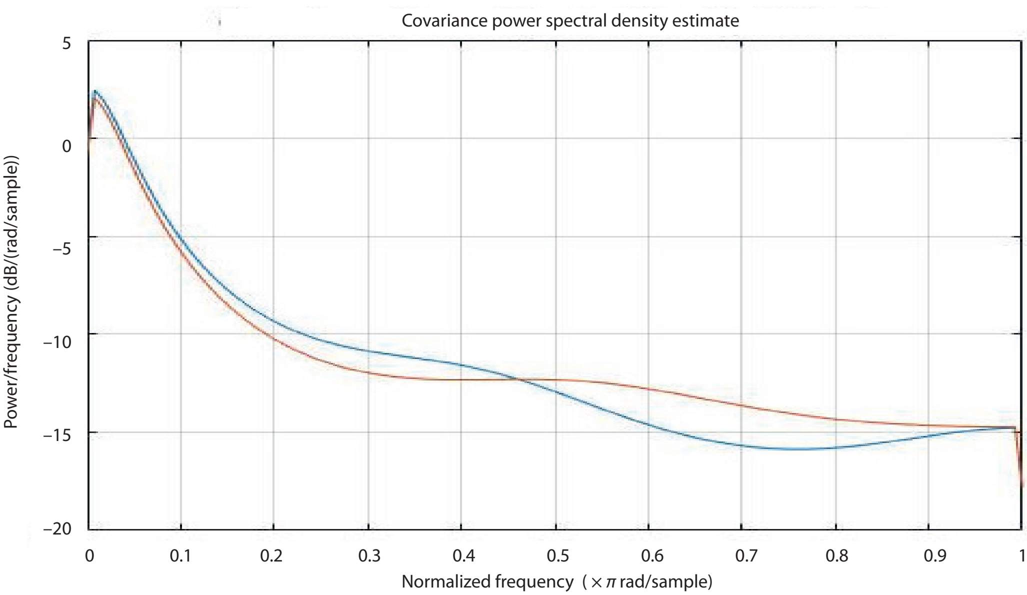
Table 10 Error values after PCA

Model	Type I	Type II	Type III	Recall	TNR
F-O $ALMM_0$	0.227	0.227	0.476	79.82	74.61

Note: To evaluate the classification accuracy more specifically, the most important measures that help in determining the model error were used, type I, Mean Absolute Error, type II, Mean Square Error, type III, Root Mean Square Error. Although Recall and TNR are elements of the confusion matrix, these metrices are shown in this table for clarification purposes. Recall to assess the model's capacity in detecting instances of bankruptcy. TNR to evaluate the model's proficiency in identifying healthy instances.
Source: Own construction

Table 10 illustrates the values of the model's error. It is noteworthy that these values have significantly decreased, indicating an improvement in the model's quality in predicting bankruptcy. This is reflected in the overall accuracy of 77.42. Additionally, the Recall and TNR indicate suitable values as well. It is interesting to note that the TNR rate still stands below the Recall rate, indicating that the model still tends to misclassify healthy instances in comparison with bankruptcy instances. It can be noted that there is a difference between the actual and expected values from Figure 2.

Figure 2 Predicted values vs actual plot



Note: A figure expressing the relationship between the actual values and the predicted values in the form of two curves, the first curve in blue represents the actual values, while the red curve represents the predicted values. The figure highlights the observed convergence between the two curves at some point, and the observed dissonance at some point.
Source: Own construction

The impact of the PCA technique is clearly evident through Figure 2, where the level of compatibility between the actual values and the expected values is noticeable. In Figure 1, the compatibility was limited to the horizontal range (0–0.1) only, but in this case, the compatibility between the two curves takes a longer range (0–0.3). Then, a slight divergence in the range (0.3–0.7) is observed, followed by renewed compatibility in the range (0.7–1). Table 11 illustrates the comparison between the results of the model before and after using PCA.

Table 11 Parameters for evaluation

Measure	Before PCA	After PCA
Error 1	0.327	0.227
Error 2	0.327	0.227
Error 3	0.572	0.476
Sig.	0.00	0.00
R^2	0.116	0.297
Cov.	0.084	0.136
Recall	68.10	79.82
TNR	66.20	74.61
Precision	66.20	74.69
F_1	0.672	0.771
Acc.	67.27	77.42

Note: To compare the different results of the model before and after using PCA, the most important mathematical and statistical measures for performance evaluation were combined. Firstly, the error measures, type I, Mean Absolute Error, type II, Mean Square Error, type III, Root Mean Square Error. Secondly, the elements of the confusion matrix, Recall, TNR, Precision, F1, and Accuracy. Thirdly, the statistical measures, Significance, Coefficient of determination, and Covariance.
Source: Own construction

Through Table 11, the model can be evaluated mathematically using error measures, and statistically using certain statistical measures. The statistical significance of the model can be assessed through (Sig), the correlation between the actual and predicted values can be evaluated using (R^2), and the degree of correlation in the variation between actual and predicted values can be assessed using (Cov). F1-score is the harmonic of Recall and precision, and the higher the F1, the better the predictive accuracy of the classification procedure. All in all, it can be noted that all the values given in Table 11 reflect an improvement in the quality of the model after applying the PCA.

5 DISCUSSION

The results presented in Tables 3 to 11 provide valuable insights into the performance and improvements made to the F-O $ALMM_0$ model for bankruptcy prediction. In this discussion, the analysis and interpretation of these results aim to assess the model's accuracy, identify challenges faced, and evaluate the impact of Principal Component Analysis (PCA) on model enhancement.

5.1 Interpreting findings in the context of existing research

Table 3 illustrates the initial classification accuracy of the F-O $ALMM_0$ model. The overall attained accuracy of 67.27% is at a moderate level for an intelligent model. Even though it classifies 254 instances of bankruptcy correctly, it struggles with the classification of healthy instances, as it misclassified 119 of them. This obviously proves that there are major challenges in separating the two instances, which is very important in financial risk assessment. This agrees with previous research indicating that most financial models often misclassify healthy firms because their financial characteristics overlap with those of distressed firms (Altman, 1968; Ohlson, 1980).

5.2 Challenges in model performance

Table 4 presents an overview of error measures used to evaluate model performance. A relatively high RMSE with a medium range for Recall and TNR, it indicates that the model suffers from classifying bankruptcy correctly. Besides, one can mention that the rate of TNR is lower than Recall indicating thus a greater challenge in classifying healthy instances. This challenge is also consistent with the findings from related studies where models create a bias towards the bankruptcy instances due to its relatively lower occurrence in datasets (Beaver, McNichols and Rhie, 2005).

5.3 Improving input data quality with PCA

The discussion then focuses on the necessity of optimizing the quality of input data. It will be shown that the number of 83 predictors will cause problems with the training of the model. A solution will be the systematic use of PCA in extracting influential independent variables and eliminating multicollinearity among predictors, as presented in Table 5. In this table, the results indicate that there is a significant problem of multicollinearity since Tolerance values approaching zero and VIF valuesexceeding 10, a fact that means the necessity of using PCA.

Table 6 reveals that the extraction of principal components in all instances is above 0.75, which proves that it is appropriate to apply PCA for reducing dimensions. From the PCA test shown in Table 7, it can be seen that 26 principal components are obtained. Notably, 18 are strongly correlated and 8 are weakly correlated to financial ratios. The selection procedure reduced the multicollinearity, as confirmed in Table 8 with Tolerance reaching the constant value of 1 and VIF values not exceeding 3. Remarkably, it is relying on all 26 components, which seems more efficient to improve the accuracy of classification.

The extraction of 26 principal components, of which 18 correlated highly with financial ratios, supports the literature that suggests dimensionality reduction can be a method to enhance the performance of models by reducing multicollinearity (Jolliffe, 2002).

5.4 Enhanced model performance post-PCA

Table 9 presents the improved performance of F-O $ALMM_0$ model after the use of PCA. The accuracy increased to 77.42%, hence there is a significant improvement. It can be noted that this model misclassifies fewer healthy instances, demonstrating the efficacy of principal component analysis in addressing the challenges of the model. Table 10 further highlights the improved quality of the model in the significantly decreased values of error. The Recall and TNR values improve considerably; however, the rate of TNR remains low, indicating the continued challenge in classifying healthy instances. Table 11 presents a comprehensive assessment of model performance, including statistical measures. It is shown that the improvement in the quality of the model is very high. The results obtained from F1-Score also prove the predictive ability of the model. The results align with previous studies advocating PCA's utility in optimizing predictive models by improving feature relevance andreducing dimensionality (Wold, Esbensen and Geladi, 1987).

5.5 Explanation for results

The improved performance of the model can be attributed to many factors. Dimensionality reduction in the input data through PCA certainly helped lessen the impact of both multicollinearity and overfitting. By selecting the most influential principal components, the model focused on a lesser number of relevant features, hence improving the predictive accuracy. Further, from the result showing strong correlations between the selected components and financial ratios indicate that PCA effectively retained significant information for accurate classification.

The initial moderate performance and improvement afterwards underline quite significantly that data preprocessing is very essential for a machine learning model. In this case, probably the large number of predictors used initially might have introduced noise and redundancy, which PCA effectively reduced. This aligns with prior literature highlighting feature selection and dimensionality reduction as a significant approach in improving model performance (Guyon and Elisseeff, 2003).

5.6 Discussion of similarities and differences

Compared to existing studies, we notice both similarities and differences. The medium accuracy initially, then its improved performance after PCA are align with prior studies that highlight the advantages of dimensionality reduction (Wold, Esbensen and Geladi, 1987; Jolliffe, 2002; Guyon and Elisseeff, 2003). In contrast, Chen and Du's (2009) study experimental results show that factor analysis exacerbates the misclassification errorleading to failure companies being incorrectly identified as healthy companies. This may be due to the peculiarity of sample, such as the distribution of financial health or due to economic environment during the collection of data.

5.7 Summarizing the discussion

In summary, the application of PCA played a significant role in the enhancement of the performance of the F-O ALMM$_0$ model for bankruptcy prediction. Accuracy of the model, statistical significance, and error measures have all improved, with particular benefits in reducing misclassification of healthy instances. These results suggesting proper preprocessing and dimensionality reduction are important steps when developing effective predictive models within the financial domain.

Future research may explore more dimensionality reduction techniques and integration of alternative machine learning algorithms to increase further robustness in the model. Further, examination into how the diverse financial environments and different sample sizes impact model performance may provide deeper insights into the generalizability of the findings.

By contextualizing these results within existing research, providing explanations for observed outcomes, and summarizing key points, this discussion section aligns with standard expectations and offers a comprehensive analysis of the study's findings and implications.

CONCLUSION

This paper tests the predictive ability of the intelligent Multi-model, F-O ALMM$_0$ for bankruptcy prediction. A large study sample is used in this respect, consisting of a training sample with 2 001 financial instances and a testing sample with 660 financial instances. After reviewing the literature and explaining the model's structure, the practical part was divided into four main stages. In the first stage, the model's performance was tested after training it using 83 predictors. However, the model yielded only average or modest results, achieving a classification accuracy of only 67.27 %. This raised the question: What is wrong? And how can the model's results be improved?

The first thing that caught attention was the sheer number of predictors, which is indeed beneficial for gaining a comprehensive understanding of a company's financial status in a given fiscal year. However, as much as it is advantageous, it can also become a drawback, because the data may contain impurities and conflicting information that impede the model's learning ability. Therefore, as a second stage, the data was processed using Principal Component Analysis (PCA) technique, extracting 26 principal components, including 8 weak components. Nevertheless, experimental results demonstrated that relying on all components without excluding the weak ones yielded better outcomes.

In the third stage, the performance of the model was tested once more with the extracted predictors. Obvious improvement in the quality of the model was realized as it attained a classification accuracy of 77.42%. In the fourth stage, a comparison was made between the results before and after applying PCA on the model with relying on mathematical and statistical measures. It has been concluded that this intelligent model achieves highly appropriate results in bankruptcy prediction, especially when the input features are pre-processed using the PCA.

The research would develop and validate the F-O $ALMM_0$ model for the advancement of financial prediction field, wherein, through the application of principal component analysis to improve the quality of variables provided as input, it would not be merely a theoretical advancement about autonomous learning method but providing a tangible solution to enhance financial stability and decision-making. The findings are of practical relevance to investors, financial analysts, and policymakers, providing a robust tool for the early warning system of potential bankruptcies.

Besides these significant findings, the research presents a number of limitations. The first major limitation pertains to conduct a comparison analysis between the initial and subsequent versions of the model. Further, this study may involve testing the model using a larger and diverse sample that includes diverse temporal and spatial scope.

This approach can be adapted for application in other markets using more realistic data from established sources. Besides, the same approach can be adapted to categorize challenges across various fields beyond finance. The future research is expected to develop hybrid intelligent models further to address classification issues in both the finance and marketing fields. Also, it is anticipated to test other data processing tools, with a focus on Lasso Regression particularly, be used to enhance the processing methodology of raw data.

ACKNOWLEDGMENT

This research was supported by Institute of Technology and Business in České Budějovice, the project: IVSUZO2301 – the impact of the circular economy on the share prices of companies listed on the stock exchange.

This research was supported by the Scientific Grant Agency of Slovak Republic under progect VEGA No. 1/0479/23 – Research of circular consumer behavior in the context of STP marketing model. The authors would like to express their gratitude to the Scientific Grant Agency of the Ministry of Education, Research, Development, and Youth of the Slovak Republic for financial support of this research and publication. However, the responsibility for the facts stated, opinions expressed, and the conclusions drawn are entirely of the authors.

This work is financed by Portuguese national funds through FCT – Fundação para a Ciência e Tecnologia, under the project UIDB/05422/2020.

References

ALIU, F., HASKOVA, A., SULER, P. (2022). Sustainability of electricity prices and the consequences for the Prague Stock Exchange [online]. *Entrepreneurship and Sustainability Issues*, 10(2): 473–494. <https://doi.org/10.9770/jesi.2022.10.2(30)>.

ALTMAN, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, 23(4): 589–609.

ALTMAN, E. I., BALZANO, M., GIANNOZZI, A., SRHOJ, S. (2023). The Omega Score: An improved tool for SME default predictions [online]. *Journal of the International Council for Small Business*, 4(4): 362–373. <https://doi.org/10.1080/26437015.2023.2186284>.

ANGELOV, P. (2012). *Autonomous learning systems: from data streams to knowledge in real time*. John Wiley & Sons, Ltd. ISBN 978-1-118-48176-9

ANGELOV, P., GU, X. (2017). Autonomous learning multi-model classifier of 0-Order (ALMMo-0). *Evolving and Adaptive Intelligent Systems,* Ljubljana, Slovenia, pp. 1–7.

ANGELOV, P. P., GU, X. J. C., PRÍNCIPE, J. C. (2018). Autonomous Learning Multimodel Systems From Data Streams [online]. *IEEE Transactions on Fuzzy Systems*, 26(4): 2213–2224. <https://doi.org/10.1109/TFUZZ.2017.2769039>.

BARBOZA, F., KIMURA, H., ALTMAN, E. (2017). Machine learning models and bankruptcy prediction [online]. *Expert Systems With Applications,* 83: 405–417. <https://doi.org/10.1016/j.eswa.2017.04.006>.

BAUER, J. (2012). *Bankruptcy Risk Prediction and Pricing: Unravelling the Negative Distress Risk Premium*. PhD Thesis, Cranfield School of Management, Cranfield University, England, 255 p.

BEAVER, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4: 71–111.

BEAVER, W. H., MCNICHOLS, M. F., RHIE, J. W. (2005). Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy [online]. *Review of Accounting Studies*, 10(1): 93–122. <https://doi.org/10.1007/s11142-004-6341-9>.

BELAS, J., MISANKOVA, M., SCHONFELD, J., GAVUROVA, B. (2017). Credit risk management: financial safety and sustainability aspects [online]. *Journal of Security and Sustainability Issues*, 7: 79–93. <https://doi.org/10.9770/jssi.2017.7.1(7)>.

BLUM, M. (1974). Failing Company Discriminant Analysis [online]. *Journal of Accounting Research*, 12(1): 1–25. <https://doi.org/10.2307/2490525>.

CAO, Y. (2012). MCELCCh-FDP: Financial distress prediction with classifier ensembles based on firm life cycle and Choquet integral [online]. *Expert Systems with Application,* 39(8): 7041–7049. <https://doi.org/10.3390/math8081275>.

CHEN, N., RIBEIRO, B., VIEIRA, A. S., DUARTE, J., NEVES, J. C. (2011). A genetic algorithm-based approach to cost-sensitive bankruptcy prediction [online]. *Expert Systems with Applications,* 38(10): 12939–12945. <https://doi.org/10.1016/j.eswa.2011.04.090>.

CHEN, W., DU, Y. (2009). Using neural networks and data mining techniques for the financial distress prediction model [online]. *Expert Systems with Applications*, 36(2): 4075–4086. <https://doi.org/10.1016/j.eswa.2008.03.020>.

CLEOFAS-SANCHEZ, L., GARCIA, V., MARQUES, A. I., SANCHEZ, J. S. (2016). Financial distress prediction using the hybrid associative memory with translation [online]. *Applied Soft Computing,* 44: 144–152. <https://doi.org/10.1016/j.asoc.2016.04.005>.

COOPER, J. C. B. (1999). Artificial neural networks versus multivariate statistics: an application from economics. *Journal of Applied Statistics,* 26(8): 909–921.

DESAI, V. S., CROOK, J. N., OVERSTREET JR, G. A. (1996). A comparison of neural networks and linear scoring models in the credit union environment. *Eur. J. Oper. Res*, 95(1): 24–37.

DUFOUR, M., ORHANGAZI, O. (2014). Capitalism, Crisis, and Class: The United States Economy after the 2008 Financial Crisis [online]. *Review of radical political economics,* 46(4): 461–472. <https://doi.org/10.1177/0486613414537981>.

FINAL, M. Y., FATIH OGLU, Y. (2002). Self organizing map and associative memory model hybrid classifier for speaker recognition. In: *Proc. 6th Seminar on Neural Network Applications in Electrical Engineering*, Belgrade, pp. 71–74.

GIORDANI, P., JACOBSON, T., SCHEDVIN, E. VON, VILLANI, M. (2014). Taking the Twists into Account: Predicting Firm Bankruptcy Risk with Splines of Financial Ratios [online]. *Journal of Financial and Quantitative Analysis*, 49(4): 1071–1099. <https://doi:10.1017/S0022109014000623>.

GLEZAKOS, M., MYLONAKIS, J., OIKONOMOU, K. (2010). An empirical research on early bankruptcy forecasting models: Does logit analysis enhance business failure predictability? *European Journal of Finance & Banking Research*, 3: 1–15.

GU, X., ANGELOV, P. P. (2018). First-order autonomous learning multi-model system (Source code, Matlab version) [online]. [cit. 9.8.2023] <https://www.researchgate.net/publication/322446053_First-Order_Autonomous_Learning_Multi-Model_System_source_code_Matlab_version>.

HORVÁTHOVÁ J., MOKRIŠOVÁ, M. (2018). Risk of Bankruptcy, Its Determinants and Models [online]. *Risks,* 64(117). <https://doi.org/10.3390/risks6040117>.

HSIEH, N. C. (2005). Hybrid mining approach in the design of credit scoring models [online]. *Expert Syst. Appl*, 28(4): 655–665. <https://doi.org/10.1016/j.eswa.2004.12.022>.

JO, H., HAN, I., LEE, H. (1997). Bankruptcy prediction using case-based reasoning, neural networks, and discriminant analysis [online]. *Expert Systems with Applications*, 13(2): 97–108. <https://doi.org/10.1016/S0957-4174(97)00011-0>.

JOLLIFFE, I. T. (2002). *Principal Component Analysis.* 2nd Ed. Springer Series in Statistics, Springer.

KANAPICKIENĖ, R., KANAPICKAS, T., NEČIŪNAS, A. (2023). Bankruptcy Prediction for Micro and Small Enterprises Using Financial, Non-Financial, Business Sector and Macroeconomic Variables: The Case of the Lithuanian Construction Sector [online]. *Risks*. 11(5): 1–33. <https://doi.org/10.3390/risks11050097>.

KARAS, M., REZNAKOVA, M. (2017). Predicting the bankruptcy of construction companies: A CART-based model [online]. *Engineering Economics*, 28: 145–154. <https://doi.org/10.5755/j01.ee.28.2.16353>.

