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What Financial Markets in the CEE Region Tell Us about Inflation Expectations

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Abstract

Inflation expectations have become a significant concern for monetary policy settings in the CEE region due to the sharp rise in inflation. The absence of market-based inflation expectations complicates the assessment of anchoring inflation expectations in the economy, especially during periods of extreme shock. The experience of the EM space with more developed financial markets allows for the estimation of unobserved long-term inflation expectations in the CEE region replicating market-based expectations. A panel regression model was used to estimate long-term marked-based inflation expectations in Czechia, Poland, and Hungary. The results show that market-based inflation expectations in the CEE region have significantly lower volatility compared to survey-based expectations, which are often used as proxy variables by central banks for monetary policy decision-making. The results are indicating that survey-based inflation expectations cannot be used as a proxy for long-term inflation expectations due to significantly different developments and characteristics that could lead to erroneous monetary policy decisions.[2]

Keywords	***DOI***	***JEL code***
CEE region, inflation expectations, panel regression	*https://doi.org/10.54694/stat.2025.17*	*E31, D84, C33*

INTRODUCTION

A reliable and accurate estimate of inflation expectations is a key issue for any central bank given the impact of inflation expectations on inflation and economic activity. Moreover, inflation expectations can serve as an indicator of the horizon at which the central bank's target is expected to be reached. Thus, overall, they are an important indicator for the decision-making of the central bank itself (Grothe and Meyler, 2015) and often enter the macroeconomic models of monetary policymakers. The estimation and measurement of inflation expectations is thus a key issue in the concept of inflation targeting.

There are two main ways of measuring inflation expectations: (1) survey-based expectations and (2) market-based expectations. Survey-based expectations are often based on questionnaire surveys of households, firms or professional forecasters. As an example, we can refer to the ECB survey

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of professional forecaster (ECB, 2024). Market-based expectations, on the other hand, are based on market data from which market inflation expectations can be effectively extracted. Two types of financial market tools are commonly used for this purpose, inflation-linked interest rate swaps (IRS) that measure expectations directly, and the difference between nominal and inflation-linked government bond yields. The use of inflation-linked bonds to gauge inflation expectations has a history dating back to the 1980s, with the UK being a pioneer by issuing index-linked gilts (Liu et al., 2015). The US introduced Treasury Inflation-Protected Securities (TIPS) in 1997, which have since become a key instrument for observing market-based inflation expectations. Inflation swaps, another important tool, are more recent but have grown in prominence, offering a more direct measure of inflation expectations by allowing market participants to trade inflation risk.

This study focuses on market-based measures of inflation expectations in Central and Eastern European (CEE) countries with their own currency and semi-developed financial markets, i.e. Czechia, Poland and Hungary. All these countries have in common having own currency and monetary policy, an active local currency government bond market and, on the other hand, the absence of tradable financial instruments from which inflation expectations can be derived. Given that inflation within emerging economies such as the CEE countries is relatively high and volatile, it is particularly difficult to distinguish between nominal and real variables over time. Moreover, it is the absence of market instruments that createscompounds this problem. In the absence of such instruments, surveys with a typically one-year horizon are often used as a proxy variable for long-term inflation expectations by central banks and market participants. However, in the caseexample of developed countries (DM) where both instruments are available, different behaviour can be observed, implying (Gerlach et al., 2011; Henry et al., 2023) that surveys are not a suitable proxy for inflation expectations, which are of key importance for monetary policy decisions.

Thus, the aim of this paper is to estimate market-based inflation expectations in the CEE countries in the absence of financial instruments that reflect these expectations, to identify the factors that affect these expectations and to compare with survey-based inflation expectations. In a first stage, the model will be estimated on emerging economies (EM) where financial instruments reflecting these expectations are available, such as interest rate swaps or government bonds linked to CPI developments with sufficient liquidity. The model should identify global and local factors influencing the evolution of these instruments in financial markets and then transfer these relationships to CEE countries using panel regression. This work should result in a more accurate measurement of inflation expectations and their retrospective assessment and comparison with available survey-based measures of expectations in the context of monetary policy.

The first chapter shows the state of research in this area where the emphasis is on advanced economies with more developed financial markets, while emerging markets are as yet under-covered in this sense. In general, there is no consensus on the best way to measure inflation expectations, and typically comparing market-based and survey-based expectations has different results. However, it is clear from the evidence in the literature that it is a good idea to look at both options or to combine them. The available literature points to technical or liquidity problems with inflation expectations, which complicates the situation for central banks as the main users within the inflation targeting concept. The second section discusses the challenges of inflation expectations and shows not only the difference between DM and EM space but also within EM, where we can find a difference in the development of financial markets and the availability of survey-based inflation expectations. Nevertheless, this provides an opportunity to take the experience from one side of EM and apply it to less developed countries or countries with less developed financial markets. In the third section, we then estimate a panel regression model explaining market-based inflation expectations using data from South Africa, Brazil, Mexico and Chile. We then apply the estimated model to data from the CEE region, i.e., Czechia, Poland, and Hungary, which have sufficient data but lack market-based inflation expectations in financial markets.

1 RELATED LITERATURE

Previous work has focused mainly on the measurement of inflation expectations themselves and the anchoring of inflation expectations. Comparisons are often made between countries with different monetary policies and regimes (Castelnuovo, 2003; Demertzis 2010).

A significant part of the literature is devoted to comparing and contrasting market-based and survey-based measures of inflation expectations. Gerlach et al. (2011) point out that both survey-based and market-based measures of expectations have advantages and disadvantages. Surveys for long-term inflation expectations typically cover a long-time horizon and are often compiled at a three- or six-month frequency, which complicates their usefulness. Market-based expectations are usually available on an intraday basis, based on trading on financial markets. In addition, market-based expectations reflect the current position of the financial market and market participants, whereas in a questionnaire survey, the participant has no financial incentive to provide credible answers. Of course, both methods have their technical problems. Survey-based measures of expectations are sensitive to the number of respondents. Market-based measures of expectations depend on market liquidity, which can be low precisely in stressed situations when accurate measurement of inflation expectations is crucial.

Mandel and Vejmelek (2025) examines the inflation expectations of financial analysts and corporate managers in the Czech Republic from 1999 to 2024. The authors find that the formation of expectations differs between the two groups: corporate managers rely more on adaptive reasoning, while financial analysts pay closer attention to the Czech National Bank's (CNB) one-year inflation forecasts. Neither group fully meets the criteria for rational expectations, and their yearly inflation expectations contain systematic errors. The findings suggest that inflation expectations are shaped differently by financial analysts and corporate managers, with neither group fully adhering to rational expectations.

Diercks et al. (2023) examine the forecasting performance of inflation swaps and survey-based expectations over a one-year horizon. The study finds that inflation swaps, using US data as an example, provide a better inflation forecast in most cases. It also shows that earlier studies (Ang et al., 2006; Bacchetta et al., 2009) showed the poor performance of inflation swaps as forecasts have been distorted by liquidity problems during the periods of elevated volatility. When these periods are excluded, swaps have significantly better predictive performance. Moreover, we show that a combination of survey-based and market-based measures of expectations improves the inflation forecast with roughly equal weight for both explanatory variables.

Also, Banbura et al. (2021) show that the inclusion of inflation expectations in any form improves the inflation forecast in the short run, demonstrating its relevance for monetary policy and decision-making. The improvement in forecast accuracy is not typically large but statistically significant. Both short- and long-term inflation expectations provide useful information for inflation forecasting. In particular, the inclusion of expectations improves the upward bias correction in periods of low inflation, making the model more robust, especially in periods of high volatility.

Grothe and Meyler (2015) contribute to this literature by analysing and comparing the predictive power of market-based and survey-based measures. Focusing on the euro area and the United States, the authors use inflation swaps and the survey of professional forecasters to represent market-based and survey-based expectations, respectively. Their analysis demonstrates that both measures are informative predictors of inflation at shorter-term horizons (one and two years), suggesting that both market participants and professional forecasters provide valuable insights into future inflation dynamics. This implies that both measures are relevant for policymakers.

Also, Chen et al. (2022) examine the systematic biases present in survey-based inflation forecasts. It identifies a persistent overestimation of future inflation rates by respondents, attributed to psychological and behavioural factors such as anchoring and availability heuristics. These biases have significant implications for economic policy-making, potentially leading to suboptimal decisions by relying on inaccurate data. The paper advocates for methodological improvements in survey design and data collection to mitigate these biases, thereby enhancing the reliability of inflation expectations and supporting more effective monetary policy. Accurate inflation forecasting is crucial for economic stability and growth, underscoring the importance of addressing these biases in survey data.

Reis (2020) shows evidence of high business-cycle fluctuations in inflation expectations in the US data, which are influenced by monetary policy and driven by disagreement across population groups and disagreement among market traders. It also shows a greater ability of market-based expectations, or the ability of market participants to learn better from past and sticky information, while survey-based household expectations are often biased over longer periods of time.

Some studies focus on the technicalities and challenges of deriving inflation expectations from financial instruments. Fleming and Sporn (2013) point out the difference between inflation expectations derived from inflation swaps and inflation-indexed government bonds. In theory, these expectations should be the same, but in practice, we see deviations due to market frictions and financial market technicals. Christensen and Gillan (2011) explain that, in the case of the United States, this difference can be explained by financing costs for inflation buyers and hedging costs for inflation sellers. Moreover, in the case of bonds, the market price and the inflation expectations derived from it are influenced by Treasury supply.

Deacon and Derry (1994) demonstrate, using the example of the UK with a developed financial market and liquid instruments reflecting inflation expectations, several problems in deriving these expectations. In particular, in the inflation-linked bond market, despite the high development and liquidity of the financial market, there is an absence of some maturities, which creates a problem in constructing the full yield curve. Of course, various methods of interpolation can be employed here, but the issue of term premia still remains. The second problem is the tax aspect, which is different for each investor, which can create damage to the yield curve and mispricing of inflation expectations embedded in the price of a given bond. However, the Bank of England is a good example here of working with market-based inflation expectations that enter into the central bank's decision-making process.

Liu et al. (2015) address the challenge of imperfect information in market-based measures of inflation expectations, specifically in the UK where instruments reference inflation. To better understand inflation expectations, the authors develop a no-arbitrage term structure model. This model decomposes the forward inflation curve into inflation expectations, the expected spread between financial instrument and inflation, and estimates of risk premia, further broken down into inflation and liquidity risk premia. By modelling liquidity premia and estimating the spread, this research provides valuable insights for policymakers and market participants seeking to extract accurate inflation expectations from market data.

Other studies analyse the determinants and role of inflation expectations. El-Shagi (2011) compares market-expected inflation with econometric inflation forecasts using several forecasting techniques in the environment of ten developed countries from 1988 to 2007. The results show very clear overperformance of market expectations, but not significant. The paper concludes that the rational expectations hypothesis cannot be rejected. Furthermore, it could be shown that expectations are not only based on the past development of inflation but that further economic indicators are considered by market participants. Also, expectations seem to capture certain nonlinearities in inflation behaviour very well compared to forecasts, leading to far better results in times of high inflation and in times of increasing inflation.

The study of Cerisola and Gelos (2005) examines the macroeconomic determinants of survey inflation expectations in Brazil since the adoption of inflation targeting in 1999. The results show that inflation targeting has anchored inflation expectations significantly. But it also shows that, in addition to inflation targeting, fiscal policy plays a role in shaping inflation expectations. The importance of past inflation in determining expectations appears to be relatively low, and the overall empirical evidence does not suggest the presence of substantial inertia in the inflation process. Sousa and Yetman (2016) discuss how inflation expectations are measured in emerging countries (EM) and the approach of central banks. They point out the absence of financial market-derived inflation expectations in most emerging countries. Although they argue that inflation expectations become more anchored over time in these countries, inflation expectations measured through surveys introduce a number of problems and potential errors in assessing the anchoring of expectations and hence jeopardise the effectiveness of monetary policy.

While the existing literature provides valuable insights into the measurement, determinants, and role of inflation expectations, it has primarily focused on developed economies with well-established financial markets. Research on inflation expectations in emerging market economies, particularly those in the CEE region, remains limited. To address this gap, this paper aims to estimate market-based inflation expectations in CEE countries, which lack financial instruments that directly reflect these expectations. By employing a panel regression model built on the experience of emerging economies with more advanced financial markets, this study seeks to identify the factors that influence inflation expectations in the CEE region. Furthermore, it will compare these estimates with available survey-based inflation expectations, providing a more accurate measurement and retrospective assessment of inflation expectations in the context of monetary policy in these countries. This approach will contribute to a more nuanced understanding of inflation dynamics in emerging markets and provide valuable insights for policymakers in the CEE region.

2 CHALLENGES IN MEASURING INFLATION EXPECTATIONS

Given the relatively high and volatile inflation rates in emerging market economies, the distinction between nominal and real variables is particularly important when comparing long-term government bond yields and interest rate swap levels across countries and time. In DM economies, there is typically a deep and liquid market for inflation-linked government bonds and inflation interest rate swaps from which inflation expectations can be derived on a daily basis with different time horizons. Unfortunately, these instruments are not available in CEE countries and typically only survey-based measures of inflation expectations can be used.

However, in large EM economies, financial markets provide a limited supply of inflation-linked tools that can provide guidance on how market inflation expectations evolve in type-similar economies and can be used to estimate these expectations in CEE countries. Although previous research (Fleming and Sporn, 2013) shows that inflation swaps offer the best unbiased estimates of market inflation expectations, in emerging economies, when such instruments exist, it is always inflation-linked government bonds. However, these do not always provide an unbiased reading of market inflation expectations due to variations in the inflation risk premium and market technicals such as limited liquidity or supply. Nonetheless, there is no alternative in EM space at the moment and these shortcomings will have to be taken into account when evaluating the results of this paper.

At the moment, inflation-linked government bonds are only available in five countries with sufficiently developed financial markets and history which determines the sample used in this paper: South Africa (*sa*), Brazil (*bra*), Mexico (*mex*), Chile (*chil*) and Turkey. Due to the currency crisis in Turkey resulting in an extreme inflation profile including inflation expectations, this country will be excluded from further research in this paper.

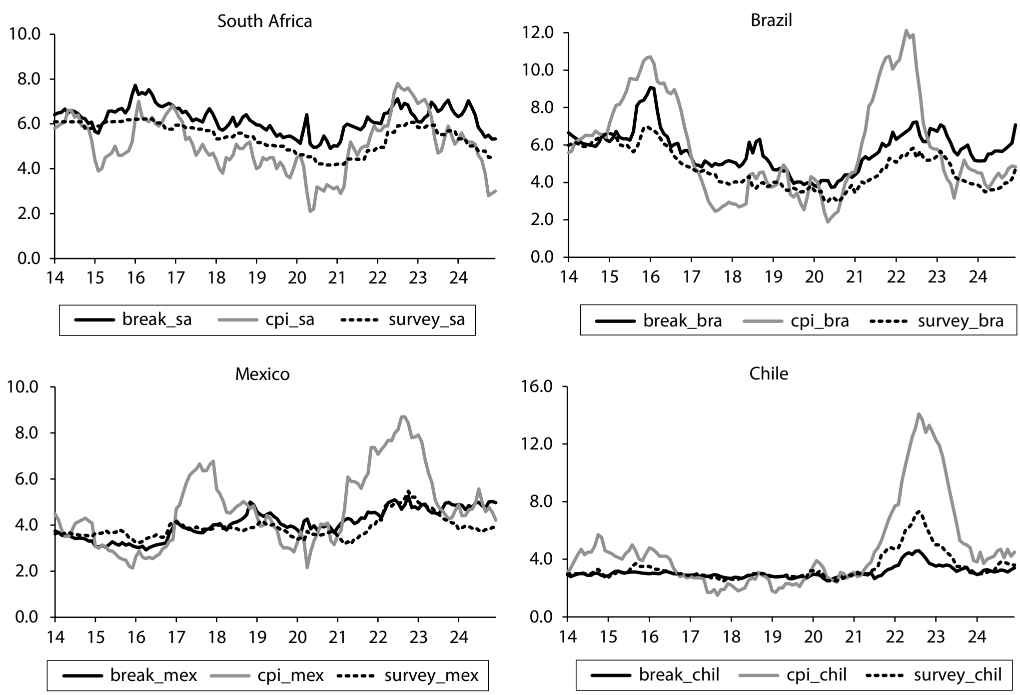
For most EM countries, in the absence of market-based measures of inflation expectations, it is common practice to use survey-based measures of inflation expectations with a one-year horizon as a proxy for long-term expectations. The countries mentioned are the only ones in the EM space that can offer both options. Thus, their reading (Figure 1) suggests that they are developing differently suggesting that survey-based inflation expectations are not a good proxy for long-term expectations.

The correlation analysis (Table 1) reveals systematic differences in predictive capacity: market-based expectations (*break*) demonstrate stronger alignment with actual inflation across all sample countries. For instance, in Brazil, market-based expectations show a much stronger correlation with actual inflation versus survey measures. Similarly, Chile exhibits near-perfect correlation of market-based measures of inflation expectations and actual inflation. These patterns persist even when controlling for crisis periods, consistent with Dierks et al. (2023) who found market measures outperformed surveys when excluding liquidity-distorted periods.

The structural divergence is visually apparent in Figure 1, where survey expectations overreact to transient inflation shocks while market-based measures maintain closer alignment with fundamental trends. This echoes findings from Grothe and Meyler (2015) that market prices incorporate forward-looking risk premia absent in surveys and aligns with Mandel and Vejmelek (2025) Czech evidence of survey respondents' adaptive biases. Overall, this evidence is confirming market-based measures of inflation expectations superior information content than survey-based measures of inflation expectations.

To obtain market-based inflation expectations for CEE countries with no market for inflation-linked instruments, inflation expectations can be estimated using available data in combination with the relationships observed in countries with more developed financial markets. To explain market-based inflation expectations, we choose variables that in theory contain some form of information about inflation or are indirectly driven by inflation developments in a given country. Using data from the EM space that has inflation-linked instruments available (South Africa, Brazil, Mexico and Chile), we estimate the relationship of 10y market-based measure of inflation expectations (*break)* with actual consumer inflation (*cpi)*, 1y ahead inflation survey (*survey)*, 10y nominal sovereign bond yield (*yield*), 5y credit default swaps (*cds*) and 10y market-based inflation expectations in DM countries (*break_global*). For the purposes of this paper, the *break_global* is taken to be the simple average of 10y market-based inflation expectations in the US and euro area. We first conduct the analysis using a country-specific model and then estimate a panel regression model of the behaviour of market inflation expectations. We then compare the fitted against actual market-implied inflation expectations, which we then apply to CEE countries.

Figure 1 Market-based measures of inflation expectations derived from inflation swaps versus actual inflation and 1y-ahead survey-based measure (YoY%, 2014–2024)



Source: Macrobond, Bloomberg

The explanatory variables were systematically chosen through an iterative process balancing theoretical foundations, empirical validation, and data constraints. Core determinants of market-based inflation expectations were identified using established frameworks from inflation expectation literature. Actual consumer inflation (*cpi*) serves as the adaptive expectations anchor, while survey measures (*survey*) capture short-term consensus views, following evidence that professional forecasts retain predictive value at one-year horizons. Nominal bond yields (*yield*) incorporate Fisher equation components, and credit default swaps (*cds*) account for country risk premia influencing inflation pricing. Global inflation expectations (*break_global*) reflect cross-border transmission effects documented in emerging markets research. Practical constraints necessitated prioritizing variables with consistent coverage across both baseline EM countries and CEE economies. Alternative candidates like exchange rates showed limited explanatory power in preliminary regressions and were excluded through general-to-specific reduction.

Table 1 Inflation versus expectations correlation matrix

	Survey	Break
cpi_sa	0.694	0.747
cpi_bra	0.305	0.729
cpi_mex	0.716	0.642
cpi_chil	0.742	0.892

Source: Authors' Author's calculations

3 MODEL SPECIFICATION: PANEL REGRESSION APPROACH

Panel data refer to data sets containing several observations for each sampling unit. This could be generated by pooling time-series observations across a variety of cross-sectional units (Baltagi, 2021; Hiestand, 2005). Panel regression models offer several advantages over traditional time series and cross-sectional models. Firstly, they allow for the control of time-invariant unobserved heterogeneity, which can be a significant source of bias in traditional models. This is achieved by incorporating entity-specific intercept terms, which capture the unique characteristics of each entity. Secondly, panel regression models provide a more flexible framework for analysing dynamic relationships between variables. Cross-sectional models, limited to a single point in time, cannot adequately capture the evolution of relationships over time. Panel models, on the other hand, can incorporate time lags and dummy variables for specific time periods to capture the changing nature of relationships. Finally, panel regression models can address the issue of omitted variable bias by incorporating time-varying independent variables. This is particularly useful in situations where traditional fixed effects models may be prone to bias due to the presence of time-varying omitted variables.

$$\gamma_{it} = \alpha_i + \beta X_{it} + \mu_t + \varepsilon_{it}, \tag{1.1}$$

where:

γ_{it} is the dependent variable for entity i at time t,
α_i is the entity-specific intercept, capturing the unique characteristics of entity i,
βX_{it} is the linear combination of independent variables for entity i at time t,
μ_t is the time-specific effect, representing the impact of factors that vary over time,
ε_{it} is the error term, capturing unobserved factors that affect γ_{it} but are not captured by the independent variables.

In this model, the entity-specific intercepts, α_i, are assumed to be fixed over time. This implies that the unique characteristics of each entity remain constant throughout the observation period.

To ensure the validity of the panel regression model and the interpretation of its results, several econometric tests should be conducted before applying it. These tests address various aspects of the data and the assumptions underlying the model. Before proceeding with panel regression, it is essential to check whether the pooled OLS assumptions are met. This involves testing for homoscedasticity, normality of errors, no autocorrelation, and lack of multicollinearity.

$$var(\varepsilon it) = \sigma^2, \forall i, t, \tag{1.2}$$

$$\varepsilon it \sim N(0, \sigma^2), \tag{1.3}$$

$$cov(\varepsilon it, \varepsilon jt) = 0, \forall i, t, s, \tag{1.4}$$

$$\det(\mathrm{Xit}) \neq 0, \forall \mathrm{i}, \mathrm{t}. \tag{1.5}$$

After establishing the validity of the pooled OLS assumptions, additional tests are needed to verify the suitability of the panel regression model. These tests specifically address the model's assumptions, including the fixed effects assumption, serial correlation, unit roots, and Hausman test. Beyond the standard tests, additional diagnostic checks can be conducted to further evaluate the performance of the panel regression model. These include heteroscedasticity-robust standard errors. By conducting these econometric tests, one can gain confidence in the validity of panel regression models and the reliability of inferences drawn from the analysis.

The redundant fixed effects test, also known as the Hausman test, is used to determine whether the fixed-effects (FE) or random-effects (RE) model is more appropriate for a given panel data set. The test compares the statistical significance of the entity-specific effects () between the two models. The redundant fixed effects test compares the likelihood ratio (LR) test statistic between the fixed-effects and random-effects models:

$$LR = -2ln\big(L(RE)/L(FE)\big), \tag{1.6}$$

where:

L(RE) is the likelihood of the random-effects model,

L(FE) is the likelihood of the fixed-effects model,

If the LR statistic is greater than the critical value, then the null hypothesis of the random-effects model is rejected, and the fixed-effects model is preferred.

The redundant fixed effects test is a valuable tool for selecting the most appropriate panel data model, particularly when the relationship between the dependent variable and the independent variables may be affected by unobserved entity-specific characteristics. By comparing the explanatory power of the two models, this test helps researchers identify the model that better captures the underlying relationships and provides more reliable inferences.

4 MODELLING INFLATION EXPECTATIONS IN FINANCIAL MARKETS

To estimate the country-specific models first, we run simple linear regressions on 10y market-based measures of inflation expectations (Table 3) using monthly data with a sample from 2014M01 to 2024M12 (N = 132), which is given by data availability especially the short trading history of inflation-linked financial instruments. All time series come from the Bloomberg and Macrobond databases. The time series are seasonally adjusted where necessary. A unit root test is performed to assess the properties of the used series. The results of the Augmented Dickey Fuller (ADF) test show that all-time series are integrated of order one, I(1), in line with others studies (Table 2). Thus, for the purposes of model estimation, series employed in the form of a first difference logarithm to ensure stationarity.

Table 2 List of variables and tests of stationarity

Variable	Median	Max	Min	S.D.	ADF			
					Level		First difference	
					t-Stat	Prob	t-Stat	Prob
BREAK_SA	6.29	7.72	4.90	0.60	−2.365	0.154	−9.273	0.000
BREAK_BRA	5.69	9.07	3.74	1.11	−2.045	0.268	−8.728	0.000
BREAK_MEX	4.04	5.26	2.93	0.63	−1.217	0.666	−11.066	0.000
BREAK_CHIL	2.98	4.59	2.52	0.40	−2.227	0.198	−9.143	0.000
CPI_SA	2.07	2.90	1.00	0.36	−1.839	0.360	−8.728	0.000
CPI_BRA	1.27	2.86	0.48	0.53	−2.053	0.264	−6.329	0.000
CPI_MEX	5.05	7.80	2.10	1.23	−1.881	0.341	−8.424	0.000
CPI_CHIL	4.83	12.13	1.88	2.68	−2.382	0.149	−3.614	0.007
SURVEY_SA	4.44	8.70	2.13	1.63	−0.967	0.764	−4.919	0.000
SURVEY_BRA	3.95	14.10	1.50	2.95	−1.714	0.422	−8.744	0.000
SURVEY_MEX	5.61	6.22	4.17	0.63	−1.627	0.466	−6.119	0.000
SURVEY_CHIL	4.42	6.99	2.95	1.07	−2.054	0.264	−6.704	0.000
YIELD_SA	3.80	5.46	3.17	0.47	−1.643	0.458	−10.262	0.000
YIELD_BRA	3.00	7.30	2.50	1.00	−1.680	0.439	−8.889	0.000
YIELD_MEX	2.55	18.00	0.00	4.69	−0.802	0.815	−8.903	0.000
YIELD_CHIL	2.40	18.40	−1.60	4.98	−1.751	0.403	−9.439	0.000
CDS_SA	3.10	25.70	−1.40	6.26	−3.700	0.105	−9.185	0.000
CDS_BRA	3.42	16.76	−3.46	4.66	−2.407	0.138	−8.207	0.000
CDS_MEX	9.09	12.35	7.46	1.16	−2.449	0.103	−9.413	0.000
CDS_CHIL	11.40	16.37	6.57	2.21	−2.308	0.171	−9.673	0.000
BREAK_GLOBAL	7.21	10.19	5.50	1.34	−1.890	0.336	−8.045	0.000

Source: Macrobond, author's calculations

Lags were included in the model estimation however they proved to be non-significant or did not improve the quality of the model much. Since the goal is to find a model built on a time series that indicates inflation expectations rather than a model that explains inflation expectations, the criteria for selecting variables is based primarily on their correlation with inflation expectations and their availability.

Table 3 Country-specific market-based inflation expectations models

	South Africa	Brazil	Mexico	Chile
CPI	0.097* (0.008)	0.038* (0.001)	0.049* (0.025)	–0.180* (0.000)
SURVEY	0.703* (0.000)	0.176* (0.000)	0.271* (0.001)	0.624* (0.000)
YIELD	0.170* (0.000)	0.304* (0.000)	0.411* (0.000)	–0.047 (0.218)
CDS	0.002* (0.010)	0.003* (0.000)	–0.001 0.254)	0.008* (0.000)
BREAK_GLOBA	0.082* (0.039)	0.369* (0.000)	–0.125** 0.093)	0.775* (0.000)
N	132	132	132	132
Adj. R-squared	0.849	0.952	0.817	0.701

Notes: * coefficient statistically significant at 5% level, ** at 10% level.
Source: Author's calculations

Given that country-specific models have proven sufficiently robust, one can on their experience estimate a panel regression model that can incorporate all the data obtained for all the mentioned cross sections of interest over time and stack them and run a panel regression model. Several variants of the model were estimated (Table 5) without and with CDS, representing the country risk premium, and fixed effects, showing the differences between the countries included in the panel.

All cross-sectional time series (N = 4) were tested with panel unit root LLC and IPS tests (Table 4: Levin, Lin and Chu, 2002; Im, Pesara and Shin, 2003) and standard time series were tested with the conventional ADF unit root test. Most of the results showed stationarity of the time series at a 5% significance level and some were well below 10%. However, in the analyses, we consider FE or RE in the model, which handles potential problems with non-stationary variables by controlling for individual or group-specific trends, mitigating the spurious regression problem.

Table 4 LLC and IPS panel unit root tests

Method	Stat.	Prob.
Im, Pesaran and Shin (W-stat)	–2.911	0.002
Levin, Lin & Chu (t-stat)	–0.810	0.029

Source: Author's calculations

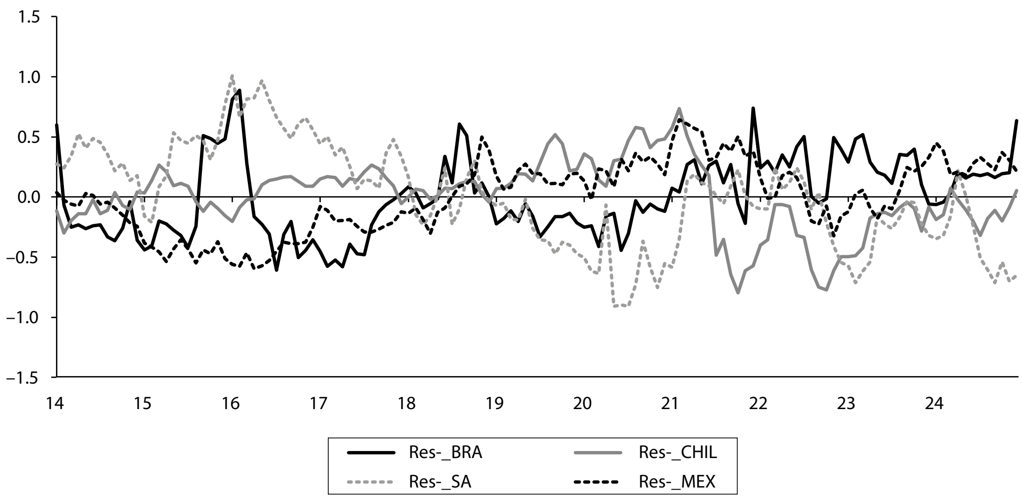
One of the assumptions underlying ordinary least squares estimation is that all observations have the same error variance and that errors are uncorrelated with one another. Although the estimated models do not show a significant correlation across observations and differential variance, cross-sectional weighting (estimated generalized least square) was employed here to avoid heteroskedasticity. Here, the estimates confirmed more statistically significant estimates. The panel model including CDS and fixed effects has proven to be the BEST variant with decent robustness with no major flaws. Relevant tests confirm the decision to employ the fixed effect in this case, which improves the accuracy of the estimation. The resulting model is thus sufficiently robust and can be applied to data from Czechia, Poland and Hungary. The graph (Figure 2) and correlation matrix (Table 6) show model residuals randomly distributed and concentrated around zero with no apparent trend.