KHASHEI, M., REZVAN, M. T., HAMADANI, A. Z., BIJARI, M. (2013). A bi-level neural-based fuzzy classification approach for credit scoring problemss [online]. *Complexity*, 18: 46–57. <https://doi.org/10.1002/cplx.21458>.

KIM, M. J., KANG, D. K., KIM, H. B. (2015). Geometric mean based boosting algorithm with over-sampling to resolve data imbalance problem for bankruptcy prediction [online]. *Expert Systems with Applications,* 42(3): 1074–1082. <https://doi.org/10.1016/j.eswa.2014.08.025>.

KOU, G., PENG, Y., WANG, G. (2014). Evaluation of clustering algorithms for financial risk analysis using MCDM methods [online]. *Information Sciences,* 275: 1–12. <https://doi.org/10.1016/j.ins.2014.02.137>.

KRULICKÝ, T., KALINOVÁ, E., KUČERA, J. (2020). Machine learning prediction of USA export to PRC in context of mutual sanction [online]. *Littera Scripta*, 13(1): 83–101. <https://doi.org/10.36708/Littera_Scripta2020/1/6>.

LI, Z., CROOK, J., ANDREEVA, G. (2017). Dynamic prediction of financial distress using Malmquist DEA [online]. *Expert Systems with Applications*, 80: 94–106. <https://doi.org/10.1016/j.eswa.2017.03.017>.
LIN, C., YANG, T. (2012). Validation the Role of Previous Information in Predicting TSE Corporation Bankruptcy. *Procedia – Social and Behavioral Sciences*, 57: 560–565.
MIN, J., LEE, Y. (2005). Bankruptcy Prediction Using Support Vector Machine with Optimal Choice of Kernel Function Parameters [online]. *Expert Systems with Applications,* 28(4): 603–614. <https://doi.org/10.1016/j.eswa.2004.12.008>.
ODOM, M. D., SHARDA, R. (1990). A neural network model for bankruptcy prediction. *IJCNN International Joint Conference on Neural Networks,* 2: 163–168.
OHLSON, J. A. (1980), Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research,* 18(1): 109–131.
RAINARLI, E., SABEK, A. (2023). Mitigating challenges: Handling mis sing values and imbalanced data in bankruptcy prediction using machine learning [online]. *Littera Scripta, Economics, Corporate finance, Finance and Valuation*, 16(2): 79–96. <https://doi.org/10.36708/Littera_Scripta2023/2/6>.
SABEK, A. (2023). Unveiling the diverse efficacy of artificial neural networks and logistic regression: A comparative analysis in predicting financial distress [online]. *Croatian Review of Economic, Business and Social Statistics (CREBSS)*, 9(1): 16–32. <http://doi.org/10.2478/crebss-2023-0002>.
SABEK, A. (2024). A Comparative Analytical Evaluation of CA Score, Kida, Springate Models for Financial Distress Prediction: The Case of Algeria. *Revue Finance & marchés,* 11(1): 38–50.
SABEK, A., HORAK, J. (2023). Gaussian Process Regression´s Hyperparameters Optimization to Predict Financial Distress [online]. *Retos, Revista de Ciencias Administracion y Economia*, 13(26): 273–289. <http://doi.org/10.17163/ret.n26.2023.06>.
SABEK, A., SAIHI, Y. (2023). Crunching Numbers, Making Decisions: Artificial Intelligence and Statistics for Financial Distress Forecasting in Algeria and Saudi Arabia [online]. *CAFI, Comptabilité, Actuariat, Finance & Information*, 6(2): 183–201. <https://doi.org/10.23925/cafi.62.60718>.
SAFI, SA-D, CASTILLO, P.A., FARIS, H. (2022). Cost-Sensitive Metaheuristic Optimization-Based Neural Network with Ensemble Learning for Financial Distress Prediction [online]. *Applied Sciences*, 12(14): 1–32. <https://doi.org/10.3390/app12146918>.
SALEHI, M., POUR, M. D. (2016). Bankruptcy prediction of listed companies on the Tehran Stock exchange [online]. *International Journal of Law and Management*, 58: 545–561. <https://doi.org/10.1108/IJLMA-05-2015-0023>.
SANTOS, F., VENTURA, R., SOUSA, J. M. C., VIEIRA, M. S. (2022). First-Order Autonomous Learning Multi-Model Systems for Multiclass Classification tasks. *2022 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE),* Padua, Italy, 1–6.
SERRANO-CINCA, C. (1996). Self organizing neural networks for financial diagnosis [online]. *Decision Suport Systems,* 17(3): 227–238. <https://doi.org/10.1016/0167-9236(95)00033-X>.
SERRANO-CINCA, C., GUTIÉRREZ-NIETO, B. (2013). Partial Least Square Discriminant Analysis for bankruptcy prediction [online]. *Decision Support Systems*, 54(3): 1245–1255. <https://doi.org/10.1016/j.dss.2012.11.015>.
SMARANDA, C. (2014). Scoring functions and bankruptcy prediction models – case study for Romanian companies [online]. *Procedia Economics and Finance*, 10: 217–226. <https://doi.org/10.1016/S2212-5671(14)00296-2>.
SOARES, E., ANGELOV, P., GU, X. (2020). Autonomous Learning Multiple-Model zero-order classifier for heart sound classification [online]. *Applied Soft Computing,* Vol 94. <https://doi.org/10.1016/j.asoc.2020.106449>.
SREBRO, B, MAVRENSKI, B, BOGOJEVIĆ, V., KNEŽEVIĆ, S., MILAŠINOVIĆ, M., TRAVICA, J. (2021). Bankruptcy Risk Prediction in Ensuring the Sustainable Operation of Agriculture Companies [online]. *Sustainability,* 13(14): 1–17. <https://doi.org/10.3390/su13147712>.
ŠTEFKO R, HORVÁTHOVÁ J., MOKRIŠOVÁ M. (2020). Bankruptcy Prediction with the Use of Data Envelopment Analysis: An Empirical Study of Slovak Businesses [online]. *Journal of Risk and Financial Management*, 13(9): 1–15. <https://doi.org/10.3390/jrfm13090212>.
TANG, Y., J. JI, J., ZHU, Y., GAO, S., TANG, Z., TODO, Y. (2019). A Differential Evolution-Oriented Pruning Neural Network Model for Bankruptcy Prediction [online]. *Complexity,* pp. 1–21. <https://doi.org/10.1155/2019/8682124>.
TRACZYNSKI, J. (2017). Firm Default Prediction: A Bayesian Model-Averaging Approach [online]. *Journal of Financial and Quantitative Analysis*, 52(3): 1211–1245. <https://doi:10.1017/S002210901700031X>.
TSAI, C. F., HSU, Y. F., YEN, D. C. (2014). A comparative study of classifier ensembles for bankruptcy prediction [online]. *Applied Soft Computing,* 24: 977–984. <https://doi.org/10.1016/j.asoc.2014.08.047>.
VALASKOVA, K., GAJDOSIKOVA, D., BELAS, J. (2023). Bankruptcy prediction in the postpandemic period: A case study of Visegrad Group countries [online]. *Oeconomia Copernicana*, 14(1): 253–293. <https://doi.org/10.24136/oc.2023.007>.
WILSON, R., SHARDA, R. (1994). Bankruptcy prediction using neural networks [online]. *Decision Support Systems*, 11(5): 545–557. <https://doi.org/10.1016/0167-9236(94)90024-8>.
WOLD, S., ESBENSEN, K., GELADI, P. (1987). Principal Component Analysis. *Chemometrics and Intelligent Laboratory Systems*, 2(1–3): 37–52.
WU, C., WANG, X.M. (2000). A neural network approach for analyzing small business lending decisions [online]. *Review of Quantitative Finance and Accounting,* 15: 259–276. <https://doi.org/10.1023/A:1008324023422>.

YU, Q. (2013). *Machine Learning for Corporate Bankruptcy Prediction*. PhD Thesis, School of Science, Aalto University, Department of Information and Computer Science, Finland.
ZHANG, Y., LIU, R., HEIDARI, A. A., WANG, X., CHEN, Y., WANG, M., CHEN, H. (2021). Towards augmented kernel extreme learning models for bankruptcy prediction: Algorithmic behavior and comprehensive analysis [online]. *Neurocomputing*, 430: 185–212. <https://doi.org/10.1016/j.neucom.2020.10.038>.
ZHOU, L., LAI, K. K., YEND, J. (2012). Empirical models based on features ranking techniques for corporate financial distress prediction [online]. *Computers and Mathematics with Applications*, 64(8): 2484–2496. <https://doi.org/10.1016/j.camwa.2012.06.003>.
ZIEBA, M., TOMCZAK, S. K., TOMCZAK, J. M. (2016). Ensemble boosted trees with synthetic features generation in application to bankruptcy prediction [online]. *Expert Systems with Applications*, 58: 93–101. <https://doi.org/10.1016/j.eswa.2016.04.001>.
ZVARÍKOVÁ, K., MACHOVÁ, V., NICA, E. (2022). Cognitive Artificial Intelligence Algorithms, Movement and Behavior Tracking Tools, and Customer Identification Technology in the Metaverse Commerce. *Review of Contemporary Philosophy,* 21: 171–187.

Monetary Policy and Economic Stability: a DSGE Approach to Trend Inflation in Morocco

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Received 1.3.2024 (revision received 3.5.2024), **Accepted** (reviewed) 30.5.2024, **Published** 13.12.2024

Abstract

This article explores the impact of trend inflation on monetary policy under a higher inflation target. Adding trend inflation to DSGE models helps us understand the inflation gap better; the gap is less persistent when it is measured as a deviation from trend instead of as a constant average. A high inflation target is likely to overshoot unless the monetary authorities adopt restrictive measures to keep output below its deterministic equilibrium. Indeed, Bank Al-Maghrib raised its key rate by 0.25 percentage points to achieve an inflation rate of 2%, underscoring the importance of maintaining this trajectory. The study identifies key policy implications: higher trend inflation destabilizes expectations, forcing monetary policy to react more to inflation deviations and less to output gaps in high-target environments. These conclusions hold for different parameterizations and specifications of the Taylor rule (backward-looking, forward-looking, and inertial). In addition, Taylor rules based on output growth rather than output gaps widen the zone of determinism, making it easier to adopt a single reference value.

Keywords	***DOI***	***JEL code***
Trend inflation, monetary policy analysis, economic stability assessment, Morocco's DSGE model	*https://doi.org/10.54694/stat.2024.10*	*E52, E58, E61, C53*

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INTRODUCTION

Price stability, as defined in modern monetary theory and practiced by central banks, is generally based on pursuing a moderate rate of inflation. This idea implies that the economy functions optimally when prices rise in a controlled and predictable manner, allowing economic agents to make informed decisions (Blanchard and Brancaccio, 2019). Against this backdrop, economic theory has developed models for understanding the mechanisms underlying inflation and predicting its future evolution. One of these models is the DSGE (Dynamic Stochastic General Equilibrium) model, which is a powerful tool for studying the interactions between the real economy and monetary policy (Woodford and Walsh, 2005). Monetary policy is a key instrument for maintaining price stability and preventing inflation. The financial community generally agrees that the best way for a central bank to contribute to public welfare and economic growth is to ensure price stability (Friedman, 1995). In general, central banks use monetary policy to influence interest rates and the money supply in circulation in order to keep inflation low and stable (Svensson, 2001).

Recently, the world has witnessed unprecedented crises that have had a significant impact on global economies. In particular, the COVID-19 pandemic and the war in Ukraine have presented major challenges for African countries, including Morocco. These crises not only disrupted economies but also highlighted the need for increased resilience and innovative solutions to overcome these challenges. For the effects on African countries, Anyanwu and Salami (2021), on the one hand, examined the consequences of the COVID-19 pandemic on African economies using a theoretical model and a numerical simulation of economic growth. Their findings indicate that, while the pandemic has had a short-term negative impact on economic growth, it has the potential to improve long-term growth through innovation. On the other hand, Zongo and Ndong Ntah (2023) study the effects of Russia's invasion of Ukraine on African economies using structural VAR models and focus on six countries, three of which are net oil exporters and three importers, using time series for the period 1980–2021 and a simulation for the period 2022–2023. Their results show that an oil shock leads to a positive reaction in the budget balance of oil-exporting countries and a negative reaction in oil-importing countries, but the effect is asymmetric.

Similarly, Morocco suffered a serious economic harm from the COVID-19 epidemic and the effects of the Russo-Ukrainian war. On the one hand, Moustabchir and Ouakil (2023) presented a hybrid model (SEIQR-DSGE) to assess the macroeconomic effects of the COVID-19 pandemic in Morocco. The model shows how the pandemic could lead to a drop in consumption and productivity. As a complement to this study, Moustabchir et al. (2023) also examined the impact of monetary policy through the pandemic loan instrument to cope with the effects of COVID-19. They used a hybrid financial DSGE-SIR model for this analysis, providing an additional perspective on policy responses to the pandemic. On the other hand, El Ouazzani et al. (2023) conducted a detailed study of the macroeconomic impacts of the Russian-Ukrainian war in Morocco. Using a DSGE model, they analyzed in detail the interactions between different macroeconomic variables, such as inflation, exchange rates, and trade balances. Their findings demonstrate the critical importance of considering risk premium shocks in these policies. Finally, Moustabchir et al. (2024) extended this analysis to examine the impact of oil shocks on the Moroccan economy in the context of the Russian-Ukrainian war. According to the DSGE simulation, these shocks, aggravated by the conflict in Ukraine, led to a reduction in the output gap, consumption, investment, and savings, as well as an increase in inflation.

In the context of repetitive crises, inflation in Morocco continued to accelerate, reaching 8.2% in March 2023, after an average of 10.1% in February and 6.6% for the year 2022 as a whole. This rise mainly reflects the accentuation of the change in volatile food prices to 21.7% from 16.4% a quarter earlier, the rise to 8.5% from 7.9% in core inflation, and the increase of 0.2% after 0.1% in regulated tariffs (Bank Al-Maghrib, 2023). With this in mind, the DSGE models can be used to simulate different economic scenarios and measure the impact of monetary policies on inflation and other macroeconomic variables.

This approach enables us to better understand the underlying economic mechanisms and, thus, formulate more effective economic policies. In addition, the DSGE models can also be used to assess future inflation risks, taking into account factors such as rising commodity prices, production costs, domestic and foreign demand, and government economic policies.

In our study, we look at the macroeconomic implications of the long-term trend in inflation, drawing mainly on the model of Ascari (2014). This work, adapted specifically to the Moroccan context, incorporates the inflation phenomenon into the model. We also incorporate positive trend inflation and price indexation, while taking into account nominal rigidities on prices according to the Calvo model. Our analytical framework explores the origins of trend inflation and its implications for monetary policy.

The remainder of this article proceeds as follows: Section 1 provides an overview of the literature on the impact of positive trend inflation on the economy and its role in the effective conduct of monetary policy. Section 2 describes the DSGE model used and the parameter choices adopted. The results are presented in Section 3, and last Section concludes the article.

1 LITERATURE REVIEW

In recent years, macroeconomics has relied heavily on the widespread use of dynamic stochastic general equilibrium (DSGE) models, which are based on log linearization around a stationary state while assuming that the inflation rate remains stable in the long term. However, an analysis of economic data over the last three decades in most developed nations reveals a trend towards higher inflation. The new Phillips curve encountered difficulties reproducing the inflationary inertia observed in the data, except for assuming an extremely low price adjustment frequency. This shortcoming prompted researchers to look for new mechanisms to better understand this phenomenon.

Dynamic extensions of DSGE models have also been used to study how inflation trends interact with other macroeconomic variables. In this way, El Ouazzani et al. (2024) examined the impact of monetary policy on unemployment in Morocco, incorporating labor market frictions and Nash-type wage bargaining. Their results highlight the key role of monetary policy in managing structural challenges while containing inflationary pressures.

Yılmaz and Tunc (2022) reformulated a standard open economy model to account for positive trend inflation. When trend inflation is positive, the model is used to understand the effects of macroeconomic shocks in a small, open economy. Their results show that the inclusion of trend inflation significantly affects the dynamics of the model through the dynamics of the real exchange rate rather than through the slope of the New Keynesian Philips curve. More specifically, higher trend inflation induces slightly more persistent real exchange rate responses to shocks.

Chen et al. (2023) estimated a stochastic dynamic general equilibrium (DSGE) model for a small open economy. Their study examined the evidence that interest rate policy may not be sufficient to stabilize output and inflation following capital outflow shocks. They also explored the extent to which foreign exchange market interventions can improve policy trade-offs. Their results revealed significant structural differences between advanced and emerging market economies. The results of their study also showed how important it is to think about how the foreign exchange market affects itself when figuring out how deep it is and what the policy choices were when capital flows were unstable in the past.

Lukmanova and Rabitsch (2023) have explored monetary transmission, taking account of imperfect information. They incorporated two types of shocks: a standard temporary interest rate shock and a persistent inflation target shock. Their study revealed delayed neo-Fisherian behavior in response to the persistent shock, where both the interest rate and inflation increased, but with a lag. These results suggest that a central bank pursuing a higher inflation target should implement an expansionary monetary policy by lowering its real interest rate and also initially lowering the nominal rate to boost inflation and inflation expectations.

Peykani et al. (2023) examined the risk channel of monetary policy in Iran. According to their empirical studies, expansionary monetary policy increases bank risk, while, on the other hand, bank risk affects economic activities and price levels. They used the dynamic stochastic general equilibrium (DSGE) model to investigate how the credit channel and the risk channel (as a new channel) work, as well as how monetary policy affects real variables and price levels in the Iranian economy. The model took information from the banking system, moral hazards, and bad choices into account. Their results show that there is a credit channel and a monetary policy risk channel for the Iranian economy, and the expansionary monetary policy shock causes an increase in output, inflation, private sector consumption, investment, net worth in the economy, and lending. In addition, when a credit shock occurs, as banks' lending power increases, output, private-sector consumption, investment, net worth, and total loans rise, and the level of inflation falls.

Iania et al. (2023) studied the role of the inflation cost channel in determining the risk premium in a Keynesian DSGE model. They showed that although the inflation cost channel generates the desired forward premium moments, it suffers from non-trivial and counter-intuitive approximation errors in the price dispersion function. In addition, they have proposed ways to mitigate them, including a quasi-wound demand function as a risk-generating mechanism. Their research offers valuable insights into how monetary policies can be optimized to meet the economic challenges associated with the inflation cost channel.

Fasani et al. (2023) examined monetary policy uncertainty and firm dynamics. They used a FAVAR model with external instruments to show that policy uncertainty shocks are recessionary and are associated with an increase in firm exit and a decrease in entry. To explain this result, they constructed a large-scale DSGE module featuring firm heterogeneity and endogenous firm entry and exit. Versions of the model with constant firms or constant firm exit are unable to reproduce the FAVAR response of firm entry and exit and suggest a much smaller effect of this shock on real activity.

Hohberger et al. (2023) compared the macroeconomic effects of unconventional monetary policy (UMP) measures in the eurozone and the US within a unified framework. They used shadow rate estimates to describe monetary policy's overall stance. They also estimated a large-scale 3-region DSGE model using data from 1999–Q1 to 2019–Q4, and ran counterfactual simulations (without UMP) with the short-term policy rate set at the effective lower bound (ELB). They found that the contributions of unconventional monetary policy to output growth and inflation are of the same order of magnitude in the eurozone and the US (0.1–0.4 pp p.a. for real GDP growth; 0.2–0.7 pp p.a. for CPI inflation). The counterfactual suggests that US output and price levels would have been 3.4% and 6.7% below real levels in 2020–Q4, respectively. In addition, the earlier and stronger rebound in US activity and prices has led to the normalization of US monetary policy during 2016–2019.

Similarly, Ouakil et al. (2024) analyzed the impact of unconventional monetary policy during the Covid-19 pandemic, specifically in Morocco, using a hybrid model that combines a financial DSGE model with an epidemiological framework. Their results underscore that while unconventional monetary policy can provide economic support during crises, it has limitations; indeed, an exogenous increase in Central Bank claims was required to partially offset the pandemic's effects. They also found that Bank Al-Maghrib's unconventional measures contributed to higher inflation, highlighting the need for caution in the prolonged use of such policies to avoid potential long-term adverse effects.

Chang et al. (2021) examined the origins of monetary policy changes by adopting a new regime-switching approach in DSGE models. They introduced a latent regime factor, which, when it crosses a certain threshold, allows the policy in response to inflation to switch endogenously between two regimes. This endogeneity derives from the historical impacts of transition innovations on the regime factor. By estimating their DSGE model using US data, they were able to measure how each structural shock affected the regime factor. This helped them figure out where the policy changes came from. This new approach sheds new light on the complex interplay between regime shifts and measured economic behavior.

McKnight et al. (2020) have developed a new forecasting procedure based on the New Keynesian Phillips curve, which incorporates the time-varying trend inflation. This approach aims to capture changes in central bank preferences and monetary policy frameworks. They generate theoretical predictions for the trend and cyclical components of inflation and recombine them to obtain an overall inflation forecast. Using quarterly data for the Eurozone and the USA spanning almost half a century, they compare their inflation forecasting procedure with the most popular time series models. Their findings suggest that skepticism about the use of theory in forecasting is unjustified, and that theory should continue to play an important role in policy-making.

2 THE MODEL

The model we use is mainly inspired by Ascari (2014), which focuses on analyzing the macroeconomic implications of the long-term trend in inflation. By incorporating the inflation phenomenon, we adapt it specifically to the Moroccan context. Our model incorporates positive trend inflation and price indexation while taking account of nominal rigidities on prices, according to the Calvo model. It explores the origins of trend inflation and its implications for monetary policy. In addition, it includes a representative agent with an infinite lifetime, and firms adjust their prices according to their own pricing choices.

2.1 Households

On the demand side, the model features representative households maximizing an intertemporal utility function, separable into consumption (C) and labor (N).

The household utility function is given by:

$$\max_{\{C_t, N_t, B_{t+1}\}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{\chi N_t^{1+\eta}}{1+\eta} \right]. \tag{1}$$

Under budget constraints:

$$P_t C_t + B_{t+1} = (1 + i_{t-1}) B_t + W_t N_t + T_t, \tag{2}$$

where C_t is real consumption, N_t is labor supply, B_{t+1} is nominal savings, E_0 is the expectation operator conditional on the information available at date 0, β is the discount factor, σ is the coefficient of relative risk aversion, χ is the labor disutility parameter, η is the intertemporal substitution elasticity coefficient of consumption, P_t is the general price level, i_{t-1} is the nominal interest rate, W_t is the nominal wage, and T_t are nominal government transfers.

The household optimization problem is subject to the following first-order conditions:

$$\text{Euler equation: } C_t^{-\sigma} = \beta E_t \left[\left(\frac{P_t}{P_{t+1}} \right) (1 + i_t) \left(C_{t+1}^{-\sigma} \right) \right]. \tag{3}$$

Following the first-order condition with respect to labor supply, the wage equation is obtained:

$$\text{Labor supply equation: } \chi N_t^{\eta} = C_t^{-\sigma} \frac{W_t}{P_t}. \tag{4}$$

2.2 Calvo pricing

The company produces a homogeneous good from labor and capital. It faces capital adjustment costs and productivity shocks. It maximizes its expected profit over an infinite horizon, taking into account nominal rigidities à la Calvo (1983) that limit its ability to change its prices. Christiano et al. (2005) showed that a DSGE model that includes Calvo price rigidity and wage contracts can reproduce inflation inertia and output persistence after a monetary shock, as long as certain assumptions are met. This ability to reproduce empirical facts is a key advantage of the DSGE model in the analysis of inflation and monetary policy.

In each period t, a final good, Y_t, is produced by perfectly competitive companies, which combine a continuum of intermediate inputs, $Y_{i,t}; i \in [0,1]$ via technology:

$$Y_t = \left[\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{5}$$

where $\varepsilon > 1$ expresses the elasticity of substitution between the various intermediate inputs. Profit maximization and compliance with the zero-profit condition allow us to deduce that the price index corresponding to the final good Y_t can be obtained by integrating the prices of intermediate inputs $P_{i,t}$ from the following CES function:

$$P_t = \left[\int_0^1 P_{i,t}^{1-\epsilon} di \right]^{\frac{1}{1-\varepsilon}}, \tag{6}$$

and the demand program for the intermediate good $Y_{i,t}$ is:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\varepsilon} Y_t \, . \tag{7}$$

A continuum of firms provides intermediate inputs. Each firm i uses labor $N_{i,t}$ as the sole input for production, employing a production technology characterized by decreasing returns to scale:

$$Y_{i,t} = A_t N_{i,t}^{\alpha}, \tag{8}$$

where A_t denotes the aggregate technology's stationary process. The real marginal costs of each firm i, $MC_{i,t}$, depend only on aggregate variables, consistent with the assumption that a technology has constant returns to scale. This assumption is based on the idea that nominal wages are fixed in perfectly competitive markets, which implies that real marginal costs are the same for all firms:

$$MC_{i,t} = MC_t = \frac{W_t}{A_t P_t} \, . \tag{9}$$

2.3 The price-setting mechanism

Companies can finance their investments by borrowing or lending in the financial markets. The nominal interest rate is determined by the equilibrium in the market for loanable funds. Low substitutability creates market power for producers of intermediate goods, allowing them to set prices. We assume that there are random intervals between price changes: in each period, a firm can reoptimize its nominal price with a fixed probability of 1 – θ, while it maintains the price charged in the previous period with probability θ. The problem for company i, which sets its price at time t, is to choose P_i^* to maximize its expected profits:

$$E_t \sum_{j=1}^{\infty} \theta^j D_{t,\, t+j} \left[\frac{P_{i,t}^*}{P_{t+j}} Y_{i,\, t+j} - TC_{t+j}\left(Y_{i,t+j}\right) \right]. \tag{10}$$

$D_{t,t+j}$ is a stochastic discount factor, and $TC_{t+j}\left(Y_{i,t+j}\right) = \frac{W_{t+j}}{P_{t+j}} \frac{Y_{i,t+j}}{A_{t+j}}$ is the total cost function. $P_{i,t}^*$ denotes the relative price of the optimizing firm. The first-order condition of this problem can be written as follows:

$$P_{i,t}^* = \frac{\varepsilon}{\varepsilon - 1} \frac{E_t \sum_{j=0}^{\infty} \theta^j D_{t,t+j} Y_{t+j} \Pi_{t,t+j}^{\varepsilon} MC_{t+j}}{E_t \sum_{j=0}^{\infty} \theta^j D_{t,t+j} Y_{t+j} \Pi_{t,t+j}^{\varepsilon-1}}, \tag{11}$$

where $\Pi_{t,t+j}$ represents the cumulative gross inflation rate over j periods:

$$\Pi_{t,t+j} = \begin{Bmatrix} 1 \\ \left(\frac{P_{t+1}}{P_t}\right) \times \ldots \times \left(\frac{P_{t+j}}{P_{t+j-1}}\right) \end{Bmatrix} \qquad \begin{matrix} \text{for } j = 0 \\ \text{for } j = 1, 2, \ldots \end{matrix} \tag{12}$$

In what follows, we refer to the gross inflation rate as $\pi_t = \frac{P_t}{P_{t-1}}$.

Note that expected future inflation rates have an impact on the relative weights of future variables in Formula (7). The numerator represents the present value of future marginal costs. Forward-looking companies know that they may have to maintain the price set at time t and that inflation will progressively reduce their profit margin over time. They therefore use expected future inflation rates to discount future marginal costs. The higher the expected future inflation rates, the greater the relative weight of expected future marginal costs. Companies thus become more forward-looking, giving greater weight to future economic conditions than to current ones.

Note also that Formula (7) in a steady state with constant inflation is:

$$P_i^* = \frac{\varepsilon}{\varepsilon - 1} \frac{\sum_{j=0}^{\infty} \left(\beta\theta\overline{\pi}^{\varepsilon}\right)^j MC}{\sum_{j=0}^{\infty} \left(\beta\theta\overline{\pi}^{\varepsilon-1}\right)^j}, \tag{13}$$

where P_i^* is the value of the relative price in steady state $P_{i,t}^*$ $\overline{\pi}$ is the steady state (trend) inflation, β is the steady-state value of the stochastic discount factor $D_{t,t+j}$ and MC is the steady-state value of real marginal cost. Thus, the model constrains the achievable steady-state inflation rate: if the steady-state inflation rate is positive, $(\text{i.e., } \overline{\pi} > 1)$ the convergence of the sum in (9) requires that $\beta\theta\overline{\pi}^{\varepsilon-1} < 1$ and $\beta\theta\overline{\pi}^{\varepsilon} < 1$ This implies upper bounds on trend inflation:

$$\overline{\pi} < \left(1/\theta\beta \right)^{1/(\varepsilon-1)} \text{ and } \overline{\pi} < \left(1/\theta\beta \right)^{1/\varepsilon}.$$

The overall price level evolved as follows:

$$P_t = \left[\int_0^1 P_{i,t}^{\,1-\varepsilon} di \right]^{\frac{1}{1-\varepsilon}} = \left[\theta P_{t-1}^{1-\varepsilon} + \left(1-\theta\right) P_{i,t}^{*\,1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \tag{14}$$

With respect to production, the first-order condition gives the labor demand equation:

$$W_t = (1-\alpha)\frac{P_t^* Y_t}{N_t}. \tag{15}$$

The first-order condition with respect to capital gives the capital demand equation:

$$Q_{0,t}R_t = Q_{0,t+1}\left[\alpha\frac{P_{t+1}^* Y_{t+1}}{K_{t+1}} + H_1(K_{t+2}, K_{t+1}) - H_2(K_{t+2}, K_{t+1})K_{t+2}\right]. \tag{16}$$

With respect to the optimal price, the first-order condition gives the following pricing equation:

$$\sum_{k=0}^{\infty}\theta^k E_t\left[Q_{t,t+k}Y_{t+k|t}\left(P_t^* - \frac{\in}{\in -1}\frac{MC_{t+k}}{P_{t+k}}\right)\right] = 0, \tag{17}$$

where $Q_{t,t+k}$ is the discount factor between periods t and t + k. $Yt+k|t$ is the demand for the good produced by the company in period t + k as a function of the price set in period *t*, and MC_{t+k} is the real marginal cost in period t + k.

Considering s_t as an additional measure of price dispersion:

$$s_t = \int_0^1 \left(\frac{P_t}{P_{t-1}}\right)^{-\varepsilon} di. \tag{18}$$

Overall output is expressed by:

$$Y_t = \frac{A_t}{s_t} N_t,$$

with s_t being equal to 1 only when all prices are identical, signifying the absence of price dispersion (Schmitt-Grohé and Uribe, 2007), this equation emphasizes the importance of s_t as a variable for characterizing the resource cost linked to price dispersion in this model. Indeed, the greater the relative price dispersion, the higher the s_t value, and, consequently, the greater the amount of labor required to produce a specific quantity of aggregate products. It immediately follows that, for any given level of output, price dispersion raises the equilibrium real wage (as demonstrated in Formula 4), thereby amplifying the marginal cost of conducting business (as mentioned in Formula 9). Moreover, we can deduce that price dispersion functions as an inertial variable, evolve as follows:

$$s_t = (1-\theta)\left(P_{i,t}^*\right)^{-\varepsilon} + \theta\pi_t^{\varepsilon}s_{t-1}. \tag{19}$$

The model we use is mainly inspired by Ascari (2014), which focuses on analyzing the macroeconomic implications of the long-term trend in inflation. By incorporating the inflation phenomenon, we adapt it specifically to the Moroccan context. Our model incorporates positive trend inflation and price indexation while taking account of nominal rigidities on prices, according to the Calvo model. It explores the origins of trend inflation and its implications for monetary policy. In addition, it includes a representative agent with an infinite lifetime, and firms adjust their prices according to their own pricing choices.

2.4 A generalized Neokeynesian Phillips curve

In most DSGE models, business balance conditions and the overall price ratio are approximately linear around a balance state where inflation is zero. They receive an expression of the type:

$$\left(\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} + \kappa \widehat{m_{ct}}\right), \tag{20}$$

for all variables $(x_t), \left(x_t^* = \ln\left(x_t / \bar{x}\right)\right)$.

The marginal cost coefficient κ is a combination of the parameters governing the pricing problem:

$$\left(\kappa = (1-\theta)(1-\theta\beta)/\theta\right).$$

2.5 Trend inflation and monetary policy

To illustrate the effects of persistent positive trend inflation on monetary policy, we incorporate the Phillips curve into the DSGE model. We posit that trend inflation is positive, constant, and exogenously determined, simplifying the model. We explore how a regime of persistent positive inflation influences the dynamics of the New Keynesian model and the decisions of monetary policymakers.

The central bank employs a Taylor rule to set its target nominal interest rate, i_t. It aims to stabilize current inflation and potential output.

Taylor's rule:

$$i_t = \rho i_{t-1} + (1-\rho)\left[\phi_\pi\left(\pi_t - \pi^*\right) + \phi_y\left(Y_t - Y_t^*\right)\right] + v_t, \tag{21}$$

where π_t represents current inflation, Y_t represents current production on levels, Y_t^* is the level of potential production, ϕ_π and ϕ_y are the central bank's reaction coefficients to inflation and output, respectively, and υ_t is a monetary policy shock.

Trend inflation, in response to shocks, modifies monetary policy transmission and affects the overall dynamics of the economy. These changes occur because trend inflation indirectly influences the parameters of the log-linear model, notably by affecting the slope of the Phillips curve. When there is higher trend inflation, the Phillips curve, which describes the relationship between inflation and economic activity, becomes flatter. This means that when trend inflation is high, economic activity responds less to changes in inflation. To analyze these effects, we define the following autoregressive process for a shock in our model:

the Taylor rule's monetary policy shock: $v_t = \rho_v v_{tt-1} + e_v$.

In this autoregressive process, p_v represents the shock's persistence, and e_v represents a white noise error term. The shock v_t represents unexpected changes in the monetary policy, which could be due to changes in the central bank's policy preferences, errors in measuring the target variables, or other unforeseen circumstances.

2.6 Calibration

The model's structural parameters have been set using standard values from the literature. The short-term interest rate used in the model is that adopted by the Moroccan central bank to implement its monetary policy. Table 1 below shows the parameter values, in line with generally accepted values in the literature and similar to the characteristics of the Moroccan economy. Calibration, a method commonly used to adapt a DSGE model to empirical data, involves assigning specific values to the structural parameters of the DSGE model. These values are often derived from microeconomic studies where the same parameters have been estimated on a microeconometric basis, thus ensuring consistency with existing empirical knowledge.

The discount factor (β) was set at 0.99, a commonly used value supported by studies such as Smets and Wouters (2007), which confirmed its consistency with the time preferences of Moroccan households. As for the capital share (α), a value of 0.4 was chosen based on Moroccan empirical studies, notably that of Aya Achour (2019), who analyzed sectoral data and concluded that the capital share was relatively low in Morocco compared with other countries. Finally, the sensitivity of labor supply to changes in real income, measured by the Frisch elasticity (ϕ), was set at 0.5, a level comparable to the values found in Gali and Monacalli (2005).

Following Ascari and Ropele (2007), we adopt the rigid price parameter, which is considered identical for all countries. This parameter is generally set at 0.75, corresponding to an average price period of 4 quarters. With regard to risk aversion (σ), a value of 5 has been chosen on the basis of Erceg et al. (2000), who chose 1.5 for this parameter, while Garcia et al. (2011) adopt a high value of $\sigma = 5$ and argue that this value is necessary to obtain volatile exchange rates. The elasticity of substitution between the different national commodities is set at 6. It is unlikely that substitutability is greater at the international level than at the national level. The question is raised by Engel (2000), who suggests, on the basis of his "six questions" test, that the international elasticity should be doubled compared with its current use at the international level. According to Uribe (2020), the degree of indexation is $\overline{\rho}$, with the value 0 chosen to indicate the absence of price and wage indexation.

For Morocco's monetary policy rule, the inertia of the interest rate response ρ_i is represented by a value of 0.9, with responsiveness to both inflation and the output gap relative to their respective targets, with $\phi_\pi = 1.25$ for inflation and $\phi_y = 0{,}34$ for the output gap. This means that monetary authorities gradually adjust interest rates in line with the economic situation, rather than doing so unexpectedly each period.

For the exogenous shock affecting the model, we have chosen a value for the standard deviation equal to equal to 0.01. This value is widely used in the DSGE model simulations. Ambler et al. (2004) estimated a standard deviation equal to $\sigma_{\in R} = 0.01$, while Amano and Shukayev (2009) obtained a similar value for the monetary shock. For their part, Ambler et al. (2012) concluded with an estimated value of $\sigma_{\in R} = 0.006$.

Table 1 Calibrated parameter values

Parameter	Symbol	Value
Discount factor	β	0.99
Share of capital	α	0.4
Frisch elasticity	ϕ	0.5
Calvo parameter	θ	0.8
Risk aversion	σ	5
Elasticity of substitution	ε	6
Taylor Rule: inflation feedback rule	ϕ_π	1.25
Producing the Taylor rule	ϕ_y	0.34
Degree of indexing	ρ	0
Interest rate smoothing parameter	ρ_i	0.9

Source: Authors

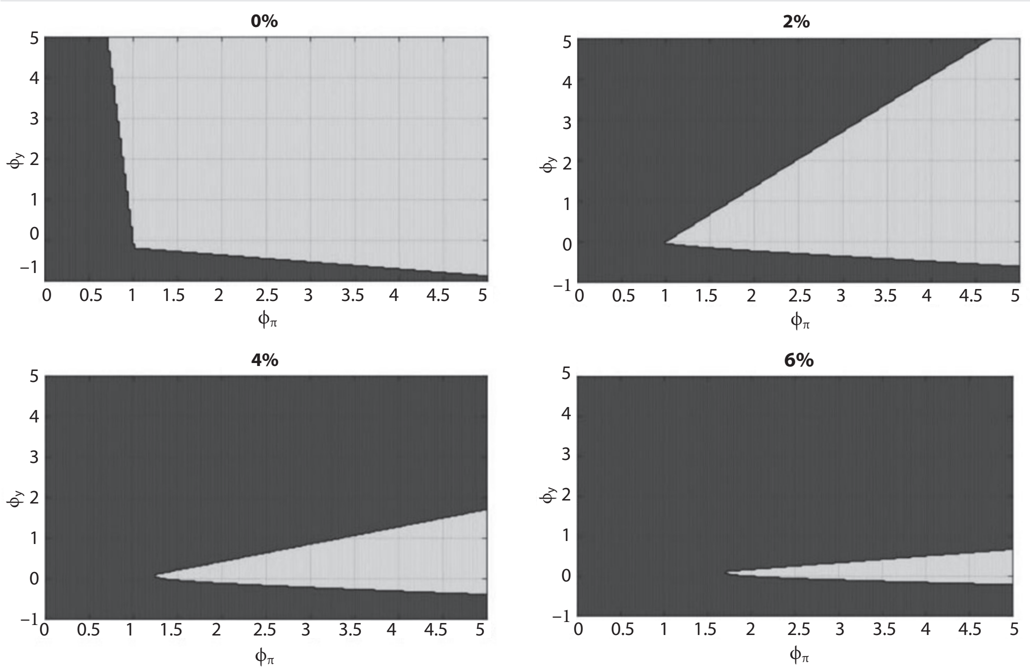
Finally, the various steps involved in the resolution of the model were carried out using Matlab R2015 and Dynare version 4.6 software, as described in the work of Adjemian et al. (2011). The program used a second-order approximation to calculate the equilibrium conditions of the model around its deterministic steady state.

3 RESULTS AND DISCUSSION

For the model's reference calibration, we simulate the determinism region (see calibration section). Figure 1 illustrates the relationship between trend inflation and the Rational Expectations Equilibrium (REE). The REE is a state of the economy where agents' expectations about future variables are consistent with the actual outcomes of these variables. In an REE, agents use all available information and rationality to form their expectations, and their decisions are optimal given these expectations. The REE can be interpreted as a measure of the model's determinacy. A lower REE implies a more deterministic model, where monetary policy can effectively control inflation and keep it close to the target. Conversely, a higher REE implies an indeterminate model, where monetary policy has less control over inflation, making it more vulnerable to demand shocks.

Figure 1 shows that the indeterminate region (shown in grey) decreases sharply as trend inflation rises. This suggests that as trend inflation increases, the model becomes more indeterminate. For instance, if trend inflation is 4%, the model is indeterminate for any value of the reaction parameter (which measures the sensitivity of monetary policy to price differentials) greater than 0.8. Conversely, if trend inflation is zero, the determined region is much larger, implying that monetary policy can stabilize price inflation even with a weak reaction to price deviations. The relationship between trend inflation and the indeterminate region can be understood in terms of the impact of trend inflation on the parameters of the model. Higher-trend inflation can affect the Phillips curve's slope, making it flatter and reducing monetary policy's effectiveness.