Table 5 Panel regression market-based inflation expectations model

Panel regression results				
Fixed effects	**N**	**Y**	**N**	**Y**
CDS	**N**	**N**	**Y**	**Y**
CPI	–0.084* (0.000)	0.046* (0.000)	–0.086* (0.000)	0.034* (0.007)
SURVEY	0.664* (0.000)	0.300* (0.000)	0.552* (0.000)	0.307* (0.000)
YIELD	0.308* (0.000)	0.279* (0.000)	0.234* (0.000)	0.252* (0.000)
CDS			0.004* (0.000)	0.001* (0.002)
BREAK_GLOBAL	–0.143* (0.000)	–0.133* (0.002)	0.132* (0.002)	–0.032** (0.066)
C		1.174* (0.000)		1.049* (0.000)
_BRA-C		–0.007		0.011
_CHIL-C		–0.412		–0.397
_SA-C		0.748		0.693
_MEX-C		–0.335		–0.307
N	528	528	528	528
Adj. R-squared	0.912	0.943	0.926	0.945
AIC	1.463	0.726	1.368	0.712

Notes: * coefficient statistically significant at 5% level, ** at 10% level.
Source: Author's calculations

Figure 2 Resulted model residuals



Source: Author's calculations

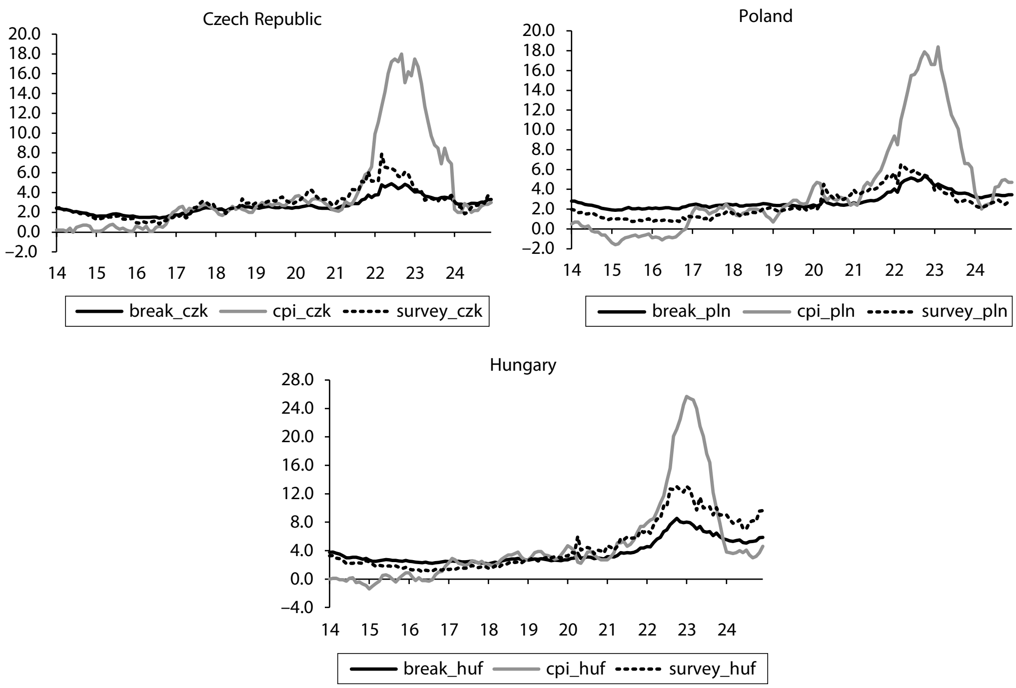
Table 6 Residual correlation matrix

	_bra	_chil	_sa	_mex
_bra	1.000	–0.185	–0.043	–0.144
_chil	–0.185	1.000	–0.157	–0.230
_sa	–0.043	–0.157	1.000	–0.119
_mex	–0.144	–0.230	–0.119	1.000

Source: Author's calculations

As a result of the estimated panel regression model, we can see the development of annual inflation, survey-based inflation measures of expectations for the 1y horizon and estimated market-based inflation expectations for the 10y horizon as output from the estimated model (Figure 3), which can be considered as long-term inflation expectations.

Figure 3 Estimated market-based inflation expectations vs actual inflation and 1y-ahead survey (%)



Source: Author's calculations

In the case of the Czech Republic, we see that both types of inflation expectations remain anchored close to the central bank's 2% inflation target at the beginning of the period when year-on-year inflation was only slightly above zero. Later in the 2017–2019 period, both types of inflation expectations stay close to the central bank's inflation target. In 2020, there is a noticeable increase in survey-based inflation expectations while market-based expectations remain stable. At the same time, despite an initial slight increase, actual inflation subsequently falls again. More interesting then is the period 2021–2023 when actual inflation rises significantly into double digits to which survey-based expectations respond significantly more with a peak at 7.87% in March 2022 while market-based expectations peak only nine months later at 5.13%. It is also worth noting that market-based expectations later decline more slowly than survey-based expectations despite the steep decline in actual inflation in 2023. Thus, at the end of the period under review, market-based expectations remain close to survey-based inflation expectations.

Similar results can be seen in Poland. More interesting here is the period 2014–2016 when the price level was in deflation with a peak in March 2015 at –1.50%. Survey-based inflation expectations are well below the central bank's inflation target of 2.50% in this period. However, market-based expectations remain close to the inflation target during this period. Again, we see a temporary increase in actual inflation and survey-based expectations in 2020, while marked-based expectations remain roughly stable. Also, in the 2021–2023 period, we see survey-based expectations rise significantly faster following rising actual inflation. As in the Czech Republic, survey-based expectations then fall faster relative to market-based expectations at the end of the observation period, where market-based expectations remain higher.

The results in Hungary show the same divergence of inflation expectations at the beginning of the period under review. However, here market-based expectations come in below survey-based expectations for the short term in 2014 but both are well below the central bank's inflation target of 3.00% following actual inflation of around zero over the period. In 2020, as in the Czech Republic and Poland, we may see a rise in survey-based expectations even though actual inflation and market-based expectations remain broadly stable. In the period 2021–2023, as in the other countries, survey-based expectations are followed by a rapid rise in actual inflation well above the rise in market-based expectations. However, here we can see that, in contrast to the results in the Czech Republic and Poland, survey-based inflation expectations remain above market-based expectations throughout the period, which is likely explained by significantly higher actual inflation keeping survey-based expectations elevated.

In general, we can draw several conclusions here. (1) The results show significantly lower volatility of estimated market-based inflation expectations compared with survey-based expectations. This is consistent with expectations given that these should be more long-term expectations whereas the survey corresponds to a one-year horizon. It can also be explained by the more sophisticated source of inflation expectations i.e. financial markets, whereas in the case of surveys, it is households. (2) Estimated market-based inflation expectations show a significantly higher correlation with actual inflation (Table 5) compared with survey-based inflation expectations in all countries examined. The relationship between actual inflation and market-based inflation expectations is an almost perfect positive correlation with a coefficient close to 1. In particular, in the Czech Republic and Poland, the difference in the strength of the relationship between the two types of inflation expectations with actual inflation is striking. In Hungary, the relationship is more similar but still marked-based expectations proved to be more correlated with actual inflation. Although this would need further research, it can be assumed here that market-based inflation expectations would have better predictive power for actual inflation compared to survey-based expectations.

Table 7 Inflation versus expectations correlation matrix

	Survey	Break
cpi_czk	0.797	0.935
cpi_pln	0.833	0.943
cpi_huf	0.844	0.866

Source: Author's calculations

Also, (3) based on the results, we can say that in Czechia, Poland and Hungary the relationship between inflation, inflation expectations in the economy, their anchoring and the success of the central bank's inflation targeting concept is most similar to Chile from the baseline sample of countries based on which the panel regression model was estimated. This is consistent with the assumptions of all the economies mentioned in this study given that Chile is the most similar to the CEE region countries in terms of the size and openness of the economy and the advancedness and setting of monetary policy. Finally, (4) the main question at the beginning of this paper is whether the central bank can use survey-based expectations with shorter horizons as a proxy in the absence of long-term inflation expectations. Here, the analysis shows that the two types of inflation expectations have different paths at different times, sometimes with significant variation. Thus, if survey-based inflation expectations are used, decision-makers may misjudge inflation dynamics, resulting in monetary policy errors.

CONCLUSION

Inflation expectations have become a key issue for monetary policy settings due to the sharp rise in inflation in the CEE region. Given the low level of financial markets in this region, the absence of market-based inflation expectations significantly complicates the assessment of the anchoring of inflation expectations in the economy. Moreover, this problem intensifies during periods of extreme shock, when it is difficult to identify whether it is on the supply or demand side. Yet in such a situation, it is more important than usual to identify in a timely manner whether inflation expectations are detached or not for the central bank.

The experience of the EM space with more developed financial markets provides enough information and experience to estimate unobserved long-term inflation expectations in the CEE region replicating market-based expectations. A panel regression was used to estimate a model of inflation expectations based on data from South Africa, Brazil, Mexico and Chile. Subsequently, this model was used to estimate long-term marked-based inflation expectations in Czechia, Poland and Hungary. Market inflation expectations derived from 10y inflation swaps, actual inflation, survey-based inflation expectations, 10y government bond yield, 5y credit default swaps and global market-based inflation expectations were employe to construct the panel regression model. The resulting model proved more robust with fixed effects included.

The results show that market-based inflation expectations in the CEE region have significantly lower volatility compared to survey-based inflation expectations, which are often used as proxy variables by central banks for monetary policy decision-making. At the same time, the correlation of estimated market-based expectations is significantly higher with actual inflation compared to survey-based expectations, especially in the Czech Republic and Poland, while the difference in correlation is not as significant in Hungary. It can thus be assumed that estimated market-based inflation expectations should provide better forecasting power than survey-based expectations. The results also show that compared to the original sample of countries used to estimate unobserved market-based expectations, the CEE region most closely matches Chile in terms of the characteristics of inflation expectations and their anchoring. Overall, we thus conclude that survey-based inflation expectations cannot be used as a proxy for long-term inflation expectations due to significantly different developments and characteristics that could lead to erroneous monetary policy decisions.

Looking forward, estimated unobserved market-based inflation expectations may have more applications in setting monetary policy or valuing fixed income securities, which could be the focus of further research in this area.

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The Relationship between Economic Indicators and Population Aging in Slovakia

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Abstract

The aim of the paper is to identify the relationships between economic and demographic indicators in the Slovak Republic by NUTS 3 over a 10-year period. The demographic indicators used in the analysis are population, share of seniors, crude migration rate, crude mortality rate, crude fertility rate and economically active population. The economic indicators were GDP per capita, Gini coefficient and poverty risk rate. We used panel data models. It can be concluded that the population, the share of the seniors, the crude migration balance and the crude mortality rate have a positive effect on GDP per capita. Particularly surprising is the result of the analysis concerning the share of seniors, as GDP per capita is expected to grow in the next period as the share of seniors in the population increases. The share of seniors, the crude migration balance and the share of the economically active population have a negative impact on the poverty risk ratio.

Keywords	***DOI***	***JEL code***
Panel data, population aging, regional differences, economic indicators, demographic indicators	*https://doi.org/10.54694/stat.2025.15*	*C23, J14*

INTRODUCTION

Recent decades have witnessed a significant increase in the number of older people, not only in developed countries but also in developing economies. The total world population is projected to reach approximately

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10 billion by 2100, with projections suggesting that by 2050 the number of people aged 65 years and over will double compared to the number of children under 5, indicating significant changes in the context of fertility in recent decades. This demographic shift brings challenges that will need to be addressed to a greater extent, such as the higher costs of caring for the seniors, the need to adapt labour markets and social systems. Migration can also have a negative impact on social systems, in particular the departure of young people from their countries of origin or regions, which reduces the share of young workers contributing through taxes and contributions to the financing of pensions for the seniors. At the same time, the social and health care sector is increasingly burdened by raising number of people aged 50 to 74 in countries. This trend leads to an increasing proportion of older workers qualifying for old-age pensions. The social phenomenon associated with an increase in the proportion of older people in society has significant implications for the development and prosperity of the society. Changes in the age structure of population, migration, mortality and birth rates have a major impact on social and economic development. Their dynamics have an impact on the structure of the labour market, which, in turn, affects economic growth and social stability.

1 LITERATURE REVIEW

Population size, its status and age-sex composition closely correlate with a country's economic growth. The latter is a key factor influencing the lives of people in a society. The economic situation of a country includes important aspects such as GDP development, inflation rate, unemployment rate, state of trade balance, automation rate and other important indicators at local, national and global levels.

Among other things, the automation of production processes has a certain impact on unemployment. This topic was addressed by the authors of Yilmaz and Vardar (2023), who presented results from several studies. Many studies suggest that automation can explain employment and wage stagnation to some extent. Other studies point to a job loss in industries for routine jobs. On the other hand, certain recent research using firm-level data has revealed positive effects of automation on employment in automobile plants in countries such as France, the United States, the United Kingdom, Canada, Denmark and Spain.

According to Kaytaz, Özmucur and Yürükoglu (2023), there has been low or no inflation in the world for almost three decades due to globalization and an increasing independence of central banks. Globalization has led to the integration of more economies, thus injecting more labour resources into the global economy. The availability of cheap labour has thus helped to accelerate economic growth and increase trade.

Some authors are unanimous in arguing that the rise in inflation is partly linked to energy prices, especially the rise in oil prices in 2021 (Blot et al., 2022). Bernoth and Ider (2021) agree with this view and point out that this increase in inflation is the result of recovery of energy prices after their fall and the reversal of VAT cuts in several European countries, also due to the impact of Covid.

Uramova et.al. (2017) conducted an analysis examining which component of GDP has been the most stable over the period 2004–2015. The result of the analysis suggests that the main stable component of GDP in the V4 countries was private household consumption expenditure. More serious problem was the fluctuating private business investment in the countries uncer review. The authors mean that economic policy actors should focus on identifying and removing the barriers that constrain business investment activity. According to the authors, the structure of government spending needs to be evaluated in order to allocate public resources more efficiently, not only in Slovakia, but also in the other V4 countries.

Environmental issues and their impact on our planet are important. Authors Wang et al. (2020) conducted research focusing on the calculation of green GDP in China. Over the past two decades, the Chinese economy has achieved rapid growth. However, with continuous industrialization and urbanization, China is facing major challenges in energy security and environmental issues. In the research, the costs of environmental pollution including CO_2, SO_2, wastewater and waste export were taken into account. The cost of resource consumption, including fossil fuels and water consumption, was also considered.

An examination of the relationship between demographic phenomena, primarily fertility, which is associated with the postponement of childbearing, the increase in fertility at later age and the decline in total fertility, and economic processes is addressed in Beaujouan's (2023) article, acknowledging also the influence of factors such as economic crises, pandemics, etc.

The impact of mortality, while questioning the significant impact of low fertility on population aging, has been addressed by De Santis and Salinari (2023), who in their study examined the importance of mortality in shaping the age structure of the population in the long run and pointed out that changes in the age structure of countries could be explained mainly by changes in survival, with fertility and migration not being as important as assumed. Their study uses time series data (in some cases going back to 1820) from several populations in Europe, North America or Oceania. As a result of the analyses, it was found that it was possible to predict satisfactorily the evolution of the age structure on the basis of mortality rates alone.

The impact of migration, especially of young people leaving for work, on population aging is undeniable. The proportion of young people in the labour force is declining, causing a reduction in the ratio of workers to non-workers, which can lead to economic problems with social welfare. In Poland, this issue has been addressed by White (2010). The article focuses on young people from poorer towns and villages with a high incidence of migration.

The increasing proportion of seniors may have a negative impact on economic growth in the sense that health care costs are rising. Authors Páleník and Musilová (2020) argue: If the aging trend in the Slovak health care system is not slowed down or prevented, we may face a total collapse of the Slovak health care system.

Williams et al. (2022) have produced a study that discusses a proposal to address population aging in Mongolia. By 2060, Mongolia's senior population is expected to grow rapidly, with the proportion of people over 65 years of age estimated to increase more than threefold.

A study on how to mitigate the effects of population aging by promoting education has been undertaken by Kelin et.al. (2022). They used data from 15 European countries: Belgium, Czechia, Estonia, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Poland, Portugal, Romania, Spain and Slovakia. The study shows that people with higher education are more likely to be employed and able to support the dependent population longer and more effectively than those with lower education. Investing in education can be beneficial for economic sustainability at a time when the population is getting older and can help mitigate the negative effects of aging on public finances and the economies of European countries. These findings are reminiscent of the concept of successful aging proposed by Rowe and Kahn (1997). In their publication, they describe how people can achieve a high quality of life even at an advanced age.

The main objective of the paper is to find out the correlations between the selected, below mentioned, economic and demographic indicators. Panel data models will be used. Ullah (2001) in his econometrics handbook describes developments in panel data econometrics. He gives an overview of linear panel data models with predetermined variables, discussing the implications of assuming that the explanatory variables are predetermined, as opposed to strictly exogenous in dynamic structural equations with unobserved heterogeneity.

2 METHODS

The data base of the analyses consisted of data drawn from the public database DATAcube of the Slovak Statistical Office[5] and from the EU SILC publications – Indicators of Poverty and Social Exclusion.

[5] *<https://datacube.statistics.sk/#!/view/sk/vbd_dem/om7011rr/v_om7011rr_00_00_00_sk>.*

From the methodological point of view, panel data models are used, since from the spatial point of view the analysis is focused on the NUTS3 regions of Slovakia and the time horizon is 10 years (2014–2023). The analyses were carried out using Gretl, EViews, Phyton – Spyder software.

The demographic indicators used were population size, mean population size processed by the balance method as of 1 July of a given year (SR Statistical Office, 2023), share of seniors in the population, crude migration rate, crude mortality rate, crude birth rate and economically active population:

– Economic indicators: GDP per capita, Gini coefficient, poverty risk rate.

The following abbreviations are used:

– Population – popul (in thousands),
– Seniors (relative representation of seniors in the total population),
– Crude rate of net migration – CRM (net migration per 1 000 inhabitants),
– Crude death rate – CDR (the number of deaths per year per 1 000 inhabitants),
– Crude birth rate – CBR (the number of birth per year per 1 000 inhabitants),
– Share of economically active population – EAP (relative representation of EAP in the total population),
– GDP per capita – GDP (euro per capita),
– GINI coefficient – GINI (%),
– At-risk-of-poverty rate – RPR (%).

2.1 Regional abbreviations

Slovakia is often divided into three basic regions: Western, Central and Eastern Slovakia. This regional classification is not officially established by law, but is used in various statistical, geographical or administrative contexts.

BA – Bratislava Region, TT – Trnava Region, TN – Trenčín Region, NR – Nitra Region – western Slovakia, ZA – Žilina Region, BB – Banská Bystrica Region – central Slovakia, PO – Prešov Region, KE – Košice Region – eastern Slovakia.

2.2 Panel data models

The impact of demographic characteristics on the evolution of economic indicators was investigated through econometric models using panel data. Fixed effects, random effects and pooled regression model estimates were used through the least squares method. The shape of each model is given by Formulas (1), (2) and (3). The suitability of the models was assessed using the Hausman test.

$$GDP_{it} = \beta_0 + \beta_1 popul + \beta_2 seniors_{it} + \beta_3 CRM_{it} + \beta_4 CDR_{it} + \beta_5 CBR_{it} + \beta_6 EAP_{it} + u_{it} \,, \tag{1}$$

where:

i – sectional dimension i = 1, 2, ...N,
t – time dimension t = 1, 2, ...T,
u – random term of the model,
βk – estimated regression coefficient,
k – index of exogenous variables, k = 1, 2, ...6).

$$GINI_{it} = \beta_0 + \beta_1 popul + \beta_2 seniors_{it} + \beta_3 CRM_{it} + \beta_4 CDR_{it} + \beta_5 CBR_{it} + \beta_6 EAP_{it} + u_{it} \,, \tag{2}$$

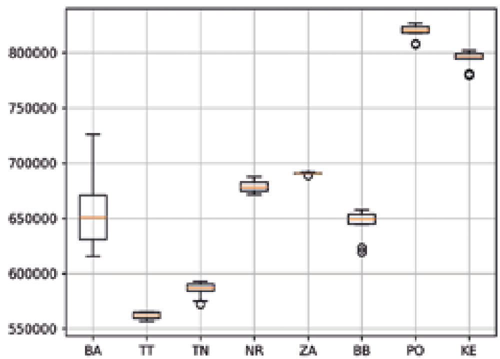
$$RPR_{it} = \beta_0 + \beta_1 popul + \beta_2 seniors_{it} + \beta_3 CRM_{it} + \beta_4 CDR_{it} + \beta_5 CBR_{it} + \beta_6 EAP_{it} + u_{it} \,. \tag{3}$$

3 RESULTS

3.1 Comparison of regions

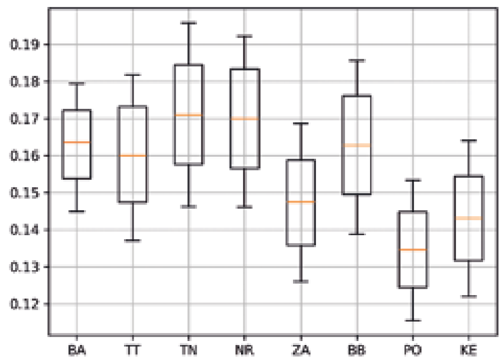
In the first part of the paper, a comparison of the regions of the Slovak Republic in terms of selected demographic (population, share of seniors, crude migration balance, crude mortality rate, crude live birth rate, share of economically active population) and economic (GDP per capita, GINI coefficient, at-risk-of-poverty rate) indicators was carried out with the help of box plot charts (e.g. see Figures 1–9).

Figure 1 Population (in number)



Source: Own processing in Spyder software

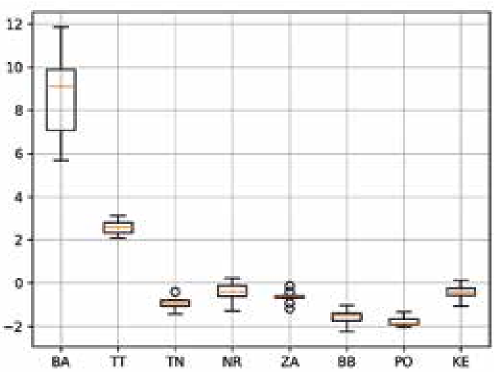
Figure 2 Seniors (relative representation of seniors in the total population)



Source: Own processing in Spyder software

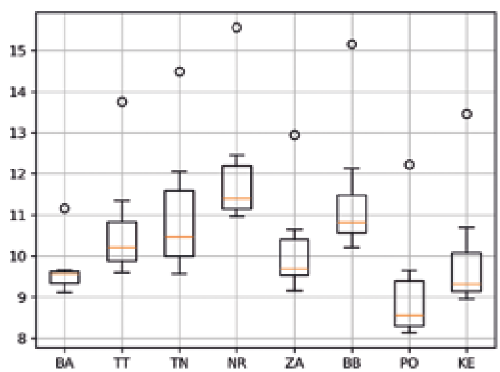
The greatest variability in the number of inhabitants over ten years is in the BA region, i.e. during the period under study the number of inhabitants measured by the mean population has changed the most compared to other regions of Slovakia (e.g. see Figure 1). In Figure 2 (e.g. see Figure 2) – share of seniors it can be seen that all boxplots are relatively symmetrical. The highest Share of seniors was recorded in the TN and NR region in the period under study, the youngest population was in PO region.

Figure 3 Crude rate of net migration (migration per 1 000 inhabitants)



Source: Own processing in Spyder software

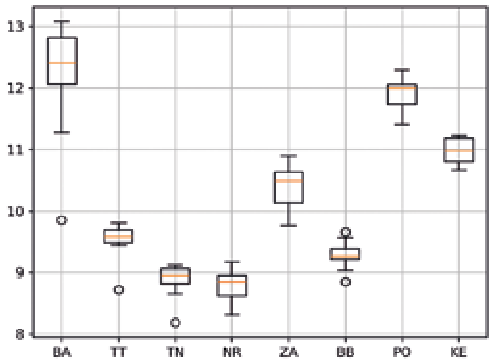
Figure 4 Crude death rate (number of deaths per year per 1 000 inhabitants)



Source: Own processing in Spyder software

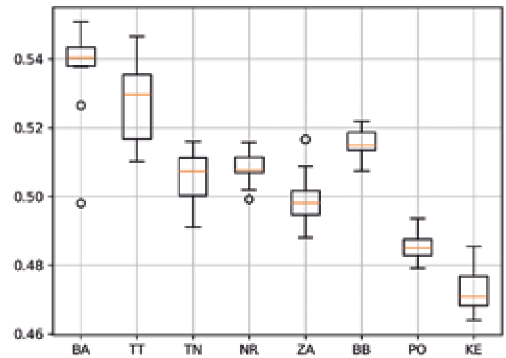
The Crude rate of net migration indicator shows the highest positive migration balance, which is significantly different during the whole period in the BA region, the least attracted people are in the PO and BB regions (e.g. see Figure 3). Crude death rates between 2014 and 2023 reached the highest level in the NR and TN regions, and lowest in the PO region (e.g. see Figure 4). In all regions of the Slovak Republic there were found outlying years, these are years of high mortality rates in the whole area – the Covid period.

Figure 5 Crude birth rate (number of birth per year per 1000 inhabitants)



Source: Own processing in Spyder software

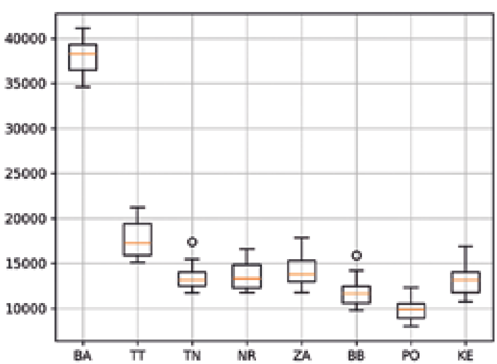
Figure 6 Share of economically active (relative representation of EAP in the total population)



Source: Own processing in Spyder software

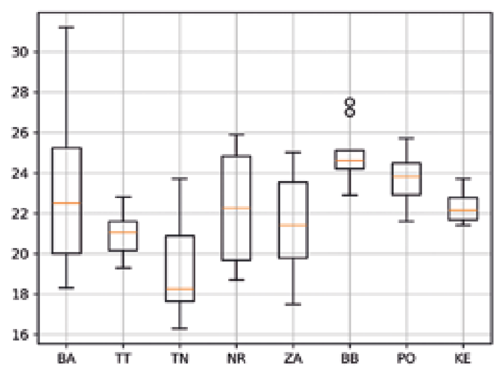
The average Crude birth rate during the period under study is approximately 10.24‰. This trend is associated with several factors, including economic or educational conditions, as well as social preferences regarding family and career. The highest Crude Birth Rate is in the BA region. It is followed by the PO and KE regions (e.g. see Figure 5); the situation in the eastern regions can be explained by a higher concentration of minority Roma population. The largest share of economically active population according to the LFS (the Labour Force Sample Survey) was in the BA region in the period under study (e.g. see Figure 6). As with most demographic indicators, the lowest share of economically active population is in the eastern regions of Slovakia. The significant differences between the BA region and the eastern Slovak regions are largely due to the different development of these areas, with employment opportunities also playing a non-negligible role.

Figure 7 GDP (euro per capita)



Source: Own processing in Spyder software

Figure 8 GINI coefficient (%)

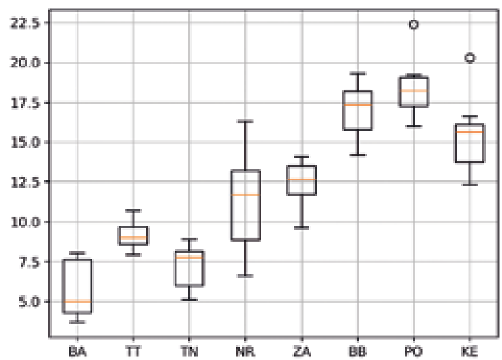


Source: Own processing in Spyder software

The BA region has a significant lead in the GDP per capita indicator. It is followed by the TT region, although with a significant difference in the values of descriptive statistics. The other regions were at approximately the same level – around 13 000 € per capita (e.g. see Figure 7). The medians of the BA, TT, NR, ZA and KE regions in the GINI coefficient indicator are in the interval from about 21% to about 23%, which means that the level of income inequality in the territory of the Slovak Republic is relatively low. Nevertheless, there are not negligible differences between the richest and the poorest regions of Slovakia (e.g. see Figure 8).

The BA region can be considered as the region with the lowest at-risk-of-poverty rate, which is related to the greater availability of job opportunities typical for larger cities and more economically developed areas. On the contrary, the highest at-risk-of-poverty rate is shown by the PO region, where the median rate is 17.6% e.g. see (e.g. see Figure 9).

Figure 9 At-risk-of-poverty rate (%)



Source: Own processing in Spyder software

3.1.1 Regional differences in socio-economic development of Slovakia

Slovakia has long been characterised by significant regional disparities, which are most pronounced between the BA region and the regions of eastern Slovakia, especially the PO and KE regions. These disparities are the result of a combination of historical, economic, geographical and institutional factors that affect the quality of life of the population and the level of regional development.

The BA region is the most developed region of the Slovak Republic in terms of socio-economic indicators. It is characterised by the highest crude domestic product (GDP) per capita, which in the long term exceeds not only the Slovak, but also the European average. The region benefits from a concentration of state institutions, international corporations, research centres and a highly skilled workforce. In addition, thanks to its favourable location close to the borders with Austria and Hungary, Bratislava as the capital city has direct access to advanced Western European markets. A well-developed transport infrastructure, including motorway connections, a railway network and an international airport, significantly increases the attractiveness of the region for both domestic and foreign investors. On the contrary, eastern Slovakia has long lagged behind in the main indicators of economic and social development. Unemployment rates in the PO and KE regions are among the highest in the republic, while the economic activity of the population is significantly lower than in the western part of the country. This situation is partly a consequence of historical marginalisation of the region, which was reflected in the lower rate of industrialisation in the past, as well as the insufficient development of transport and innovation infrastructure. In addition, eastern Slovakia is also facing a population outflow, especially of young and educated people, which further weakens its development potential.