Figure 1 Trend inflation and the determinacy region

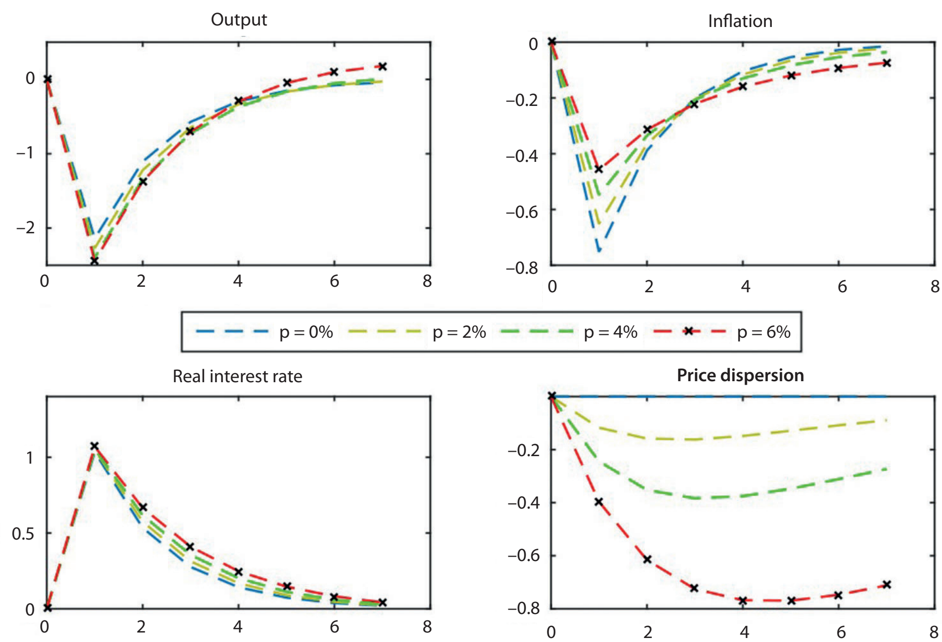


This result can be contextualized in relation to Morocco's economic situation, which saw a sharp rise in inflation in 2022, reaching 6.6%. This inflation was caused by a rise in commodity prices in international markets, linked to the war in Ukraine, and a historic drought that affected agricultural production. Morocco has adopted measures to mitigate the effects of inflation on household purchasing power, including subsidies and regulated prices. The Moroccan central bank has also raised key interest rates to curb inflation.

Figure 2 shows the effects of a 1% Taylor Rule shock on output, inflation, and price dispersion in the Moroccan economy. When the trend inflation rates are higher, firms adjusting their prices react less to the current fall in output, resulting in less dynamic inflation. Consequently, higher interest rates induce a greater output response, in line with the predictions of the Euler equation. The slope $\lambda\ (\hat{\pi}_t)$ of the new extended Phillips curve, which measures the relationship between inflation and output, is influenced by the trend inflation rate. When the latter is high, the slope is reduced, which lessens the impact of monetary policy shocks on inflation. Moreover, trend inflation also has an impact on price dispersion, which contributes to inflation persistence.

This result is consistent with those presented in the article by Amano et al. (2007), one of the first papers in the literature to examine the macroeconomic implications of trend inflation. Amano et al. (2007) use a model simulation with a second-order approximation to look at how trend inflation changes the random means of the variables. Their findings indicate that the gap between the variables' deterministic steady states and their stochastic means increases with trend inflation. When trend inflation is zero, the stochastic mean of inflation is slightly higher than the deterministic trend inflation rate, while the stochastic means of output, consumption, and employment are slightly lower than their steady-state equivalents. However, when inflation is positive, these deviations increase significantly. The effect is particularly pronounced for the stochastic mean of inflation, which reaches a high level of 7.8% when the inflation target is set at 4%.

Figure 2 Impulse response (monetary policy shock)



CONCLUSION

The existing literature lacks a comprehensive analysis of trend inflation and its macroeconomic effects when implementing monetary policy with a higher inflation target. Our contribution aims to fill this gap by examining the key empirical and theoretical issues raised by the assumption of positive trend inflation in a DSGE model. The theoretical underpinnings of trend inflation's time variation and its relationship with policymakers' inflation objectives are still under investigation. We demonstrate that accounting for the evolution of trend inflation in empirical models of inflation dynamics allows us to better define the properties of the inflation gap. In our study, we show that the persistence of the inflation gap is less pronounced when it is measured as the deviation of inflation from the trend rather than from a constant average.

This work reveals that if the monetary authorities do not take measures to keep output below its deterministic equilibrium value, inflation is likely to exceed the high inflation target. In this context, Bank Al-Maghrib (BAM) has adjusted its key interest rate to address inflationary pressures, reflecting an easing inflation trend and a focus on supporting economic recovery. BAM's monetary policy aims to stabilize inflation within manageable ranges rather than targeting a specific rate like 2%. These measures demonstrate BAM's commitment to balancing inflation control with sustainable economic growth.

This strategy has several major implications for economic policy. Firstly, higher trend inflation tends to destabilize inflation expectations, as agents find it harder to predict future price trends. Secondly, in an inflation-targeting environment, monetary policy should focus more on inflation deviations from the target and less on output deviations, as recommended by the Taylor Standard rule. Ascari and Ropele (2009) show that these conclusions are robust to different parameters and types of Taylor rule, including backward-looking, forward-looking, and inertial policies. Inertial policies, in particular, help stabilize expectations, even in the presence of positive steady-state inflation. Similarly, Taylor rules that adjust to output growth rather than the output gap widen the zone of determinism, making it easier for monetary authorities to impose a single reference value (Coibion and Gorodnichenko, 2009).

In this context, Bank Al-Maghrib has demonstrated a proactive mastery of monetary policy instruments in response to recent inflationary pressures while taking care to preserve a balance between price stability and economic dynamics. Its decisions, based on a rigorous analysis tailored to the specific features of the Moroccan economy, have helped to limit the negative effects of external shocks on inflation and to strengthen macroeconomic resilience.

References

ADJEMIAN, S., BASTANI, H., JUILLARD, M., MIHOUBI, F., PERENDIA, G., RATTO, M., VILLEMOT, S. (2011). *Dynare: Reference manual, version 4.* Dynare Working Papers 1, CEPREMAP.

AMANO, R., AMBLER, S., REBEI, N. (2007). The macroeconomic effects of non-zero trend inflation [online]. *Journal of Money, Credit and Banking*, 39(7): 1907–1930. <https://doi.org/10.1111/j.1538-4616.2007.00088.x>.

AMANO, R., SHUKAYEV, M. (2009). Risk Premium Shocks and the Zero Bound on Nominal Interest Rates [online]. *Journal of Money, Credit and Banking*, 44(8), Bank of Canada Working Paper, 2009-27. <https://doi.org/10.1111/j.1538-4616.2012.00541.x>.

AMBLER, S., DIB, A., REBEI, N. (2004). *Optimal taylor rules in an estimated model of a small open economy* [online]. Bank of Canada, 2004-36. <https://doi.org/10.34989/swp-2004-36>.

AMBLER, S., GUAY, A., PHANEUF, L. (2012). Endogenous business cycle propagation and the persistence problem: The role of labor-market frictions [online]. *Journal of Economic Dynamics and Control*, 36(1): 47–62. <https://doi.org/10.1016/j.jedc.2011.07.003>.

ANYANWU, J. C., SALAMI, A. O. (2021). The impact of COVID-19 on African economies: An introduction [online]. *African Development Review*, 33: S1. <10.1111/1467-8268.12531>.

ASCARI, G., ROPELE, T. (2007). Optimal monetary policy under low trend inflation [online]. *Journal of Monetary Economics*, 54(8): 2568–2583. <https://doi.org/10.1016/j.jmoneco.2007.06.024>.

ASCARI, G., ROPELE, T. (2009). Trend inflation, taylor principle, and indeterminacy [online]. *Journal of Money, Credit and Banking*, 41(8): 1557–1584. <https://doi.org/10.1111/j.1538-4616.2009.00272.x>.

ASCARI, G., SBORDONE, A. M. (2014). The macroeconomics of trend inflation [online]. *Journal of Economic Literature*, 52(3): 679–739. <https://doi.org/10.1257/jel.52.3.679>.

AYA, A. (2019). *Réserves de change et fonctionnement de l'économie marocaine: enseignements à partir d'un modèle DSGE*. Bank Al-Maghrib, Département de la Recherche, 2019-4.

BANK AL-MAGHRIB. (2023). Inflation et Inflation sous-jacente [online]. <https://www.bkam.ma/Actualites/2023/Inflation-et-inflation-sous-jacente-mars-2023>.

BLANCHARD, O., BRANCACCIO, E. (2019). Crisis and revolution in economic theory and policy: a debate [online]. *Review of Political Economy*, 31(2): 271–287. <https://doi.org/10.1080/09538259.2019.1644730>.

CALVO, G. A. (1983). Staggered prices in a utility-maximizing framework [online]. *Journal of monetary Economics*, 12(3): 383–398. <https://doi.org/10.1016/0304-3932(83)90060-0>.

CLARIDA, R., GALI, J., GERTLER, M. (1999). The science of monetary policy: a new Keynesian perspective [online]. *Journal of economic literature*, 37(4): 1661–1707. <https://doi.org/10.1257/jel.37.4.1661>.

COIBION, O., GORODNICHENKO, Y. (2009). Monetary policy, trend inflation, and the Great Moderation: An alternative interpretation [online]. *American Economic Review*, 99(1) : 161–192. <https://doi.org/10.1257/aer.101.1.341>.

EL OUAZZANI, H., OUAKIL, H., MOUSTABCHIR, A. (2023). A simulation of the macroeconomic effects of the Russia–Ukraine War on the Moroccan economy using the DSGE model [online]. *African Development Review*. <https://doi.org/10.1111/1467-8268.12726>.

EL OUAZZANI, H., OUAKIL, H., MOUSTABCHIR, A. (2024). Monetary policy and unemployment in Morocco: A DSGE model approach with labor market frictions and Nash wage bargaining [online]. *Journal of Quantitative Economics*, 1–28. <https://doi.org/10.1007/s40953-024-00415-9>.

ENGEL, C. (2000). *Comments on Obstfeld and Rogoff's "The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?"* NBER Working Papers 7818.

FASANI, S., MUMTAZ, H., ROSSI, L. (2023). Monetary policy uncertainty and firm dynamics [online]. *Review of Economic Dynamics*, 47: 278–296. <https://doi.org/10.1016/j.red.2022.02.002>.

FRIEDMAN, M. (1995). *The role of monetary policy*. UK: Macmillan Education.

GALI, J., MONACELLI, T. (2005). Monetary policy and exchange rate volatility in a small open economy [online]. *The Review of Economic Studies*, 72(3): 707–734. <https://doi.org/10.1111/j.1467-937X.2005.00349.x>.

GARCIA, C. J., RESTREPO, J. E., ROGER, S. (2011). How much should inflation targeters care about the exchange rate? [online]. *Journal of International Money and Finance*, 30(7): 1590–1617. <https://doi.org/10.1016/j.jimonfin.2011.06.017>.

HOHBERGER, S., RATTO, M., VOGEL, L. (2023). The macroeconomic effects of unconventional monetary policy: Comparing euro area and US models with shadow rates [online]. *Economic Modelling*, 127: 106438. <https://doi.org/10.1016/j.econmod.2023.106438>.

CHANG, Y., MAIH, J., TAN, F. (2021). Origins of monetary policy shifts: a new approach to regime switching in DSGE models [online]. *Journal of Economic Dynamics and Control*, 133: 104235. <https://doi.org/10.1016/j.jedc.2021.104235>.

CHEN, K., KOLASA, M., LINDE, J., WANG, H., ZABCZYK, P., ZHOU, J. (2023). An Estimated DSGE Model for Integrated Policy Analysis [online]. <http://dx.doi.org/10.5089/9798400247187.001>.

CHRISTIANO, L. J., EICHENBAUM, M., EVANS, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy [online]. *Journal of political Economy*, 113(1): 1–45. <https://doi.org/10.1086/426038>.

IANIA, L., TRETIAKOV, P., WOUTERS, R. (2023). The risk premium in New Keynesian DSGE models: The cost of inflation channel [online]. *Journal of Economic Dynamics and Control*, 155: 104732. <https://doi.org/10.1016/j.jedc.2023.104732>.

LUKMANOVA, E., RABITSCH, K. (2023). Evidence on monetary transmission and the role of imperfect information: Interest rate versus inflation target shocks [online]. *European Economic Review*, 158: 104557. <https://doi.org/10.1016/j.euroecorev.2023.104557>.

MCKNIGHT, S., MIHAILOV, A., RUMLER, F. (2020). Inflation forecasting using the New Keynesian Phillips Curve with a time-varying trend [online]. *Economic Modelling*, 87: 383–393. <https://doi.org/10.1016/j.econmod.2019.08.011>.

MOUSTABCHIR, A., OUAKIL, H. (2023). Vaccination, treatment and containment policy to reduce the effects of the COVID-19 pandemic in Morocco [online]. *African Development Review*, 35(4): 351–364. <https://doi.org/10.1111/1467-8268.12714>.

MOUSTABCHIR, A., OUAKIL, H., EL OUAZZANI, H. (2023). Monetary policy through the pandemic loans instrument to address the effects of COVID-19: hybrid financial DSGE-SIR [online]. *Repères et Perspectives Economiques*, 7(2). <https://doi.org/10.34874/IMIST.PRSM/RPE/43218>.

MOUSTABCHIR, A., OUAKIL, H., EL OUAZZANI, H., LECHHEB, H. (2024). A DSGE model approach to examining the impact of the Russian–Ukrainian War and oil shocks on the Moroccan economy [online]. *African Development Review*. <https://doi.org/10.1111/1467-8268.12741>.

OUAKIL, H., MOUSTABCHIR, A., EL OUAZZANI, H. (2024). Unconventional Monetary Policy Response to Covid-19 and Its Impact on Inflation in Morocco [online]. *Statistika: Statistics and Economy Journal*, 104(3): 306–319. <https://doi.org/10.54694/stat.2024.8>.

PEYKANI, P., SARGOLZAEI, M., TAKALOO, A., SANADGOL, N. (2023). Investigating the monetary policy risk channel based on the dynamic stochastic general equilibrium model: Empirical evidence from Iran [online]. *Plos one*, 18(10): e0291934. <https://doi.org/10.1371/journal.pone.0291934>.

SCHMITT-GROHE, S., URIBE, M. (2007). Optimal simple and implementable monetary and fiscal rules [online]. *Journal of monetary Economics*, 54(6): 1702–1725. <https://doi.org/10.1016/j.jmoneco.2006.07.002>.

SMETS, F., WOUTERS, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach [online]. *American economic review*, 97(3): 586–606. <https://doi.org/10.1257/aer.97.3.586>.

SVENSSON, L. E. (2001). Price stability as a target for monetary policy: defining and maintaining price stability. In: *The monetary transmission process: recent developments and lessons for Europe,* London: Palgrave Macmillan, pp. 60–111.

URIBE, M. (2020). *Staggered Price Indexation* [online]. National Bureau of Economic Research, No. w27657. <https://doi.org/10.3386/w27657>.

WOODFORD, M., WALSH, C. E. (2005). Interest and prices: Foundations of a theory of monetary policy [online]. *Macroeconomic Dynamics*, 9(3): 462–468. <http://doi.org/10.1017.1365100505040253>.

YILMAZ, Y. Ö., TUNC, G. I. (2022). The Macroeconomic Effects of Positive Trend Inflation in a Small Open Economy [online]. *Applied Economics*, 54(3): 234–248. <https://doi.org/10.1080/00036846.2021.1876208>.

ZONGO, K., NDONG NTAH, M. (2023). Chocs pétroliers, effets potentiels de l'invasion de l'Ukraine par la Russie sur le solde budgétaire des économies africaines [online]. *African Development Review*. <https://doi.org/10.1111/1467-8268.12722>.

Determinants of Access to Higher Education: Evidence from Jharkhand, India

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Received 15.12.2023 (revisions received 14.4.2024, 6.7.2024), **Accepted** (reviewed) 16.8.2024, **Published** 13.12.2024

Abstract

This paper examines the access to higher education across socio-religious groups in the state of Jharkhand in India. It also examines the factors affecting access to higher education and the role of students' social background in explaining the inequality in participation in higher education. The analysis is based on cross tabulation, logistic regression and Fairlie decomposition method. The analysis shows that tribals, Muslims and Scheduled Castes are the worst performing groups in the state. The most prominent factor behind the vulnerable condition of tribals is their high concentration in rural areas as there is a remarkable gap in their performance between rural and urban areas. A large part of the gap between the privileged and the underprivileged groups could not be explained by endowment factors, namely, household size, education of the head of household and income background. The results suggest that incentives created due to family background leads to different outcomes among different socio-religious groups.

Keywords	***DOI***	***JEL code***
Higher education, human capital, inequality, discrimination, Logistic Regression Model, Fairlie decomposition method	*https://doi.org/10.54694/stat.2023.58*	*I23, J24, J71, C35*

INTRODUCTION

The conventional understanding on higher education in literature of economics is from the vantage point of the human capital theory. The human capital theory draws a parallel between the investment in human capital and physical capital. This theory was primarily developed by Schultz (1961), Becker (1964), Denison

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(1962) and Mincer (1974). This theory using cost benefit analysis argues that the expenditure on higher education is considered investment in human capital which increases productivity and provides returns in terms of improved earnings (Schultz, 1961; Becker, 1964). The endogenous growth theory propounded by Lucas (1988), Romer (1989, 1990) and Mankiw et al. (1992) showed a positive correlation between human capital and economic growth. That is, human capital has a statistically significant positive impact on economic growth (Vinod and Kaushik, 2007). In addition, higher levels of educational attainment are associated with lower income inequalities, and national expenditure (per student) (Keller, 2010).

The relation between education and growth is non-linear. Study shows higher estimated returns in developing countries than in developed countries (Duflo, 2001). Krueger and Lindahl (2001) found a positive association between education and employment in countries with the lowest educational level. In fact, they found an inverted U-shaped relation based on their cross-country study. Nelson and Phelps (1966) also stated education enhanced ability to receive, decode, and understand information. Krueger and Kumar (2004) explain the difference in growth between Europe and the United States (US) due to difference in educational policy. The calibration based on their models finds that difference in education policies play an important role in the growth difference between European countries and the US. They argue that general education helps workers in migrating to higher-productivity sectors, thereby, increasing the growth rate.

The impact of education on quality of life happens prominently through the labour market. The higher education improves the chances of getting employment and higher earnings. The workers with a relatively lower level of education are found to be highly concentrated in vulnerable employment (Sparreboom and Staneva, 2014). It also contributes in terms of improving job security (Ortiz, 2010).

Thus, the equal opportunity in access to higher education is crucial for ensuring equality in terms of economic outcomes. This study focuses broadly on the unequal access to higher education among socio-religious groups in the state of Jharkhand. The specific objectives are as follows:

a) to study the access to higher education of different socio-religious groups with a focus on the tribal population of the state,
b) to examine the factors determining the access to higher education in the state,
c) to examine the extent to which socio-religious background determines the access to higher education in the state.

The study contributes to the existing literature by using data from national sample survey on social consumption, education for the period 2017–18. The study is based on logistic model to determine the access to higher education. The Fairlie decomposition method is used to analyse the role of identity in determining access to higher education. The analysis shows that tribals and Muslims are the worst performing groups in the state. The Scheduled Castes also lag behind the privileged groups. The low performance of the underprivileged groups in education can't be fully attributed to the income inequality as an equal improvement in income does not lead to an equal improvement in participation in higher education across socio-religious groups. The group affiliation affects the participation of underprivileged groups despite improving economic conditions. The findings suggest that incentives created due to family background leads to different outcomes among different socio-religious groups. The result is more concerning due to the fact that tribals are lagging behind other socio-religious groups despite their high concentration in the state. The most prominent factor behind this is their very high concentration in rural areas as there is a remarkable gap in their performance between rural and urban areas.

1 LITERATURE REVIEW

There is a scarcity of research from the aspect of economics as to how students' background affects the access to higher education. The ethnic background affects the economic outcomes in several ways. Studies have showed that low investment on a particular ethnic identity due to the poor public policy results in poor economic condition of certain ethnic groups (Miguel and Gugerty 2005; Alesina, Baqir and Easterly 1999). The conceptualisation of discrimination from the viewpoint of economics provided theoretical ground for analysing the role of identity in the domain of economics (Becker, 1957). The presence of discrimination, active or passive, might also be a reason for the unequal economic outcomes. There are evidences that discrimination against a particular ethnic group reduces the chance of their vertical mobility irrespective of the effort by the underprivileged groups (Churchill, Ocloo and Robertson, 2017). The methodology for the estimation of discrimination was developed by Oaxaca (1973) and Blinder (1973). Fairlee (1999) has extended this method to the non-linear variables.

There are some studies on examining the role of group identity in determining the access to higher education in Indian context (Khan, 2022; Tilak and Choudhary, 2019; Khan, 2017; Thorat and Khan, 2017; Borooah, 2017). However, the analysis at the sub-national level is pertinent for India due to a wide diversity of the population across different states. This study extends the attempts to identifying the inequality in access to higher education and factors causing it at the sub-national level (Khan, 2023). Furthermore, the analysis at all India level does not capture the state specific factors. There is a wide variation in the performance of different states. For example, the GER, defined as the percentage of population in 18–23 years attending higher education is 40% or above in Kerala, Himachal Pradesh, Tamil Nadu, Uttarakhand and below the national average in Odisha, Assam, Bihar, Gujarat, and Madhya Pradesh (Khan 2023).

2 EDUCATION SYSTEM IN INDIA

The education system in India may be broadly divided into two parts: school education and higher education. The school system in India comprises of lower primary covering first five standards, upper primary divided into two standards, high school based on three and higher secondary comprising the next two standards. At the national level there are two streams of school education, namely, Central Board of Secondary Education (CBSE) and Indian Certificate of Secondary Education (ICSE). Each state has its own school body called the State Council for Educational Research and Training (SCERT). The SCERT generally follows the guidelines provided by the National Council for Educational Research and Training (NCERT) but they also have certain degree of freedom in the implementation of educational strategies. There is a large number of private self-financed schools catering to the urban middle class families. Private sponsored schools are another category of schools started by a private agency and receive grant-in-aid by the government.

The higher education in India begins after the 10 + 2 stage. The education sector in India comes under the concurrent list i.e. education policies and programmes are suggested at the national level by the central government but the state governments have freedom in implementing them. The higher education system comprises various type of institutions like universities, colleges, institutes of national importance, polytechnics etc. Universities are broadly central universities, state universities, and deemed to be universities. The central universities are formed by government of India, by an act of parliament. The state universities are formed by the state government through state legislature. The deemed to be universities means the accreditation granted to higher education institutions due to their high standard of working in a specific area. In addition, there is a large number of private universities managed by private organisation formed through state legislature.

Colleges generally offer undergraduate courses of three years. These are affiliated or constituent body of universities. The degree awarding authority is given to the universities. Bachelor's degree is awarded in Arts, Science, Commerce, etc. However, the undergraduate courses in professional subjects like Engineering, Medicine, Dentistry and Pharmacy are of four to five and a half years. Postgraduate courses are of two years ending with a Master's degree. The certificate or diploma courses are offered in disciplines like Engineering, Agricultural Sciences and Computer Technology.

India has a federal set-up comprising of twenty-eight states and eight union territories. The education is placed in concurrent list extending the responsibility to both the centre and state. The higher education in India is regulated by University Grant Commission (UGC), All India Council for Technical Education (AICTE) and Council of Architecture (COA).

3 DATA AND METHODOLOGY

This paper examines participation in higher education in the state of Jharkhand in India. The analysis is based on the 75th round National Sample Survey data on Social Consumption, Education for the year 2017–18 (NSS, hereafter). Participation in higher education is measured in terms of enrolment at the age between 17 and 35 years. This is to note that the National Sample Survey data on Social Consumption, Education provides information on attendance up to 35 years. In order to avoid the problem of sample size, all samples in the age group of 17 to 35 are considered in the econometric analysis.

The survey covered whole of the Indian Union *except* the villages in Andaman and Nicobar Islands which are difficult to access. The data is collected in four sub-rounds with equal number of sample villages/ blocks (FSUs) allotted for survey in each sub-round to ensure uniform spread of sample FSUs over the entire survey period. A stratified multi-stage design has been adopted for the 75th round survey. The first stage units (FSU) are the census villages (Panchayat wards for Kerala) in the rural sector and urban frame survey (UFS) blocks in the urban sector. The ultimate stage units (USU) are households in both the sectors. In the case of large FSUs, two hamlet-groups (hgs)/sub-blocks (sbs) from each rural/urban FSU has been selected in the intermediate stage of sampling.

Along with the basic socio-economic information, the NSS focussed on the participation and expenditure on education. The survey covers information on current attendance, basic course structure and expenditure on education. The survey provides both individual and household level information. It includes questions on enrolment, attendance, courses, institutions, expenditure, dropouts, etc. This study used the information on enrolment. The sample distribution for the enrolment in higher education is shown in Table 1.

Table 1 Sample size in higher education, Jharkhand

	ST	SC	HOBC	HHC	Muslim	Total
Male	58	31	154	84	52	380
Female	25	21	83	44	26	203
Rural	41	32	99	34	28	234
Urban	42	20	138	94	50	349
Quintile 1: 0–20%	25	18	43	9	17	112
Quintile 2: 20–40%	14	8	53	13	12	100
Quintile 3: 40–60%	12	9	56	21	18	116
Quintile 4: 60–80%	14	12	33	26	15	102
Quintile 5: 80–100%	18	5	52	59	16	153
Self employed	39	21	135	53	31	280
Regular/salaried employees	12	12	64	51	27	168
Casual labour	14	9	15	2	17	57
Others	18	10	23	22	3	78
Total	83	52	237	128	78	583

Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

3.1 Variables

The study analyses the access of different social groups to higher education in the state of Jharkhand in India. The access is measured in terms of enrolment in higher education. The enrolment in higher education includes graduate, post graduate and higher level of education. The NSS has asked the details of education of interviewee from 5 to 35 years of age. The questions pertain to both their level of education and current enrolment. The details of enrolment and course, expenditure of those currently attending are asked. The questions are asked about the particulars of those currently not attending any educational institution. The questions about reasons for drop out and details about the last enrolment are also covered in the data. This paper is based on the analysis of current enrolment in higher education. All those enrolled in graduate and above including diploma education are considered to be part of higher education and this variable is considered as dependent variable. This is a dummy variable assuming the value 1 if someone is enrolled in higher education and 0 otherwise. In order to compare the performance of different groups the Gross Enrolment Ratio (GER) is calculated. It is defined as the ratio of persons enrolled in higher education institutions to the population in the in the age group from 18 to 23 years.

In the econometric analysis for logistic regression and decomposition method, the enrolment in higher education is the dependent variable. Urban location, household size, head's education and state region are used as independent variables in the model. The state is divided into two parts, namely, region one and region two. This is different from rural-urban disaggregation because the former controls the location based on economic development while the latter controls geographical location. Out of total twenty-four districts, eleven districts are clubbed into region one while the remaining thirteen districts are included into region two. The forest cover is slightly higher in the first region while the forest cover is far lower than the state average in many districts in the second region. Household size is the only continuous variable in the model. All other variables are binary covering yes/no answers. For head's education, those households with head's education below higher secondary education are considered as a reference group for low level of head's education while households with higher secondary and higher level of head's education are treated with higher level of head's education.

India is a diverse society and so is the state of Jharkhand. It is one of the states highly dominated by tribals, namely, Scheduled Tribes (ST). They constitute 26 per cent of the total state population. These are recognised as one of the backward groups based on their geographical isolation. The Scheduled Castes (SC) are another constitutionally recognised underprivileged group based on their historical disadvantages. The other backward classes (OBC) are considered underprivileged group based on the group of socio-economic indicators. The population not belonging to SC, ST and OBC are considered higher castes. The Higher Castes among the majority Hindus are the most privileged group in terms of socio-economic background and are named by Hindu Higher Castes (HHC) in the analysis. The OBC among Hindus are the next better off group and are denoted by HOBC. Muslims are the largest and most backward religious minority. The other religious minorities comprise of Christians, Sikhs, Buddhists, Jains and Zoroastrians. The sample size for the minority group is very low in the NSS data. So, these are combined together and named as Other Religious Minorities (ORM). Hence, the total of six socio-religious groups have been identified for the analysis, namely, Scheduled Tribes (ST), Scheduled Castes (SC), Hindu Other Backward Classes (HOBC), Hindu High Castes (HHC), Muslims and ORMs. The results obtained for ORM may suffer from the limitation of low sample size and hence are not shown in the analysis. Thus, the results for only five socio-religious groups, namely, Scheduled Tribes (ST), Scheduled Castes (SC), Hindu Other Backward Classes (HOBC), Hindu High Castes (HHC), Muslims and ORMs are shown in the analysis. The NSS provides information on monthly per capita consumption expenditure (MPCE), which may be used as a proxy of income.

3.2 Logit Model

The logit model is used to examine the factors determining access to higher education in the state of Jharkhand. The following derivation shows that the linear model may be applied to binary dependent variables with some modifications (Gujarati and Porter, 2009). The model may be presented as follows. Consider the following regression model:

$$Y_i = \beta_1 + \beta_2 X_i + U_i \,, \tag{1}$$

where X_i are independent variables and $Y_i = 1$ if the person is enrolled in higher education and 0 if he/she is not enrolled. Here, U_i is error term. Note that the error term is not normally distributed if the dependent variable is binary. In fact, the error term also undertakes dichotomous values. Thus, logistic transformation is needed for estimation in this case.

Model (1) looks like a typical linear regression model but because the regressand is binary, or dichotomous, it is called a linear probability model (LPM). This is because the conditional expectation of Y_i given X_i i.e. $E(Y_i \mid X_i)$ can be interpreted as the conditional probability that the event will occur given X_i, that is, $\Pr(Y_i = 1 \mid X_i)$.

Thus, in this case, $E(Y_i \mid X_i)$ gives the probability of an individual being enrolled in higher education given X_i. The justification of the name LPM for models can be seen as follows. In order to obtain unbiased estimators, we assume $E(U_i) = 0$:

$$E(Y_i \mid X_i) = \beta_1 + \beta_2 X_i \,. \tag{2}$$

If P_i is the probability that $Y_i = 1$ (that is, the event occurs), and $(1 - P_i)$ is the probability that $Y_i = 0$ (that is, that the event does not occur). Then, by the definition of mathematical expectation, we obtain:

$$E(Y_i) = 0(1-P_i) + 1(P_i) = P_i \,. \tag{3}$$

Comparing (2) with (3), we can equate:

$$E(Y_i \mid X_i) = \beta_1 + \beta_2 X_i = P_i \,, \tag{4}$$

that is, the conditional expectation of the model (1) can be interpreted as the conditional probability of Y_i. In general, the expectation of a Bernoulli random variable is the probability that the random variable equals 1. If there are n independent trials, each with a probability P_i of success and probability $(1 - P_i)$ of failure, and X_i of these trials represent the number of successes, then X_i is said to follow the binomial distribution. The mean of the binomial distribution is nP and its variance is $nP(1 - P)$. The term success is defined in the context of the problem. Since the probability P_i must lie between 0 and 1, we have the restriction:

$$0 \leq E(Y_i \mid X_i) \leq 1, \tag{5}$$

that is, the conditional expectation (or conditional probability) must lie between 0 and 1.

Thus, Ordinary Least Square (OLS) can be extended to binary dependent variable regression models. However, there are several problems in applying LPM to estimate the occurrence of a binary variable. The notable problem is that Y_i may step outside the 0–1 range and $P_i = E(Y_i = 1 \mid X_i)$ increases linearly with X_i, that is, the marginal or incremental effect of X_i remains constant throughout is unrealistic. In reality, P_i *may be* nonlinearly related to X_i.

Thus, the most suitable model is the one having two features:

(1) As X_i increases, $P_i = E(Y_i = 1 \mid X_i)$ increases but never steps outside the 0–1 interval,

(2) the relationship between P_i and X_i is nonlinear.

These two properties are satisfied by the sigmoid, or S-shaped curve. The Logistic CDF satisfies these characteristics. This model may be depicted as follows. The LPM explaining enrolment in higher education is:

$$P_i = \mathrm{E}\,(Y_i = 1\,|X_i) = \beta_1 + \beta_2 X_i\,, \tag{6}$$

where X_i is the series of independent variables and $Y_i = 1$ means the individual is enrolled in higher education. But now consider the following representation of enrolment:

$$P_i = \mathrm{E}\,(Y_i = 1\,|X_i) = \frac{1}{1+\,e^{-(\beta_1+\beta_2 X_i)}}\,. \tag{7}$$

Formula (6) may be written as:

$$P_i = \mathrm{E}\,(Y_i = 1\,|X_i) = \frac{1}{1+\,e^{-Z_i}} = \frac{e^{Z_i}}{1+\,e^{Z_i}}\,, \tag{8}$$

here $Z_i = \beta_1 + \beta_2 X_i$.

Formula (7) represents the (cumulative) logistic distribution function. As Z_i ranges from $-\infty$ to $+\infty$, P_i ranges between 0 and 1 and that P_i is non-linearly related to Z_i (i.e. X_i). Hence, it satisfies the two requirements discussed earlier. The challenge with this model is that P_i is non-linear not only in X_i but also in the β's as shown in Formula (6). Thus, OLS procedure cannot be used to estimate the parameters. However, Formula (6) can be linearized as follows.

If P_i, the probability of enrolment is given by Formula (3), then $(1 - P_i)$, the probability of not enrolled is:

$$1 - P_i = \frac{1}{1+\,e^{Z_i}}\,. \tag{9}$$

Therefore,

$$\frac{P_i}{1-\,P_i} = \frac{1+e^{Z_i}}{1+\,e-^{Z_i}} = e^{Z_i}\,, \tag{10}$$

here, $\frac{P_i}{1-\,P_i}$ is ratio of the probability that an individual is enrolled to the probability that he is not enrolled. This is called odd ratio. By taking the natural log of Formula (9), we obtain:

$$L_i = ln\,(\frac{P_i}{1-\,P_i}) = Z_i = \beta_1 + \beta_2 X_i\,, \tag{11}$$

here L, the log of the odds ratio is linear in both X_i and the parameters. L is called the logit. This is called logit model. We will apply this model shown in Formula (11) in our estimation.

The NSS data on social consumption, education has conducted survey of the persons in the age group 3 to 35 years. The survey covers information of those attending, not attending and never attended. The survey is based on questions on the status of enrolment, expenditure on education and drop out. The determinants of the model are the income background of the household as measured by the monthly per capita consumption expenditure (mpce). The mpce is converted into log function for the convenience of interpretation. It is a continuous variable in the model. The location is denoted by the binary variable rural versus urban. The improvement in chance of enrolment in urban areas against rural is estimated to examine the impact of location. The household size is a continuous variable showing the impact of higher household size on the chance of enrolment in higher education. Head's education is also taken as an explanatory variable. The two categories of head's education are identified, namely, below higher secondary level and higher secondary and above. The NSS data has divided the state of Jharkhand into two regions, namely, region one and region two. The region two underperforms compared to the region one. In order to capture the advantage of region one over region two, the latter is used as a reference group. Finally, the Hindu High Caste who are the most privileged group in India are used as a reference group to examine the relative position of ST, SC, HOBC and Muslims.

3.3 Decomposition analysis

In order to examine the role of group-identity in determining access to higher education, decomposition method is used. The decomposition analysis is conducted using the Fairlee method (1999). This technique uses a non-linear equation such as the logit or probit model to decompose the binary outcomes into two parts, namely, the explained gap and the unexplained gap. To calculate the decomposition between two groups (say, A for privileged group and B for underprivileged group), define $\overline{Y}^j$ (where j = A or B) the average probability of the binary outcome for group j and F as the cumulative distribution function from the logistic distribution. Following Fairlie (1999), the decomposition for a non-linear equation, Y = F(X $\hat{\beta}$), can be written as:

$$\overline{Y}^A - \overline{Y}^B = \left[\sum_{i=1}^{N^A} \frac{F(X_i^A \hat{\beta}^A)}{N^A} - \sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^A)}{N^B} \right] + \left[\sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^A)}{N^B} - \sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^B)}{N^B} \right], \tag{12}$$

where N^j is the sample size for race $j \cdot \hat{\beta}^B$ and β^A are the coefficients for underprivileged and privileged groups respectively, X_i^B and $\overline{X}^A$ are the endowments for underprivileged and privileged groups, respectively. The first term in brackets of Formula (12) represents the part of the gap attributed to differences in distributions of X_i, and the second term represents the part due to differences in the identity-based processes determining levels of Y_i. The second term also captures the portion of the gap due to group differences in immeasurable or unobserved endowments. An equally valid expression for the decomposition is:

$$\overline{Y}^A - \overline{Y}^B = \left[\sum_{i=1}^{N^A} \frac{F(X_i^A \beta^B)}{N^A} - \sum_{i=1}^{N^B} \frac{F(X_i^B \beta^B)}{N^B} \right] + \left[\sum_{i=1}^{N^A} \frac{F(X_i^A \beta^A)}{N^A} - \sum_{i=1}^{N^A} \frac{F(X_i^A \beta^B)}{N^A} \right], \tag{13}$$

in this case, the underprivileged groups' coefficient estimates, $\hat{\beta}^B$ are used as weights for the first term in the decomposition, and the privileged groups' distributions of the independent variables, $\overline{X}^A$ are used as weights for the second term (Formula 13).

The contribution of each variable to the gap is equal to the change in the average predicted probability of replacing the underprivileged groups' distribution with the privileged groups' distribution of that variable while holding the distributions of the other variables constant. The sum of the contributions from individual variables will be equal to the total contribution from all of the variables evaluated with the full sample. This is to note that the gap explained by the endowment variables is purely economic in nature. Thus, it may be corrected by labelling the endowment among different groups. In this model income background, household size, head's education, urban location and geographical location are endowment variables. The part of the gap not explained by the endowment variables are attributed to the group identity. This is often considered as an indirect measure of discrimination since this part of the gap tells the difference in the average outcome variable among different groups despite having similar average endowment variable. The decomposition method is used in this paper to estimate the difference in enrolment in higher education between privileged and underprivileged groups (HHC/ST, HHC/SC, HHC/Muslims, HHC/OBC`).

4 RESULT

4.1 Study population

Given that Jharkhand is a tribal dominated state of India with one fourth of the total population belonging to the tribal ethnicity (Census, 2011), it's development would percolate the benefits to the tribal ethnic groups who are one of the most marginalised groups in India. The state is the worst performer in terms of the sustainable development goal (SDG). The performance of the state in terms of quality education (SDG 4) and decent work (SDG 8) is highly disappointing (Hindustan Times, 2021, June 21). The improved access to higher education would enable the state to improve its performance in terms of SDG indicators both directly on the parameter of education as well due to the impacts of education on other indicators related to the SDG. This study directly addresses the question of access to higher education in the state in general and the existing inequality in access to higher education in particular.

Jharkhand is one of the tribal dominated states of India. There are 24 districts, 259 Taluks, 32 394 villages and 229 towns in Jharkhand. As per the Census of India (2011), Jharkhand has 6 254 781 households, population of 32 988 134, of which 16 930 315 are males and 16 057 819 are females representing 51.3 per cent and 48.7 per cent of the population, respectively. The literacy rate of Jharkhand state is 55.56 percent, out of which 64.28 percent males are literate and 46.37 percent females are literate. The total area of Jharkhand is 79 716 sq. km with a population density of 414 per sq. km. Out of total population, 75.95 percent of population lives in urban area and 24.05 percent lives in rural area.

Jharkhand is one of the low performing states in terms of higher education. It houses a significant number of people belonging to the tribal groups. The share of other underprivileged groups, namely, Scheduled Castes (SCs), Muslims and other religious minorities is also high. There are 12.1 percent Scheduled Caste (SC) and 26.2 percent Scheduled Tribe (ST) of total population in Jharkhand. The share of Hindu population is 67.8 percent and Muslims are 14.5 percent while Christians and other religion are 4.3 percent and 12.8 percent, respectively. Nearly 37.5 per cent of the population is below the poverty line as shown by the National Sample Survey data on Consumption Expenditure, 2011–12.