Available statistical data, such as the Labour Force Sample Survey (LFS) and poverty and social exclusion indicators from the EU SILC survey, show that the BA region has the lowest risk of poverty and the highest employment rate, while the eastern regions are the most vulnerable in terms of social exclusion. These facts point to the need for a targeted regional policy that would contribute to levelling out disparities and ensure more balanced development of all parts of the country.

3.2 Exploring the relationship between selected demographic and economic indicators

In this section, we focus on the analysis of the relationships and dependencies between selected economic and demographic indicators. For this purpose, we use panel data models, fixed effects models and random effects models. In each model, we include all demographic indicators as exogenous variables, which we then analyse in the context of one particular economic indicator as an endogenous variable.

3.2.1 Impact of demographic characteristics on GDP per capita

In this section of the paper, we have included GDP per capita in place of the explanatory variable. Based on the test results reported in Table 1 (e.g. see Table 1), we compare the goodness of fit of the models. The results of testing for the presence of group effects in the fixed effects model (F-test) indicate the appropriateness of using this model. To compare the appropriateness of using the pooled regression model and the random effects model, we used the Breusch-Pagan test, which indicates the presence of individual effects, thus it is more appropriate to choose the random effects model. The crucial test for choosing between the fixed effects model and the random effects model is the Hausman test. Based on a p-value of less than 0.05, we used the fixed effects model. We report the results of the three models (e.g. see Table 2).

Table 1 Tests of panel models for the endogenous variable GDP

Statistic	Value	P-value
F-test	10.4971	2.44E-06
Breusch-Pagan test	22.5463	2.05E-06
Hausman test	155.348	5.72E-31

Source: Own processing based on outputs from the Gretl program

In the fixed effects model, four parameters were found to be statistically significant at different significance levels (e.g. see Table 2). At the 1% level, the Share of seniors lagged by one time period was significant, at the 5% level the Crude mortality rate lagged by one time period, and at the 10% level the Population and the Crude migration balance rate were significant. The positive regression coefficient for the Share of Seniors lagged by one time period suggests that a higher share of seniors in the population is associated with higher GDP per capita, which we consider an unexpected result. As the share of seniors in the population increases (e.g., in the previous year), GDP per capita is expected to increase in the next period. This relationship may signal a variety of factors, for example, that a higher share of seniors may be associated with greater consumption or investment in pensions, health care or infrastructure, which could boost the economy. To explain this phenomenon more thoroughly, it would be necessary to investigate the mechanisms that lead to such an outcome. Similarly, the positive regression coefficient on the Crude Mortality Rate lagged by one year suggests that a higher mortality rate positively affects GDP per capita. That is, regions with higher mortality rates also had higher GDP per capita values. It is important to note that this relationship is non-standard and can be influenced by a number of specific economic, political and social factors. In real life, higher mortality rates are usually associated with negative impacts on the economy, so it is important to look at this relationship in the context of other variables. Among the statistically significant variables are Crude Migration Balance and Population, which are closely related. These regressors showed a positive effect on GDP, meaning that an increase in them led to an increase in GDP per capita. Migration could mean the arrival of skilled labour to the region, thereby increasing labour productivity and economic performance. There is also a variable Share of economically active population in the model, which shows a positive effect on GDP per capita, but not statistically significant. Similarly, the parameter Crude Live Birth Rate, which has a negative but insignificant effect on the explanatory variable.

Table 2 Estimates of the impact of selected demographic indicators on GDP per capita

	Pooled OLS	FEM	REM
Const.	–31 117.1 (0.0557)*	–11 446.0 (0.1920)	–14 972.7 (0.1742)
Popul.	0.0181 (0.0834)*	0.0149 (0.0965)*	0.0188 (0.0651)*
$Seniors_1$	131 999 (0.0010)***	98 609.5 (6.41E-06)***	102 934 (2.16E-18)***
CRM	2 228.1 (1.35E-06)***	246.348 (0.0793)*	758.851 (0.0201)**
CDR_1	87.3379 (0.7991)	339.875 (0.0153)**	306.667 (0.1104)
CBR	298.443 (0.6341)	–210.018 (0.4380)	–402.120 (0.3868)
EAP	1 926.4 (0.4469)	–2 765.56 (0.7763)	7 025.39 (0.7395)
R-squared	0.9373	0.9970	
P-value	5.36E-07		
Akaike criterion	1 322.496	1 116.6160	1 475.4850

Notes: *, **, *** statistical significance of estimated parameters at the 10%, 5%, 1% level, p-value of parameters is in parentheses.
Source: Own processing based on outputs from the Gretl program

3.2.2 Impact of demographic characteristics on the GINI coefficient

In the following analysis, the GINI coefficient takes the place of the endogenous variable. Considering the test results presented in Table 3 (e.g. see Table 3), we conclude that the best fitting model is the fixed effects model. The F-test comparing the predictive ability of the fixed effects model and the pooled regression model with one locus constant for all cross-sectional units showed a p-value less than 0.05 (0.0066). Hence, the fixed effects model is more appropriate. Based on the Breusch-Pagan test (p-value = 0.0002), we preferred to use the random effects model over the pooled regression model. Due to the low p-value of the Hausman test (0.91E-17), the fixed effects model was preferred to the random effects model.

Table 3 Tests of panel models for the endogenous variable GINI

Statistic	Value	P-value
F-test	3.663	6.60E-03
Breusch-Pagan test	14.157	2.00E-04
Hausman test	87.6969	9.11E-17

Source: Own processing based on outputs from the Gretl program

We report the results of the model estimates for the endogenous variable GINI coefficient in Table 4 (e.g. see Table 4). The fixed effects model achieves a higher percentage of explained variability (coefficient of determination = 0.751). In the fixed-effects model, four parameters are found to be significant: Population, Proportion of seniors lagged by one time period, Crude Migration Balance Rate and Crude Live Birth Rate lagged by one time period (significance level 0.1), all of which have a negative regression coefficient. The parameter Population had a negative effect on the GINI coefficient. The negative regression coefficient of the variable Share of seniors indicates that a higher share of seniors in the population is associated with a lower value of the GINI coefficient, which implies greater income equality. The crude migration balance contributes by its increase to income equality. This indicator helps to achieve income equality in a similar way to the Population indicator. Based on the impact of the Crude Live Birth Rate lagged by one time period, we can argue that areas that are characterized by higher live birth rates are associated with lower GINI coefficients or greater income equality. The indicator of income inequality or equality is negatively affected by the Percentage of economically active population and positively affected by the Crude Mortality Rate lagged by one time period, but statistically insignificant.

Table 4 Estimates of the impact of selected demographic indicators on the GINI coefficient

	Pooled OLS	FEM	REM
Const.	−8.2377 (0.7111)	112.111 (0.0006)***	51.0865 (0.0027)***
Popul.	1.7662E-05 (0.0411)**	−7.5264E-05 (0.0002)***	−1.8640E-05 (0.1139)
$Seniors_1$	−106.9320 (0.0512)*	−100.857 (0.0139)**	−128.986 (0.0006)***
CRM	0.05997 (0.8366)	−0.5322 (0.0710)*	−0.1495 (0.5843)
CDR_1	0.2714 (0.3849)	0.0121 (0.9614)	0.3060 (0.1717)
CBR_1	−0.6544 (0.2243)	−1.6916 (0.0553)*	0.0066 (0.9921)
EAP	77.3754 (0.0670)*	−10.2030 (0.7834)	2.0071 (0.9548)
R-squared	0.405427	0.7512	
P-value	1.03E-03		
Akaike criterion	327.689	278.9769	361.1145

Notes: *, **, *** statistical significance of estimated parameters at the 10%, 5%, 1% level, p-value of parameters is in parentheses.
Source: Own processing based on outputs from the Gretl program

3.2.3 Impact of demographic characteristics on the risk of poverty

In the following analysis, at-risk-of-poverty rate is included in place of the endogenous variable. The most appropriate model to describe the relationship is the fixed effects model (e.g. see Table 5). An F-test was used to test for the presence of group effects in the fixed effects model. Because of P-value = 0.0002, we prefer to use the fixed effects model rather than the pooled regression model. We used the Breusch-Pagan test to prove the existence of individual effects in the model, and therefore using a random effects model would be preferable to using a pooled regression model. The crucial criterion for the choice is the Hausman test, which indicated the appropriateness of using a fixed effects model (P-value= 0.023).

Table 5 Tests of panel models for the endogenous variable Poverty Risk Rate

Statistic	Value	P-value
F-test	6.2792	2.00E-04
Breusch-Pagan test	48.4018	3.47E-12
Hausman test	14.6601	2.31E-02

Source: Own processing based on outputs from the Gretl program

The results of the model estimates for the endogenous variable RPR are reported in Table 6 (e.g. see Table 6). The fixed effects model achieves a higher coefficient of determination (0.893) compared to the pooled regression model and has the lowest value of Akaike's information criterion (295.62) among the three models.

Table 6 Estimates of the impact of selected demographic indicators on the Poverty Risk Rate

	Pooled OLS	FEM	REM
Const.	–43.6041 (0.0264)**	39.220 (0.0683)*	30.1401 (0.0846)*
$Popul._1$	2.4297E-05 (0.0075)***	–7.5462E-05 (0.6257)	–1.5259E-06 (0.9068)
$Seniors_1$	–76.5032 (0.0046)***	–70.203 (0.0002)***	–69.304 (1.13E-19)***
CRM_1	–1.02714 (3.80E-05)***	–0.4293 (0.0753)*	–0.5892 (0.0023)***
CDR_1	0.9024 (0.0031)***	0.8428 (6.66E-05)***	0.8466 (1.11E-14)***
CBR_1	0.9633 (0.0232)**	1.7352 (0.0275)**	1.5719 (0.0217)**
EAP_1	63.9498 (0.0500)**	–74.3393 (0.0257)**	–61.2655 (0.0237)**
R-squared	0.724791	0.8932	
P-value	6.61E-07		
Akaike criterion	349.7751	295.6203	374.3711

Notes: *, **, *** statistical significance of estimated parameters at the 10%, 5%, 1% level, p-value of parameters is in parentheses.
Source: Own processing based on outputs from the Gretl program

In the model estimation there are two parameters statistically significant at the 1% level ($seniors_1$, CDR_1), two parameters statistically significant at the 5% level (CBR_1, EAP_1) and one parameter statistically significant at the 10% level (CRM_1) all shifted by one period. With a higher proportion of seniors, the risk of poverty decreases, which we find an interesting and unexpected result and more research would be needed to investigate the mechanisms that lead to such a result. One reason for this may be that the older population has had a long period of working life during which they have built up savings or assets that may help to reduce the risk of poverty. These assets (e.g. real estate, investments or savings) can ensure their financial stability even after retirement. Another reason is that seniors often have a lower cost of living compared to younger generations, as they no longer have children to support or educate, and often have lower housing costs (for example, if they own a house or apartment). This factor may also contribute to their lower risk of poverty. The crude migration balance had a negative impact on the poverty risk rate. With a positive migration balance in an area, people have a lower risk of being among those with an equivalent disposable income below the poverty risk threshold, which is 60% of the national median equivalent disposable income. Both the crude death rate and the crude live birth rate had a positive effect on the endogenous variable. When the mortality/live birth rate is higher, the poverty risk of the area also increases. High fertility rates are associated with underdeveloped areas, so there is an expectation that we can also expect to see an increased risk of poverty in these areas. The proportion of the population that is economically active has a negative impact on the poverty risk rate. There is also a parameter popul1 in the model that negatively affects the endogenous variable, but this parameter is not significant due to statistical non-significance.

4 DISCUSSION

Based on the results of the analyses, we assess that GDP per capita is positively affected by population, the share of seniors, the crude migration balance and the crude mortality rate, which is in line with the results of other authors. According to Rayevnyeva et al. (2023), migration has a positive effect on GDP per capita, which means that the inflow of migrants leads to an increase in the economic output of a country. In their study, they proved that migration and GDP per capita have a correlation.

Mihajlović and Miladinov (2024) published a study that aimed to examine the impact of one of the most significant contemporary changes in demographic structure, population aging, on the economic performance of eight emerging economies in Central and Eastern Europe. Using Pooled Mean Group estimation in the ARDL panel model, the study finds that a one percent increase in the senior dependency ratio leads to a 0.52 percent decline in the GDP per capita growth rate. Their findings highlight the importance of implementing active aging programs, building fiscal buffers, promoting lifelong learning and encouraging employment among vulnerable groups to mitigate the adverse effects of population aging on economic growth in emerging economies.

In the analysis, we found that the GINI coefficient was negatively affected by the indicators of population, proportion of senior citizens, crude migration balance or crude live birth rate. Some results of various studies that have examined the relationship between the proportion of seniors in the population and income inequality suggest a positive relationship between the indicators, and thus the larger the proportion of seniors people, the more unequally income is distributed (Wang, Guanghua, Luo and Zhang, 2017). Another study by Gustafsson and Johansson 1999 found that the effect of the proportion of seniors in the population on the GINI coefficient was not significant, or that the proportion of seniors had no significant effect on income inequality. The theory has been confirmed using data from 16 OECD countries. However, there is also some support for the theory that population aging, as expressed by the proportion of seniors in the population, can reduce income inequality (Chu and Jiang, 1997). The proportion of seniors, the crude migration rate, and the proportion of the population that is economically active, all have a negative impact on the poverty risk ratio. The crude death rate and the crude live birth rate show a positive effect. Regarding the impact of the crude mortality rate, according to several studies, there is also a poverty-influenced mortality relationship (Liu et al., 2024). In their work focusing on 12 south-eastern states in the US, they concluded that household income was significantly related to mortality.

During the period of study, they also found that the life expectancy of people in the lowest income group was more than 10 years shorter than those in the highest income group. Interestingly, poor participants of pale skin experienced higher overall mortality than poor participants of dark skin.

In the context of the findings presented in the paper, i.e. that population aging, but also migration flows and other demographic factors, significantly affect GDP per capita, income inequality and the risk of poverty, some measures can be considered, such as active aging policies and the active involvement of older people in the economy and society through the development of lifelong learning programs focusing on digital and soft skills and intergenerational programs aimed at sharing experiences. Other appropriate measures would be to reduce income inequalities in the context of demographic change, e.g. tax reforms that could take into account the age structure of households, regional policies to mitigate economic disparities between areas with different demographic structures, support for families with children in the context of the positive impact of fertility rates on poverty, increasing access to quality healthcare for disadvantaged groups and investment in public health and prevention, especially in low-income regions.

CONCLUSION

The literature shows that the relationship between economic indicators and population aging is complex and interrelated. Population aging can have a negative impact on labour productivity, GDP growth and public spending. In the case of the Slovak Republic, there are large regional disparities that may affect the way these economic factors manifest themselves. Based on existing research, it appears that a comprehensive policy response by policy makers and other professionals will be needed to mitigate the negative impacts of aging, including labour market, social policy and health care reforms.

The results of the analysis in the regions of the Slovak Republic point to a number of important contexts that can serve as a basis for the development of targeted regional policy. On the basis of the findings, a number of recommendations can be formulated that take into account the specificities of individual regions according to their level of development, demographic structure and economic performance. The finding that an increasing share of seniors in the population has a positive impact on GDP per capita points to the potential of active aging. This trend may be particularly beneficial for the more developed regions of western and central Slovakia, where the share of the seniors population is higher. It is appropriate to promote the employment of older people through flexible forms of work, improving qualifications and creating conditions for their active participation in the labour market. The positive impact of the migration balance on GDP and its negative impact on the poverty risk rate point to the importance of population stabilization and support for migration to less developed regions, especially in eastern Slovakia. For the PO, KE and BB regions it is necessary to increase attractiveness for young people and families through affordable housing, quality services and job opportunities. An important part of the strategy should also be to support return migration from abroad and to reduce barriers to entrepreneurship for returnees. It is essential to strengthen policies aimed at activating the labour market, especially in regions with high unemployment rates, to promote retraining. In the longer term, a regionally specific approach to development is needed, taking into account local needs and potential. While the BA region can continue to support innovation and highly productive sectors, the regions of central and eastern Slovakia should emphasize the diversification of the economy, infrastructure development, support for small and medium-sized enterprises and the use of natural and cultural capital, for example in tourism or the green economy.

Demographic change – and in particular the aging of the population – should not only be seen as a challenge, but also as an opportunity for economic growth and social stability. The key is to actively integrate them into strategic planning and public policy-making to ensure sustainable and inclusive development across all regions of the Slovak Republic.

The paper summarizes existing research and highlights key aspects of the relationship between economic indicators and population aging that are relevant to the Slovak Republic. The conclusions provide important insights into how population aging affects the economy, while also showing that the situation in different regions of the country can cause variations in these impacts.

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Analysis of Life Insurance Contract Cancellations Using the Accelerated Failure Time Model

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Abstract

The aim of this paper is to analyse the cancellation of life insurance contracts on death using an accelerated failure time (AFT) model. The study focuses on identifying risk factors that influence the time to cancellation, with the objective of determining which to identify those insureds who cancel their policies the fastest. The analysis revealed several notable findings regarding the impact of premium payment frequency on contract cancellation. Specifically, yearly premium payments were found to extend the time to cancellation by 27% compared with monthly payments, holding all other factors constant. For contracts with monthly premiums, 10% of clients cancel within approximately 376 days, whereas for yearly premiums, the corresponding period is 476 days. Additionally, the results indicate that clients who did not conclude their contracts through the tied agent distribution channel tend to cancel their policies sooner. The AFT model was constructed using established R packages for survival analysis.

Keywords	***DOI***	***JEL code***
Survival analysis, accelerated failure time model, censoring, cancellation of an insurance contract, life insurance	*https://doi.org/10.54694/stat.2025.26*	*G22, C41*

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INTRODUCTION

Modelling the time to cancellation of insurance contracts is an important analytical tool enabling the insurer to understand better the behaviour of its clients, optimise sales strategies and manage effectively its portfolio. From a long-term point of view life insurance as a product is dependent on continuation of contracts and hence identification of cancellation risk factors is one of the key aspects of actuarial analyses (Milhaud and Dutang, 2018). High cancellation rates particularly near the start of a contract can impact on the insurer's profitability (Zelinová, 2021). To analyse cancellation occurrence and the effect of explanatory variables use has also been made in actuarial practice of logistic regression, generalised linear models and penalised regression techniques (Reck, Schupp and Reuß, 2022; Kiesenbauer, 2012; Kim, 2005; Eling, and Kiesenbauer, 2014). Such methods however cannot cope with incomplete data, i.e. with censored data. The investigated event will not arise in respect of all the subjects entering the period of observation. It would not however be correct to exclude them from the analysis. Hence the term time-censorship was introduced and for such subjects we observe the censored survival time (Kleinbaum a Klein, 2012). The most common form of censorship in survival analysis is that from the right (Moore, 2016). Regression models for survival analysis differ from classical regression models in that they allow us to make use also of censored data. Parametric models are also suitable for analysis of data censored from the left, from the right as well as within an interval, as compared with non-parametric models which are only able to deal with right-censored data (Collett, 2015).

The Cox model of proportional risk and the parametric model of the accelerated failure time are important regression models in survival analysis, whereby many authors use them for example to model client survival or insurance contract cancellations. Analysis, using the Cox proportional model, of the survival of breast cancer patients depending on the therapeutic approach adopted is dealt with in Abadi etc. (2014). The patients were divided into eight groups according to age and stage of illness. For each group they applied a suitable model according to meeting the assumed proportional risks, which they then tested with the help of Schoenfeld residuals. Sheng, Qian and Ruan (2018) investigated the factors affecting the survival of heart failure patients using the Cox proportional model. Majeed (2020) in their analysis of the length in force of insurance contracts gave preference to the accelerated failure time model over the Cox model as the latter requires fulfilment of the proportional risk assumption whilst the former does not. The analysis was carried out on life insurance data from the USA, whereby the best model according to various criteria was the AFT model using a generalised gamma distribution for the time. Aziz and Razak (2019) used the Kaplan-Meier estimate and the Cox model to identify the riskiest group of life insurance clients based on Malaysian data for the years 2012–2015. In Li (2017) the author analyses survival of patients diagnosed with breast cancer using a new model of proportional risk, namely the hypertabastic model. In recent times more use is being made of joint models for longitudinal and time-to-event data in survival analysis. These models combine the ability to analyse longitudinal data and survival data and provide better results than the classical models, see Baart, Boersma and Rizopoulos, (2019). An interactive guide to carrying out a survival analysis with data on lung cancer using Python, with the aim of developing an accessible application in Streamlit, is provided in Komara and Zelinová (2024).

Machine learning methods are amongst the most innovative approaches for data analysis and are used also in survival analysis for example Štepánek et al. (2021, 2023). Implementation of the AFT model in the XGBoost library in the Python language increased the effectiveness of modelling thanks to the technique of gradient boosting (Barnwal, Cho, and Hocking, 2022). The authors Yang et al. (2021) and Ramezankhani et al. (2017) in their papers showed the use of survival trees. Kasaraneni (2024) investigated the application of advanced machine learning techniques, including deep neuron networks and Recurrent Neural Networks (RNN) to predict cancellations. Azzone et al. (2021) use the random forest method to predict cancellations of life insurance contracts. To apply these regression models in survival analysis and visualise the results use can be made of, for example, the library `survival`, `survminer`, available in R (Therneau, 2023), (Kassambara and Kosinski, 2021). This paper focuses on analysing the impact of premium payment frequency on contract cancellations, as well as examining the influence of the distribution channel. Based on the modeling of cancellation times using the AFT model, we quantify the percentage share of insurance contracts that are expected to be cancelled within the modelled time horizon.

1 METHODS OF ANALYSIS

The most often used model for survival analysis is the Cox semi-parametric regression model of proportional risks. The proportional risk model is expressed by the regression model for the risk function (Collett, 2015):

$$h(t \mid \mathbf{x}) = h_0(t)\exp(x_1\beta_1 + x_2\beta_2 + \ldots + x_p\beta_p) = h_0(t)\exp(\boldsymbol{\beta}\mathbf{x}), \tag{1}$$

where $\mathbf{x}$ is a vector of explanatory variables, p is their number, $\boldsymbol{\beta}$ is a vector of regression coefficients, whose elements are β_m for $m = 1, 2, ..., p$ and $h_0(t)$ is a basic risk function valid for all referential observations $\mathbf{x} = \mathbf{0}$.

The hazard ratio, HR, of the two sets of observations states how the risk function of the observations with values of the explanatory variables $\mathbf{x}_1$ differs compared with the risk function of the observations for which the explanatory variables take the values of the vector $\mathbf{x}_2$. We can express this as follows (Teplanová, 2023):

$$HR = \frac{h(t \mid \mathbf{x}_1)}{h(t \mid \mathbf{x}_2)} = \frac{h_0(t)\exp(\boldsymbol{\beta}\mathbf{x}_1)}{h_0(t)\exp(\boldsymbol{\beta}\mathbf{x}_2)} = \exp\left[\boldsymbol{\beta}(\mathbf{x}_1 - \mathbf{x}_2)\right]. \tag{2}$$

We see that the hazard ratio is independent of the time t and therefore is the same for all points of time, which is the assumption of the proportional risk model. This model not only enables, by using the hazard ratio, comparison of two groups and quantification of the risk of occurrence of the investigated event but also an analysis of the effect of risk factors on its occurrence. Given the aim of this paper we will not consider this model in detail. We will give more space to the alternative AFT model, which does not require keeping proportionality of risks (Wei, 1992; Saikia and Barman, 2017). As opposed to the Cox model of proportional risk, where the multiplicative effect of the explanatory variables is applied to the risk function, in this model it is the time to the occurrence of the given event.

1.1 The accelerated failure time model

The accelerated failure time model is therefore one of the alternatives for comparing the survival time of two or more groups of objects. Also it is a parametric model and therefore it is necessary to choose the right probability distribution for the time to the occurrence of the event. It is suitable for analysing left-censored data, right-censored data and interval-censored data as compared with non-parametric models which can only cope with right-censored data (Klein and Moeschberger, 1997). The random variable of the time to occurrence of the event in the case of the AFT model is given by the Formula:

$$T = \exp(\beta_0 + \boldsymbol{\beta}\mathbf{x} + \sigma\varepsilon), \tag{3}$$

where β_0 is the intercept, $\boldsymbol{\beta}$ is the vector of regression coefficients, $\mathbf{x}$ is the vector of explanatory variables, ε represents a random error term and σ is the standard deviation of this random element. Similarly the logarithm of the time to occurrence of the event is given by (Moore, 2016):

$$\ln T = \beta_0 + \boldsymbol{\beta}\mathbf{x} + \sigma\varepsilon. \tag{4}$$

For the survival function in context with $S_0(t) = P(T > t|\mathbf{x} = \mathbf{0})$ we have:

$$S(t \mid \mathbf{x}) = S_0\left(t \cdot \exp\left(-\boldsymbol{\beta}\mathbf{x}\right)\right). \tag{5}$$

For the survival function in context with the survival function of the random error term $S_\varepsilon(t)$we have:

$$S(t \mid \mathbf{x}) = S_\varepsilon\left(\frac{\log(t) - \beta_0 - \boldsymbol{\beta}\mathbf{x}}{\sigma}\right). \tag{6}$$

In Table 1 we give a selection of possible distributions for the time T to occurrence of the event and for the random error term ε (Klein, 2014).

Table 1 Selected probability distributions for ***T*** and ***ε*** used in the AFT model

Distribution of T	Distribution of ε
Log-Normal	Normal(0;1)
Log-Logistic	Logistic(0;1)
Weibull	Gumbel(0;1)

Source: Own construction

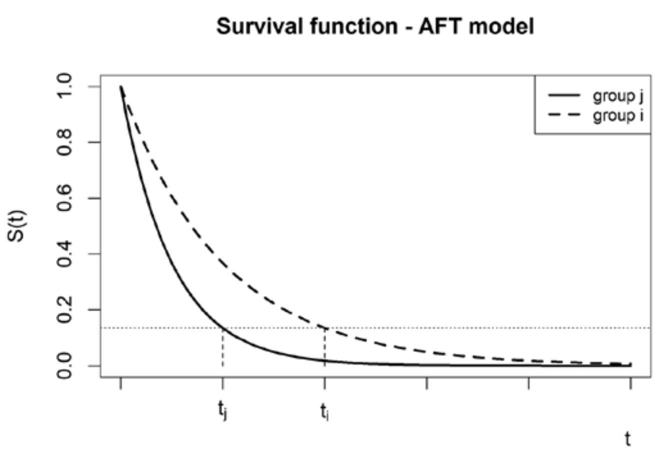
For two distinct groups i, j with differing values of covariates represented by the vectors $\mathbf{x}_i$ and $\mathbf{x}_j$, the following relationship holds between their survival functions (Collett, 2015), see Figure 1:

$$S_i(t_i \mid \mathbf{x}_i) = S_j(\kappa^{-1} \cdot t_i \mid \mathbf{x}_j) = 1 - \alpha\ , \tag{7}$$

where κ is a constant representing the acceleration factor, which can be expressed as:

$$\kappa = \exp\left[\left(\mathbf{x}_i - \mathbf{x}_j\right)\boldsymbol{\beta}\right]. \tag{8}$$

Figure 1 Survival function for groups ***i*** and ***j*** with acceleration factor ***κ*** > **1**



Source: Own construction in R

Based on Formula (7), and assuming the same value of $1 - \alpha$, the following relationship holds for the time ratio between the two groups i, j:

$$\frac{t_i}{t_j} = \kappa. \tag{9}$$

If $\kappa > 1$, the time to occurrence of the observed event for group i as compared with group j is "extended" by $100(\kappa - 1)$%, or to put it differently for group i time passes κ times "more slowly" as compared with group j.

If $\kappa < 1$, the time to occurrence of the observed event for group i as compared with group j is "shortened" by $100(1 - \kappa)$%, or to put it differently for group i time passes κ^{-1} times "faster" as compared with group j.

The most frequently used parametric model for describing time in the context of use of the AFT model is the Weibull distribution, whose density function $T \sim Weibull(\lambda; \gamma)$ is given by:

$$f(t) = \frac{\gamma}{\lambda}\left(\frac{t}{\lambda}\right)^{\gamma-1} \cdot \exp\left(-\left(\frac{t}{\lambda}\right)^{\gamma}\right), \; t > 0. \tag{10}$$

In this case the random element takes a Gumbel distribution $\varepsilon \sim Gumbel(0; 1)$. Based on Formula (6), the survival function $S(t|\mathbf{x})$ of the AFT Weibull model can be expressed as:

$$S(t \mid \mathbf{x}) = \exp\left(-\left(\frac{\mathrm{t}}{\exp(\beta_0 + \boldsymbol{\beta}\mathbf{x})}\right)^{\frac{1}{\sigma}}\right). \tag{11}$$

If we introduce the notation $\lambda = \exp(\beta_0 + \boldsymbol{\beta}\mathbf{x})$ and $\gamma = \frac{1}{\sigma}$, we obtain the survival function of the Weibull distribution (Majeed, 2020):

$$S(t \mid \mathbf{x}) = P(T > t \mid \mathbf{x}) = S(t) = \exp\left(-\left(\frac{t}{\lambda}\right)^{\gamma}\right). \tag{12}$$

If we denote $S(t \mid \mathbf{x}) = P(T > t \mid \mathbf{x}) = 1 - \alpha$, then from the expression for the quantile function $F^{-1}(\alpha)$ of the Weibull distribution with estimated parameters λ, γ, we obtain a formula for calculating the time to the occurrence of an event based on the given value of α as:

$$t_\alpha = F^{-1}(\alpha) = \left[-\log(1-\alpha)\right]^{\frac{1}{\gamma}} \cdot \lambda, \qquad \alpha \in (0;1). \tag{13}$$

1.2 Testing the statistical significance of the variables and choice of model

This part deals with testing the statistical significance of the regression coefficients and choice of the most suitable model. If a regression coefficient appears as statistically significant, then the parameter of the explanatory variable, representing this coefficient, has a statistically significant effect on the time to occurrence of the event (Kleinbaum and Klein, 2012).

We define a null hypothesis (regression coefficient is not statistically significant) and an alternative hypothesis (regression coefficient is statistically significant) thus:

$H_0 : \beta_m = 0$,
$H_1 : \beta_m \neq 0$,
for $m = 1, 2, \ldots, p$ parameters.