4.2 Unequal access to higher education

The most concerning factor with regard to higher education in the state is that the tribals despite comprising high share in total population are the most backward community. Their access to higher education is the lowest among the socio-religious groups. The GER among ST is 7.8 per cent only. The performance of Muslims, 11.4 per cent, is better than ST but they lag behind all other socio-religious groups. It is the highest among HHC at 39.7 per cent followed by 26.9 per cent among HOBC and 18.4 per cent among SC. The GER is 18.7 per cent at the state level. The GER is higher among male than female. Thus, the GER varies remarkably across socio-religious groups. The GER is consistently higher in urban areas than in rural areas among every socio-religious group. The highest improvement from urban location is observed among ST whose GER jumps from 6.1 per cent in rural areas to 40.9 per cent in urban areas. However, GER among HHC is roughly similar in rural and urban areas. The conventional hierarchy by socio-religious groups follows in rural areas but it changes in urban areas. The GER among ST, HOBC and HHC is similar in urban areas and these three groups occupy the top position. However, SC and Muslims continue to be the worst performer. The GER among SC is slightly higher than Muslims (Table 2).

Table 2 GER in higher education, Jharkhand

	Male	Female	Rural	Urban	Total
Scheduled tribes (ST)	9.8	5.9	6.1	40.9	7.8
Scheduled castes (SC)	18.2	18.5	16.2	27.9	18.4
Hindu other backward class (HOBC)	27.5	25.9	20.2	41.6	26.9
Hindu high caste (HHC)	44.4	33.6	38.9	40.7	39.7
Muslims	13.7	9.5	6.4	24.3	11.4
Total	20.9	16.3	13.5	36.7	18.7

Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

Table 3 shows the GER in higher education by socio-religious groups in different consumption range. The GER increases with the improving income level among every group. It is the lowest among the bottom income group for every socio-religious group and the highest for the top 20 per cent population. The most noteworthy observation is for Muslims whose GER is highest in the top 20 per cent of the population. However, the hierarchy across social groups remains intact. The GER among Muslims remains lowest in the lower 80 per cent population. Further, the GER of SC is higher than OBC in the middle-income group. The poorest 40 per cent among tribals, SC and Muslims are lagging far behind the state average. However, the middle-income groups among ST and SC are relatively better placed, though Muslims continue to lag behind every groups. This might be due to presence of reservation for ST and SC which led to the emergence of the middle class among them thereby improving access to higher education. However, the high GER in the top 20 per cent among Muslims shows intra-community diversity based on the economic background.

Table 3 GER by Socio-religious and income groups (INR)

	0–40	40–80	80–100	Total
Scheduled tribes (ST)	5.9	28.8	42.9	7.8
Scheduled castes (SC)	11.7	40.2	136.7*	18.4
Hindu other backward class (HOBC)	23.9	31.5	46.4	26.9
Hindu high caste (HHC)	31.6	45.6	52.8	39.7
Muslims	9.5	15.7	59.1	11.4
Total	14.1	30.6	52.5	18.7

Note: * Indicates the problem of low sample size. Thus, the estimate is not reliable.
Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

The pattern is similar also among occupational groups (Table 4). The conventional hierarchy follows for SE and CL with the GER being highest among HHC followed by HOBC, SC, Muslims and ST, respectively. However, this pattern does not hold for the household based on regular employment. In this case, the GER is the highest among HOBC followed by Muslims and HHCs. The GER among ST is the lowest followed by the SC. Worryingly, SC/ST are lagging far behind the state average which is indicative of the fact that a large number of households based on regular employment depend on low quality employment. Further, intra-group inequality is also affirmed from the GER as GER among RS households is far higher than those depending on SE and CL.

Table 4 GER by social groups and occupation groups, Jharkhand, 2017–18

	Self employed (SE)	Regular/salaried employed (RS)	Casual labour (CL)	Total
Scheduled tribes (ST)	8.5	16.6	4.8	7.8
Scheduled castes (SC)	13.9	23.2	9.9*	18.4
Hindu other backward class (HOBC)	20.4	61.2	13.5	26.9
Hindu high caste (HHC)	42.7	41.3	16.7*	39.7
Muslims	12.3	**52.8**	5.9	11.4
Total	16.9	48.8	7.7	18.7

Note: * Implies low sample size. Since the figure confirms the broader pattern, the result may be accepted despite the problem of low sample size.
Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

4.2.1 What determines participation in higher education?

This section analyses factors affecting participation in higher education as measured by enrolment in higher education. This section is based on two models: the first is a logit model that examines how social, religious and economic background influence higher education enrolment. The decomposition method which is the second model analyses the contribution of social background in creating inequality between privileged and the underprivileged groups. It analyses how variables, namely, gender, urban location, household size and the head's education can explain the gap in access to higher and professional education among different groups.

4.2.2 Participation in higher education

The socio-economic background significantly affects the chances of enrolment in the state. The economic background, ethnic identity and religious background significantly affect the chance of enrolment in higher education in the state (Table 5). The increasing income improves the chance of enrolment in higher education. Further, larger households have a higher chance of enrolment in higher education. The most concerning factor is that the chance of enrolment is far lower among tribals than the HHC despite the state being highly concentrated with the tribal population. The odd ratio for ST is 0.32 which means that their chances of enrolment are 68 per cent lower than the HHC. Muslims continue to be one of the most deprived groups in the state. They have 59 per cent lower chance of enrolment than HHC. It is to note that SC and HOBC also have relatively lower chance of enrolment than HHC by 62 per cent and 23 per cent, respectively. The chances of enrolment improve in households with heads having higher education degree by 46 per cent than the households headed by someone with education up to secondary level. The chance of enrolment is 25 per cent higher in urban areas than in rural areas. This is to note that odd ratios are statistically significant within 5 percent for ST and Muslims. This means that ethnicity and religious background play statistically significant role while caste background is not found to be statistically significant.

In order to further verify the inequality in enrolment in higher education the predicted probability is also estimated. Overall, the chance of enrolment in higher education for the age cohort under consideration is 4.2 per cent. The corresponding probability is 5 per cent in urban areas while it is 4.1 per cent in rural areas. The gap between region 1 and region 2 is notably low. The corresponding probabilities are 4.4 per cent and 4 per cent respectively.

Table 5 Odd ratio of the logistic regression model

Variables	Odd ratio	SE	Z	P>Z
Log MPCE	2.36*	0.496	4.08	0
Urban	1.25	0.375	0.75	0.45
Household size	1.09**	0.048	1.85	0.07
Head's education	1.46	0.349	1.57	0.12
NSS region (ref: region 1)	0.9	0.186	–0.53	0.6
ST (ref: HHC)	0.32*	0.131	–2.78	0.01
SC (ref: HHC)	0.58	0.248	–1.28	0.2
HOBC (ref: HHC)	0.77	0.267	–0.75	0.45
Muslim (ref: HHC)	0.41*	0.174	–2.1	0.04
Constant	0.00010*	0.0001779	–5.4	0
Pseudo R square	0.0687			
Prob>Chi square	0			
Number of observations	3 869			

Note: * Implies significant within 5 percent and ** implies significant withing 10 percent.
Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

Table 6 Predicted probability of enrolment, Jharkhand

	Predicted probability	Delta method SE	Z	P>|z|
Rural	4.1	0.0046476	8.72	0
Urban	5.0	0.0126731	3.96	0
Education of the head below	3.9	0.0045692	8.54	0
Education of the head	5.6	0.0109085	5.12	0
ST	2.6	0.0055991	4.67	0
SC	4.6	0.0114645	4.00	0
HOBC	6.0	0.0089081	6.74	0
HHC	7.7	0.0240663	3.18	0
Muslim	3.3	0.0085386	3.87	0
Region 1	4.4	0.0056268	7.83	0
Region 2	4.0	0.0062582	6.34	0
Mean	4.2	0.0042678	9.89	0

Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

4.3 Decomposition analysis

The logistic regression showed the chance of enrolment among different socio-religious groups with reference to HHC. It showed that ST and Muslims are the most underprivileged groups in this regard. The performance of SC and HOBC is also relatively lower. The decomposition analysis in this section divides the explanatory variables into two parts. Table 6 depicts the probability of enrolment by groups in higher education. The probability of enrolment is 7.7 percent among HHC while it is 2.6 percent among ST resulting in a gap of 5.1 per cent point. The probability of enrolment is relatively lower among SC and Muslims and thus the gap with HHC is relatively higher. The probabilities are 4.6 and 3.3 among SC and Muslims respectively. The corresponding probability among HOBC is 6 percent.

This is to note that nearly 54 per cent of the gap among ST and 42 per cent of the gap among SC is not explained by the endowment variables i.e., these are attributed to the social background. Almost the whole gap among Muslims is attributed to their religious identity. Head's education and income benefit them but it is offset by the disadvantages associated with household size, urban location and region.

The economic background is the most effective factor leading to the reduction in the gap in the probability of enrolment in higher education between ST and HHC. Nearly 25 per cent of the gap between them is due to the income inequality between these two groups. Similarly, nearly 14 per cent of the total gap between SC and HHC is attributed to the income inequality between them. Notably, the income gap does not play that prominent role between Muslims and HHC. Nearly 2 per cent of the gap in the probability of enrolment between them is due to income inequality. The reason for it is a high dependence of Muslims on informal sector wherein education does not play any role rather training becomes far more prominent. The reservation in the government sector might be the reason for better explanatory power of income background among ST and SC. Higher probability for getting regular employment provides an incentive for education which results in higher probability of enrolment in higher education.

Notably, household size emerges as the most important factor in reducing the gap in the probability of enrolment in higher education between SC and HHC. It explains nearly 25 per cent of the total gap between these two groups. The household size behaves negatively in the case of Muslims which means that Muslims of smaller households are less likely to get enrolled in higher education. In a backward state like Jharkhand such a role is not unexpected particularly in a scenario wherein a large number of Muslims households are dependent on the informal sector. In such cases the lower size of the household might also result in lower household income as everyone in the household attempts to earn to support the family. Thus, financing of higher education by pooling the resources of other members is highly unlikely in small families.

The educational level of the head is equally important for all the three underprivileged groups. It explains 12 per cent of the gap among SC and ST and 13 per cent of the gap among Muslims. The fact that heads are the primary sponsors of education results in a prominent role of head's educational level among every group.

Table 7 Result of decomposition method, Jharkhand

Jharkhand	ST	SC	Muslims
Log of MPCE	25.3	13.8	1.7
Urban	4.2	12.9	–1.9
Household size	4.3	24.6	–17.0
Head's education HS	11.7	11.6	13.1
Region	0.91	2.5	–11.6
Total explained	46.3	57.7	–15.6
Probability 1	0.065	0.054	0.055
Probability 2	0.024	0.044	0.040
Gap	0.041	0.010	0.015

Source: Author's calculation based on 75th round National Sample Survey data on Social Consumption: Education, 2017–18

The urban location explains nearly 13 per cent of the gap between SC and HHC while the corresponding figure is 4.2 per cent between ST and HHC. The urban location widens the gap between Muslims and HHC. This is to note that SC and ST are highly engaged in regular employment in urban areas which induces their enrolment in higher education while Muslims largely depend on self-employment. Further, being in region 2, in general, reduces the gap for SC and ST but this is not true for Muslims. The gap expands in well off regions for Muslims. This is consistent with the result for urban areas. Thus, the advantage associated with location does not percolate to the Muslim minority.

DISCUSSION AND CONCLUSION

To achieve a competitive economy, the focus should be laid on expansion of higher education which would be instrumental in improving human capital, knowledge and innovation of a country. In this context, improving access of the marginalised section and backward regions would ensure expansion of higher education along with reducing inequality. This study has examined the impact of ethnicity on participation in higher education. The participation of different socio-religious groups in higher education has been analysed. The factors affecting the participation in higher education has also been analysed. Finally, the contribution of ethnic identity to the gap between privileged and underprivileged groups has been estimated by using the decomposition analysis. The result shows that the state performs far lower than the all-India average. The underprivileged socio-religious groups are even at a higher disadvantage. The GER is very low among SC, ST and Muslims. The impact of geographical location is not significant. This indicates a uniform backwardness across the regions. Similarly, being in urban areas improves the probability of participation in higher education but this is not statistically significant. This is to note that the location might not be a significant factor on an average but the rural-urban gap is remarkably higher for tribal population which indicates that the constraints associated with the rural location affect their participation in higher education. The economic backward emerges as one of the most powerful indicators explaining the backwardness. The raising income improves the access to higher education. Similarly, head's educational level also plays a prominent role in improving the access to higher education. The chance of enrolment in higher education is higher in households with head with higher level of education. Interestingly, the chances of enrolment are higher in larger families which might be due to the poor economic condition of the households wherein financing of higher education from household resource is possible only if other earning members support it.

This is to note that merely improvement in the factors associated with economic background would not eradicate inter-group inequality in the state. A notable part of the gap is attributed to the socio-religious identity. Nearly 54 per cent of the gap among ST and 42 per cent of the gap among SC is not explained by the endowment variables i.e., these are attributed to the social background. Almost the whole gap among Muslims is attributed to their religious identity. Head's education and income benefits them but it is offset by the disadvantages associated with household size, urban location and region.

Thus, the analysis shows that ST and Muslims are the worst performing groups in the state. The performance of SC is also notably lower than HOBC and HHC. Even an improvement in income does not lead to an equal improvement in participation. This indicates that ethnicity affects the participation in higher education despite improving economic conditions. The findings suggest that incentives created due to family background leads to different outcomes among different socio-religious groups. The possibility of ethnicity-based discrimination, active or passive, can't be ruled out since the results show that labelling endowments would not eradicate the gap completely. The result is more concerning due to the fact that tribals are lagging behind other socio-religious groups despite their high concentration in the state. The most prominent factor behind this is their very high concentration in rural areas as there is a remarkable gap in their performance between rural and urban areas.

The policy implications of these results are straightforward. If policymakers wish to expand higher education, more attention must be paid to the backward states like Jharkhand and emphasis should be laid on the underprivileged groups. The improvement in economic condition may be one of the approaches towards expansion of higher education. Special attention should be paid on the rural areas and first-generation students to bridge the gap attributed to location and education of the head of household. Furthermore, the socio-religious identity also explains a notable part of the gap which indicates that policy should be sensitive towards group identity to ensure equality of opportunity.

Reference

ALESINA, A., BAQIR, R. EASTERLY, W. (1999). Public Goods and Ethnic Divisions. *The Quarterly Journal of Economics*, 114(4): 1243–1284.

BOROOAH, V. K. (2017). Measuring Inequality in Access to Higher Education in India [online]. *Journal of Quantitative Economics*, 15(2): 241-263 <https://doi.org/10.1007/s40953-016- 0053-4>.

BECKER, G. (1957). *The Economics of Discrimination*. Chicago: University of Chicago Press.

BECKER, G. (1964). *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education*. The University of Chicago Press.

BLINDER, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human Resources*, 8(4): 436–455.

CHURCHILL, S. A., OCLOO, J. E., ROBERTSON-SIAWOR, D. (2017). Ethnic Diversity and Health Outcomes. *Social Indicators Research,* 134(3), 1077–1112.

DENISON, E. F. (1962). Education, Economic Growth, and Gaps in Information. *Journal of Political Economy*, 70: 124–124.

DUFLO, E. (2001). Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. *American Economic Review*, 91(4): 795–813.

FAIRLIE, R. W. (1999). The Absence of the African-American Owned Business: An Analysis of the Dynamics of Self-Employment. *Journal of Labor Economics*, 17(1): 80–108.

GUJARATI, D. N., PORTER, D. C. (2009). *Basic Econometrics*. New York: McGraw-Hill Irwin.

KELLER, K. R. I. (2010). How can education policy improve income distribution? An empirical analysis of education stages and measures on income inequality. *Journal of Developing Areas*, 43(2): 51–77.

KHAN, K (2023). The impact of caste and religious background on participation in higher education: Evidence from Uttar Pradesh in India. *Journal of Social and Economic Development,* 25: 70–85.

KHAN, K. (2017). The Impact of Privatization among Social and Income groups. *Arthvijnana*, 60(3): 34–54.

KHAN, K. (2022). Choice of higher education in India and its determinants. *International Journal of Economic Policy Studies*, 16: 237–251.

KRUEGER, A. B., LINDAHL, M. (2001). Education for growth: Why and for whom? *Journal of Economic Literature*, 39(4): 1101–1136.

KRUEGER, D., KUMAR, K. B. (2004). Skill-specific rather than General Education: A Reason for US–Europe Growth Differences? *Journal of Economic Growth,* 9(2): 167–207.

LUCAS, R. E. (1988). On Mechanics of Economic Development. *Journal of Monetary Economics*, 22(1): 3–42.

MANKIW, N. G., ROMER, D., WEIL, D. N. (1992) A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2): 407–437.

MIGUEL, E., GUGERTY, M. K. (2005). Ethnic Diversity, Social Sanctions, and Public Goods in Kenya. *Journal of Public Economics,* 89(11–12): 2325–2368.

MINCER, J. (1974). *Schooling, Experience, and Earnings*. New York: NBER Press.

NELSON, R., PHELPS, E. (1966). Investment in Humans, Technological Diffusion and Economic Growth. *American Economic Association Papers and Proceedings,* 56: 69–75.

NSS. (2018). *Household Social Consumption: Education. Seventy-Fifth Round, July 2017 to June 2018.* National Sample Survey Office, Ministry of Statistics and Programme Implementation, Government of India, New Delhi.

OAXACA, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 14(3): 693–709.

ORTIZ, L. (2010). Not the right job, but a secure one: Over-education and temporary employment in France, Italy and Spain. *Work, Employment and Society*, 24(1): 47–64.

ROMER, P. M. (1989). Capital Accumulation in the Theory of Long Run Growth. In: BARRO, R. J. (eds.) *Modern Business Cycle Theory*, Cambridge, Mass.: Harvard University Press.

ROMER, P. M. (1990). *Capital, Labor and Productivity*. Brookings Papers.

SCHULTZ, T. W. (1961). Investments in Human Capital. *The American Economic Review,* 51(1): 1–17.

SPARREBOOM, T., STANEVA, A. (2014). *Is education the solution to decent work for youth in developing economies? Identifying qualifications mismatch from school-to-work transition surveys.* Work4Youth Publication Series No. 23, Geneva: ILO.

THORAT, S. KHAN, K. (2017), Private Sector and Equity in Higher Education: Challenges of Growing Unequal Access. In: VARGHESE, N. V., NIDHI S. SABHRAWAL, MALISH, C. M. (eds.). *India Higher Education Report 2016: Equity,* Sage Publications.

TILAK, J. B. G., CHOUDHARY, P. K. (2019). Inequality in Access to Higher Education in India between the Poor and the Rich: Evidence from NSSO data. In: HAQUE, T., REDDY, D. N. (eds.), *India: Social Development Report 2018: Rising Inequalities in India,* Oxford University Press for Council for Social Development.

VINOD, H. D., KAUSHIK, S. K. (2007). Human capital and economic growth: Evidence from developing countries. *American Economist*, 51(1): 29–39.

Revenues from EU Funds in the Context of 20 Years of Czechia Membership and their Statistical Recording

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Received 11.7.2024, **Accepted** (reviewed) 22.7.2024, **Published** 13.12.2024

Abstract

The year 2024 marks twenty years since Czechia joined the EU. This anniversary offers an opportunity to evaluate the benefits and losses associated with the membership, and a sufficiently long time series allows such an evaluation to be made on representative data sets. Among others, the evaluation of the membership based on drawing financial funds from the EU budget stands out. Since joining the EU in 2004, the Czech Republic has received one trillion crowns more from the EU budget than it has paid into it. At the same time, in no year since 2004 the balance of income and expenditure in relation to the EU budget has been negative. This article describes basic principles of the EU funds and deals with accrual recording in national accounts and the cash flow concept. In the context of 20 years of EU membership, it then evaluates the net position of Czechia in relation to the EU and the influence of income from the EU on the revenue of general government.

Keywords	***DOI***	***JEL code***
European Union, general government, national accounts, EU funds	*https://doi.org/10.54694/stat.2024.35*	*E01, E69, F15*

INTRODUCTION

One of the important arguments supporting the membership of the Czech Republic in the EU is the possibility of drawing financial resources from the European funds, which in the long term exceed the amount of financial contributions that country as a member state must pay into the EU budget. European funds are a key tool of the EU's economic policy. As an important element of European economic integration, it serves for redistribution of financial resources in order to reduce economic and social differences between individual member states and between regions in the EU. Member states draw

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subsidies from European funds either through operational programs administered at the national level, or through EU programs directly under the administration of the European Commission, or through various specifically focused funds established directly by EU institutions.