We use the Wald test, where the Wald statistic Z_m^W is calculated as follows:

$$Z_j^W = \left(\frac{\hat{\beta}_m}{sd\left(\hat{\beta}_m\right)} \right)^2. \tag{14}$$

The Wald statistic Z_m^W has an asymptotic chi-squared distribution with one degree of freedom. We reject the null hypothesis H_0 at the significance level α, if:

$$Z_m^W > \chi^2_{1-\alpha,1}, \tag{15}$$

or if the p – value is less than the chosen significance level α, whereby:

$$p - value = P\left(\chi^2 > Z_m^W\right). \tag{16}$$

For the total statistical significance of the categorical variable the Wald statistic has a chi-squared distribution with degrees of freedom equal to (number of variants – 1). To choose the most suitable model we use the Akaike information criterion (*AIC*), defined as follows:

$$AIC = -2\ln\hat{L} + 2q, \tag{17}$$

where q represents the number of estimated parameters in the model and $\hat{L}$ is the maximized value of the likelihood function for the model. The smaller the value *AIC* the more suitable is the model. There also exist other criteria, for example Bayes information criterion *BIC*.

1.3 Verification of the AFT Weibull model using standardised residuals

We calculate the standardised residuals for the AFT Weibull model for the k-th observation in accordance with Formula (6) with the help of the Formula (Collett, 2015):

$$r_k \cong \varepsilon_k = \frac{\log\left(T_k\right) - \beta_0 - \boldsymbol{\beta}\mathbf{x}}{\sigma}. \tag{18}$$

In accordance with Formula (11) we assume that the survival function of the residuals $S_r(t)$ will be identical to the survival function of the Gumbel distribution $\varepsilon \sim Gumbel(0; 1)$, which we can write as:

$$S_r\left(t\right) \cong S_\varepsilon\left(t\right) = \exp\left(-\exp\left(-t\right)\right). \tag{19}$$

2 DATA DESCRIPTION AND MODEL BUILDING

Using actual data from insurance practice we will investigate the effect of various risk factors on the cancellation of life insurance products, whose main risk element is a benefit of freely chosen amount payable on death with the possibility of critical disease and invalidity riders.

2.1 Data description

The data looked at consists of 25 364 insurance contracts sold over a period of 10 years. The individual variables appearing in the model are described in Table 2. The explanatory variable is the time a contract is in force, i.e. the time from the date of inception to the date of cancellation, to maturity, to the ending of the risk or to the date when the contract ceases to be observed.

Let us define the variable STATE as a censoring indicator. The value "1" applies to those contracts which were cancelled during the observed period. For contracts which mature, or the risk ends, or which are still in force it takes the value "0". It should be noted that for the purpose of our analysis we include amongst cancelled contracts also those where no surrender value is paid on cancellation. In the given portfolio, more than 53.2% of the contracts were cancelled, while approximately 46.8% remained active. The number of cancellations and non-cancellations is the same. So for this data base we do not have the problem of sparse data. Clients have the possibility of including an investment element in their contract. An important factor regarding client loyalty is the care they receive from the distribution channel through which they bought the contract. This particular contract was sold through its own bank-insurance channel "Bank", insurance brokers "Broker" or tied agents "TA". As already mentioned, clients could choose to include rider benefits: invalidity (INV), critical illness (CRIT) or both combined (COMB), or choose not to include them (NR). When completing the contract the client can choose how frequently the premiums will be paid: "1" = monthly, "3" = quarterly, "6" = half-yearly and "12" = yearly.

Table 2 Description of the data base for analysing the departure of clients from the insurance company

Name of the variable	Type of variable	Values	Variable description
TIME	Continuous	---	Time in force
STATE	Category	0	Indicates if contract is cancelled or not
		1	
INVEST	Category	0	Indicates if contract contains an investment element
		1	
YEARLY_PREMIUM	Continuous	---	Amount of annual premium
AGE	Continuous	---	Age of client at inception
SEX	Category	F	Sex of insured person
		M	
DCH	Category	BANK/BROKER	Distribution channel through which the contract was sold
		TA	
RIDER	Category	NR	No rider benefits
		CRIT	Critical illness
		INV	Invalidity
		COMB	Both combined
SUM_ASSURED	Continuous	---	Contractual amount insured for each risk
FREQ	Category	1	Frequency of payment of the premium (in months)
		3	
		6	
		12	

Source: Own construction

To interpret better the results it is desirable to specify the reference categories (levels) for the categorical variables. Table 3 shows the reference level for each of the category variables.

Table 3 Reference levels

Variable	Reference level
SEX	M – males
DCH	BANK/BROKER (BB)
INVEST	0 = no investment component
RIDER	0 = without rider benefits
FREQ	1 = monthly premiums

Source: Own construction

2.2 Model building

Our aim is to estimate an AFT model which suitably describes the time to cancellation of the contracts in our data base. We will create three parametric regression models (exponential, Weibull, log-logistic). To start with it is desirable to test which variables to include in the model given their contribution to the variability of the explanatory variable. To investigate the overall statistical importance of each variable, we applied the backward elimination method. This gave for all of the three models that the best in each case was a complete model including all the variables. To choose which of the three AFT models was the most suitable we used the Akaike information criterion *AIC* and the Bayes information criterion *BCI*. Based on the results we can assert that the most suitable parametric model for modelling the time to cancellation of an insurance contract with the lowest *AIC* and *BIC* is the Weibull AFT model, Table 4.

Table 4 Test statistics for the individual models considered

MODEL	AIC	BIC
Exponential model	246 708.5	246 814.5
Weibull model	**246 535.9**	**246 649.9**
Log-logistic model	246 666.4	246 780.3

Source: Own construction

The estimation of regression coefficients and the assessment of the statistical significance of the variables using the Wald test were carried out in R. All the regression coefficients, also in terms of the variations, are statistically significant at the 0.05 significance level, apart from variation FREQ6. For interpretation purposes we have however included it in the model. To calculate the time to cancellation of the contract based on Formula (13) we determine the parameter γ from these results as follows:

$$\gamma = \frac{1}{\exp\left(Log\left(scale\right)\right)} = 0.901.$$

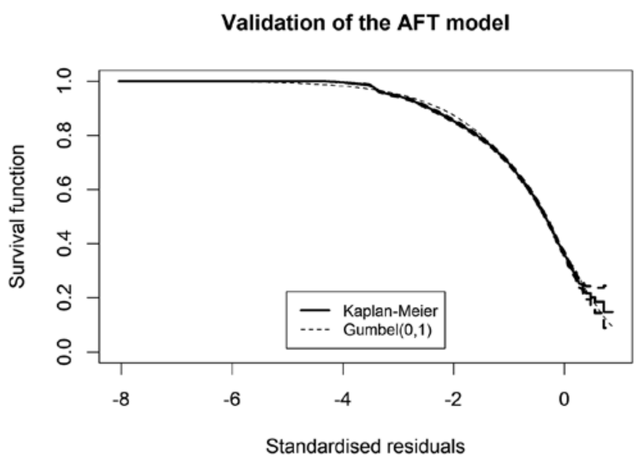
Table 5 presents the estimated regression coefficients for the AFT Weibull model, along with the corresponding acceleration factors. For categorical variables, these factors are interpreted relative to their reference category, while for continuous variables, they represent the effect of a one-unit increase, with all other conditions held constant.

Table 5 The regression coefficients and acceleration factors for the AFT Weibull model

Variables, variations	m	$\widehat{\beta}_m$	$\kappa = exp(\widehat{\beta}_m)$	$\kappa^{-1} = exp(-\widehat{\beta}_m)$
SEXF	1	0.085218302	1.088954761	0.918311793
YEARLY_PREM	2	–0.000319505	0.999680546	1.000319556
AGE	3	0.002121354	1.002123605	0.997880895
DCH_TA	4	0.326765333	1.386476079	0.721252978
INVEST1	5	4.536438584	93.35772169	0.010711487
RIDER_INV	6	0.828061500	2.288877448	0.436895388
RIDER_COMB	7	2.284567444	9.821436987	0.101818095
RIDER_CRIT	8	2.282594229	9.802076285	0.102019202
SUM_ASSURED	9	–0.000002320	0.999997683	1.000002317
FREQ3	10	–0.173958084	0.840332120	1.190005684
FREQ6	11	0.085279332	1.089021223	0.918255750
FREQ12	12	0.236618032	1.266957089	0.789292715

Source: Own construction

Figure 2 Validation of the AFT Weibull model using the standardised residuals



Source: Own construction in R

To validate the suitability of the estimated AFT Weibull model we use the standardised residuals. Figure 2 shows the survival function of the empirical data estimated using the Kaplan Meier estimate (Teplanová and Páleš, 2021) with the survival function of the Gumbel distribution. We can state in the context of Formula (19) that the estimated AFT Weibull model is a suitable model for describing the time to cancellation of an insurance contract.

3 RESULTS AND DISCUSSION

In this part of the paper we will interpret the obtained regression coefficients of the AFT Weibull model and analyse the influence of the chosen risk factors on the insurer's cancellation experience.

3.1 Interpretation of the regression coefficients and the acceleration factors

Based on the results shown in Table 5 we will bring out the importance and usefulness of the estimated regression coefficients for the purpose of interpreting the cancellation risk in the context of both quantitative (continuous) and qualitative (category) variables. First we will look at the effect of the sex of the insured on the modelled time to cancellation. The time ratio for the sex variable is $\kappa = 1.09$ (acceleration factor):

$$t_{females} = 1.09 \cdot t_{males}, \qquad S_{females}(t \mid \mathbf{x}) = S_{males}(0.92 \cdot t \mid \mathbf{x}),$$

which indicates that for females the time to cancellation passes 1.09 times "slower" than for males, respectively it extends it by 9% other things being equal. This means that on average males cancel their contracts earlier than females subject to the other variables remaining unchanged.

Let us demonstrate the calculation of the time ratio for example for a 20 and a 55 year old insured. Age in the model is a continuous variable and so we can use Formula (8) to quantify it:

$$\kappa = \exp\left(0.002121354 \cdot 35\right) \cong 1.08, \qquad S_{AGE=55}(t \mid \mathbf{x}) = S_{AGE=20}(0.93 \cdot t \mid \mathbf{x}).$$

With an increase in age at inception from 20 to 55 the time to cancellation extends by 8% other variable remaining unchanged.

The group who purchased their contracts through tied agents has on average a 1.39 times longer time before cancellation than the reference group who purchased through a bank or a broker. Time for this group passes 1.39 times "slower" other variables remaining unchanged:

$$t_{TA} = 1.39 \cdot t_{BB}, \qquad S_{TA}(t \mid \mathbf{x}) = S_{BB}(0.72 \cdot t \mid \mathbf{x}).$$

For insureds who had an investment element in their contract time passed 93.36 times "slower" than for those who did not, other variables remaining unchanged:

$$t_{INVEST1} = 93.36 \cdot t_{INVEST0}, \qquad S_{INVEST1}(t \mid \mathbf{x}) = S_{INVEST0}(0.01 \cdot t \mid \mathbf{x}).$$

The result could however have been affected by the fact that in the portfolio considered the number of contracts with an investment element was significantly smaller than the number without. So one can nevertheless say that in the given portfolio clients with an investment element hardly ever cancel their contracts.

Regarding frequency of payment of the premium, we see that for contracts with premiums paid once a year the time to cancellation "extends" by 27% compared with contracts where premiums are paid monthly, other variables remaining unchanged, i.e. we have:

$$t_{FREQ12} = 1.27 \cdot t_{FREQ1}, \qquad S_{FREQ12}(t \mid \mathbf{x}) = S_{FREQ1}(0.79 \cdot t \mid \mathbf{x}).$$

3.2 Modelling the time to cancellation using the AFT Weibull model

This section deals with modelling the time to cancellation using the estimated AFT Weibull model. First though we will analyse the effect of premium payment frequency on the time to cancellation for a contract on a 30 year old female, taken out through tied agents, with a yearly premium of € 200 and sum assured of € 5 000 without rider benefits and without an investment element. We model these times for different levels of the survival function values, $1 - \alpha$; that is, we estimate, with a predefined probability, the duration of the contract. To estimate the time to cancellation of an insurance contract, we use Formula (13) of the Weibull AFT model, based on which we obtained the resulting expression:

$$t = [-\log(1-\alpha)]^{1.11} \cdot \exp(8.026686233 + 0.085218302 \cdot sex\_female - 0.000319505 \cdot yearly\ premium + 0.002121354 \cdot age + 0.326765333 \cdot DCH\ tied\ agents + 4.536438584 \cdot investment\ element + 0.828061500 \cdot invalidity + 2.282594229 \cdot critical\ illness + 2.284567444 \cdot combined\ riders - 0.000002320 \cdot sum\ assured - 0.173958084 \cdot freq.quarterly + 0.085279332 \cdot freq.halfyearly + 0.236618032 \cdot frek.yearly).$$

Table 6 shows the values rounded to two decimal places of the times to cancellation with the values of the acceleration factors for each variation of the frequency of premium payment as compared with the reference monthly frequency. The table shows the modeled times to contract cancellation only for selected values of the survival function. The emphasised figures represent the median time $t_{0.5}^{FREQf},\ f = 1,3,6,12$ to cancellation of the contract for the client with the aforementioned risk profile for the various frequencies of payment of the premium. Given these values and subject to maintaining the conditions of the Bernoulli theorem of large numbers, we can state for example that for monthly payment of premiums 50% of contracts are still active, i.e. in force, approximately after 3 041 days.

Table 6 Modeling the time to cancellation for various premium payment frequencies

$S(t)$	$t_{monthly}$	$t_{quarterly}$	$t_{halfyearly}$	t_{yearly}	$\kappa_{\frac{quarterly}{monthly}}$	$\kappa_{\frac{halfyearly}{monthly}}$	$\kappa_{\frac{yearly}{monthly}}$
1	0	0	0	0	0	0	0
0.9	375.75	315.76	409.20	476.07	0.84	1.09	1.27
0.8	864.29	726.29	941.23	1 095.02	0.84	1.09	1.27
0.7	1 454.64	1 222.38	1 584.13	1 842.96	0.84	1.09	1.27
0.6	2 167.28	1 821.23	2 360.21	2 745.85	0.84	1.09	1.27
0.5	**3 041.22**	**2 555.64**	**3 311.96**	**3 853.10**	0.84	1.09	1.27
0.4	4 145.61	3 483.69	4 514.66	5 252.32	0.84	1.09	1.27
0.3	5 613.28	4 717.02	6 112.98	7 111.78	0.84	1.09	1.27
0.2	7 747.12	6 510.15	8 436.78	9 815.27	0.84	1.09	1.27
0.1	11 528.99	9 688.18	12 555.32	14 606.74	0.84	1.09	1.27

Source: Own construction

We can write this as follows:

$$S(3041.22 \mid \mathbf{x}) = P(T > 3041.22 \mid \boldsymbol{x}) = 0.5, \qquad t_{0.5}^{FREQ1} = 3041.22.$$

For comparison, with the yearly payment frequency (*FREQ*12)cancellation occurs after approximately 3 853 days, which we can write as:

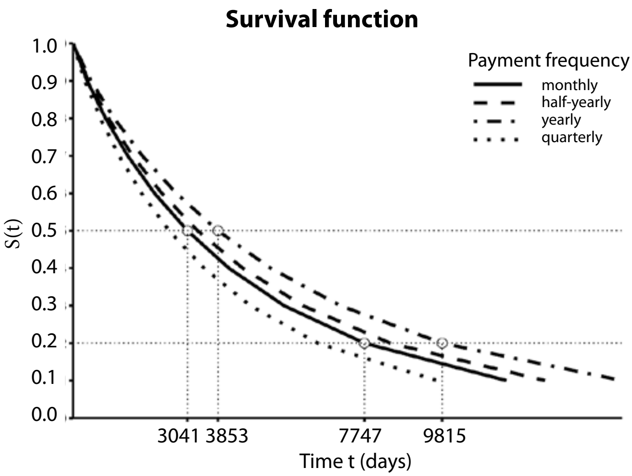
$$S(3853.10 \mid \mathbf{x}) = P(T > 3853.10 \mid \boldsymbol{x}) = 0.5, \qquad t_{0.5}^{FREQ12} = 3853.10.$$

Given these median times to cancellation (approximately 3 041 days for monthly payments and 3 853 for yearly payments), the acceleration factor, other things being equal, is $\kappa \cong 1.27$. So for the group of insureds with yearly payment of premiums time flows "slower" compared with the reference category (monthly payment of premiums). It is clear that the graph of the survival function is moved to the right of that for the reference group, as illustrated in Figure 3, $t_{0.5}^{FREQ12} = 1.27 \cdot t_{0.5}^{FREQ1}$. Figure 3 also shows the 80th percentiles of the time to cancellation for monthly and yearly payment frequencies, which we can write as:

$$S(7\,747.12 \mid \mathbf{x}) = P(T > 7\,747.12 \mid \boldsymbol{x}) = 0.2, \quad t_{0.80}^{FREQ1} = 7\,747.12,$$

$$S(9815.27 \mid \mathbf{x}) = P(T > 9815.27 \mid \boldsymbol{x}) = 0.2, \quad t_{0.80}^{FREQ12} = 9815.27.$$

Figure 3 Survival function for the given risk profile with various payment frequencies



Source: Own construction in R using package ggplot2 (Wickham, 2016)

In the case of clients who pay yearly premiums 80% cancel their contracts within approximately 9 815 days, which is 1.27 times later than for clients who pay monthly premiums: $t_{0.8}^{FREQ12} = 1.27 \cdot t_{0.8}^{FREQ1}$.

In the case of clients who pay monthly premiums 10% cancel within approximately 376 days ($t_{0.1}^{FREQ1} = 375.75$), whereas for yearly premium contracts it is 476 days ($t_{0.1}^{FREQ12} = 476.07$).

Once again we point out that these results apply for the risk profile of a female aged 30 who bought a contract via a tied agent with an annual premium of € 200 and an insured amount of € 5 000, without rider benefits or an investment element.

If the distribution channel is changed from a tied agent to a bank/broker (BB), with a yearly premium payment frequency and all other parameters held constant, the results are presented in Table 7. A comparison of these results with those in Table 6 shows that where a client buys the contract via a bank or broker time passes "faster". This means that they cancel their contracts earlier than those who buy via tied agents. Just for comparison 10% of bank/broker clients cancel within approximately 343 days ($t_{0.1}^{BB} = 343.3514$), whereas it is 476 days ($t_{0.1}^{TA} = 476.07$) for tied agent clients.

Table 7 Estimate of selected quartiles for a client with distribution channel BB

$S(t) = 1 - \alpha$	t_{α}^{BB}
0.9	343.4
0.5	2 779.0
0.2	7 079.1

Source: Own construction

CONCLUSION

The parametric regression AFT model allows us to model the time to the cancellation of an insurance contract, as well as to analyse how individual risk factors affect it. In this context it is also suitable for comparing client groups with different risk profiles using the acceleration factor. These calculated time ratios quantify in which of the compared groups time passes “slower” or “quicker”. The quantile values of the AFT model allow us to predict the percentage of contracts, with a given risk profile, which will be cancelled up to an estimated time. After processing actual data relating to a portfolio of life insurance contracts whose main benefit was an amount payable on death, it was determined that the most suitable model for describing the time to cancellation was the AFT Weibull model. Given the structure of the observed time from inception of the contract right-censoring was used in the context of death of the insured, ending of the contract or continuation of the contract in force. Only observations relating to cancellation of the contract were treated as non-censored. For a particular client risk profile we analysed in the paper the effect for example of premium payment frequency on the time to cancellation. Yearly payment of premiums “extends” the time to cancellation by 27% compared with contracts with premiums paid monthly other things being equal. For monthly payment of premiums 10% of clients cancel within approximately 376 days whereas for yearly premium payments it is 476 days. If the client took out a contract with yearly payment of premiums through a bank or insurance broker they would cancel within approximately 343 days which is a 28% shorter time than if they had bought via a tied agent, assuming the other parameters of the contract remain unchanged. Cancellation of insurance contracts has a significant impact on the cash-flows and profitability of the insurer and therefore modelling of cancellations is one of the key aspects of actuarial analyses. A notable challenge in addressing survival analysis lies in the implementation of machine learning methods. Beyond achieving improved predictive accuracy, a key consideration in actuarial analyses is ensuring model interpretability, particularly with respect to quantifying the influence of individual risk factors on the predicted variable.

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From Growth to Jobs: Empirical Inquiry into China's Employment Elasticity and Its Macroeconomic Drivers

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Abstract

China has remained one of the fastest growing economies of the world for an appreciable period; however, there are concerns around the employment content of these growth achievements. These concerns become more important keeping in view demographic profile of China. To this end current study attempts to estimate employment elasticity of China's economic growth and examine its macroeconomic determinants. The study uses annual time series data for the period of 1980–2019. Time varying Kalman filter is used to estimate employment elasticity and ARDL is used to examine its macroeconomic determinants. The results of the study revealed drastically low level of employment elasticity in China during the study period. Further the study found that inflation and openness had a negative impact while depreciation had a positive impact on employment elasticity in the long run. Additionally, human capital formation and services sector share have positive but insignificant impact. Further, as a robustness check, the Dynamic Ordinary Least Squares (DOLS) estimation was conducted, and its results were found to be consistent with the ARDL model.

Keywords	***DOI***	***JEL code***
Economic growth, employment growth, employment elasticity, TVP approach, China	*https://doi.org/10.54694/stat.2025.23*	*E24, O40, C32, F62, J2*

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INTRODUCTION

China has witnessed a tremendous growth in recent decades making it one of the fastest growing economies of the world. This remarkable economic performance over the past four decades has been characterized by rapid industrialization, technological advancement, and urbanization. China's GDP grew 38.8 times between 1978 and 2020, and, therefore, the economy was ranked second globally, Zhou et al. (2023). After reaching a peak of 14.2% in 2007, China's economic growth rate started to decline, falling to around 6% in 2019. This halt in development has been dubbed as China's "New Normal" by the government and academicians, Wu et al. (2022).

On the other hand, mining jobs in China have steadily decreased as the country moves toward environmentally sustainable growth, dropping from 6.36 million in 2013 to 3.41 million in 2022 – almost half the workforce lost since the coal industry's peak in 2012. As a result of this manufacturing jobs have also decreased dramatically (Zhang et al., 2024). Expectedly, the unemployment rate in China has kept on increasing especially since 2000.

After surpassing the growth rate of 0.9% in 2015, China's labor force growth rate decreased annually between 2013 and 2020 due to the country's population aging process. Additionally the proportion of the population in the age group of 65 and older increased from 9.7% in 2013 to 13.5% in 2020, Hsu et al. (2018). Keeping this in view encouraging high-quality economic development and quickening the shift from the demographic dividend to the talent dividend have emerged as major priorities, Zhao and Said (2023).

Table 1 depicts the economic growth and employment growth performance of China for the period of 1980–2017. From 1980 to 2017, China's witnessed and average GDP growth rate of 7.22%; however, employment growth lagged behind significantly, averaging only1.42% during the same period. For the decade of 1980–1990, GDP grew at 5.59%, along with it; employment growth was relatively higher at 3.21%, indicating an appreciable job creation economy. However, in subsequent decades, employment growth sharply declined – from 1.06% (1991–2000) to 0.59% (2001–2010) and further to 0.28% (2011–2017). All this happened despite the GDP growth peaking at 9.94% during 2001–2010. This widening gap points to dismissive employment performance of Chinese economy, highlighting a structural shift that limits employment opportunities despite sustained economic growth.

Table 1 Employment and economic growth (averages)

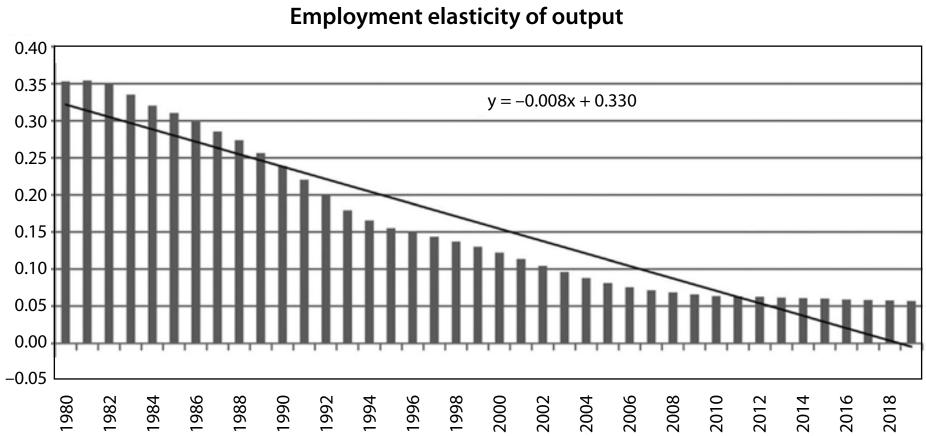
Time period	1980–1990	1991–2000	2001–2010	2011–2017	Overall (1980–2017)
GDP growth	5.59	7.04	9.94	5.57	7.22
Employment growth	3.21	1.06	0.59	0.28	1.42

Source: Authors calculations

This empirical evidence suggests a clear case of decoupling between economic growth and employment generation which poses questions regarding China's labor market performance especially in terms of employment generation. During the 1990s, China's manufacturing sector experienced a significant decline in employment elasticity with respect to output. By the late 1990s, this elasticity was estimated to be around 0.10, Zhang and Cai, (2002). Numerous studies have examined the phenomenon of "jobless growth" in Chinese manufacturing, attributing it primarily to the reform of state-owned enterprises (SOEs). These reforms led to large-scale layoffs as part of efforts to enhance efficiency and performance, Zhang and Cai (2002).

For further clarity regarding employment content of economic growth, Figure 1 depicts the evolution of employment elasticity of economic growth in China over the period 1980–2019. Employment elasticity has been estimated using time varying Kalman filter. This representation provides insights regarding employment intensiveness of economic growth at every point of time, enabling one to identify the periods with growth having higher employment content.

Figure 1 Estimated employment elasticity of economic growth (1980–2019)



Source: Authors estimations

Figure 1 represents evolution of employment elasticity of economic growth in China during the study period. The results revealed a significantly low and continuously declining employment elasticity of economic growth in China during the study period. The average elasticity during this period stayed around 0.15 which is markedly lower than globally accepted employment elasticity band of 0.3–0.5. As noted by Manning and Purnagunawan (2013), the "normal" range of employment elasticity from international comparisons is usually 0.3–0.5 for the economies experiencing 1–2 percent annual growth in labour force. This raises questions regarding the job creation capacity of China's economic growth which needs immediate attention.

In the past empirical literature Slimane (2015), estimated employment elasticity of economic growth for 90 developing countries for the period of 1991–2012, where he found employment elasticity was 0.10 for China. Also Lam et al. (2015), in IMF working Paper estimated employment elasticity for China, the authors found employment elasticity of 0.08 for the period of 1993–2013.

In the background of this puzzling issue, current study first aims to estimate employment elasticity of economic growth in China and secondly the paper seeks to explore the macroeconomic determinants of employment elasticity in China. By analyzing the structural, institutional, and policy factors that have shaped employment elasticity in China, the study aims to derive insights that can prove vital for policy makers to improve employment creation capacity of China's economic growth. To this end, we apply a time varying methodology i.e. state space Kalman filter to estimate employment elasticity keeping in view the dynamic nature of relationship between economic growth and employment. To the best of our knowledge no study on Chinese literature has applied this methodology for examining this particular issue.

The study is organized: Section 1 provides enlists review of literature, Section 2 discusses data and methodology used and Section 3 brings the results.

1 REVIEW OF LITERATURE

Economic growth and employment creation are studied under the framework of Okun's law approach and employment elasticity approach, while Okun's law associates reduction of unemployment due to economic growth, employment elasticity links increase in employment to increase in output. Employment elasticity approach shows certain advantages over Okun's law as it avoids the issues related to estimation of unemployment rate, and labor force participation rate.

Employment elasticity measures the percentage change in employment associated with a percentage change in economic growth. This approach is suitable in situations when research aims to identify the determinants of employment intensiveness of economic growth.

Inflation may increase uncertainty and costs for businesses, leading to lower investment and employment. Under conditions of uncertainty, firms find it in their interest to employment more of capital in comparison to labor in their production processes, as labor is more demanding and can raise hike in wages in line with increase in the rate of inflation.

Inflation affects employment elasticity by creating uncertainty in prices and economic activity, which in turn makes it feasible for producers to stop creating additional employment or even make them lay-off some workers (Judson and Orphanides, 1999; Ramey and Ramey, 1991; Imbs, 2007; Furceri, 2010). Inflation effects employment creation via two effects: the grease effect (Tobin, 1972), which aids adjustment to equilibrium, and the sand effect (Friedman, 1977), which causes resource misallocation, input substitution and employment declines.

Empirical literature suggests that grease effect dominates in developed countries, while developing countries experience stronger sand effects, Loboguerrero and Panizza (2003). Studies carried by (Kapsos, 2006; Bhat et al., 2022; Pattanaik and Nayak, 2014; Ghazali and Mouelhi, 2018) revealed that inflation uncertainty leads to decline in employment elasticity of economic growth. In Indian case, Pattanaik and Nayak (2014) using (Inflation WDI) as a proxy for economic uncertainty has found that inflation has a negative impact on employment elasticity of economic growth. Additionally, it has been found that macroeconomic policies that reduce macroeconomic uncertainty enhance long-term investments and employment by providing greater economic visibility (Furceri et al., 2012; Ali et al., 2017).

The studies of Bhat et al. (2022), Ben and Zmami (2021), and Victoria and Elias (2017) along with some others have attempted to examine the impact of services sector share on employment elasticity in different economies of the world. Kapsos (2005) and Furceri et al. (2012) have highlighted that employment elasticities are positively related to the share of services in the economy, indicating that countries with larger service sectors tend to have higher employment elasticity of economic growth. Padalino and Vivarelli (1997) found out that G-7 nations exhibited relatively higher employment elasticity in services sectors, which does mean the biggershare of services sector, the higher employment elasticity in the economy. Also Dopke (2001) noted that higher employment elasticity raised the importance of the role of services. Similarly, Löbbe (1998) and Mourre (2004) suggest that increased employment intensity is closely tied to the expanding role of services. Collectively, these findings underscore the service sector's capacity to enhance employment elasticity across different economies.