The most important European funds include the European Regional Development Fund, the Cohesion Fund, the European Social Fund, the European Agricultural Guarantee Fund and the European Agricultural Fund for Rural Development. European funds do not only provide classic subsidies, but also provide specific financial instruments, which can take the form of loans, loan guarantees and direct capital participation supporting various development projects. In addition, the European Union creates other specifically focused funds in response to some emergency situations, such was the so-called "Recovery Fund" (officially "Recovery and Resilience Facility"), which was created in response to the coronavirus pandemic in 2020. As a tool for implementing of the European Green Deal, there was established so-called "Modernisation Fund" for a purpose of improvement of energy efficiency in lower-income EU Member States.

This article focuses in first part on basic principles of the EU funds and EU budget rules and in second part deals with accrual recording of the flows in national accounts and the cash flow concept in other statistics in Czechia. In the context of 20 years of EU membership, it then in third and fourth part evaluates the net position of Czechia in relation to the EU with pointing to some specifics and evaluates the influence of income from the EU on the revenue of the Czech general government.

1 BASIC FEATURES OF THE EU BUDGET RULES

The regular EU budget is annually proposed by the European Commission and approved by the EU Council and the European Parliament. It must be drawn up as balanced, which is a significant difference compared to the budgets of the Member States. Annual expenditure must not exceed the ceilings given by the programming period for individual years, whereby the programming period (sometimes also called the multiannual financial framework) represents the allocated EU funds for the member states for a period of seven years (specifically, for example for the years 2000–2006, 2007–2013, 2014–2020 and 2021–2027). Specific goals and priorities are set for each of these periods, which the EU and the member states are trying to achieve. Budgetary funds can usually be used two or three years after the end of the relevant programming period (the so-called N+2 or N+3 rule).

The so-called the EU‘s own resources, derived from the gross national income (GNI) and paid by the member states, represent the largest source of revenue for the EU budget. Their amount varies slightly each year depending on the total revenue that needs to be supplemented to cover expenses after taking into account the remaining EU revenue from customs duties, contributions derived from Member States‘ VAT based on the so-called weighted average VAT rate and other sources (e.g. fines and penalties, contributions of third parties, etc.). Accordingly, a uniform GNI levy ratio is used for all member states, with an annual cap of 1.40% of GNI currently in force.

The calculation of the GNI of each member state is determined according to the uniform methodology of national accounts (ESA 2010 regulation). This is also one of the reasons why Eurostat consistently verifies the data sources and methods used by the Czech Statistical Office and other member states statistical offices for the calculation of GNI in their national accounts. Such verification is done in the form of regular Eurostat dialogue visits, preparing of regular reports and answering regular queries on the data being sent by statistical offices.

2 METHODOLOGY − ACCRUAL VERSUS CASH RECORDING

The issue of recording EU flows is important for national accounts as well as for the correct calculation of the deficit and debt of general government. EU member countries must exclude flows from the EU to their budgets from the general government accounts and record them instead at the time when related domestic expenditure is realized. The basic rule is that EU funds must not affect the balance of the general government in member states (often referred to as the „rule of neutralization of EU flows" in national accounts).

Revenue from EU funds is thus recorded in the national accounts already at the moment of pre-financing from domestic budgets (realization of domestic expenses) and at the same time, in order to cover the expenditure, a claim against the EU is recorded for individual projects. The claim will disappear after the project is reimbursed in cash from the EU, which, however, can be up to many years later.

The concept of national accounts is different from the cash concept, which is monitored regularly by the Czech Ministry of Finance when monitoring the balance of income and expenditure against the EU budget, respectively monitoring the so-called net position of the Czech Republic in relation to the European Union. EU flows are monitored in the state budget on a cash basis. They affect the balance of the state budget directly during the years of the programming period in the form of pre-financing of projects from the state budget, additional financing during their implementation and on the revenue side at the time of financial closure and accounting of the project or when advances are provided.

In order to avoid distortion of the total cash balance of the state budget by extraordinary revenues from the EU and pre-financed projects, the Ministry of Finance also regularly publishes the results of the state budget after adjustment for revenues and expenditures for projects from the EU. At the same time it is necessary to mention that the vast majority of EU projects are financed through the state budget, even if the beneficiaries of the funds are units outside of general government.

The recording methods described above are important primarily because the volume of funds from the EU budget is significant and unstable over time, so the economic results / balance of general government would be somewhat misrepresented by their inclusion in different time than relevant expenditure. Even if the weight of EU flows in the total volume of government revenue is not so great (as will be seen later in the text), the impact of net revenue from the EU on the government balance (the difference between total government revenue and expenditure) would be in some years significant.

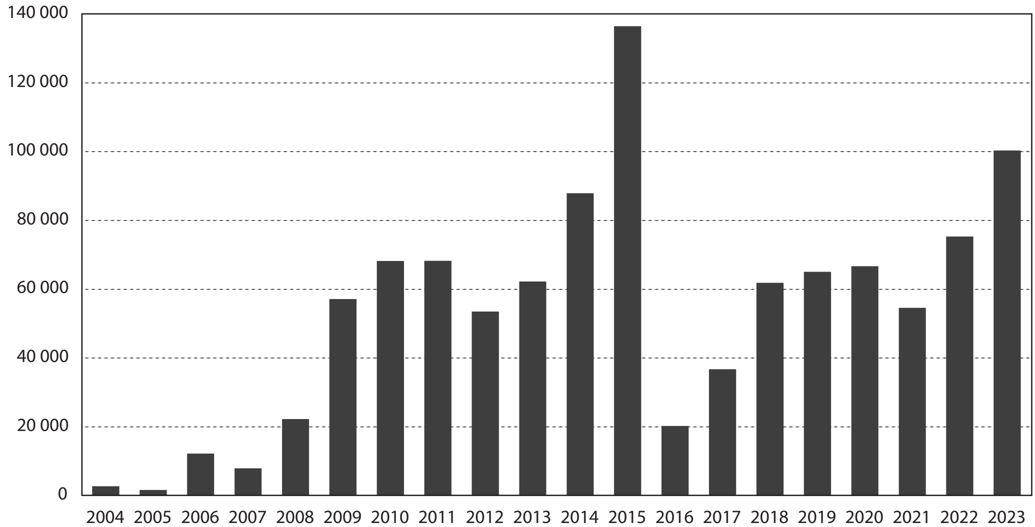
3 CZECH BALANCE THROUGHOUT 20 YEARS OF MEMBERSHIP IN THE EU

3.1 Revenue from the EU exceeded expenditure all the time

As stated in the previous chapter, the development of income from the EU is unstable over time, so the results of the balance (deficit) of general government would be distorted by their inclusion in different time than relevant expenses. From the Figure 1, which shows the total balance of income and expenditure of Czechia with the EU since 2004 (net position or "net revenue"), it is evident that the increased use of EU funds is usually at the very end of the programming period or not long after its end according to the N+2 rule (as described above). We therefore witness a high increase in the positive balance mainly in 2015 (last possibility of drawing up of EU subsidies from the period 2007–2013), the similar effect can also be seen in 2022 (final drawing up of subsidies from the programming period 2014–2020). At the same time, it is important to point out that in the cash balance overview monitored regularly by the Ministry of Finance, the mentioned effect is usually seen some time later (at the time of financial closure and accounting of the projects), even if the basic trend is the same as in the national accounts figures.

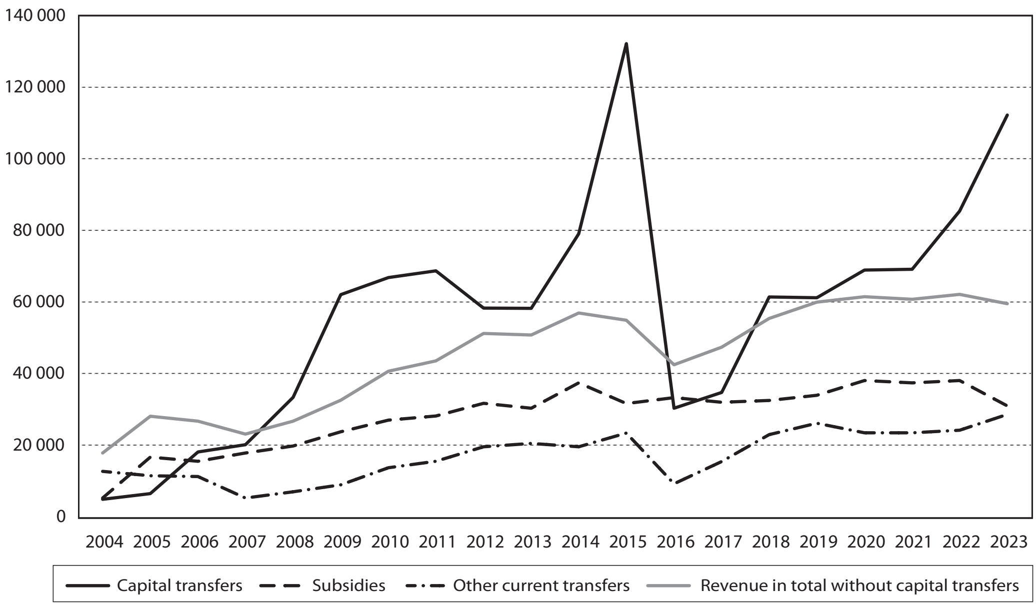
In total, Czechia received CZK 1 061.5 billion more from the EU budget for the entire period from 2004 to 2023 than it paid into it. The influence of the programming period on the dynamics of drawing funds from European funds is also evident when looking at the structure of Czech revenues from the EU according to individual items of the national accounts (see Figure 2). While a relatively stable, slightly increasing growth of revenue since 2008 can be observed for subsidies and, in most cases, for other current transfers, the development is much more deviating for capital transfers, reflecting the above-mentioned effects of drawing funds within programming periods. Especially the amount of received capital transfers from the EU in 2015 is extreme in the observed time series. In 2023, the relatively higher growth of capital transfers from the EU was mainly caused by drawing funds for energy savings for houses and flats from the "Modernisation Fund", which increased the share of income from the EU budget for non-governmental sectors, especially for households (compared to the past).

Figure 1 Balance of revenues and expenditure of Czechia with the EU budget in period 2004–2023 (CZK mill)



Source: Czech Statistical Office

Figure 2 Revenue from the EU budget in period 2004–2023 by category (CZK mill)



Note: Capital transfers – represent mainly investment subsidies used to finance the costs of fixed assets acquisition; other current transfers – represent mainly non-investment transfers, e.g. to cover operating expenses, wages, etc.
Source: Czech Statistical Office

3.2 Excluded EU projects – unpaid EU projects

Any future non-payment of the cash subsidy from the EU or its reduction results in a worsening of the deficit of general government in national accounts at the relevant moment as a counterweight to the previously recorded (at the time of pre-financing from national sources) income from the EU. This also occurs as a result of corrections in the event of errors of a systemic nature at the level of ministries (e.g. non-compliance with the control system, errors in the tender process, etc.). In such a case, government expenditures in the amount of the relevant correction are recorded in the national accounts and claims to the EU are reduced at the moment when the EU authorities decided on this correction. Physically, there is no returning of funds back to the EU budget, but it means a reduction in the value of expenses that will be reimbursed by the EU in future. Unlike the national accounts recording, there is no direct impact on the cash balance of the state budget.

4 DISCUSSION

There are often objections from professional and wider public critics that net revenues from the EU budget cannot be assessed separately from other transactions from and to the EU, and that a positive balance with the EU budget is compensated by a negative balance in dividend payments abroad. According to these opinions the export of Czech foreign controlled companies profits to their parent companies in the EU should be also taken into account. However, such different kind of transactions cannot be simply mixed up, as the free movement of capital is an established global standard even outside the EU and independent of the EU membership. The outflow of dividends from Czechia also occurs to non-European countries, while revenue from the EU budget to the extent that it was seen over the past 20 years are exclusively linked to our EU membership. The higher outflow of dividends abroad is also a logical consequence of the privatization processes and the policy of investment incentives implemented by the Czech governments even before the country joined the EU (and not a direct consequence of membership in the Union).

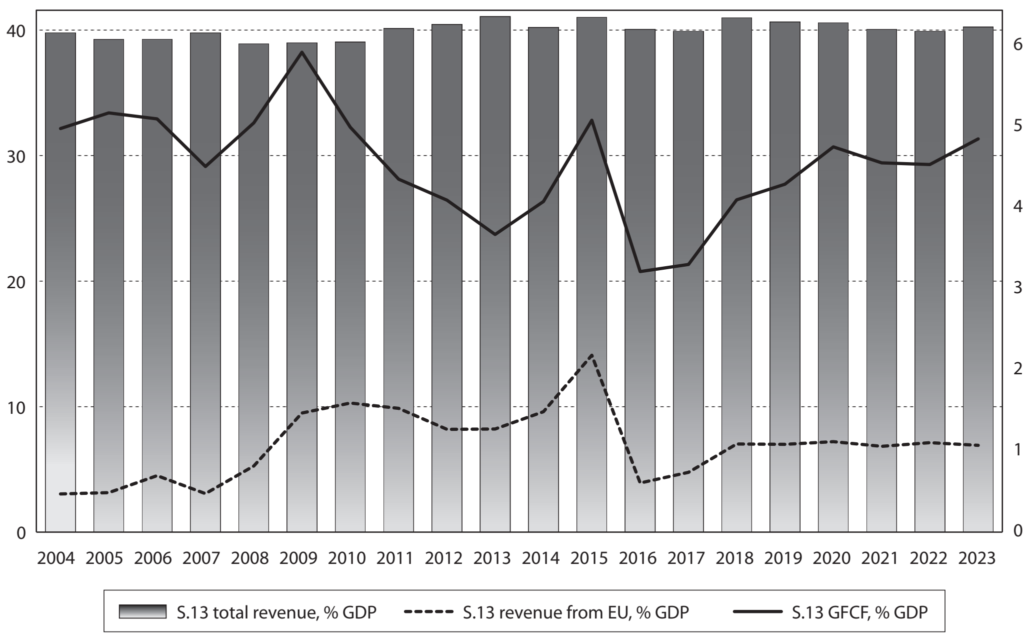
4.1 Causes of the Czech positive balance

Of course, so that the Czech Republic be able to get more from the EU budget than it pays into it, the other countries, on the contrary, have to pay more than they received. As in the case of other countries that joined EU in 2004, the positive balance of new members was consequently paid by the richer EU member states. This is due to the fact that, for example, the European Regional Development Fund is set to help less developed regions whose GDP per capita does not reach 75% of the EU average. In recent years, in addition to Prague, the regions NUTS 2 of Central Bohemia and the Southeast (South Moravian and Vysočina Region) have consistently exceeded this level, but the current set of rules allows subsidies to be drawn even for the so-called transitional regions, whose GDP per inhabitant is between 75 and 100% of the EU average. All remaining Czech NUTS 2 regions are also close to the 75% level, with the Southwest (South Bohemian and Pilsen Region) consistently exceeding it (with some exceptions), while only the Northwest (Ústí and Karlovy Vary Region) is consistently below this level. The Cohesion Fund is then reserved for member states whose GNI per inhabitant is below 90% of the EU average, and although Czech has been moving close to this level in recent years, it has not yet exceeded it. All the factors mentioned above contribute to the fact that the country remains for the time being a net recipient of funds from the EU budget.

4.2 Revenues from the EU in relation to the general government revenue

Figure 3 shows the general government (S.13) total revenue in relation to GDP (columns, left axis) and government revenue from the EU and government gross fixed capital formation (GFCF) in relation to GDP (lines, right axis). In this relative concept, the investment activity of the general government peaked in 2009 (5.9% of GDP), which was largely due to a slowdown in investment activity in the private sectors and a significant drop in GDP that year. However, there can be also observed an increase in total revenues from the EU for general government at the same time (from 0.5% of GDP in 2007 to 1.5% of GDP in 2009), which could have stimulated this government investment activity. From the development, it can be deduced that national institutions began to more efficiently draw funds from the EU only about 5 years after joining the EU (this also corresponds to the development of net revenue and revenue from the EU for the all sectors in Figures 1 and 2).

Figure 3 General government total revenue and gross fixed capital formation (GFCF) in relation to GDP



Source: Czech Statistical Office

Figure 3 also shows in columns that for the entire period of EU membership, the share of total government revenue on GDP remained stable (more precisely it reached 39.8% of GDP in 2004, while in 2023 it was 40.2% of GDP). So, surprisingly, regardless of the development of revenues from the EU, as well as political changes and changes in taxes that occurred in Czechia over a period of twenty years, the total revenue of general government represented a constant share of 40% of GDP. Even the often-discussed significant reduction in payroll taxes from 2021 did not have an impact on it. Since 2018, the general government' revenues from the EU have been steadily reaching the level of 1.1% of GDP, which is only 0.6 p.p. more than it was in 2004. It can be therefore concluded that in the total volume of revenue of the Czech general government, revenue from the EU does not represent a significant share.

CONCLUSION

European funds paid from the EU budget are one of the supporting tools of economic integration established in order to reduce economic and social differences between individual member states and regions in the EU. Since joining the European Union in 2004, the Czech Republic has received one trillion crowns more from the EU budget than it has paid into it. At the same time, in no year from 2004 to 2023 the balance of revenue and expenditure in relation to the EU budget has been negative. Accrual and cash recording provided in data of the Czech Statistical Office and the Ministry of Finance show a different time of recording of revenue and expenditure, but in the context of 20 years of membership, they offer the same picture of the overall positive balance of the country in relation to the EU budget. The dynamic of positive balance was influenced in time by the rules established for drawing funds in the framework of seven-year programming periods and was therefore relatively unstable, which was particularly evident on the side of capital transfers revenue at the end of individual programming periods. Czechia remains a net recipient of EU funds especially due to ongoing EU financial support to Czech NUTS 2 regions whose GDP per capita is still near to 75% of the EU average and also because of national GNI per capita remaining below 90% of the EU average. Both of these mentioned relative indicators represent the criteria for entitlement to support under the EU's structural and cohesion policy. Even though the balance of revenue and expenditure with the EU can distort the cash balance of the general government, in the total volume of revenue of the Czech general government, revenue from the EU represents only limited share.

References

CZECH STATISTICAL OFFICE. (2024). *Database of National Accounts: Regional Accounts*. Prague: Czech Statistical Office.

EUROPEAN COMMISSION. (2024). *Budget* [online]. <https://european-union.europa.eu/institutions-law-budget/budget_en>.

EUROSTAT DATABASE. (2024). *Government revenue, expenditure and main aggregates* [online]. <https://ec.europa.eu/eurostat/data/database>.

EUROSTAT. (2023). *Manual on Government Deficit and Debt – Implementation of ESA 2010*. Luxembourg.

KAHOUN, J. (2024). Získali jsme bilion. *Statistika&My*, 4/2024: 21–23.

MINISTRY OF FINANCE. (2024): *Čistá pozice ČR ve vztahu k rozpočtu EU: 2004–2023* [online]. Prague. <https://www.mfcr.cz/cs/zahranici-a-eu/hospodareni-eu/pozice-cr-vuci-rozpoctu-eu/2023/cista-pozice-cr-ve-vztahu-k-rozpoctu-eu-52262>.

MINISTRY OF REGIONAL DEVELOPMENT. (2024): *EU funds in the Czech Republic* [online]. Prague. <https://www.dotaceeu.cz/en/evropske-fondy-v-cr>.

26th International Scientific Conference *Applications of Mathematics and Statistics in Economics (AMSE 2024)*

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The 26th International Scientific Conference *Applications of Mathematics and Statistics in Economics* was held from 28 August to 1 September 2024 in Pawłowice, a suburb of Wrocław, Poland. The organiser of this year's conference was the Department of Statistics of the Wrocław University of Economics and Business. The conference was attended by more than 40 experts from Czechia, Slovakia, and Poland representing the Matěj Bel University in Banská Bystrica, Prague University of Economics and Business, Wrocław University of Economics and Business, University of Pardubice, Slovak Statistical and Demographic Society, the Statistical Office in Wrocław, the Czech Statistical Office, and the Statistical Office of the Slovak Republic.