Regarding the impact of exchange rate, Nucci and Pozzolo (2010) have highlighted that exchange rate changes affect employment through appreciation and depreciation channels. This may happen due to a weaker currency that makes exports more competitive, potentially boosting labor-intensive industries. The findings are similar to Bhat et al. (2022) and a World Bank study (Asia, 2008), were it has been found that exchange rate appreciation lowers employment elasticity, which in other words, does mean that depreciation increases employment elasticity. In developing countries, currency depreciation does discourage imports, reducing reliance on capital-intensive imports and encouraging labor-intensive exports in sectors such as manufacturing and textiles. Campa (2005) identifies three key mechanisms: import penetration raises local market competition, potentially leading to firm closures and job losses; export orientation boosts sector-specific job growth in exporting sectors.

Depreciated currency boosts demand for labor-intensive exports and increasing employment in export-oriented sectors like manufacturing, textiles etc. Simultaneously, depreciation raises the cost of capital-intensive imports, encouraging domestic production of import-substituting goods, which can further stimulate labor demand. This dual effect shifts production toward labor-intensive activities. Additionally, depreciation reduces the competitive pressure on domestic firms by making imported goods more expensive, allowing high-cost domestic producers to survive and expand, thereby supporting job creation.

2 DATA AND METHODOLOGY

Current study uses annual time series data on the economy of China for the period of 1980–2019. Data on employment and real GDP is taken from Penn World Table 10.01, while data on trade openness, Human capital, inflation, exchange rate and services sector share are taken from word development indicators, (WDI) World Bank database. For first step i.e. estimation of employment elasticity data on employment and GDP is regarded as growth rate (% change annual). Similarly, for the second step i.e. identifying macroeconomic determinants of employment elasticity of economic growth date on all variables is scaled by converting all data in terms of annual % change. This step is done for two purposes; firstly, to interpret results in terms of elasticity and, secondly, estimated employment elasticity falls within the band of 0-1, so to bring all the variables on single scale – this procedure is adopted.

2.1 Methodology

Employment elasticity estimated using the time varying Kalman filter. The time-varying parameter model with the Kalman filter is expressed in state-space form as follows:

$$Y_t = X_t b_t + u_t \, , \tag{1}$$

$$b_t = \varnothing b_{t-1} + e_t \, , \tag{2}$$

here: Y_t denotes employment, while X_t represents the explanatory variable gross domestic product (GDP). b_t is measure of employment elasticity. u_t is the error terms with zero mean and a constant covariance. Finally, u_t, and e_t are g × 1 vectors of serially uncorrelated residuals.

The model estimated in current study is as follows:

$$ES_t = \propto_0 + \propto_1 INF_t + \propto_2 OPN_t + \propto_3 HU_t + \propto_4 EXR_t + \propto_5 SS_t + \varepsilon_t \, , \tag{3}$$

where: ES represents employment elasticity, OPN represents trade openness (imports and exports % GDP), EXR represents official exchange rate, HU represents Human capital, SS represents services sector share in GDP and lastly ϵ represents error correction term. It is important to note here that all the variables are taken in annual % change form.

ARDL specification of underlying model is as:

$$\mathrm{ES_t} = \propto_0 + \sum_{i=1}^{n} \propto_{1i} \mathrm{ES_{t-i}} + \sum_{i=0}^{o} \propto_{2i} \mathrm{INF_{t-i}} + \sum_{i=0}^{p} \propto_{3i} \mathrm{OPN_{t-i}} + \sum_{i=0}^{q} \propto_{4i} \mathrm{HU_{t-i}} + \sum_{i=0}^{r} \propto_{5i} \mathrm{EXR_{t-i}}$$

$$+ \sum_{i=0}^{s} \propto_{5i} \mathrm{SS_{t-i+\beta_1 INF_{t-1}}} + \beta_2 \mathrm{OPN_{t-1}} + \beta_3 \mathrm{HU_{t-1}} + \beta_4 \mathrm{EXR_{t-1}} + \beta_5 \mathrm{SS_{t-1}} + \epsilon_t \, . \tag{4}$$

Short run specification of Formula (4) is expressed as:

$$\Delta ES_t = \propto_0 + \sum_{i=1}^{n} \propto_{1i} ES_{t-i} + \sum_{i=0}^{O} \propto_{2i} INF_{t-i} + \sum_{i=0}^{P} \propto_{3i} OPN_{t-i} + \sum_{i=0}^{Q} \propto_{4i} HU_{t-i} + \sum_{i=0}^{r} \propto_{5i} EXR_{t-i} + \sum_{i=0}^{S} \propto_{6i} SS_{t-i} + \lambda_1 ECM_{t-1} + \epsilon_t . \quad (5)$$

In the above equations, n, o, p, q, r, s represents lag structure and ECM represents the error correction term, illustrating the rate of adjustment and remaining variables in the equation are already explained in Formula (3).

3 EMPERICAL ANALYSIS

Before any econometric analysis it is important to examine the nature of data to be used in empirical analysis. To this end, we tested for normality of data using descriptive statistics, were the Jarque-Bera statistics confirmed the normality of data. Additionally, the presence of unit root is tested using augmented dickey fuller test (ADF). The results of augmented dickey fuller test are presented in Table 2.

Table 2 Unit root results

Variable	Level	First difference	Remark
Employment elasticity	–2.22	–3.90**	I(1)
Trade openness	–1.47	–3.52**	I(1)
Human capital	–0.62	–7.22**	I(1)
Inflation	–2.93*	–6.18**	I(0)
Exchange rate	–2.22	–5.32**	I(1)
Services share	–0.35	–4.42**	I(1)

Note: * and ** represents 5% and 1% levels of significance respectively.
Source: Authors estimations

Unit root results presented in Table 2 collectively suggest that underlying variables are combination of I(0) and I(1). The results specifically revealed that inflation is stationary at level and other study variables including employment elasticity, trade openness, human capital, exchange rate and services sector share are stationary at their first difference.

3.1 Cointegration test

Keeping in view stationary nature of study variables, ARDL is found to be optimal for estimation purposes. For estimating ARDL model, first step is to test for existence of long run relationship among study variables. Bounds test is used to identify whether there exists a long run relationship or not. The results of ARDL bounds test are presented in Table 3.

Bounds test results presented in Table 3 reveal the F-statistic value of 3.64, which is higher than upper bound values at all the levels of significance. This evidence suggests that there exists a long run relationship between employment elasticity and accounted determinants during the study period.

Table 3 Pesaran et al. (2001) test for cointegration

Significance level	Lower bound I(0)	Upper bound I(1)	K
10%	1.81	2.93	
5%	2.14	3.34	5
1%	2.82	4.21	
F-value	3,6		

Source: Authors estimations

3.2 Long run and short run results

Based on the evidence provided by bounds test results, we estimated long run relationship. The results of ARDL long run and short run Cointegration are presented in Table 4.

Table 4 ARDL long run and short run results

Variables	Coefficients	Std. error	t-statistic	P-value
Panel-A: long-run				
INF	–0.79	0.16	–4.74	0.00
OPN	–0.14	0.06	–2.31	0.02
HU	3.70	3.10	1.19	0.24
EXR	0.36	0.13	2.76	0.00
SS	0.07	0.11	0.66	0.51
Panel-B: short-run				
DINF	0.16	0.05	2.94	0.00
DOPN	0.12	0.06	1.74	0.09
DHU	1.28	0.70	1.82	0.06
DEXR	0.59	0.18	3.23	0.00
DSS	0.30	0.21	1.39	0.17
ECM(-1)	–0.43	0.16	–2.71	0.01
R-square			0.94	
Adjusted R-square			0.90	
CUSUM			Stable	
Durban-Watson stat.			1.99	
Model selection criteria			Akaike info criterion (AIC)	

Source: Authors estimations

Long run results presented in Table 4 revealed that inflation had significantly negative impact on employment elasticity in the long run with relatively strong relationship coefficient of –0.79. This does mean that a 1% increase in inflation decreases employment elasticity by 0.79%. Inflation negatively affects employment elasticity by increasing uncertainty and production costs, discouraging firms from hiring more workers. Under inflationary conditions, businesses substitute labor with capital, as labor demands wage hikes in response to rising prices. This substitution lowers employment elasticity, reducing the responsiveness of employment to economic growth. The sand effect Friedman (1977) further worsens employment conditions by causing resource misallocation and inefficiencies. Empirical studies show that inflation uncertainty significantly lowers employment elasticity, especially in developing economies like India, Pattanaik and Nayak (2014). Reducing macroeconomic uncertainty through stable policies can enhance investment and employment growth, Crivelli et al. (2012).

Regarding the impact of trade openness, the results revealed a negative and significant relationship relatively weak coefficient of –0.14, meaning that a 1% increase in openness leads to decline in long run employment elasticity by 0.14%.

Openness tends to increase competition, which makes firms to go for least cost production processes. This mostly leads to substitutions of labour with capital in the process of production. Additionally, openness enables certain spillovers which push productivity up, and according to kapoos (2006) there is a trade-off between productivity increase and employment elasticity. Once productivity increases owing the process of openness, it ultimately shows a negative impact on employment elasticity.

Human capital reveals to have a positive but statistically insignificant impact on long run employment elasticity. Regarding the impact of exchange rate, the results show that currency depreciation has significantly positive impact on employment elasticity in the long run were 1% increase in currency depreciation increase employment elasticity by 0.36%.

Currency depreciation can impact employment elasticity positively by boosting exports and discouraging imports. A weaker currency makes exports more competitive, increasing demand in sectors like manufacturing and textiles, which are labor-intensive. Simultaneously, higher import costs encourage domestic production of import substitutes, creating more jobs. This shift toward labor-intensive industries raises employment elasticity, as seen in developing countries (Bhat et al., 2022; World Bank, 2008). Depreciation also reduces competitive pressure from cheaper imports, allowing domestic firms to expand and sustain employment (Campa, 2005).

Lastly, services sector share reveals to have a positive but statistically insignificant impact on employment elasticity of economic growth in China in the long run.

Short run results presented in panel-B of Table 4, suggest that inflation and openness have significantly positive impact on employment elasticity in the short run, while this impact turns negative in the long run, suggesting a non-linear impact of these two macroeconomic variables on employment elasticity of economic growth in China during the study period. Human capital has a significantly positive impact on employment elasticity in the short run. However, similar to the long run currency depreciation reveals to have positive impact in short run as well. Further increase in exchange rate (currency depreciation) has a positive impact on employment elasticity in short run. More importantly with a coefficient of –0.43, the ECM results suggest that disequilibrium is corrected at a speed of 43% per year.

The model statistics demonstrates a strong fit, with an R-squared of 0.94 and an adjusted R-squared of 0.90, indicating that 90% of the variation in the dependent variable is explained by the model after adjusting for the number of predictors. Durbin-Watson statistic of 1.99 suggests no serious autocorrelation in the residuals. Additionally, the CUSUM test confirms the stability of the model over time, supporting the reliability of the estimated long-run relationship. Lastly, the selection of the model based on the Akaike Information Criterion (AIC) further ensures optimal lag structure and model efficiency.

3.3 Diagnostic statistics

For diagnostic inspection, several statistical tests were used, such as the Breusch-Godfrey Lagrange multiplier (LM) test to verify serial correlation and the Breusch-Pagan-Godfrey (BG) test to confirm for heteroscedasticity. Ramsey RESET Test examines model specification and Jarque-Bera tests for normality. These tests are used to check for the assumptions of the model and to ensure the validity of the results. Table 5 displays the outcomes of the diagnostic tests.

Table 5 Diagnostic tests

	Obs. *R-squared	Test-statistic	P-value
Breusch-Godfrey serial Correlation LM test	3.25	1.06	0.19
Breusch-Pegan-Godfrey heterokedasticity test	10.45	0.69	0.65
Ramsey RESET test		0.62	0.54
Jarque-Bera		2.17	0.33

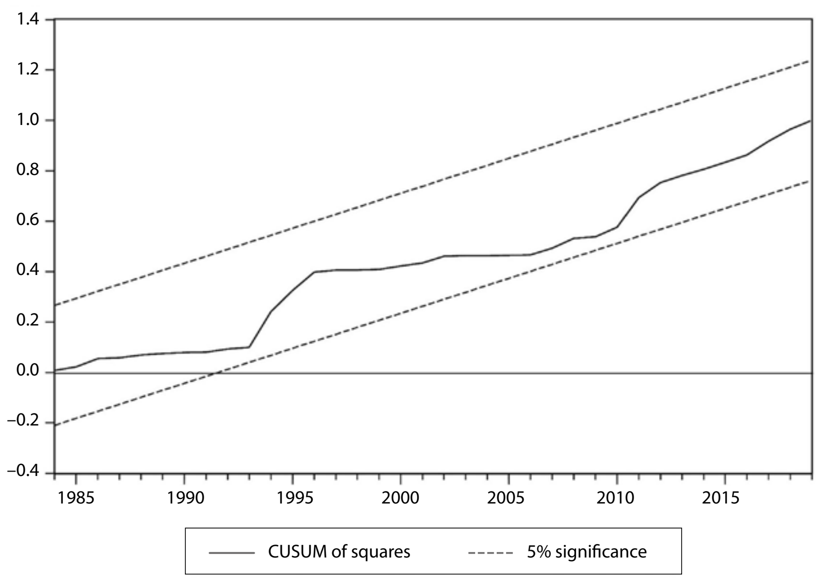
Source: Authors estimations

The Breusch-Godfrey test with (p-value 0.19) indicates no significant serial correlation in the residuals. The Breusch-Pagan-Godfrey test with (p-values 0.65) suggests that there is not any presence of heteroskedasticity in the model. Further, Ramsey RESET test (p-value: 0.54) does not indicate model misspecification. Lastly, the Jarque-Bera test with (p-value 0.33) suggests that residuals are normally distributed. Overall, the model appears to be well-specified, with no major econometric issues.

3.4 Parameter stability test

In order to examine parameter stability we used the CUSUM square test. Figure 2 represents the results of this step. There is a rule of thumb, if the blue line stays inside the red lines, one can conclude that parameters in estimated model are stable. Red lines represent 5% level of significance. The results of CUSUM square for the present study suggests that estimated model parameters are stable across the study period.

Figure 2 CUSUM Square



Source: Authors estimations

3.5 Robustness check

Further, in order to test for the robustness of the ARDL results we have applied the Dynamic Least Square (DOLS). The results of this econometric exercise are presented in Table 6.

Table 6 Dynamic Least Square (DOLS) (robustness check)

Variables	Coefficients	Std. error	t-statistic	P-value
INF	–0.31	0.11	–2.71	0.01
OPN	–0.24	0.05	–4.77	0.00
HU	3.46	0.71	4.87	0.00
EXR	0.12	0.05	2.40	0.03
SS				
R-square			0.94	
Adjusted R-square			0.88	

Source: Authors estimations

The results presented in Table 6 reveal that the DOLS estimates are consistent with the findings of the ARDL model in terms of direction of coefficients along with level of significance. These findings add to the reliability of our results, confirming the stability of the long-run relationship between the variables. This consistency across methodologies strengthens the overall validity of our empirical. Lastly, the convergence in results also implies that policy inferences drawn from the model are grounded in stable long-run dynamics, making them more dependable for real-world application.

CONCLUION AND POLICY IMPLICATIONS

China has witnessed a tremendous growth in the recent decades making it one of the fastest growing economies of the world. This remarkable economic performance has been characterized by rapid industrialization, technological advancement, and urbanization. However, there are concerns regarding employment performance of these growth achievements. Employment growth has shown a continuous decline from being around 2% for the period of 1980–2000 to just 0.43 during 2000–2017. In the background of this dismissive employment performance, current study attempts to examine this issue. We have used a tow step approach, first we estimated employment elasticity of economic growth using a time varying methodology, and, secondly, we have used estimated employment elasticity as dependent variable, in order to identify macroeconomic variables which are having impact on it.

The findings of the study revealed that China's economic growth has been least employment intensive with employment elasticity of just 0.15, which is lower than globally acceptable medium, range of 0.3–0.5. Regarding macroeconomic determinants of employment elasticity, we found that inflation and trade openness had significantly negative impact on China's employment elasticity while currency depreciation has a positive impact on employment elasticity of economic growth in China during the study period.

Keeping in view the findings of the study, it is advised that policymakers should focus on stabilizing inflation through prudent monetary policies to be able to boost job creation in the economy. While trade openness enhances efficiency, consumer welfare, and overall economic growth, its adverse effect on employment elasticity underscores that trade is not universally advantageous when viewed through the lens of inclusive and job-rich development. Strategic trade policies, such as targeted tariffs or incentives for domestic industries, can help mitigate the adverse effects of openness on job creation. Additionally, balancing capital-intensive investments with labor-driven growth by promoting labor-intensive industries and incentivizing employment-generating sectors is crucial. Lastly, leveraging currency depreciation to enhance the competitiveness of labor-intensive exports can further stimulate job creation and improve employment elasticity in China.

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The Impact of Military Spending on Sustainable Development: a Bayesian Analysis for BRICS Countries

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Abstract

This study provides evidence that military expenditure hinders sustainable development within the BRICS nations. Analyzing data from 2000 to 2022 using a Bayesian regression methodology for panel data, the results reveal that increased military spending negatively impacts sustainability in these emerging economies. Policymakers are urged to prioritize sustainable initiatives over expanding military spending to promote a long-term growth and stability. The effects of military spending on sustainable development vary depending on measurement metrics, such as military spending per capita or as a percentage of GDP. Additionally, it is found that international commerce and foreign direct investment (FDI) are vital for advancing sustainable development, while factors like corruption and energy consumption reduce sustainable development levels. The effect of economic growth on sustainable development remains ambiguous. The findings strongly indicate that military expenditure has a detrimental effect on the progress of BRICS countries toward achieving the Sustainable Development Goals (SDGs).

Keywords	***DOI***	***JEL code***
Bayesian regression, BRICS, military spending, sustainable development	*https://doi.org/10.54694/stat.2025.21*	*C11, H56, Q56*

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INTRODUCTION

Sustainable development is not merely an economic indicator; it is the indispensable foundation for a thriving future. It demands a profound understanding of our present consumption, compelling us to harmonise economic advancement, social equity, environmental conservation, and resource preservation for generations to come (Nguyen et al., 2025). This is not an option, but an imperative for our collective survival and prosperity (Dembicka-Niemie, Buczyński and Mołodowicz, 2023). The imperative of sustainable development has transcended a mere academic discourse, emerging as a critical economic variable demanding the urgent attention of policymakers and economic analysts alike. Its profound impact on long-term development achievements, spanning generations, necessitates immediate and decisive action. The United Nations, recognizing this global exigency, established 17 Sustainable Development Goals (SDGs) in 2015. These goals are not merely aspirational; they are a comprehensive blueprint for confronting and overcoming the most pressing global challenges of our time, including the eradication of poverty, reduction of inequality, creation of employment opportunities, reversal of biodiversity loss, and improvement of public health outcomes. Failure to prioritize and vigorously pursue these SDGs will undoubtedly lead to dire consequences for our planet and its inhabitants (Chasek et al., 2016). Consequently, over the past decade, achieving the SDGs has become a prominent objective on the agenda of most governments and international organizations. However, achieving this goal has proven to be very challenging, particularly in the context of increasing warfare, armed conflicts, and geopolitical tensions (Jiang et al., 2023), along with the growing trend of nations to increase their military spending. Military spending touches on the funds allocated to a nation's defence budget (Akusta, 2024). Elevated military investment is not merely a defensive measure; it is a proactive strategy for national prosperity. By fortifying security and guaranteeing peace, a nation cultivates an environment ripe for robust investment, thereby igniting and sustaining powerful economic growth (Atesoglu, 2009; Uddin and Shafiq, 2023).

In today's societies, the military stands as an indispensable pillar, wielding cutting-edge weaponry forged by advanced manufacturing powerhouses and supported by vast infrastructures crucial for safeguarding national defence (Asongu and Ndour, 2023). These entities not only focus on the development of cutting-edge technology but also play an absolutely critical role in shaping geopolitical dynamics and ensuring security on a global scale. The Stockholm International Peace Research Institute (SIPRI) reported that global military expenditure attained a historic peak of \$2.4 trillion USD in 2023 (SIPRI, 2024), and this upward trajectory is seen as an escalating challenge for governments in their pursuit of the SDGs. Scarce resources directly constrain governmental expenditures, including critical areas like military spending, thereby severely compromising the quality of budget allocations for the SDGs and, as a direct consequence, undermining the capacity to achieve these vital objectives. Perlo-Freeman (2016) posits that the influence of military spending on the SDGs is significant, suggesting that reallocating slightly under half of global annual military expenditures would suffice to achieve the majority of the SDGs. Consequently, governments are compelled to strike a critical balance between safeguarding national security through robust military expenditure and vigorously pursuing solutions to attain the SDGs.

Numerous empirical studies have explored the factors influencing sustainable development, aiming to identify pathways for improvement. This research endeavours to critically examine the profound influence of military spending on sustainable development within a sample of five pivotal BRICS nations (Brazil, Russian Federation, India, China, and South Africa), highlighting its crucial implications. BRICS constitutes one of the most significant economic coalitions globally, representing about a quarter of the world's GDP and 42% of the global population (Duong et al., 2021; Nguyen and Duong, 2021; Nguyen et al., 2025; UNCTAD, 2023). BRICS has increased its economic influence over the past decades, acting as a driver of growth, trade, and global investment. This paper examines this topic as Sustainable Development Goal 16 (SDG 16) – encompassing peace, justice, and robust institutions – is deemed essential for the achievement of other goals (Thorp, 2022). This paper spotlights the BRICS nations because their immense budget allocations for weapons, ammunition, and military-industrial advancement are not just substantial – they are a critical anomaly. While global military expenditure has thankfully declined due to the undeniable benefits of peace, the BRICS nations stubbornly funnel a disproportionate share of their central government budgets into military sectors and enterprises, a trend that demands urgent scrutiny. The five BRICS countries accounted for 21.56% of total global military spending in 2023 (SIPRI, 2024), and the amount allocated for investment in the military sector in the BRICS countries has increased significantly compared to other blocs and regional groups (Oladotun et al., 2019). There are eleven countries in the BRICS right now: Brazil, China, India, Russia, and South Africa were the original five members, and Egypt, Ethiopia, Indonesia, Iran, Saudi Arabia, and the United Arab Emirates joined in 2024–25. Brazil, Russia, India, and China formed the group in 2006. South Africa joined in 2011, and the new additions that started in 2024 came from the Johannesburg Declaration, which was made in August 2023 (BRICS Brasil, 2025). The expansion of new members into the group (BRICS+) implies that the world is fragmenting into opposing blocs, and geopolitical competition is intensifying (Patrick, 2024). A second, even more compelling reason is that BRICS leaders have not merely pledged, but have consistently demonstrated an unwavering commitment in summit statements to actively enhance collaboration to foster peace, establish a truly representative international order, fundamentally reform and significantly improve the multilateral system, vigorously promote sustainable development, and ensure genuinely equitable growth for all. These five influential countries possess a unique opportunity to leverage the BRICS summit as a powerful platform to not only reflect but actively champion the SDG agenda with other nations, especially given that all BRICS summits are strategically hosted in one of the five BRICS nations, with the host nation extending crucial invitations to other key regional leaders, thereby amplifying their collective impact. Such events can be used to rally regional support for the implementation of the SDGs (Papa, 2017). The internal struggle among BRICS nations renders this empirical inquiry not merely intriguing but critically imperative to examine. The undeniable conflict between India and China, while acknowledged, belies the profound truth that these nations, as the fastest-growing global powers, possess a collaborative potential that could irrevocably reshape the political landscape. Their ability to transcend internal friction and forge a unified front is not just a matter of economic growth, but a pivotal determinant of future global power dynamics.

Building upon the compelling arguments presented, this groundbreaking research meticulously investigates the profound impact of military spending on sustainable development. Employing sophisticated Bayesian regression models and leveraging comprehensive annual data from the five BRICS nations spanning 2000 to 2022, our findings unequivocally demonstrate a detrimental effect of military expenditure on sustainable development. This work significantly enriches the existing literature in three crucial ways. Firstly, to our knowledge, this is the inaugural empirical research to rigorously examine the influence of military spending on the level of sustainable development, specifically within the BRICS nations. We decisively address this critical gap by providing a robust empirical evidence illuminating the intricate correlation between military spending and sustainable development in these pivotal economies. Secondly, our analysis offers an unparalleled, holistic perspective, meticulously encompassing the economic, social, and environmental dimensions of military spending's impact on sustainable development. This paper delivers an exhaustive and nuanced analysis of military expenditure's far-reaching consequences. Thirdly, by pioneering the application of the Bayesian linear regression technique for panel data, this paper delivers results that are demonstrably more robust and inherently reliable than those yielded by conventional frequentist regression techniques, thereby setting a new standard for methodological rigour in this field.

The subsequent sections of the paper are organized as follows: Section 1 offers a review of the literature about the correlation between military expenditure and sustainable development; Section 2 delineates the model and research methods; Section 3 articulates the findings; and last Section provides the conclusion.

1 LITERATURE REVIEW ON THE RELATIONSHIP BETWEEN MILITARY SPENDING AND SUSTAINABLE DEVELOPMENT

Sustainable development is a complex notion defined as progress that fulfils existing demands without hindering the next generations' capacity to meet their own needs (WCED, 1987). It is widely recognized that sustainable development encompasses three main components: economic, social, and environmental pillars (Dembicka-Niemie et al., 2023). These components are absolutely vital for rigorously evaluating and measuring progress and sustainability in a country's development process. The SDGs, unequivocally established by the United Nations in 2015, are universally recognized and comprise 17 primary objectives and 169 subsidiary targets, forming an indispensable framework. Simultaneously, the SDG indicators powerfully illuminate diverse facets of economic, social, and environmental concerns. The SDGs include a series of interconnected, urgent plans for nations and regions worldwide, aimed at achieving sustainable development by 2030 – a critical deadline. These objectives are the essential successors of the Millennium Development Goals (MDGs), a collection of international development targets established in 2000, building upon their legacy with renewed ambition and scope. The SDGs aim to perpetuate the agenda established by the MDGs (Akusta, 2024).

Military spending, a portion of public funds, has an impact on national economies and global stability, making the study of military expenditure not merely important but essential for both general economics and the specialized field of defence economics. Ganesh (2017) argues that it is difficult to define military spending because its composition varies across countries and organizations. Moreover, governments wield the power to define military spending according to their own strategic imperatives and national aspirations. Simply put, military spending represents the critical investment a country makes to fortify and sustain its armed forces, ensuring robust defence capabilities and safeguarding national interests. This includes the salaries of military personnel, the purchase of weapons and ammunition, research and development (R&D) activities, military operations, and maintenance costs (Akusta, 2024; Ganesh, 2017).

The undeniable influence of military spending on sustainable development is powerfully illuminated by the Peace Economics Theory. This compelling theory unequivocally asserts that robust economic interconnectedness not only fosters peace but also actively mitigates violence. The profound truth is that economic interdependence is a cornerstone of peace, as collaborative efforts among private entities demonstrably yield significant national economic advantages, paving the way for a more sustainable and prosperous future (Bijaoui, 2014). Increasing military spending is not only destructive and inefficient, but it also diverts crucial resources from peaceful and productive endeavours. Empirical evidence overwhelmingly demonstrates the detrimental impact of military expenditure across economic, social, and environmental spheres. Economically, elevated military spending leads to a severe misallocation of resources, actively hindering sustainable growth. While it may temporarily boost aggregate demand by replacing a non-defence governmental expenditure, this surge is fleeting and fails to translate into long-term economic prosperity. Instead, the redirection of resources towards the military industry stifles innovation and limits productivity growth, ultimately impeding overall economic advancement (Arshad et al., 2017; Saeed, 2025). Previous research has shown diverse findings regarding the influence of military expenditure on health, education, inequality, and overall social welfare. Previous research has unequivocally demonstrated diverse and often detrimental findings regarding the influence of military expenditure on health, education, inequality, and overall social welfare, demanding immediate and critical re-evaluation. For example, Lin et al. (2015) show a positive trade-off between military expenditure and two categories of social welfare spending (i.e., spending on education and health) in the OECD nations. Lin et al. (2015) propose that one reason for this phenomenon may be that the OECD countries allocate greater resources to social welfare programs; hence, when military expenditure rises (e.g., military personnel and conscripts), the government may concurrently augment spending on health and education. Töngür and Elveren (2015) demonstrate a positive correlation between income inequality and the proportion of military expenditure in central government budgets, indicating that the frequency of terrorist incidents significantly affects both military expenditure and inequality across a sample of 37 nations. Military activities, along with the weapons and ammunition used in these operations, contribute to environmental pollution and deplete natural resources (Asongu and Ndour, 2023; Mahmood, 2024; Tarczyński et al., 2023). According to Asongu and Ndour (2023), military spending contributes directly to environmental deterioration through increased carbon emissions. Elgin et al. (2022) analysed a sample of 160 nations from 1950 to 2018 to investigate the correlation between military expenditure and economic indicators, encompassing health, education, environmental factors, and social dimensions of sustainable development. The comprehensive findings indicate that military expenditure is inversely correlated with educational achievement, life expectancy, rates of infant and maternal mortality, gender equality, women's labour force participation, and access to potable water, electricity, and sanitary facilities. It is positively correlated with mortality and levels of poverty, as well as air pollution. The comprehensive findings clearly demonstrate that military expenditure is not merely inversely correlated with crucial societal indicators, but actively undermines them. It directly erodes educational achievement, diminishes life expectancy, tragically inflates rates of infant and maternal mortality, stifles gender equality, restricts women's labour force participation, and severely limits access to potable water, electricity, and sanitary facilities. Conversely, it is a direct catalyst for increased mortality, exacerbated levels of poverty, and intensified air pollution. This is not a mere correlation; it is a devastating causal link that demands immediate re-evaluation of priorities. Furthermore, Elgin et al. (2022) findings indicate a stronger (weaker) relationship between military spending and stronger (weaker) development indices in less (more) developed nations. When examining the impact of military expenditure on the level of sustainable development for military organizations specifically, the North Atlantic Treaty Organization (NATO), Akusta (2024) used annual data from 1995 to 2019 and found that military spending has a negative impact on sustainable development in 26 NATO countries. The analysis of military expenditure's effect on sustainable development in individual NATO nations reveals that such spending significantly influences sustainable development in 20 countries (79.9%). In 13 out of 20 nations (65%), the detrimental effect of military spending on sustainable development was substantiated. The analysis of military expenditure's effect on sustainable development in individual NATO nations reveals that such spending significantly influences sustainable development in 20 countries (79.9%). In 13 out of 20 nations (65%), the detrimental effect of military spending on sustainable development was substantiated, underscoring a critical need for re-evaluation and policy shifts to prioritize sustainable growth over military expansion.

In summary, the evidence from past research unequivocally demonstrates that the defence expenditures – sustainable development relationship is intricate and subtle. In some cases, the destructive impact of defence expenditures is quite considerable, but in other cases, defence expenditures have other implications when interacted with the variables of the economy or the variables of the defence's strategy. These compelling findings underscore the critical requirement of rigorously evaluating the defence policies and defence expenditures' probable impacts upon sustainable development.

2 MODEL AND RESEARCH METHODOLOGY

2.1 Model and dataset

The framework for examining the influence of military spending on the level of sustainable development is structured as follows:

$$SDI_{i,t} = \beta_0 + \beta_1 ME_{i,t} + \gamma X_{i,t} + \alpha_i + \varepsilon_{i,t}, \tag{1}$$

where i represents a country and t represents the year. The SDI signifies the sustainable development indicator, used as the dependent variable. SDI measures the capacity to meet present and future needs. Specifically, the SDI is developed from the human development index (HDI), incorporating environmental aspects to gauge sustainable development based on a balance of economic, social, and environmental progress (Hickel, 2020). This indicator was used by Akusta (2024) when analysing the impact of military spending on the level of sustainable development in NATO nations. ME represents military spending and is measured by two indicators: military spending per capita (MEpc) and military expenditure as a percentage of GDP (MEgdp). Military expenditure per capita and as a percentage of GDP are two distinct ways to measure a country's military spending, each offering a different perspective. Military expenditure per capita reflects the average amount spent on the military for each person in a country. This metric divides the total military expenditure of a country by its population, providing a per-person cost. It reflects the individual financial burden of military spending. This metric reveals the individual financial burden of military spending on each citizen. A high per capita expenditure might suggest a significant commitment to defence. In contrast, military expenditure as a percentage of GDP indicates the proportion of a nation's economic output that is allocated to its military. It's a useful indicator of the relative economic burden of military spending (Ganesh, 2017). This measure reflects the relative economic effort a country is putting into its military. A higher percentage indicates a greater portion of the nation's resources being dedicated to defence, potentially impacting other sectors. The computed coefficient β_1 quantifies the effect of military spending on the sustainable development index. X denotes supplementary control variables incorporated in the analysis, while γ signifies the regression coefficients associated with these variables. Regarding the control variables, we considered a broad set of control variables commonly used in the sustainability literature (Akusta, 2024; Khan and Farooq, 2019; Sheikh et al., 2021). These control variables include: international trade (Trade), foreign direct investment (FDI), corruption (CORRP), energy consumption (PEC), and economic growth (GDPgr). α_i represents the individual country fixed effects, and ε_{it} represents the random error term.

This study gathers annual data from 2000 to 2022 for the five BRICS countries. The SDI data are sourced from Hickel (2020), military spending data from the SIPRI, corruption data from Standaert (2015), PEC data from the US Energy Information Administration (IEA), and all remaining data are from the World Bank's World Development Indicators (WDI). The study period is determined by the availability of data, specifically the SDI data. In this study, the MEpc and PEC data are transformed using the natural logarithm to reduce skewness and minimize heteroscedasticity. The notation "Ln" is applied before the variables in indicating the use of this transformation.

115 observations make up the final sample. A more precise breakdown of the measurement as well as the variables' sources in the model is indicated in the ensuing Table 1.

Table 1 Definitions and data sources of variables

Variable	Symbol	Measurement	Source
Dependent variable			
Sustainable development	SDI	Sustainable development index (values range from 0 to 1, higher values indicate greater sustainability)	Hickel (2020)
Independent variables			
Military expenditure	MEpc	Military expenditure per capita (USD)	SIPRI
Military expenditure	MEgdp	Military expenditure as % of GDP	SIPRI

Table 1 (continuation)

Variable	Symbol	Measurement	Source
Control variables			
International trade	Trade	Total value of goods and service exports and imports as % of GDP	WDI
Foreign direct investment	FDI	Net FDI inflows as % of GDP	WDI
Corruption	CORRP	Bayesian corruption index (values range from 0 to 100, higher values indicate higher corruption)	Standaert (2015)
Energy consumption	PEC	Primary energy consumption per capita (kilowatt-hours)	EIA
Economic growth	GDPgr	Annual percentage growth of GDP (%)	WDI

Source: Own calculation

2.2 Regression strategy

This study employs Bayesian linear regression in analysing the effect of defence expenditures on sustainable development since Bayesian regression is less likely to encounter convergence problems when using limited sample sizes (Kruschke and Liddell, 2018) This is applicable since the sample size of the present paper is limited at 115 observations per year. Bayesian models can also be applied with the use of the preexisting knowledge about the relationship between predictor variables and the outcome variables (Gelman and Hill, 2006; Kruschke and Liddell, 2018). Bayesian models also measure the uncertainty level after considering the input of the data as well as the preexisting set's knowledge.

Bayesian linear regression employs Bayes' theorem in updating our beliefs about model parameters from the use of the observed data (Bayes, 1763). Bayesian linear regression is tasked with finding the posterior distribution of the model parameters as compared to finding a single "optimum" value for the model parameters. Bayesian linear regression's posterior model parameters depend entirely upon the input as well as the output as seen from the equation:

$$p(\theta|\text{data}) = \frac{p(\text{data}|\theta)p(\theta)}{p(\text{data})}, \tag{2}$$

where θ denotes a set of parameters, $p(\theta|data)$ represents the posterior distribution of the parameters, $p(\theta)$ is the prior distribution of the parameters, $p(data|\theta)$ is the likelihood function, and $p(data)$ is the marginal likelihood of the data, which can be treated as a constant; therefore, it can be omitted from Formula (2). Consequently, Formula (2) can be rewritten as follows:

$$p(\theta|\text{data}) \propto p(\text{data}|\theta)p(\theta). \tag{3}$$

Prior information be incorporated into the likelihood to derive the Bayesian posterior distribution. To conduct Bayesian regression, this study uses an uninformative prior, following the work of Nguyen and Duong (2021), Nguyen et al. (2025), and Duong et al. (2021). The reason for using uninformative priors is that we avoid the appearance of subjectivity. Non-informative priors are essential in Bayesian statistics, signifying negligible prior knowledge regarding parameters. Their objective is to allow facts to govern posterior distributions, in accordance with unbiased inference goals. These priors seek to eliminate the incorporation of subjective judgments or biases into analysis (Banner et al., 2020; Wesner and Pomeranz, 2021). The likelihood function is assumed to be derived from Formula (1). The Markov Chain Monte Carlo (MCMC) technique and the Gibbs sampling algorithm are employed to generate the posterior distribution. The levels of evidence for the impact of military spending on sustainable development depend on the posterior probability of each mean parameter, as proposed by Raftery (1995).

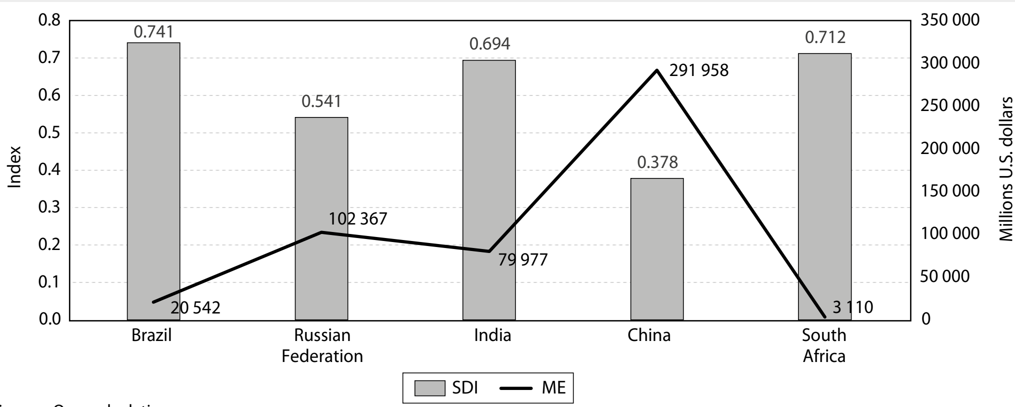
3 RESEARCH RESULTS

3.1 Descriptive statistics

Figure 1 vividly illustrates the stark disparities in military expenditure (ME) and their profound implications for sustainable development within the BRICS nations. The 2022 data, representing the culmination of the study period, reveals a critical juncture. South Africa, with its remarkably modest military spending of just over 3 billion USD, stands in stark contrast to its BRICS counterparts. Brazil's expenditure, at approximately 20.5 billion USD, pales in comparison to India's nearly 80 billion USD. Russia's staggering outlay of over 102 billion USD is dwarfed only by China's colossal military spending, approaching 292 billion USD – an astonishing 2.9 times greater than Russia's and an almost unfathomable 97 times greater than South Africa's. It is a sobering reality that three BRICS members – China, Russia, and India – were among the top five global military spenders in 2022, diverting immense resources that could otherwise fuel sustainable progress. When examining military spending as a percentage of GDP, Russia's alarming 4.69% (a direct consequence of the Russia-Ukraine conflict) underscores the devastating economic toll of militarization. India's 2.36%, China's 1.62%, and Brazil's 1.07% further highlight this trend, with South Africa's commendable 0.77% serving as a beacon of fiscal prudence. These figures are not mere statistics; they represent a critical choice between investing in instruments of war and fostering a future of sustainable prosperity for all.

The SDI unequivocally highlights the critical importance of sustainability in developmental processes, serving as a powerful metric for a nation's commitment to a healthy environment, elevated living standards, and equitable educational opportunities for future generations. Brazil (0.741) and South Africa (0.712) stand out with the highest scores for the Sustainable Development Index, demonstrating their remarkable success in environmentally sustainable investments, energy savings, and maintaining robust educational standards. In stark contrast, India (0.694) and Russia (0.541) exhibit only a mediocre level of sustainable development, underscoring the urgent need for improvement. Most concerning is China, with a dismal 0.378, indicating the lowest levels of sustainable development and revealing a profound deficit in achieving essential advancements in environmental management, health, and education. This data compels us to recognize that sustainable development is not merely an aspiration, but a fundamental imperative for global well-being and future prosperity.

Figure 1 Military spending and sustainable development in BRICS countries for 2022



Source: Own calculation

Figure 1 shows an inverse relationship between military expenditure and sustainable development in BRICS nations. Brazil and South Africa, for example, achieve high SDI values with moderate military spending, powerfully illustrating how prioritizing education, health, and environmental sustainability over excessive defence spending maximizes national development. Conversely, Russia and China's high military expenditure coupled with low SDI values starkly reveals the detrimental impact of diverting crucial economic resources to military endeavours, neglecting vital investments in environmental management and social services.

Table 2 Descriptive statistics of the variables

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
SDI	115	0.6622	0.0827	0.3780	0.7620
LnMEpc	115	4.4434	0.9446	2.5974	6.5616
MEgdp	115	2.1637	1.0253	0.7678	5.4251
Trade	115	44.4182	11.7438	22.1060	68.0939
FDI	115	2.3080	1.4421	–1.7564	9.6603
CORRP	115	52.5935	5.2309	42.7773	62.5274
LnPEC	115	9.8310	0.8055	8.1511	10.9963
GDPgr	115	4.4968	3.9405	-7.8000	14.2309

Source: Own calculation

Table 2 compellingly reveals that sustainable development (SDI) in the BRICS nations, while moderate with a mean of 0.6622, still presents significant room for growth, ranging from a concerning low of 0.3780 to a promising high of 0.7620. This average level underscores the urgent need for enhanced strategies to elevate sustainable practices across the board. Simultaneously, the substantial military spending, averaging 4.4434 for LnMEpc (approximately 135 USD per capita) and consuming an average of 2.16% of GDP (with a striking range of 0.7% to 5.43%), highlights a critical allocation of resources that could potentially be redirected towards bolstering sustainable development initiatives. The descriptive data on control variables further enriches this picture, offering crucial insights for strategic interventions.

3.2 Regression results

Table 3 compellingly showcases the results of our Bayesian regression model from Formula (1), providing crucial insights into the mean and posterior probability of the parameters. Furthermore, Table 3 offers essential information for a thorough MCMC diagnosis. This study rigorously employs two distinct military spending variables: military spending per capita (Column 1) and military spending as a percentage of GDP (Column 2), ensuring a comprehensive and robust analysis.

The posterior distributions of the parameters are generated using the MCMC technique in Bayesian estimation, as outlined in the regression strategy section. Kruschke (2015) underscores that researchers must prioritize representativeness (convergence) and stability (accuracy) when employing the MCMC approach to produce the posterior distribution. Before analysing the experimental effect of military spending on the level of sustainable development, MCMC diagnostics are rigorously conducted. This study employs the Rc statistic to definitively test convergence and sampling efficiency to robustly ensure stability, thereby strengthening the reliability of our findings. The results from Table 3 reveal that the highest values of the Rc statistic are 1.1150 and 1.1670 (both less than 1.2), which means that the model parameters have converged (Brooks and Gelman, 1998). Simultaneously, the average sampling efficiency varies from 11.30% to 11.75% (greater than 1%); therefore, the Bayesian estimates demonstrate sufficient accuracy.

Table 3 Bayesian regression results

Independent variables	Column (1)		Column (2)	
	Mean	Posterior probability	Mean	Posterior probability
LnMEpc	–0.0171 (–0.0499; 0.0155)	0.8468**		
MEgdp			–0.6108 (–3.9955; 2.7640)	0.6443**
Trade	0.0040 (0.0024; 0.0056)	0.9999*	0.0 43 (0.0028; 0.0058)	1.0000*
FDI	0.0054 (–0.0015; 0.0124)	0.9377*	0.0043 (–0.0025; 0.0112)	0.8951*
CORRP	–0.0095 (–0.0137; –0.0053)	1.0000**	–0.0095 (–0.0134; –0.0052)	1.0000**
LnPEC	–0.1289 (–0.2249; –0.0278)	0.9968**	–0.1699 (–0.2322; –0.0918)	1.0000**
GDPgr	–0.0001 (–0.0034; 0.0032)	0.5079**	0.0001 (–0.0032; 0.0034)	0.5328*
_cons	2.3605 (1.3014; 3.3343)	1.0000*	2.9698 (1.6933; 4.0436)	1.0000*
σ_i	0.0657		0.4412	
$\varepsilon_{i,t}$	0.0017		0.0017	
Number of observations	115		115	
Number of countries	5		5	
MCMC diagnostics				
Average sampling efficiency	0.1130		0.1175	
Maximum Rc value	1.1150		1.1670	

Notes: The dependent variable is SDI; ME in column (1) is measured by LnMEpc; ME in column (2) is measured by MEgdp; a Bayesian 95% credible interval in brackets. * The probability that the mean coefficient is positive. ** The probability that the mean coefficient is negative.
Source: Own calculation

Next, this study investigates the influence of military expenditure on the level of sustainable development. Specifically, the results in Column 1 show that the mean of the LnMEpc variable is –0.0171, with a probability of 84.68% that this parameter negatively affects sustainable development (SDI). Therefore, it is concluded that military spending (measured by military expenditure per capita) exerts a moderate and adverse impact on sustainable development. In Column 2, the mean of the MEgdp variable is –0.6108, with a probability of 64.43% that this parameter harms sustainable development (SDI). Therefore, it has been concluded that military spending (measured as a percentage of GDP) had a weak negative effect on sustainable development. In general, the experimental results of this paper suggest that the greater the military spending, the less likely there will be sustainable development. The impact of military spending on sustainable development is weak or moderate, depending on how military spending is measured. There is a difference in the impact of the two measures of military spending on sustainable development in the five BRICS countries that can be explained as follows. Firstly, military expenditure per capita is a significant indicator, reflecting the resources a country allocates to its military relative to its population. It offers observations about a nation's security priorities, economic capacity, and potential for military engagement. Higher per capita military spending can indicate a greater perceived threat, a strong military focus, or the ability to afford a larger military force. Conversely, the vast differences in national economies distort military expenditure as a percentage of GDP. A large, wealthy nation, for example China, spends a relatively small percentage of its GDP on defence and still commands an enormous budget in absolute terms, capable of funding advanced research, large forces, and global reach. A smaller economy, such as South Africa, may achieve only a fraction of that absolute spending, even with a higher percentage of its GDP dedicated, which limits the scale and sophistication of its capabilities. Both conflict/war and geopolitical tensions are undeniably potent catalysts for escalating military spending within BRICS nations. This expenditure, far from being a mere line item, consumes a disproportionately large share of government budgets, often at the expense of vital sectors like healthcare and education. The implications of this prioritization are profound and warrant immediate attention. This field is often among the top four in government budgetary decisions (Anifowose, 2019). Given resource scarcity, changes in government expenditure of the BRICS countries can profoundly affect the nature of budget allocation for SDGs, with dire consequences for the prospect of accomplishing these vital goals. Specifically, public expenditures such as military spending, in which increasing military spending has the potential to severely impede the path towards SDGs, because the scarcity of resources inherently limits the extent to which governments can increase resources for military purposes and also continue to adequately allocate resources for critical goals such as education, poverty, equality, and the environment. This is not merely a matter of competing priorities; it is a fundamental trade-off that demands urgent attention and strategic foresight to ensure a sustainable and equitable future. Military activities are associated with the use of fossil fuels, which are the main sources of greenhouse gas emissions (Bargaoui and Nouri, 2017). Additionally, Jorgenson et al. (2010) argue that the production and maintenance of military equipment, construction and maintenance of military infrastructure, and defence R&D activities also increase emissions. Military activities degrade ecosystems because they use a large amount of natural resources and pollute them through the use of toxic and radioactive substances (Singer and Keating, 1999). Additionally, military spending impacts the environment by increasing the mobility of military personnel and large military hardware, both of which require high energy consumption (Clark et al. 2010). Similarly, military experiments, training, and exercises use large amounts of fuel, such as on ships, missiles, and aircraft. Such activities increase the amount of pollutant emissions into the atmosphere (Asongu and Ndour, 2023; Jorgenson et al., 2010). Thus, the literature unequivocally agrees that the opportunity cost of military spending serves as a critical and undeniable causal factor contributing to the severe and detrimental adverse effects of military spending on national sustainability. Our findings corroborate the Peace Economics Theory and the research of Akusta (2024) and Elgin et al. (2022), which emphasize the substantial adverse effect of military expenditure on sustainable development.

Regarding the control variables, our results unequivocally demonstrate that international trade and FDI are powerful catalysts for sustainable development. Conversely, increased corruption and energy consumption are significant impediments, actively diminishing sustainable development. Moreover, while the influence of economic growth on sustainable development presents a nuanced picture, the impact of trade is crystal clear. With mean coefficient estimates for trade of 0.0040 in Column 1 and 0.0043 in Column 2, and an astounding probability of 99.99 to 100% for a positive impact, it is undeniable that a rise in international trade is a direct pathway to enhanced sustainable development. Our findings contradict those of Sheikh et al. (2021), yet align with the conclusions of Khan and Farooq (2019), who reached analogous results. worldwide commerce enhances employment, elevates living standards, boosts domestic and worldwide demand, expands production, and facilitates technological adaptation. Furthermore, international commerce is a powerful engine for progress, dramatically boosting both the quantity and quality of goods and services exchanged. This leads to the most efficient and effective utilization of global resources, forming the bedrock of sustainable development. The strategic expansion of trade is not merely about economic growth; it is a commitment to safeguarding our natural resources and environment, pioneering advanced conservation methods for future generations, and significantly elevating economic and social mobility across the BRICS nations. Moreover, the compelling evidence from FDI coefficients, at 0.0054 (Column 1) and 0.0043 (Column 2), reveals an overwhelming probability – ranging from 89.51% to an impressive 93.77% – of a positive and transformative impact on sustainable development. This isn't just a possibility; it's a near certainty for a brighter, more sustainable future. Therefore, a higher level of FDI tends to increase the level of sustainable development. This finding is consistent with earlier evidence, for instance, Khan and Farooq (2019), since they contend that increased FDI results in increased sustainability due to technological advancement. Third, the average coefficient of CORRP is negative with a 100% probability of the negative effect of this variable on sustainable development. The results show that corruption significantly discourages sustainable growth in the BRICS economies. This is consistent with Khan and Farooq (2019) and supports the sand in wheels hypothesis, which contends that corruption has a negative effect on economic growth due to inefficient allocation of resources and poor decisions, thereby negatively affecting socioeconomic development. The estimated coefficients of LnPEC are negative, with 99.68% (Column 1) and 100% (Column 2) probability of a negative effect on sustainable development, showing that primary energy consumption is associated with lower sustainable development. These results align with Akusta (2024). Ultimately, we observe a mixed impact of economic growth on sustainable development within the BRICS nations. Specifically, the mean coefficient of GDPgr is negative (Column 1) and positive (Column 2). In addition, the probability that the economic growth variable affects sustainable development is between 50.79% and 53.28% (indicating a weak impact), so the relationship between economic growth and sustainable development remains ambiguous.

3.3 Robustness test

To test robustness, we control for country fixed effects to eliminate all sources of constant heterogeneity at the country level and use year dummies to account for shocks that are common across our sample countries. We assess how strong our main results are by comparing them with results from Bayesian models that include year-fixed effects, country-fixed effects, and both year- and country-fixed effects.

Tables 4, 5, and 6 display the results of the robustness test. The convergence and stability diagnostics for MCMC show that the largest Rc statistic values are 1.0731 (less than 1.2) in Column 1 of Table 5 and the smallest average efficient sampling index is 23.11% (greater than 1%) in Column 1 of Table 4. Therefore, the posterior distribution has stopped at the target distribution, and the Bayesian inferences are reliable.

Table 4 presents the outcomes of the Bayesian panel regression that includes year-fixed effects for our sample. The results show that the mean parameter of the variable LnMEpc is negative and its posterior probability is 99.93% (Column 1). Therefore, the impact of military spending, measured by LnMEpc, on sustainable development is very strong. For the expenditure variable, measured by MEgdp, its mean parameter is negative and its posterior probability is 90.60% (Column 2), so there is moderate evidence of a negative impact of military spending on sustainable development.

Table 4 Bayesian regression results with year-fixed effects

Independent variables	Column (1)		Column (2)	
	Mean	Posterior probability	Mean	Posterior probability
LnMEpc	–0.1129 (–0.1739; –0.0509)	0.9993**		
MEgdp			–2.3404 (–6.0292; 1.2919)	0.9060**
Trade	0.0009 (–0.0014; 0.0032)	0.7922*	0.0043 (0.0028; 0.0058)	1.0000*
FDI	0.0094 (0.0028; 0.0159)	0.9966*	0.0079 (0.0007; 0.0151)	0.9843*
CORRP	–0.0118 (–0.0155; –0.0079)	1.0000**	–0.0107 (–0.0145; –0.0068)	1.0000**
LnPEC	–0.0753 (–0.1740; 0.0228)	0.9334**	–0.2039 (–0.2787; –0.1268)	1.0000**
GDPgr	0.0014 (–0.0033; 0.0060)	0.7460*	0.0017 (–0.0033; 0.0068)	0.7621*
_cons	1.8844 (0.4405; 3.1783)	0.9980*	2.8381 (1.7454; 3.9734)	1.0000*
Year fixed effects	Yes		Yes	
Country fixed effects	No		No	
$\varepsilon_{i,t}$	1.4841		0.2227	
σ_i	0.0012		0.0014	
Number of observations	115		115	
Number of countries	5		5	
MCMC diagnostics				
Average sampling efficiency	0.2311		0.2507	
Maximum Rc value	1.0252		1.0363	

Notes: The dependent variable is SDI; ME in column (1) is measured by LnMEpc; ME in column (2) is measured by MEgdp; a Bayesian 95% credible interval in brackets. * The probability that the mean coefficient is positive. ** The probability that the mean coefficient is negative.
Source: Own calculation

Table 5 presents the results of the Bayesian panel regression that includes country-fixed effects for the entire sample. This table shows that the mean parameter of the variable LnMEpc is negative and its posterior probability is 80.60% (Column 1), so the impact of military expenditure, measured by LnMEpc, on sustainable development is moderate. Meanwhile, the impact of the variable MEgdp on sustainable development is found to be weak because the posterior probability of the parameter MEgdp is only 69.22% (Column 2).

Table 5 Bayesian regression results with country-fixed effects

Independent variables	Column (1)		Column (2)	
	Mean	Posterior probability	Mean	Posterior probability
LnMEpc	–0.0127 (–0.0419; 0.0163)	0.8060**		
MEgdp			–0.7385 (–3.6713; 2.2642)	0.6922**
Trade	0.0041 (0.0027; 0.0055)	1.0000*	0.0043 (0.0030; 0.0055)	1.0000*
FDI	0.0049 (–0.0018; 0.0115)	0.9252*	0.0041 (–0.0024; 0.0106)	0.8950*
CORRP	–0.0103 (–0.0139; –0.0066)	1.0000**	–0.0103 (–0.0139; -0.0066)	1.0000**
LnPEC	–0.1543 (–0.2462; –0.0610)	0.9988**	–0.1864 (–0.2473; –0.1259)	1.0000**
GDPgr	0.0001 (–0.0027; 0.0029)	0.5318*	0.0002 (–0.0027; 0.0031)	0.5563*
_cons	2.7787 (1.6008; 3.9232)	1.0000*	3.2417 (1.5565; 5.1804)	1.0000*
Year fixed effects	No		No	
Country fixed effects	Yes		Yes	
$\varepsilon_{i,t}$	2.6		1.9	
σ_i	0.0		0.0	
Number of observations	115		115	
Number of countries	5		5	
MCMC diagnostics				
Average sampling efficiency	0.5		0.5	
Maximum Rc value	1.1		1.1	

Notes: The dependent variable is SDI; ME in column (1) is measured by LnMEpc; ME in column (2) is measured by MEgdp; a Bayesian 95% credible interval in brackets. * The probability that the mean coefficient is positive. ** The probability that the mean coefficient is negative.
Source: Own calculation

The regression results in Table 6, which include both year and country fixed effects, indicate that military spending, measured by LnMEpc, has a very strong effect (with a 99.99% posterior probability in Column 1). Column 2 shows that the average effect of the variable MEgdp has a 93.70% posterior probability, providing strong evidence that military spending negatively affects sustainable development.

The findings obtained by the estimate align closely with the Bayesian estimated coefficients in Table 3, but the posterior probabilities of the mean parameter of the military spending variable in Tables 4, 5, and 6 are stronger than those in Table 3. These results again confirm evidence that military spending has had a negative impact on sustainable development in the BRICS countries.

Table 6 Bayesian regression results with year-fixed and country-fixed effects

Independent variables	Column (1)		Column (2)	
	Mean	Posterior probability	Mean	Posterior probability
LnMEpc	–0.1135 (–0.1690; –0.0578)	0.9999**		
MEgdp			–2.2664 (–5.2208; 0.7354)	0.9370**
Trade	0.0009 (–0.0012; 0.0029)	0.7927*	0.0043 (0.0030; 0.0056)	1.0000*
FDI	0.0092 (0.0031; 0.0153)	0.9977*	0.0077 (0.0009; 0.0144)	0.9878*
CORRP	–0.0122 (–0.0156; –0.0087)	1.0000**	–0.0108 (–0.0145; –0.0070)	1.0000**
LnPEC	–0.0843 (–0.1737; 0.0042)	0.9693**	–0.2092 (–0.2784; –0.1394)	1.0000**
GDPgr	0.0016 (–0.0023; 0.0055)	0.7943*	0.0019 (–0.0024; 0.0062)	0.8112*
_cons	3.0036 (1.8849; 4.2497)	1.0000*	3.0253 (1.9041; 4.2608)	1.0000*
Year fixed effects	Yes		Yes	
Country fixed effects	Yes		Yes	
$\varepsilon_{i,t}$	0.9		0.5	
σ_i	0.0		0.0	
Number of observations	115		115	
Number of countries	5		5	
MCMC diagnostics				
Average sampling efficiency	0.8		0.8	
Maximum Rc value	1.1		1.0	

Notes: The dependent variable is SDI; ME in column (1) is measured by LnMEpc; ME in column (2) is measured by MEgdp; a Bayesian 95% credible interval in brackets. * The probability that the mean coefficient is positive. ** The probability that the mean coefficient is negative.
Source: Own calculation

CONCLUSION

This paper illustrates a critical inverse association: escalating military spending actively undermines sustainable development. Through rigorous Bayesian linear regression applied to extensive panel data from the BRICS nations (2000–2022), we unequivocally show that both military spending per capita and as a percentage of GDP are detrimental to sustainable progress. Our findings serve as an urgent call to action, highlighting the imperative to reallocate resources from military expenditures towards initiatives that genuinely foster sustainable development.

This research offers critical policy implications rooted in compelling empirical findings. Firstly, given the unequivocally detrimental effects of military expenditure on sustainable development, the governments of the BRICS nations should reallocate resources from the defence industry to vital sectors such as health, education, and innovation. This strategic shift is essential for fostering long-term societal well-being. Secondly, the significant positive impact of international trade and foreign direct investment on sustainable development cannot be overstated. Therefore, BRICS nations must proactively cultivate an environment that is exceptionally attractive to investors, streamlining investment procedures to maximize this beneficial influence. Moreover, by rigorously integrating environmental and social criteria, direct investment can be channelled into truly sustainable projects, thereby generating both robust economic and profound social benefits over the long term. Concurrently, a concerted effort to dramatically increase exports and imports of green trading products is crucial. Thirdly, enhancing institutional quality through the vigorous implementation of anti-corruption measures, alleviating economic burdens, and unequivocally reinforcing the rule of law is not just important, but absolutely critical, as these factors are powerful and undeniable predictors of sustainable development. Fourthly, while increasing energy demand is a pervasive trend across developed and rising economies, including the BRICS nations, our results starkly reveal that greater energy consumption will diminish sustainability. Consequently, the governments of the BRICS countries must urgently prioritize and invest heavily in the renewable energy sector. This is not merely an option, but an indispensable tool for drastically reducing CO_2 emissions and significantly boosting sustainability. Policymakers must deploy a comprehensive suite of instruments, including robust tax incentives, accessible low-interest loans, and targeted subsidies, to aggressively encourage both consumers and the private sector to accelerate their transition to renewable energy usage. Finally, it is paramount to vigorously promote economic progress to reach that pivotal turning point where additional GDP growth will unequivocally enhance the sustainable development levels of these nations.

While our findings significantly advance the current body of literature, we acknowledge certain limitations and propose compelling avenues for future exploration. To robustly validate or challenge our conclusions, we strongly advocate for an expanded analysis encompassing diverse regions and countries affiliated with various international organizations. Furthermore, a deeper understanding of the intricate dynamics between military expenditure and sustainable development levels necessitates a thorough investigation into their potential nonlinear relationship.