At the opening of the conference, all conference participants were formally welcomed by Marek Kośny, Vice-Rector for Research and Academic Staff of the Wroclaw University of Economics and Business. He also delivered a salutation to the organisers and participants of the conference from Boguslawa Drelich-Skulska, Vice-Rector for Accreditation and International Cooperation.

The expert programme of the conference was opened by the President of the Czech Statistical Office Marek Rojíček with an invited lecture entitled *Macroeconomic Statistics Standards Implication in Measuring Economy*, in which he summarised the history of the development of national accounts standards and outlined the main changes that can be expected with the adoption of the SNA 2025 and ESA 2028 standards. The changes that the revised standards will bring are driven by the desire to (better) capture globalisation, digitalisation, well-being, environmental protection, and sustainability. The influence of digitalisation should be particularly evident in the recognition of data as a produced asset. In the longer term, the statistical office should focus on building a system of synthetic indicators reflecting well-being and/or sustainability, on the valuation of natural capital, and on other dimensions – human capital, health, and the like. In terms of data sources and valuation options, it will undoubtedly be a problem that solar, water, wind, and geothermal energy resources will be considered as economic assets.

The second invited lecture on *Responding to the Needs of Recipients: Data Disseminating Tools in Public Statistics on the Example of Statistics of Local Self-Government and Industrial Products* was given by representatives of the Statistics Poland (formerly Central Statistical Office) – Małgorzata Kowalska and Paweł Sobik.

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Other conference sessions were held in 4 sections: *Microeconomics and Financial Issue, Pension System and Ageing Issue*, *Application of Statistical Methods and History of Statistics, Demographic and Social Issue.* A *Poster Session* was newly included, in which five contributions were presented. It is very difficult to highlight the most interesting contributions; therefore, I would like to highlight only some of the contributions that I consider to be of high quality, interesting, and methodologically innovative.

In the *Microeconomics and Financial Issue* section, the most attention was caught by a contribution called *Regional Price Levels in the Czech Republic – 2020 Edition*. The authors (Petr Musil and Jana Fischerová) underlined that regional price levels represent a topic that is currently under spotlight. However, regional price levels, which would allow appropriate intra-regional comparison, are not officially published. The researcher team of the Prague University of Economics and Business has been dealing with this topic for a decade. The latest estimates for the reference year 2020 have been recently calculated; nevertheless, the results are preliminary and subject to further validation and accuracy improvement. The results are the latest estimates of regional price levels in Czechia reflecting long-term development in the Czech economy and its NUTS 3 Regions.

Delivered papers in the section of *Pension System and Ageing Issue* focused on current topics related to ageing of population, sustainability of pension systems, economic activity of the silver generation, and the like. Alena Kaščáková, Ľudmila Ivančíková, and Zuzana Rigová in their contribution called *Active Ageing in Slovak Regions* dealt with a concept of active ageing and possibilities of its statistical monitoring and evaluation. Population ageing puts a big pressure on the public health and social care systems. Therefore, the concept of active ageing is namely one of the proposed solutions how to mitigate part of this burden. The authors tried to compare success of regional policies on the level of individual domains of active ageing on data from regions of Slovakia. Petra Medveďová in her paper called *Integrity Sub-Index of the Global Pension Index in the Context of Indicator Weights* highlighted that a stable, efficient, and long-term sustainable pension system needs well-functioning pension plans in the private sector, as state pensions are not sufficient as the only source of pension income. That is why the integrity sub-index includes the quality of private pension plans, as well as the meaningful amount of costs associated with determining the amount of pensions and paying them out in the long term. The author offered the determination of the value of the integrity sub-index of the Global Pension Index for Slovakia for the year 2023 based on the criteria of Mercer, which does not yet include Slovakia among the evaluated countries. The method used appears to be the most effective in terms of the relatively most accurate determination of weights.

In the section of *Application of Statistical Methods and History of Statistics*, a theoretical paper of a collective of authors – Jana Cibulková, Veronika Nováková, and Zdeněk Šulc – on A*lternative Methods for Visualizing Categorical Data in Cluster Analysis* enjoyed a lot of attention and a broad discussion. The authors introduced four novel visualisation techniques for cluster analysis outputs on categorical datasets, aiming to achieve an analogue to the cluster scatterplot. The methods, named HCADM, HCAKL, LBCADM, and LBCAKL, display the results of cluster analysis in a two-dimensional space and they are derived from a contingency table. These methods are designed to arrange clusters into the most compact regions possible in order to provide coherent visualisation outcome. They emphasised that it is impossible to definitively choose one method of distance determination and clustering that is suitable for identifying observation clusters in all cases. The selection of methods must always be approached individually and adapted to the specific situation. A critical step in graph creation is the identification of the category order.

In the last section, *Demographic and Social Issue*, a rich discussion was sparked by a paper entitled *Fertility Rates in the Czech Republic: Past Development and Possibilities of Projections to the Future* (authors: Ondřej Šimpach and Marie Šimpachová Pechrová). The authors presented the development of the total fertility rates in the Czech Republic and introduced the Lee-Carter model and its adjustments for modelling and the projections of the age-specific fertility rates. Modelling of the age-specific fertility rates by the stochastic Lee-Carter model has the advantage that the previous development of the indicator is taken into account while older data have lower weight than newer ones. However, the main drawback is that fertility rates are also influenced by economic and social variables that are not included in the model. The authors emphasised that the projected fertility rates can be than lower or higher than an expert guess – for example, expected fertility rates in a pessimistic, middle, or optimistic variant of the Czech Statistical Office in its population projection.

Contributions in the Poster *Session* mainly focused on the issue of quality of life, which has been addressed by Polish colleagues for a long time already. Of these, I consider it appropriate to highlight the contribution called *Enhancing Quality of Life for Seniors: A Comparative Study of Poland, Czechia and Slovakia* (authors: Joanna Dębicka, Agata Girul, and Edyta Mazurek). Their study evaluates older adults' quality of life and prioritises their needs across Poland, Czechia, and Slovakia. Additionally, a comparison between these countries has been conducted, highlighting differences and similarities in assessing older adults' quality of life. Through this analysis, best practices have been identified, along with areas requiring greater attention from the social policies of each country. The authors utilised ranking methods that account for the total and distribution of ranks within the sample, interaction analysis among various needs, and ProFit analysis and logit model to assess the impact of selected factors on the quality of life evaluations in these countries.

The Editor-in-Chief of *Statistika: Statistics and Economy Journal* kindly invited participants to submit papers on relevant topics to the journal.

A full programme of AMSE 2024 including abstracts of the papers presented, can be found at: <*http://www.amse-conference.eu*>. There you can also find information about the history of AMSE and links to previous years of the international conference.[2]

The tradition of alternating hosts (Slovakia – Poland – Czechia) continues and the 27th AMSE conference, which will be hosted by colleagues from the Faculty of Informatics and Statistics of the Prague University of Economics and Business, will be held in Czechia in the city of Hradec Králové at the turn of August and September 2025.

[2] In this report on the Conference, texts of the Book of abstracts <*www.amse-conference.eu*> were used.

32nd International Conference *Interdisciplinary Information Management Talks (IDIMT 2024)*

Petr Doucek[1] | *Prague University of Economics and Business, Prague, Czech Republic*
Lea Nedomová[2] | *Prague University of Economics and Business, Prague, Czech Republic*

The *Interdisciplinary Information Management Talks* conference is traditionally organized by the Department of Systems Analysis of the Faculty of Informatics and Statistics at the Prague University of Economics and Business, in co-operation with the Institute of Networks and Security of Johannes Kepler University Linz. This year's 32nd annual conference, which took place from September 4th to 6th in Hradec Králové, was held under the general title "Changes to Information and Communication Technology, Management and Business Processes through Artificial Intelligence". The whole meeting was divided into eleven sessions, one of which was devoted to presentations by PhD students. We have chosen the following eleven topics for the IDIMT 2024 conference:

- AI Support for Crisis Management,
- Cyber Security,
- AI in Virtual Collaboration, Teaching & Learning,
- Autonomous Vehicles and Smart Environments,
- ICT Systems and Business,
- Digital Transformation and Digital Business Models,
- Social Media and the Role of AI,
- Data and AI in Supply Chain Management,
- Academic Business Co-operation,
- Ethical Integrity of Research in AI,
- Special doctoral session: Early Career & Student Showcase.

A total of 54 papers from 126 authors, 66 of them from abroad, were presented in parallel sessions. The authors come from 11 different countries: Armenia, Austria, Czechia, Estonia, Germany, Greece, Netherlands, Poland, Slovakia, Slovenia and Spain.

As the overall title of the conference suggests, one of its very important topics was artificial intelligence and its potential and actual deployment in economic and academic life. This topic was the subject of the opening panel discussion immediately after the opening ceremony, which was conducted by Michael Sonntag from Johannes Kepler University in Linz. During the discussion invited guests from Germany, Austria, Slovakia and Czechia exchanged views not only on the possible application of artificial intelligence in practical informatics for business applications, but also on its use to improve the quality of scientific work. In addition to positive views on the future of business informatics under the baton of artificial

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intelligence, there were also critical views that assessed the emerging risks such as the possibility of very high quality plagiarism without the creative power of the authors, especially in scientific and research activities, as well as the need for ever more training data, which we might be running out of soon.

The panel discussion was smoothly followed by the "Special doctoral session: Early Career & Student Showcase", which was dedicated to the presentation of doctoral students' dissertation topics. Here, the PhD students had the opportunity to present the results of their work, but also to get feedback from the experts present at the international forum. There was a great interest in the individual sessions among the conference participants. Traditionally high quality sessions included those devoted to cyber security and ethical aspects of informatics related to the use of information technology and the deployment of artificial intelligence. Nevertheless, this year's outstanding session was the "AI Support for Crisis Management" session, which was mainly devoted to the issues of crisis management and the application of information technology and artificial intelligence in these situations. In their well-prepared presentations, the staff of AGES (Austrian Agency for Health and Food Safety) and AIT (Austrian Institute of Technology) demonstrated the possibility of fulfilling the protection of human lives and values in crisis situations using computing and artificial intelligence. Two sessions were devoted to the classical application of information systems in business practice, namely "Data and AI in Supply Chain Management", led by colleagues from the Technical University of Košice and the Faculty of Business Administration of the University of Economics in Košice, and the session "Digital Transformation and Digital Business Models", led by the University of Maribor in Slovenia.

The benefits and possibilities of artificial intelligence in education were presented in the session "AI in Virtual Collaboration, Teaching & Learning", which was held under the auspices of Dr. Anne Jantos from the Technical University of Dresden.

We will therefore look forward again to the next IDIMT conference to see what new issues it will bring. The event will traditionally take place next year in Hradec Králové in September 2025. For more information about the conference and previous editions, please visit the website <*https://idimt.org*>.

As a result of the conference, besides the presented results of the scientific work, the collaboration between Prague University of Economics and Business, Johannes Kepler University Linz and other universities and research institutions from Germany, Slovakia, and Slovenia, which were represented in the wide plenary of participants, was deepened.

This conference was partially co-funded through project IGA 409033 of the Faculty of Informatics and Statistics, Prague University of Economics and Business, and Johannes Kepler University Linz, Austria.

18th Year of the *International Days of Statistics and Economics (MSED 2024)*

Tomáš Löster[1] | *Prague University of Economics and Business, Prague, Czech Republic*

From 5th to 6th September 2024, a worldwide conference of the International Days of Statistics and Economics (MSED) took place at the Prague University of Economics and Business. The conference belongs to traditional professional events; this year, the sixteenth year of this event was held. Prague University of Economics and Business (the Department of Statistics and Probability and the Department of Managerial Economics) was the main organizer, as usual; and was helped by the Faculty of Economics, the Technical University of Košice, and Ton Duc Thang University, as co-organizers. The conference ranks among important statistical and economic conferences, which can be proved by the fact that Online Conference Proceedings were included in the Conference Proceedings Citation Index (CPCI), which has been integrated within the Web of Science, Clarivate Analytics since 2011.

The traditional goal of this international scientific conference was a presentation of the contributions of individual authors and a discussion of current issues in the field of statistics, demography, economics, and management and their interconnection. As part of this year's scientific conference, a section for young scientists was created. This section focused on programming and using the Python programming language.

This year's conference and presentation were again in a hybrid form (online and real presentation at the university), which caused the participation of foreign nationals to be active.

The online implementation of the conference took place in individual channels of the conference teams in MS Teams (according to partial sections). The number of registered conference participants was a total of 91, of which 52 were foreign, e.g. Turkey, Slovakia, Vietnam, etc. Among the conference participants were 21 doctoral students.

The received papers were first evaluated in terms of scientific content and suitability of the topic concerning the focus of the conference. After the exclusion of unsatisfactory abstracts, a double independent anonymous review procedure took place in the spring of this year.

We would also like to invite researchers, doctoral students, and the wide professional public to the next International Days of Statistics and Economics, which will take place at the Prague University of Economics and Business traditionally in early September 2025. More at: <*http://msed.vse.cz*>.

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ROBUST 2024, 23rd International Statistical Conference

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The 23rd event of the well-established biennial statistical conference ROBUST 2024 took place in the historical town Bardějov (Slovak Republic) during September 8–13, 2024. It was organized by a joint effort of the Expert Group of Computational Statistics of the Czech Mathematical Society (Section of the Union of Czech Mathematicians and Physicists), Department of Probability and Mathematical Statistics of the Faculty of Mathematics and Physics, Charles University, Prague, Czech Statistical Society, and Slovak Statistical and Demographic Society. It is important to note that ROBUST was originally scheduled in Bardějov in 2020. However, it was postponed twice due to the Covid-19 pandemics in 2020 and the relative proximity of the battlefields of the conflict in Ukraine in 2022. This year it has been merged with the Amistat 2024 conference.

In total, almost 90 participants from ten countries presented and discussed contributions covering a broad spectrum ranging from theoretical statistics, probability and stochastic analysis, machine learning and computer science to applied statistics in several fields, including forestry, insurance and finance mathematics, medicine, health and epidemiology, metrology, traffic safety, online advertisement, and official statistics. The participants came from Slovakia (12), USA (4), Austria (3), Sweden (2), Belgium (1), Canada (1), France (1), Great Britain (1) and Nigeria (1), and the rest coming from the Czechia. The idea behind the ROBUST conferences has always been to bring together statisticians of all generations and all fields from different Czech and Slovak institutions, Czech and Slovak experts living abroad and top specialists from abroad, to enable the exchange of ideas and to provide them with interdisciplinary insight into the research in statistics.

Five invited lectures were given:

1. Doc. Daniel Klein (Faculty of Science, Pavol Jozef Šafárik University in Košice) delivered a lecture on estimation and testing covariance matrices in multivariate linear models combining both recent theory and result for special cases of covariance structures relevant in real life application. These methods are widely used in psychometry, clinical studies, and biology applications.
2. Doc. David Kraus (Faculty of Science, Masaryk University in Brno) presented new results in functional analysis with censoring with application to HIV-related research. He discussed how to apply models to sparse data observed in irregular time, estimate separate components of the model, and the trajectories of individual patients.
3. Prof. Tomáš Mrkvička (Faculty of Economics, University of South Bohemia in České Budějovice) addressed the issue of false rate envelopes, focused on functional data. False rate discovery control

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is an important issue in multiple hypotheses testing when comparing more populations simultaneously. Envelopes provide suitable graphical tool in this setting.

4. Doc. Michal Pešta (Faculty of Mathematics and Physics, Charles University, Prague) delivered a lecture on changing intensities and band bootstrap. The theoretical part is focused on multivariate, non-stationary processes in time and on the study of tests to identify structural breaks. This setting is motivated by real-life problems in the insurance industry. In the application part, an unsupervised data-driven procedure was presented through an actuarial problem concerning claims from various insurance lines of business.
5. Dr. Samuel Rosa (Faculty of Mathematics, Physics and Informatics, Komenského University in Bratislava) provided an interesting presentation on optimal design of experiments, graphs and networks. Optimal experiment design is a well-established statistical methodology enabling to design experiments guaranteeing as much information as possible with a given amount of expertise. Among others, he demonstrated that optimization of some classes of experiment is equivalent to studying the optimality of graphs in graph theory.

This conference continues a long tradition of participation of doctoral and master's degree students in the dedicated section, who orally presented 26 posters. The prizes were awarded in three categories: Bachelor's degree students, Master and first-year Doctoral students, and advanced Doctoral students. The prizes were sponsored by the Czech Mathematical Society and RSJ Securities, a.s. The conference fee for several students and invited speakers was sponsored, as in the past Robust conferences, by the Czech Statistical Society and RSJ Foundation. More at: <*www.karlin.mff.cuni.cz/~antoch*>.

The Editor-in-Chief of *Statistika: Statistics and Economy Journal* kindly invited participants to submit papers on relevant topics to the journal.

42nd International Conference on *Mathematical Methods in Economics (MME 2024)*

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Josef Jablonský[2] | *Prague University of Economics and Business, Prague, Czech Republic*

The 42nd International Conference on Mathematical Methods in Economics was held at the Faculty of Science, Jan Evangelista Purkyně University in Ústí nad Labem from September 11th to 13th. This annual conference is a traditional gathering of professionals from universities and businesses who are interested in the theory and applications of operations research and econometrics. The event was organized by a team from Jan Evangelista Purkyně University, led by Hossein Moosaei and Jiří Škvor, in collaboration with the Czech Society for Operations Research and the Czech Econometric Society.

The conference received more than 80 submissions and had more than 80 active in-person participants who came from various countries, including Czechia, Slovakia, Poland, Germany, Ukraine, Switzerland and the USA. Accepted peer-reviewed papers were published in the Proceedings of the MME 2024, with an additional opportunity to publish extended articles in a special issue of the Central European Journal of Operations Research.

The event commenced with two invited lectures. The first was delivered by Prof. Panos M. Pardalos from the Department of Industrial and Systems Engineering at the University of Florida. Prof. Pardalos, a leading expert in global and combinatorial optimization, discussed the use of artificial intelligence in economics and finance. He highlighted the significant impacts of AI tools in these fields and explored recent and future developments and limitations. He also presented details on neural network embeddings on corporate annual filings for portfolio selection.

The second invited lecture was given by Prof. Michal Černý from the Department of Econometrics at the Prague University of Economics and Business. His lecture focused on both old and new results and challenges in linear programming.

As is tradition, the conference included a competition for PhD students, sponsored by the Czech Society for Operations Research, with a prize of 10 000 CZK. This year's winner was Dominik Kavřík from the Prague University of Economics and Business for his paper *A Comparative Analysis of SVAR and Traditional Filtering Methods in Output Gap Estimation*. Second place went to Michaela Sedláková from the Technical University of Ostrava for her paper *Impact of Asset Price History on Price Volatility,* and third place was awarded to Lukáš Veverka from the Prague University of Economics and Business for his paper *Refining Fourier Approach with Constrained Parameter Estimation and Penalizing Seasonal Distortions.*

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The conference also featured a variety of trips, with strong interest in a tour of the local brewery. Other options included a tour of the historic Osek Cistercian Monastery and a visit to the Lehnschafter Mine, one of the oldest and most extensive mining sites in the Mikulov ore region. More at: <*https://mme2024.ujep.cz*>.

The next conference is scheduled for a similar date next year, with the venue yet to be decided.

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Authors and contacts
Rudolf Novak,[1] Institution Name, City, Country
Jonathan Davis, Institution Name, City, Country
[1] Address. Corresponding author: e-mail: rudolf.novak@domainname.cz, phone: (+420) 111 222 333.

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Phone: (+420) 274 054 299
E-mail: statistika.journal@csu.gov.cz | **web:** www.csu.gov.cz/statistika_journal
Address: Czech Statistical Office | Na padesátém 81 | 100 82 Prague 10 | Czechia

Subscription price (4 issues yearly)
CZK 66 per copy + postage.
Printed copies can be bought at the Publications Shop of the Czech Statistical Office (CZK 66 per copy).
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Design: Toman Design
Layout: Ondřej Pazdera
Typesetting: Václav Adam
Print: Czech Statistical Office

104th year of the series of professional statistics and economy journals of the State Statistical Service in Czechia: ***Statistika*** (since 1964), ***Statistika a kontrola*** (1962–1963), ***Statistický obzor*** (1931–1961) and ***Československý statistický věstník*** (1920–1930).

Published by the Czech Statistical Office
ISSN 1804-8765 (Online)
ISSN 0322-788X (Print)
Reg. MK CR E 4684