Finally, the relationship between military spending and sustainable development may be causal. This idea is implicit in the concept of the development-security nexus, which the United Nations reiterates in its SDGs (United Nations, 2015): "Sustainable development cannot be realized without peace and security, and peace and security will be at risk without sustainable development." Therefore, future studies may examine this causal relationship.

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APPENDIX

Table A1 Some parameters of sample data for BRICS countries (2000–2022)

ID	Country	Year	SDI	LnMEpc	MEgdp	Trade	FDI	CORRP	INF	LnPEC	GDPgr
1	Brazil	2000	0.7120	4.1667	1.7307	22.6398	5.0339	52.4032	52.5316	9.5030	4.3879
1	Brazil	2001	0.7170	4.1163	1.9519	26.9363	4.1476	52.2633	56.1249	9.4645	1.3899
1	Brazil	2002	0.7210	3.9806	1.8958	27.6184	3.2536	52.0011	60.8676	9.4744	3.0535
1	Brazil	2003	0.7250	3.8277	1.5035	28.1404	1.8134	51.7541	69.8242	9.4813	1.1408
1	Brazil	2004	0.7320	3.9693	1.4613	29.6783	2.7135	51.5362	74.4306	9.5174	5.7600
1	Brazil	2005	0.7380	4.2870	1.5240	27.0868	1.7339	51.2370	79.5437	9.5319	3.2021

Table A1											(continuation)
ID	**Country**	**Year**	**SDI**	**LnMEpc**	**MEgdp**	**Trade**	**FDI**	**CORRP**	**INF**	**LnPEC**	**GDPgr**
1	Brazil	2006	0.7400	4.4645	1.4811	26.0417	1.7531	50.9656	82.8714	9.5483	3.9620
1	Brazil	2007	0.7430	4.6764	1.4663	25.2926	3.1908	50.6406	85.8890	9.6004	6.0699
1	Brazil	2008	0.7430	4.8435	1.4419	27.2576	2.9906	50.2982	90.7663	9.6327	5.0942
1	Brazil	2009	0.7470	4.8817	1.5386	22.1060	1.8885	49.9952	95.2030	9.6161	-0.1258
1	Brazil	2010	0.7400	5.1543	1.5394	22.7722	3.7300	49.6064	100.0000	9.6941	7.5282
1	Brazil	2011	0.7330	5.2277	1.4119	23.9344	3.9152	49.4577	106.6364	9.7190	3.9744
1	Brazil	2012	0.7330	5.1355	1.3787	25.1143	3.7550	49.2084	112.3985	9.7388	1.9212
1	Brazil	2013	0.7420	5.0936	1.3294	25.7860	3.0415	48.9053	119.3721	9.7539	3.0048
1	Brazil	2014	0.7470	5.0784	1.3302	24.6854	3.5714	48.8167	126.9272	9.7710	0.5040
1	Brazil	2015	0.7490	4.7873	1.3655	26.9536	3.5921	48.6126	138.3886	9.7492	–3.5458
1	Brazil	2016	0.7590	4.7631	1.3480	24.5337	4.1374	48.3060	150.4826	9.7167	–3.2759
1	Brazil	2017	0.7600	4.9441	1.4140	24.3197	3.3383	48.1532	155.6688	9.7177	1.3229
1	Brazil	2018	0.7620	4.8984	1.4697	28.8762	4.0786	47.7374	161.3738	9.7135	1.7837
1	Brazil	2019	0.7600	4.8067	1.3828	28.8903	3.6927	46.6364	167.3979	9.7221	1.2208
1	Brazil	2020	0.7500	4.5206	1.3267	32.3021	2.5926	45.1783	172.7743	9.6754	–3.2768
1	Brazil	2021	0.7470	4.4945	1.1637	37.6563	2.7798	45.4104	187.1174	9.7208	4.7626
1	Brazil	2022	0.7410	4.5581	1.0698	38.8161	3.8222	45.7417	204.4821	9.7604	3.0167
2	Russia	2000	0.7470	4.1406	3.3070	68.0939	1.0312	60.5855	30.7596	10.8022	10.0001
2	Russia	2001	0.7520	4.3807	3.5463	61.1109	0.9287	60.4199	37.3658	10.8220	5.1001
2	Russia	2002	0.7560	4.5620	3.7563	59.6454	1.0055	60.0956	43.2654	10.8224	4.7000
2	Russia	2003	0.7590	4.7631	3.6708	59.1283	1.8424	59.8663	49.1768	10.8472	7.3000
2	Russia	2004	0.7510	4.9779	3.3004	56.5819	2.6062	59.6910	54.5315	10.8600	7.1999
2	Russia	2005	0.7430	5.2476	3.3312	56.7132	2.0298	59.8159	61.4490	10.8625	6.4000
2	Russia	2006	0.7300	5.4840	3.2464	54.7334	3.7977	59.8097	67.3903	10.9091	8.2001
2	Russia	2007	0.7060	5.7177	3.1185	51.7061	4.2990	59.8800	73.4603	10.9160	8.5000
2	Russia	2008	0.6870	5.9729	3.1495	53.3825	4.5027	58.9145	83.8262	10.9208	5.2000
2	Russia	2009	0.7120	5.8860	3.9241	48.4351	2.9921	58.4590	93.5897	10.8694	–7.8000
2	Russia	2010	0.7050	6.0160	3.5851	50.3555	2.8308	58.2257	100.0000	10.9069	4.5000
2	Russia	2011	0.6670	6.1942	3.4330	48.0354	2.6924	57.5460	108.4405	10.9396	4.3000
2	Russia	2012	0.6530	6.3407	3.6892	47.1514	2.2908	57.8745	113.9435	10.9436	4.0241
2	Russia	2013	0.6360	6.4196	3.8540	46.2871	3.0194	59.6136	121.6390	10.9295	1.7554
2	Russia	2014	0.6620	6.3750	4.1130	47.8013	1.0699	59.7610	131.1553	10.9304	0.7363
2	Russia	2015	0.6510	6.1293	4.8715	49.3593	0.5026	59.7949	151.5295	10.9118	–1.9727

Table A1 (continuation)

ID	Country	Year	SDI	LnMEpc	MEgdp	Trade	FDI	CORRP	INF	LnPEC	GDPgr
2	Russia	2016	0.7040	6.1679	5.4251	46.5181	2.5485	59.7079	162.2008	10.9282	0.1937
2	Russia	2017	0.6970	6.1313	4.2490	46.8765	1.8141	60.3721	168.1752	10.9319	1.8258
2	Russia	2018	0.6600	6.0473	3.7198	51.5809	0.5301	61.0483	173.0158	10.9663	2.8072
2	Russia	2019	0.6120	6.1034	3.8603	49.2288	1.8885	60.3651	180.7503	10.9583	2.1981
2	Russia	2020	0.5690	6.0493	4.1715	45.9669	0.6349	60.4302	186.8626	10.9238	–2.6537
2	Russia	2021	0.5770	6.1186	3.6117	50.1964	2.1943	60.5002	199.3721	10.9586	5.6143
2	Russia	2022	0.5410	6.5616	4.6900	43.2587	–1.7564	60.4318	226.8000	10.9963	–2.0697
3	India	2000	0.5280	2.6015	2.9489	26.9009	0.7652	62.5274	54.3383	8.1650	3.8410
3	India	2001	0.5330	2.6051	2.9244	25.9933	1.0564	62.4175	56.3919	8.1511	4.8240
3	India	2002	0.5400	2.5974	2.8269	29.5087	1.0116	62.3699	58.8152	8.1674	3.8040
3	India	2003	0.5530	2.6822	2.6778	30.5924	0.6059	62.3307	61.0536	8.1852	7.8604
3	India	2004	0.5630	2.8798	2.8288	37.5038	0.7656	62.2457	63.3536	8.2508	7.9229
3	India	2005	0.5730	2.9948	2.9106	42.0017	0.8861	61.5069	66.0439	8.2919	7.9234
3	India	2006	0.5830	3.0170	2.6804	45.7245	2.1302	59.0308	69.8721	8.3287	8.0607
3	India	2007	0.5920	3.1676	2.4782	45.6863	2.0734	58.8537	74.3250	8.3959	7.6608
3	India	2008	0.6000	3.3087	2.6315	53.3682	3.6205	57.1905	80.5306	8.4384	3.0867
3	India	2009	0.6060	3.4546	3.1294	46.2729	2.6516	56.0946	89.2942	8.4963	7.8619
3	India	2010	0.6160	3.6150	2.8895	49.2552	1.6350	55.3213	100.0000	8.5249	8.4976
3	India	2011	0.6310	3.6755	2.7045	55.6239	2.0021	54.9194	108.9118	8.5644	5.2413
3	India	2012	0.6400	3.6122	2.6182	55.7937	1.3129	54.0247	119.2355	8.6038	5.4564
3	India	2013	0.6470	3.6032	2.5488	53.8441	1.5163	53.0550	131.1804	8.6234	6.3861
3	India	2014	0.6580	3.6622	2.5440	48.9222	1.6957	51.6458	139.9244	8.6764	7.4102
3	India	2015	0.6670	3.6578	2.4575	41.9229	2.0921	50.0527	146.7905	8.6986	7.9963
3	India	2016	0.6790	3.7450	2.5432	40.0825	1.9374	48.2217	154.0540	8.7305	8.2563
3	India	2017	0.6850	3.8644	2.5315	40.7425	1.5073	47.2760	159.1812	8.7564	6.7954
3	India	2018	0.6850	3.8795	2.4243	43.6170	1.5582	46.3160	165.4511	8.8006	6.4539
3	India	2019	0.6870	3.9449	2.5460	39.9054	1.7848	45.2922	171.6216	8.8153	3.8714
3	India	2020	0.6870	3.9557	2.8072	37.7581	2.4062	44.0900	182.9888	8.7518	–5.7777
3	India	2021	0.6810	3.9934	2.4804	45.4231	1.4122	44.3333	192.3787	8.8261	9.6896
3	India	2022	0.6940	4.0331	2.3639	49.9653	1.4892	44.5718	205.2662	8.8719	6.9870
4	China	2000	0.6300	2.8674	1.8358	39.4110	3.4751	53.1070	80.9700	9.1415	8.4901
4	China	2001	0.6410	3.0383	1.9831	38.5272	3.5130	52.9119	81.5523	9.1899	8.3357
4	China	2002	0.6520	3.1630	2.0594	42.7472	3.6091	52.6446	80.9554	9.2688	9.1336

Table A1 (continuation)

ID	Country	Year	SDI	LnMEpc	MEgdp	Trade	FDI	CORRP	INF	LnPEC	GDPgr
4	China	2003	0.6590	3.2471	1.9963	51.8042	3.4874	52.4037	81.8682	9.4152	10.0380
4	China	2004	0.6650	3.3752	1.9385	59.5055	3.4836	51.9729	84.9994	9.5661	10.1136
4	China	2005	0.6720	3.4902	1.8719	62.2080	4.5543	51.6821	86.5093	9.6875	11.3946
4	China	2006	0.6770	3.6683	1.8696	64.4792	4.5086	51.3531	87.9362	9.7730	12.7210
4	China	2007	0.6830	3.8506	1.7502	62.1936	4.4010	50.8664	92.1719	9.8498	14.2309
4	China	2008	0.6790	4.0821	1.7160	57.6123	3.7336	50.3005	97.6333	9.8813	9.6507
4	China	2009	0.6580	4.2786	1.8935	45.1850	2.5689	49.5536	96.9224	9.9174	9.3987
4	China	2010	0.6370	4.3602	1.7335	50.7171	4.0035	48.4821	100.0000	9.9782	10.6359
4	China	2011	0.6040	4.5253	1.6591	50.7409	3.7088	49.3138	105.5539	10.0472	9.5508
4	China	2012	0.5800	4.6653	1.7009	48.2675	2.8271	49.8371	108.3189	10.0805	7.8637
4	China	2013	0.5530	4.7810	1.7143	46.7444	3.0399	49.9313	111.1580	10.1105	7.7662
4	China	2014	0.5410	4.8788	1.7384	44.9052	2.5592	49.9039	113.2941	10.1295	7.4258
4	China	2015	0.5390	4.9489	1.7768	39.4642	2.1922	49.6920	114.9221	10.1350	7.0413
4	China	2016	0.5240	4.9532	1.7689	36.8944	1.5556	49.5159	117.2206	10.1332	6.8488
4	China	2017	0.5110	5.0054	1.7112	37.6324	1.3491	47.8811	119.0881	10.1654	6.9472
4	China	2018	0.4900	5.1004	1.6736	37.5658	1.6939	46.3539	121.5589	10.2075	6.7498
4	China	2019	0.4420	5.1301	1.6829	35.8901	1.3107	44.7397	125.0832	10.2494	5.9505
4	China	2020	0.4190	5.1987	1.7567	34.7543	1.7232	43.0762	128.1094	10.2792	2.2386
4	China	2021	0.3930	5.3010	1.6053	37.3020	1.9308	42.7773	129.3662	10.3337	8.4485
4	China	2022	0.3780	5.3218	1.6231	38.3515	1.0637	43.5311	131.9194	10.3488	2.9507
5	South Africa	2000	0.6580	3.6991	1.3873	46.2207	0.6384	50.4248	59.9007	10.1394	4.2000
5	South Africa	2001	0.6550	3.6418	1.4832	49.1709	5.3683	50.2123	63.3162	10.1357	2.7000
5	South Africa	2002	0.6580	3.6124	1.5293	53.4655	1.1464	49.9880	69.3279	10.1008	3.7004
5	South Africa	2003	0.6490	3.9799	1.4688	45.7239	0.3975	49.9191	73.2653	10.1716	2.9491
5	South Africa	2004	0.6460	4.1561	1.3557	45.6436	0.2742	49.8601	72.7583	10.2496	4.5546
5	South Africa	2005	0.6480	4.2873	1.2348	47.4278	2.2578	49.8527	74.2592	10.1852	5.2771
5	South Africa	2006	0.6510	4.2605	1.1539	53.7681	0.2051	49.8047	76.6681	10.1959	5.6038
5	South Africa	2007	0.6540	4.2559	1.0585	57.1251	1.9776	49.7536	81.4045	10.2127	5.3605
5	South Africa	2008	0.6640	4.1741	1.0394	65.9745	3.1269	49.7970	89.6056	10.2705	3.1910
5	South Africa	2009	0.6780	4.2515	1.0895	49.5875	2.3122	49.5811	96.0710	10.2541	-1.5381

Table A1 (continuation)

ID	Country	Year	SDI	LnMEpc	MEgdp	Trade	FDI	CORRP	INF	LnPEC	GDPgr
5	South Africa	2010	0.6840	4.3929	1.0035	50.4061	0.8849	49.6762	100.0000	10.2496	3.0397
5	South Africa	2011	0.6920	4.4728	1.0027	54.6364	0.9034	49.5415	104.9993	10.2247	3.1686
5	South Africa	2012	0.7010	4.4365	1.0335	55.5826	1.0649	49.1719	111.0101	10.1958	2.3962
5	South Africa	2013	0.7090	4.3365	1.0278	58.8750	2.0536	48.6918	117.4315	10.1866	2.4855
5	South Africa	2014	0.7200	4.2644	1.0219	59.4996	1.5193	48.3710	124.6298	10.1824	1.4138
5	South Africa	2015	0.7280	4.1342	1.0069	56.7267	0.4387	48.0846	130.2888	10.1414	1.3219
5	South Africa	2016	0.7170	4.0189	0.9710	55.8613	0.6846	48.7471	138.8506	10.1763	0.6646
5	South Africa	2017	0.7300	4.1496	0.9436	53.5359	0.5397	49.5412	146.0490	10.1687	1.1579
5	South Africa	2018	0.7360	4.1460	0.8948	54.4855	1.3743	50.2979	152.6462	10.1180	1.5568
5	South Africa	2019	0.7450	4.0800	0.8824	53.8980	1.3141	50.6937	158.9356	10.1495	0.2599
5	South Africa	2020	0.7230	4.0064	0.9556	50.7597	0.9331	51.6027	164.0375	10.0727	–6.1689
5	South Africa	2021	0.7200	4.0453	0.8074	56.0347	9.6603	52.3545	171.6024	10.0722	4.9550
5	South Africa	2022	0.7120	3.9498	0.7678	64.7830	2.2705	51.5503	183.6827	10.0255	1.9115

Source: Own editing

Determinants of Tanzanian Exports in the Light of Gravity Model Results

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Abstract

Tanzania's exports are mainly based on unprocessed agricultural products and mineral resources, which is not beneficial and does not improve the international competitiveness of the country's economy. Proper identification of factors that provide opportunities for improving the situation in Tanzanian exports requires the construction of appropriate econometric models. This paper proposes the use of a gravity model of trade, as it allows for the inclusion of foreign trade flows in bilateral relations. This paper argues that in gravity models, foreign direct investment (FDI) inflow limits Tanzanian exports. Factors that have a significant and positive impact on Tanzania's exports are GDP of partner countries, GDP of Tanzania, imports of Tanzania, the common language and the colonial ties with partner trading countries. The results presented in the article allowed for the indication of the strengths and weaknesses of Tanzanian exports and the formulation of recommendations that may be useful for decision-makers in taking actions to improve the competitiveness of the Tanzanian economy.

Keywords	***DOI***	***JEL code***
Export, gravity trade model, competitiveness of the economy, Tanzania	*https://doi.org/10.54694/stat.2025.1*	*C33, F1, Q17*

INTRODUCTION

The share of Tanzanian exports of goods and services in GDP is 15%, which indicates its great importance for the country's economy. The bulk of Tanzania's exports are agricultural goods, including tobacco, coffee, cotton, cashews, tea and cloves. Additionally, Tanzania is also one of the region's leading exporters of gold and other mineral resources (including diamonds). The structure of Tanzania's exports corresponds to the profile of the country's economy, which is clearly agricultural in nature: the agricultural sector employs over 2/3 of workers, and its contribution to GDP is over 20%.[3]

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For comparison, Tanzania's manufacturing sector employs less than 3% of employees and generates approximately 10% of GDP (Mgangaluma et al., 2023; Epaphra, 2016). Tanzania's more important export destinations are India, Japan, China, the United Arab Emirates, the Netherlands, Germany and Switzerland.

It should be emphasized that Tanzania is also an importer of agricultural products, including cereals necessary to feed the population. For many years, Tanzania's foreign trade balance has been negative, which is due to slowly growing exports and much faster growing imports. The trade deficit negatively affects economic growth and employment in the country (Luhwago, et al., 2023; Epaphra, 2016). The weakness of Tanzania's exports is that they are based mainly on unprocessed products, which often have an inelastic demand, which results in the prices of products falling compared to processed goods also due to the lack of differentiation between producers. The solution to limiting the foreign trade deficit would be to increase the share of processed goods and services in exports, the prices of which are more stable. Moreover, the significant share of gold in Tanzanian exports makes the entire economy highly susceptible to fluctuations in the exchange rate of this raw material (Mahona and Mjema, 2014; Epaphra, 2016). Export restrictions are also influenced by the very poor transport and energy infrastructure in this country. Strict international sanitary and phytosanitary regulations also pose a significant limitation to the export of Tanzanian food (Luhwago et al., 2023).

This situation could improve because Tanzania's potential export opportunities, also in the agricultural market, are much greater, but the country would have to modify its agricultural production technology to improve its quality and efficiency. Increasing exports and overcoming Tanzania's negative trade balance, however, requires identifying the factors that act as determinants of Tanzanian exports and will allow them to be appropriately controlled. There are few studies on Tanzania's exports, and even fewer that use the gravity model of foreign trade (Mahona and Mjema, 2014). Meanwhile, this model allows for taking into account foreign trade flows in bilateral relations, which improves the reliability of the modeled relationships between macroeconomic variables. More often than gravity models, you can find ARIMA or VAR models, which, although they focus on predicting temporal trends in exports, do not sufficiently isolate structural connections between countries that are important in international trade (Kingu, 2014; Luhwago et al. 2023; Epaphra, 2016). Thus, this article attempts to bridge this methodological gap. The aim of the article is to build a gravity model of foreign trade for Tanzania. The results of the model will indicate important determinants of the country's contemporary foreign trade and may be useful for decision-makers responsible for shaping trade policy.

1 LITERATURE REVIEW

The issue of examining the determinants of exports is not new and has been addressed many times in scientific research. Many researchers point to the relationship between exports and GDP and the dynamics of its changes. The positive impact of GDP on exports is confirmed, among others, by: Kumar (1998) and Fugazza (2004). Researchers also emphasize that economic growth measures the sustainability of production levels, so it is a more reliable determinant of exports compared to GDP (Epaphra, 2016). Many works analyze the two-way dynamic relationship between exports and GDP using the Granger causality test (Ahdi et al., 2015). The results in this regard are not clear. In linear models, these relationships are often insignificant (Ahdi et al., 2015), and in the case of non-linear models, a one-way relationship from GDP to exports is generally shown (Hiemstra and Jones, 1994), and less often a two-way relationship is indicated (Diks and Panchenko, 2005).

Ahdi at al. (2015) using linear and non-linear Granger causality tests analyze the dynamic cause-and-effect relationship between economic growth and exports for South Africa over the period 1911–2011. The one-way relationship between the impact of economic growth on exports was confirmed by, for example, Abdul-Khaliq et al. (2014), Shan and Sun (1998).

Numerous studies also point to trade liberalization as a factor creating exports, especially in developing countries. It is not surprising that the abolition of customs barriers and quantitative restrictions on exports should stimulate exports. This is confirmed by numerous empirical studies (Joshi and Little 1996; Ahmed, 2000). In fact, in some studies, trade liberalization is considered a key factor in the development of exports (Santos-Paulino, 2002). But there are also studies that do not confirm such a clear relationship (Jenkins, 1996).

An obvious factor that directly affects the prices of goods sold abroad is the exchange rate (Nyeadi et al., 2014). The increase in the real exchange rate causes domestic products to become less competitive in terms of prices compared to foreign products. As a consequence, this may lead to a reduction of exports in terms of quantity (Yi Lu and Zhou, 2013). In addition, an increase in the exchange rate reduces exporters' profits, making exports less profitable, which may also contribute to reducing the volume of exports. Balogun (2007) showed that the impact of exchange rate policy on exports is not clear and depends on the country under study. In the case of Gambia and Nigeria, a positive and significant impact on export performance was confirmed, while the exchange rate did not significantly affect the export performance of Ghana and Guinea. In turn, in the case of Sierra Leone, the results indicate a negative and significant impact of currency devaluation on export performance. Mohamad et al. (2009) showed the existence of a strong and negative impact of real exchange rate appreciation in Indonesia, Singapore, Malaysia and Thailand on export performance. Johnson et al. (2007) showed that appreciation reduced exports and led to a decline in economic growth. Haddad and Pancaro (2010), and Eichengreen and Gupta (2013) proved that exchange rate depreciation could be treated as a tool to stimulate exports only in the short term. In turn, Aryal (2024), using dynamic relationships between time series for the Nepalese economy, did not confirm the existence of a long-term relationship between exports and the exchange rate.

Another determinant of exports considered in the literature on the subject is foreign direct investment (FDI). There are extensive economic theories that explain the mechanism of the connection between FDI and exports. Mention should be made of Mundell's theory (1957), the theory of comparative advantages (Kojima, 1973), or the theory of dynamic comparative advantages (Ozawa, 1992). Although, as a rule, FDI supports foreign trade, in certain circumstances these categories are substitutes. Therefore, there are both empirical studies that confirm the positive impact of FDI on exports (Caetano and Galego, 2007) and studies showing that the impact of FDI on foreign trade, depending on various conditions, may have a substitutive nature (Shun-Chiao, 2009). The negative impact of FDI on the exports of the Philippines, Indonesia, Malaysia and Thailand was shown by Sieng et al. (2020).

Inflation is also mentioned among the factors affecting exports, and economists generally agree that high inflation has a negative impact on export activities (Abidin and Sahlan, 2013; Sieng et al., 2020). Gylfason (1998), based on studies of 160 countries, showed that one of the factors responsible for the decline in exports is high inflation. Dexter et al. (2005) using the Granger causality test confirmed the existence of a two-way causal relationship between inflation and exports. Many analyzes of exports also point to imports as one of the determinants. Exports and imports usually remain in a long-term relationship, and their time series often show cointegration (Mukhtar and Rasheed, 2010). Mostly, the correlation between exports and imports is positive, Arize (2002), although there are also studies that do not confirm a significant relationship between these categories (Fountas and Wu, 1999). The long-term relationship between exports and imports was also not confirmed by Aryal's research (2024).

When discussing possible factors shaping exports, we cannot ignore the geographical distance between trading partners. This is one of the factors influencing transport costs, delivery time and transport risk. It is natural that the increase in the distance between trading partner countries increases the costs of exports, so it may lead to their reduction. There is an abundant evidence for this in empirical research (Rauch, 2016). Research on Tanzania's exports generally uses dynamic econometric VAR or VECM models (Kingu, 2014; Luhwago et al., 2023), and less frequently, gravity models of foreign trade (Mahona and Mjema, 2014). It is worth paying attention to the research of Darku (2009), who built a gravity model for Tanzania's foreign trade with the aim of identifying the effects of regional integration. However, this model does not take into account many important variables that may determine Tanzanian exports. The literature search indicates that there is a lack of gravity models that would comprehensively describe Tanzania's trade with its main partners, taking into account the key macroeconomic factors shaping exports. Thus, a research niche appears, which this article tries to fill by proposing this type of model of the Tanzanian economy.

2 METHODOLOGY AND DATA

We used the form of gravity model as it has been introduced by Tinbergen (1962), assuming that the volume of foreign trade between countries Y_{ij} is proportional to the size of their economies ($X_i^{a_1}, X_j^{a_2}$) measured by GDP and is inversely proportional to a distance between the said countries ($d_{ij}^{a_3}$). The basic form of the gravity model of foreign trade referring to Newton's law of gravity is as follows:

$$Y_{ij} = \frac{a_0 X_i^{a_1} X_j^{a_2}}{d_{ij}^{a_3}}. \tag{1}$$

Tinbergen (1962) based his theory on a static empirical analysis of the trade flows of 18 developed countries. The author had already noticed a significant impact of trade agreements between countries on the volume of their exchange, therefore he extended the study by introducing additional dummy variables into the model, indicating participation in the British Commonwealth organization, membership in the Benelux, as well as the existence of a common border with a country that is an exchange partner. Formula (1) is adapted in this paper in an extended form to model Tanzania's exports. Based on literature studies, a set of macroeconomic variables was selected that could potentially affect Tanzanian exports, and then, using a backward stepwise regression model (backward elimination), a gradual selection of explanatory variables was made, discarding subsequent statistically insignificant variables. Ultimately, the following form of the gravity model was adopted:

$$EXP_{i,t} = \beta_0 \cdot GDP_{i,t}^{\beta_1} \cdot GDP\_Tanz_t^{\beta_2} \cdot DIST_i^{\beta_3} \cdot FDI_{i,t}^{\beta_4} \cdot IMP_{i,t}^{\beta_5} \cdot e^{\beta_6 ComLang_i} \cdot e^{\beta_7 ComBorder_i} \cdot$$
$$\beta_8 ColonialTies_i \cdot e^{\varepsilon_{i,t}}, \qquad t = 1, \ldots, n, \tag{2}$$

where:

$EXP_{i,t}$ – volume of export from Tanzania in the year t to country i,
$GDP_{i,t}$ – gross domestic product in country i (trade partner of Tanzania) and the year t,
GDP_Tanz_t – gross domestic product in Tanzania in the year t,
$DIST_i$ – distance between the capital cities of Tanzania and country i (trade partner of Tanzania), which is time invariant,
$FDI_{i,t}$ – cumulative volume of foreign direct investment from country i (trade partner of Tanzania) to Tanzania in the year t,
$IMP_{i,t}$ – volume of Tanzania imports from country i (partner in the year t),
$ComLang_i$ – binary variable which is equal to 1 if Tanzania and the trading partner country i share a common language,
$ComBorder_i$ – binary variable which is equal to 1 if Tanzania borders the trading partner country i,
$ColonialTies_i$ – binary variable which is equal to 1, if the country i has colonial ties with Tanzania,
$\beta_0, \beta_1, \beta_3, \beta_5, \beta_6, \beta_7, \beta_8$ – model parameters,
$\varepsilon_{i,t}$ – error term.

The above Formula (2) can be transformed to the linear equation as:

$$lnEXP_{i,t} = ln\beta_0 + \beta_1 lnGDP_{i,t} + \beta_2 GDP\_Tanz_t + \beta_3 lnDIST_i + \beta_4 lnFDI_{i,t} + \beta_5 lnIMP_{i,t} + \beta_6 ComLang_i + \beta_7 ComBorder_i + \beta_8 ColonialTies_i + \varepsilon_{i,t}, \qquad t = 1, \dots, n. \tag{3}$$

The parameters of model (3) were estimated using the fixed effects estimator (FE) and the random effects estimator (RE). It should be noted that dummy variables, such as a common language or a common border, which are constant over time for a given pair of countries may be perfectly correlated with fixed effects, which means that with fixed effects the parameters of such variables are impossible to estimate (they are "absorbed" by fixed effects). Model 3 was estimated for Tanzania's main foreign trade partner countries. These countries come from different continents namely Africa, Asia, Australia, Europe and North America. There are: Kenya, Uganda, South Africa, Mauritius, Zambia, China, India, Australia, United Kingdom, Netherlands, Switzerland, Sweden, Norway, France, Germany, Canada and United States. The selection of the countries depends on the significant volumes of trade and FDI inflows between these countries and Tanzania. The models were estimated based on data from the World Integrated Trade Solution (WITS) integrated database, which combines the data resources of the following organizations: The World Bank, United Nations Conference on Trade and Development (UNCTAD), International Trade Center, United Nations Statistical Division (UNSD) and the World Trade Organization (WTO).[4] The calculations used data covering the years 1999–2022.

3 EMPIRICAL RESEARCH RESULTS AND DISCUSSION

For the estimation of models (3), the OLS estimator and panel data estimators: fixed effects (FE) and random effects (RE) were taken into account. The Wald test statistic of $F = 8.56114$ ($p<0.05$) indicates that the use of the OLS estimator is not justified, because the intercepts in Formula (3) are different for individual objects (Tanzania's trade partner countries). Finally, the results of model estimation using the FE and RE estimators will be presented (see Tables 1 and 2).

Table 1 Gravity model estimation results using the FE estimator for Tanzanian exports

Variables	Coef.	Std. err.	*t-stat*	*p*
const	3.7165	1.2443	2.9869	0.0030
LnGDP	0.4539	0.1202	3.7761	0.0002
LnGDP_Tanz	0.0698	0.0292	2.3876	0.0175
LnFDI	–0.2355	0.1024	–2.2990	0.0221
LnIMP	0.7805	0.0788	9.9068	0.0000
LnDIST	–	–	–	–
ComBorder	–	–	–	–
ComLang	–	–	–	–
ColonialTies	–	–	–	–

Source: Authors

[4] *<https://wits.worldbank.org>.*

The coefficient of determination R^2 for model with fixed effects is equal to 61.67%, which proves that the model fits the empirical data quite well. F test is equal to 66.5692 ($p<0.05$) so indicates that the model is statistically significant. Tanzania's exports are statistically significantly influenced by: GDP of trade partner countries, Tanzania's GDP, Tanzania's imports, and sharing borders. Tanzanian imports have the strongest impact on Tanzanian exports: their increase by 1% results in an increase in exports on average by approximately 0.78%, *ceteris paribus*. GDP of trade partner countries also has the significant and positive impact on Tanzanian exports: an increase in this variable by 1% results in an increase in the export of Tanzanian goods and services by approximately 0.45% *ceteris paribus*, while GDP in Tanzania has a weaker impact on exports, as its increase by 1% raises the value of exports by approximately 0.07% on average, *ceteris paribus*. Foreign direct investments located in Tanzania are substitutes for exports; an increase in FDI in Tanzania by 1% results in a decrease in the country's exports, on average, by approximately 0.24%, *ceteris paribus*.

The results of estimating the parameters of model (3) in the case using the RE estimators are presented in Table 2.

Table 2 Gravity model estimation results using the RE estimator for Tanzanian exports

Variables	Coef.	Std. err.	*t-stat*	*p*
const	1.1593	0.5279	2.1959	0.0288
LnGDP	0.8714	0.1686	5.1689	0.0000
LnGDP_Tanz	0.0785	0.0255	3.0770	0.0023
LnFDI	–0.2746	0.1280	–2.1449	0.0327
LnIMP	0.5414	0.0815	6.6395	0.0000
LnDIST	–2.4824	0.6207	–3.9992	0.0001
ComBorder	–0.1927	130.1670	–0.0015	0.9988
ComLang	0.0330	0.0160	2.0683	0.0394
ColonialTies	0.2297	0.0838	2.7423	0.0064

Source: Authors

In the model with random effects, the coefficient of determination R^2 is equal to 46.51% and F = 35.9759 ($p<0.05$) indicates that the model is statistically significant. The way in which individual explanatory variables affect Tanzanian exports in models with FE and RE estimators is similar. In the RE model, significant export stimulators are the GDP of the trade partner countries, the GDP of Tanzania, imports, the common language and colonial ties of the countries, with the strongest positive impact on exports being the GDP of the partner countries: an increase in this variable by 1% results in an increase in exports by an average of approx. 0.87% *ceteris paribus*. The presence of colonial connections causes an increase in exports by approx. $(e^{0.2297} - 1) \cdot 100\% \approx 25.92\%$ FDI replaces Tanzania's exports: their increase by 1% reduces exports on average by approximately 0.27%, *ceteris paribus*. The *DIST* variable has the strongest negative impact on exports: its increase by 1% results in a decrease in exports on average by approximately 2.48%, *ceteris paribus*. To assess which of the FE or RE models is more appropriate for modeling Tanzania's exports, the Hausman test was used, the result of which was 9.58478 (p = 0.048034) indicating that the estimator in the gravity model used to describe the dependence of Tanzania's exports on other variables is FE estimator.

From results above we have seen there is a positive relationship between Tanzania export and GDP of trade partners. We were expected to get such relationship because Tanzania exports more raw materials such as cotton, coffee, tea, sisal, cloves, tobacco and cashew nuts. Those commodities are used to feed the partners' industries to produce GDP. The more the trade partners produce the more Tanzania exports for them. Tanzania exports also minerals such as gold, diamond, and gemstones such as Tanzanite. This non-traditional export strengthens trade between Tanzania and its partner countries. Tanzania imports more than exports from its partner countries. The relationship is also positive between export and import. Tanzania imports products such as chemicals and related products, machinery and transport equipment, animals and vegetable oils, fats & waxes and crude materials, inedible except fuels. We were expecting to get positive sign between export from Tanzania and import of Tanzania from its partner countries.

Distance is a proxy for cost due to transport charges which is incorporated in products. We were expecting to get negative relationship between export and distance. The two trade-resistance variables, tariff and distances, adversely affect trade flows between countries, so their coefficient is expected to be negative. With regard to the distance variable, for example, long distance between trading countries, *ceteris paribus*, leads to higher costs and lower profit margin to the importer. Long distance also leads to increased "Psychic distance" between trading countries. All these elements of distance will reduce trade flows between countries, Hansen and Rand (2014).

It is widely recognized that trade and FDI are vital factors of the economic growth process. Past empirical studies such as Balasubramanyam et al. (1999) have mostly concluded that both FDI inflows and trade promote economic growth. However, there are clear indications that the growth enhancing effects from FDI and trade vary from country to country. In some country FDI and trade can even negatively affect the growth process. The growth enhancing effect of FDI and trade interaction is not automatic but depends on various country specific factors such as the trade openness. In this study unfortunately the relationship between trade and FDI is negative. Other hypotheses such as unbalanced distribution of FDI in favor of mining sub-sector and construction industry can also be considered. From this results require profound study to investigate the reasons of this negative relationship.

CONCLUSIONS

Exports goods and services are an important element of Tanzania's economy. The income obtained from exports allows to finance imports and the internal needs of the economy. This paper argues that in gravity models, FDI inflow limits Tanzanian exports. Factors that have a significant and positive impact on Tanzania's exports are GDP of partner countries, GDP of Tanzania, imports of Tanzania, the common language and colonial ties with partner trading countries. Despite the identified negative impact of FDI on exports, it can be expected that adequate saturation of the market with foreign investments will also make them more pro-export, because they will improve production efficiency and strengthen the economies of scale, which will not only improve supply on the internal market but also increase the competitiveness of exported goods and services in the future. Therefore, it is important for the Tanzanian government to gradually introduce further tax, legal and institutional facilitations and incentives for potential foreign investors. In the interim, the situation in Tanzania's exports may be improved by the government's creation of a broader package of tools to strengthen the position of companies exporting goods and services (an appropriate certification system, appropriate promotional activities, guarantees and insurance of export credits, diplomatic activities). Long-term improvement of the competitiveness of Tanzanian exports also requires modernization of the country's communication infrastructure (expansion of railway lines, sea ports, power lines), increasing the share of processed goods in the export structure (it is more advantageous to export processed products than raw materials in their original state), increasing attention to the quality of agricultural products intended for export, so that they better meet international phytosanitary standards. Tanzania's export competitiveness can also be improved by developing its human resources employed in agriculture, industry, and services, the sectors that provide export products. Qualified, aware staff facilitates more efficient and qualitatively better production. This effect can be achieved through further improvement of education, investments in vocational education, as well as supporting innovation and technology transfer.

The gravity model used here is one of the most effective tools for analyzing international trade, which has been confirmed by research by other authors. However, one must bear in mind its limitations, such as the inability to determine the direction of causality of variables, rigid assumptions as to the constancy of variables over time, which may not reflect dynamic changes in trade, such as technological changes or changes in trade policy, omission of some qualitative factors, such as value chains, economic crises, etc. This opens the way to further in-depth research on Tanzania's exports also using other econometric models.

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Testing for a Unit Root in the Logistic STAR Framework with a Fourier Function: an Application to the Unemployment Rates

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Abstract

This paper introduces the Fourier-LSTAR (FLSTAR) test, which addresses the critical challenge of testing for unit roots in time series characterized by both unknown structural breaks and nonlinear dynamics. We propose and evaluate this novel unit root test, which integrates a logistic smooth transition autoregressive (LSTAR) model with a flexible Fourier function to capture such complexities. Critical values and simulation properties of the test are derived, demonstrating its robustness and stable performance across varying conditions. We apply the FLSTAR test to annual unemployment rates for CIVETS countries and find that unemployment hysteresis holds for most nations, except Colombia, where the plucking model is applicable. These results highlight the heterogeneous nature of unemployment dynamics in emerging economies and underscore the importance of employing robust testing procedures that accommodate data complexities to avoid misleading policy inferences. The FLSTAR test demonstrates superior power and size properties in Monte Carlo simulations, offering a valuable new tool for empirical researchers.

Keywords	***DOI***	***JEL code***
Unemployment hysteresis, Unit Root Test, Fourier-LSTAR, structural breaks, nonlinear dynamics, CIVETS countries	*https://doi.org/10.54694/stat.2025.25*	*C22*

INTRODUCTION

The concept of stationarity is fundamental in time series analysis, as non-stationarity can lead to spurious inferences. Although traditional unit root tests, such as the Dickey-Fuller and Augmented Dickey-Fuller

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(ADF) tests, provided the foundational methodology, they often prove inadequate when applied to real-world data characterized by complexities such as structural breaks and nonlinear dynamics (Enders, 2014; Kočenda and Černý, 2015). Neglecting these features can compromise the reliability of stationarity testing.

Recognizing the limitations of assuming linearity and stability, research has focused on developing more robust unit root tests. To address structural changes, particularly multiple and smooth breaks of unknown timing and form, Fourier functions have proven effective (e.g., Becker et al., 2004, 2006). Concurrently, the prevalence of nonlinear behavior in economic time series (Tong, 2015; Enders and Granger, 1988) spurred the development of tests based on regime-switching models. Among these, Smooth Transition Autoregressive (STAR) models, particularly their Logistic (LSTAR) and Exponential (ESTAR) variants, allow for gradual transitions between different economic states (Teräsvirta and Anderson, 1992). LSTAR models are especially adept at capturing asymmetric dynamics, such as differing behaviors during economic expansions and contractions (Skalin and Teräsvirta, 1999).

While existing approaches have combined Fourier functions with ESTAR models to jointly account for structural breaks and symmetric nonlinearity (e.g., Christopoulos and Leon-Ledesma, 2010, 2011; Guris, 2019; Ranjbar et al., 2018), a notable gap remains in the development of tests capable of accommodating both structural breaks and LSTAR-type asymmetric nonlinearity.

This study addresses this gap by proposing a novel two-stage unit root test, termed the Fourier-LSTAR (FLSTAR) test. Following the methodology of Christopoulos and Leon-Ledesma (2010, 2011), the first stage involves removing deterministic components (constant/constant trend) and accounting for structural changes in the series using a Fourier approximation. In the second stage, the stationarity of these filtered residuals is examined using the LSTAR-based unit root test developed by Pascalau (2007). The FLSTAR test proposed herein uniquely combines the strengths of Fourier approximations for capturing smooth breaks with the LSTAR framework's capacity to model nonlinear mean reversion. This explicit integration represents a significant advancement over existing approaches, which may exhibit low power or size distortions when applied to the complex data generating processes increasingly encountered in time series analysis.

The remainder of this paper is structured as follows: next section details the theoretical framework of the STAR model, the derivation of the LSTAR-based unit root test, and the integration of Fourier functions to account for structural breaks; Section 2 presents the simulation studies, including the generation of critical values for the FLSTAR test and an assessment of its size and power properties under various conditions; Section 3 presents the empirical application of the FLSTAR test to unemployment rates in the CIVETS economies, that is, in Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa, discussing the findings regarding unemployment hysteresis; Finally, last section concludes the paper, summarizing the main contributions, discussing policy implications, and suggesting avenues for future research.

1 MODEL

A STAR model is a regime-switching model that allows a time series to transition smoothly between two different autoregressive (AR) structures. A STAR model of order p can be represented as follows:

$$Y_t = \alpha_{10} + \alpha'_1 z_t + \left(\alpha_{20} + \alpha'_2 z_t\right) F\left(Y_{t-d}\right) + e_t, \qquad \text{for } t = 1,\ldots,\mathrm{T}, \tag{1}$$

here, Y_t represents the time series variable of interest, and e_t is a white noise error term, and $\alpha_j = \left(\alpha_{j1},\ldots,\alpha_{j1},\right)'$ and $z_t = \left(Y_{t-1},\ldots,Y_{t-p}\right)'$ denote the AR coefficients for the two distinct regimes (Teräsvirta and Anderson, 1992). The transition between these regimes is governed by the transition function, F(.), which is continuous, and bounded between 0 and 1 as:

– If $F(.) = 0$, the model behaves according to the first AR structure (defined by $\alpha_{10} + \alpha'_1 z_t$).
– If $F(.) = 1$, the model operates under the second AR structure (defined by $\alpha_{10} + \alpha_{20} + (\alpha'_1 + \alpha'_2) z_t$).
– If $0 < F(.) < 1$, the model's behavior is a weighted average of the two structures.

The logistic function that can be substituted for $F(.)$ is defined as:

$$F(Y_{t-d}) = \left(1 + \exp\left[-\gamma\left(Y_{t-d} - c\right)\right]\right)^{-1}. \tag{2}$$

In this function, d is the delay parameter, c is the threshold parameter, and γ is the slope parameter (with $\gamma > 0$), which regulates the speed of transition between regimes. A large γ creates a rapid, almost instantaneous switch (approaching a Threshold Autoregressive Model), while a small γ results in a very slow, gradual transition. When γ approaches zero, the LSTAR model simplifies to a standard linear AR model (Teräsvirta and Anderson, 1992). Substituting Formula (2) into Formula (1) yields the formal LSTAR model:

$$Y_t = \alpha'_1 z_t + \left(\alpha'_2 z_t\right)\left(1 + \exp\left[-\gamma\left(Y_{t-d} - c\right)\right]\right)^{-1} + e_t. \tag{3}$$

Following the suggestions of Kapetanios et al. (2003), Teräsvirta (2006), and Pascalau (2007) imposed the constraint $d = 1$ and rearranged the parameters of Formula (3) to obtain:

$$\Delta Y_t = \delta z_t + \alpha'_2 z_t \left(1 + \exp\left[-\gamma\left(Y_{t-1} - c\right)\right]\right)^{-1} + e_t, \tag{4}$$

here, $\delta = 1 - \alpha_1$ through Formula (4), it is possible to represent the unit root null hypothesis as $H_0: \delta = \alpha_2 = \gamma = 0$ against the alternative hypothesis $H_1: \delta + \alpha_2 < 0,\ \gamma > 0$. However, the parameters γ and c are not identified under the null hypothesis, precluding a direct test. To address this, Pascalau (2007), drawing on Balke and Fomby (1997), and Kapetanios et al. (2003), assumed $\delta = 0$. This assumption implies stationarity in the regime where the value of Y_{t-1} is small (close to zero) and non-stationarity in the remaining part of the sample. With this assumption, model (4) was redefined as:

$$\Delta Y_t = \alpha'_2 z_t \left(1 + \exp\left[-\gamma\left(Y_{t-1} - c\right)\right]\right)^{-1} + e_t. \tag{5}$$

As unidentified parameters persist under the null hypothesis in Formula (5), Pascalau (2007) imposed the constraint $c = 0$ on Formula (5), applied a third-order Taylor expansion and obtained the following testable equation:

$$\Delta Y_t = \lambda_1 Y_{t-1}^2 + \lambda_2 Y_{t-1}^4 + e_t, \tag{6}$$

here, the unit root null hypothesis $H_0: \lambda_1 = \lambda_2 = 0$, is tested against the LSTAR-type stationarity alternative hypothesis. For series with a non-zero mean or a deterministic trend, the data are first de-meaned or de-trended before applying this test.

The Pascalau (2007) test may yield misleading results if the time series contains structural breaks. To address this, we adopt the two-stage approach of Christopoulos and Leon-Ledesma (2010), combining the LSTAR test with a Fourier function that can approximate smooth and gradual structural changes of unknown form. In the first stage, we remove the deterministic components (constant/constant and trend) and account for structural breaks by estimating one of the following regressions:

$$Y_t = \phi_0 + \phi_2 \sin\left(2\pi kt / T\right) + \phi_3 \cos\left(2\pi kt / T\right) + u_t, \tag{7}$$

$$Y_t = \phi_0 + \phi_1 t + \phi_2 \sin\left(2\pi kt / T\right) + \phi_3 \cos\left(2\pi kt / T\right) + u_t. \tag{8}$$

In these models, sin(2πkt/T) and cos(2πkt/T) are trigonometric terms, π is the mathematical constant pi, k is the endogenously determined frequency value of the Fourier function, t is the trend term, and T is the number of observations. The value of k is not known as a priori. The selection of the optimal frequency, k, for the Fourier function is a critical step in the FLSTAR testing procedure. Following Enders and Lee (2012), we employ a grid search approach for k, typically ranging from 1 to 5, as higher frequencies can capture overly erratic movements. For each integer value of k within this range, Formula (7) or (8) is estimated. The optimal k (denoted k*) is then selected as the value that minimizes the sum of squared residuals (SSR). After determining the optimal frequency value (k*), the relevant model is estimated by substituting k*, and the residuals of this model are calculated as:

$$\hat{u}_t = Y_t - \left[\hat{\phi}_0 + \hat{\phi}_2 \sin\left(2\pi k^* t / T\right) + \hat{\phi}_3 \cos\left(2\pi k^* t / T\right) \right], \tag{9}$$

$$\hat{u}_t = Y_t - \left[\hat{\phi}_0 + \hat{\phi}_1 t + \hat{\phi}_2 \sin\left(2\pi k^* t / T\right) + \hat{\phi}_3 \cos\left(2\pi k^* t / T\right) \right]. \tag{10}$$

In these models, $\hat{u}_t$ represents the series Y_t after demeaning and/or detrending and adjustment for structural changes. In the second stage, we test the stationarity of the filtered residuals, using the LSTAR auxiliary regression from Formula (5):

$$\Delta\hat{u}_t = \lambda_1 \hat{u}_{t-1}^2 + \lambda_2 \hat{u}_{t-1}^4 + e_t. \tag{11}$$

The unit root null hypothesis is again tested with an F-test on $H_0 : \lambda_1 = \lambda_2 = 0$. This F-statistic, which we term the FLSTAR test statistic, follows a non-standard distribution for which we simulate critical values. To handle potential serial correlation, Formula (11) can be augmented with lagged values of the dependent variable ($\Delta\hat{u}_{t-i}$). If the unit root null is rejected, it implies the series is stationary around a deterministic component that exhibits smooth structural changes, with an asymmetric, LSTAR-type adjustment process. As a final step, one can test for the significance of the structural breaks in the case of stationarity, by applying a standard F-test to the null hypothesis that all Fourier coefficients are jointly zero. Critical values for this test are provided by Becker et al. (2006).

The parameters for all models within the two-stage FLSTAR testing framework are estimated using Ordinary Least Squares (OLS). This choice is both computationally straightforward and statistically appropriate for the task at hand. While alternative estimation techniques like the Generalized Method of Moments (GMM) exist, OLS is preferred here for its simplicity and efficiency. GMM is more powerful in contexts with endogenous regressors or when the model is defined by moment conditions that OLS cannot handle. However, in this framework, the regressors in the auxiliary equation are predetermined, and the standard assumptions for OLS are met under the null hypothesis. In this context, OLS is equivalent to the Method of Moments and is the most direct and efficient method for estimating the parameters and constructing the necessary F-statistics.

2 SIMULATIONS

2.1 Critical values

Critical values for the proposed unit root test are derived by applying an F-test to the null hypothesis $H_0 : \lambda_1 = \lambda_2 = 0$ within the framework of Formula (11). This was performed for sample sizes (T) of 50, 100, and 250, and for T = 1 000 to obtain asymptotic critical values, with 50 000 simulations conducted for each scenario. The resulting critical values are presented in Table 1. These critical values were calculated for Fourier frequencies (k) of 1, 2, 3, 4, and 5.

Table 1 Critical values

Sample size	Frequency	Demeaned			Detrended		
		1%	5%	10%	1%	5%	10%
T = 50	1	7.6106	4.6831	3.5326	6.2567	3.7626	2.7285
	2	5.4050	3.2489	2.4240	5.6405	3.4990	2.6102
	3	5.1770	3.3523	2.6354	5.4502	3.3081	2.4938
	4	5.2799	3.4915	2.7132	5.3878	3.2558	2.4223
	5	5.2050	3.4517	2.6894	5.2446	3.2039	2.3736
T = 100	1	7.3603	4.4841	3.3482	4.8159	2.9274	2.2025
	2	4.8931	3.0120	2.2789	4.7591	2.9751	2.2754
	3	4.9500	3.3577	2.6658	4.6047	2.9373	2.2736
	4	5.0904	3.4586	2.7190	4.4998	2.8885	2.2239
	5	5.1053	3.4601	2.7079	4.5117	2.8678	2.2177
T = 250	1	7.1524	4.4650	3.3316	3.9219	2.5155	1.9057
	2	4.8832	2.9303	2.1815	4.2477	2.7391	2.1073
	3	4.9104	3.3582	2.6635	4.2458	2.7586	2.1515
	4	5.1057	3.4758	2.7147	4.1749	2.7041	2.0890
	5	5.0572	3.4296	2.7014	4.1196	2.7178	2.0912
T = 1 000	1	7.4843	4.4930	3.3351	3.5554	2.2581	1.7120
	2	4.8800	2.8837	2.1198	4.0122	2.5739	1.9765
	3	4.8594	3.3341	2.6651	3.9854	2.5834	2.0340
	4	5.1302	3.4802	2.7397	3.9789	2.6318	2.0289
	5	5.0647	3.4680	2.7340	3.9701	2.5823	2.0094

Source: Author's own elaboration

2.2 Power and size properties

In this section, we evaluate the size and power properties of the test. The size of the FLSTAR test measures how often the test will incorrectly conclude that a time series is stationary when, in fact, it truly has a unit root (is non-stationary). The power of the FLSTAR test measures how likely the test is to conclude that a time series is stationary (by rejecting the unit root null hypothesis) when the series truly is stationary.

To evaluate the size properties of the test statistic, the following data generating process is considered:

$$Y_t = \beta_1 + \beta_2 \sin\left(\frac{2\pi kt}{T}\right) + \beta_3 \cos\left(\frac{2\pi kt}{T}\right) + u_t , \tag{12}$$

$$u_t = u_{t-1} + \varepsilon_t, \tag{13}$$

here, ε_t denotes standard normally distributed residuals. To assess the size properties, frequency values (k) of 1, 2, and 3, sample sizes (T) of 100 and 250 are considered. Additionally, the coefficients of the trigonometric terms $\beta_2 = \beta_3$ are set to 1, 0.5, and 0.1. Values of β_2 and β_3 close to 0 imply that the series approaches linearity. The simulation results are presented in Table 2.

Table 2 Size properties of the test

Data generation process	T = 100		
	$k = 1$	$k = 2$	$k = 30$
$\beta_2 = \beta_3 = 1$	0.042	0.046	0.045
$\beta_2 = \beta_3 = 0.5$	0.045	0.043	0.045
$\beta_2 = \beta_3 = 0.1$	0.047	0.043	0.045
Data generation process	**T = 250**		
	$k = 1$	$k = 2$	$k = 30$
$\beta_2 = \beta_3 = 1$	0.042	0.046	0.045
$\beta_2 = \beta_3 = 0.5$	0.042	0.046	0.045
$\beta_2 = \beta_3 = 0.1$	0.042	0.046	0.045

Note: Computed using 10 000 simulations at the 5% significance level.
Source: Author's own elaboration

As shown in Table 2, the proposed test does not exhibit significant size distortions, with empirical sizes remaining close to the nominal 5% significance level across all scenarios. A more detailed examination reveals that the empirical sizes are consistently slightly below the 5% nominal level, typically ranging between 4.2% and 4.7%. This indicates that the FLSTAR test is slightly conservative. The stability of the size properties, even with the inclusion of Fourier terms of varying magnitudes, confirms the robustness and reliability of the FLSTAR testing procedure. The magnitude of the trigonometric term coefficients appears to have a negligible impact on the test's size, particularly as the number of observations increases.

To determine the power properties of the test, an LSTAR model augmented with a Fourier function is considered:

$$Y_t = \beta_1 + \beta_2 \sin\left(\frac{2\pi kt}{T}\right) + \beta_3 \cos\left(\frac{2\pi kt}{T}\right) + v_t, \tag{14}$$

$$\Delta v_t = \beta v_{t-1}\left[1 + \exp\left(-\gamma v_{t-1} - c\right)\right]^{-1} + \epsilon_t. \tag{15}$$

The power properties are examined using various parameter configurations: smoothing parameter $\gamma = 0.05, 0.1, 1$; location parameter $c = \{-10, -5, 0.5, 10\}$; Frequency value $k = 1$ and 2; $\beta = \{-1.9, -1.0, -0.2\}$. These evaluations were conducted for sample sizes of 100 and 250 observations, with 10 000 simulations performed for each experimental setting.

Table 3 Power properties of the test

Data generation process			T = 100		T = 250	
β	c	γ	$k = 1$	$k = 2$	$k = 1$	$k = 2$
		0.05	0.1435	0.2150	0.1742	0.2549
	−10	0.1	0.1451	0.2153	0.1725	0.2586
		1	0.0206	0.0533	0.0206	0.0665
		0.05	0.136	0.2048	0.1638	0.2440
	−5	0.1	0.1448	0.2146	0.1750	0.2582
		1	0.0516	0.1077	0.0791	0.1597
−1.9		0.05	0.1204	0.2048	0.1449	0.2288
	0.5	0.1	0.1260	0.2146	0.1560	0.2372
		1	0.2267	0.1077	0.2595	0.3235
		0.05	0.0910	0.1512	0.1068	0.1915
	10	0.1	0.0661	0.1186	0.0756	0.1561
		1	0.0490	0.0547	0.0489	0.0655
		0.05	0.0770	0.1317	0.0862	0.1692
	−10	0.1	0.0910	0.1515	0.1065	0.1913
		1	0.1268	0.2000	0.1466	0.2321
		0.05	0.0777	0.1207	0.0727	0.1571
	−5	0.1	0.0694	0.1323	0.0876	0.1726
		1	0.1140	0.1859	0.1322	0.2171
−1		0.05	0.0596	0.1075	0.0608	0.1402
	0.5	0.1	0.0603	0.1077	0.0649	0.1413
		1	0.0843	0.1211	0.0890	0.1590
		0.05	0.0843	0.0870	0.0422	0.1083
	10	0.1	0.0307	0.0675	0.0289	0.0847
		1	0.0414	0.0461	0.0421	0.0591
		0.05	0.0153	0.0379	0.0133	0.0479
	−10	0.1	0.0163	0.0417	0.0139	0.0518
		1	0.0221	0.0521	0.0203	0.0661
		0.05	0.0144	0.0345	0.0122	0.0444
	−5	0.1	0.0151	0.0374	0.0127	0.0469
		1	0.0188	0.0446	0.0154	0.0515
−0.2		0.05	0.0129	0.0328	0.0107	0.0427
	0.5	0.1	0.0129	0.0324	0.0096	0.0419
		1	0.0310	0.0385	0.0354	0.0530
		0.05	0.0108	0.0281	0.0086	0.0375
	10	0.1	0.0090	0.0260	0.0065	0.0326
		1	0.0090	0.0298	0.0294	0.0407

Source: Author's own elaboration

Examination of the results in Table 3 reveals a significant increase in the test's power with higher Fourier frequency values (k) and larger sample sizes (T). Conversely, the power of the test diminishes as the absolute value of the location parameter (c) increases. Furthermore, holding other parameters constant, the test's power decreases as the value of the autoregressive parameter β (representing the speed of mean reversion under the alternative) moves closer to zero (i.e., becomes less negative). A notable observation from Table 3 states that the overall power of the FLSTAR test can be quite low, particularly in smaller samples (T = 100) and for certain parameter configurations. This finding, while a limitation, is not unexpected and reflects a well-known trade-off in time series econometrics. Unit root tests, in general, are known to have low power, and this issue is often magnified for tests designed to detect complex alternatives involving both nonlinearity and structural breaks.

Several factors contribute to the observed low power: First, when the mean-reversion parameter θ is close to zero (e.g., –0.2), the process is "nearly non-stationary." Distinguishing such a slowly mean-reverting process from a true random walk is an inherently difficult statistical problem for any test. Second, power is highly sensitive to the location parameter c. When the absolute value of c is large, the time series crosses the threshold infrequently. This means the stationary behavior specified by the alternative hypothesis is rarely observed in the data, giving the test very little information with which to reject the null. Third, the FLSTAR test is designed to detect a highly specific alternative: stationary, asymmetric adjustment around a smoothly breaking deterministic trend. The cost of this flexibility is a reduction in power compared to simpler tests. If the true nonlinearity is weak (small γ) or the structural breaks are very subtle, the test may struggle to distinguish this complex alternative from a simple unit root process. Despite these challenges, it is crucial to note that the power systematically improves with the sample size, which is a desirable property.

3 EMPIRICAL APPLICATION

Following the first oil shock, observed changes in unemployment rates, particularly in developed countries, spurred a significant increase in research aimed at understanding their dynamics. Friedman (1968), and Phelps (1967, 1968) proposed that unemployment rates are a stationary process, implying that the effects of shocks are temporary, and introduced the natural rate hypothesis to the literature. Conversely, Blanchard and Summers (1986) argued that unemployment rates follow a unit root process, where the effects of shocks are permanent, thereby introducing the unemployment hysteresis theory. To distinguish between these two fundamental hypotheses, unit root tests are extensively employed in the literature (see, for example, León-Ledesma and McAdam, 2004; Yilanci et al., 2020; Ball and Onken, 2022; Dadam and Viegi, 2024; Guisinger et al., 2024; Yilanci et al., 2024).

This study examines the validity of unemployment hysteresis in the CIVETS countries using the newly introduced Fourier LSTAR (FLSTAR) unit root test. The acronym CIVETS was coined in 2009 by Robert Ward, global forecasting director at the Economist Intelligence Unit, who identified these nations as a second tier of countries poised to drive economic growth in the subsequent decade. CIVETS comprises Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa. These countries are generally characterized by young and growing populations, as well as diverse and dynamic economies (Geoghegan, 2010). The annual data for this analysis were obtained from the IMF e-data service, covering the following periods: 1980–2023 for Colombia, South Africa, and Turkey; 1990–2023 for Egypt and Vietnam; and 1983–2023 for Indonesia. These specific period ranges were selected based on data availability. The analysis is conducted using annual data, a choice motivated by several key considerations. First and foremost, the study's focus is on unemployment hysteresis, a long-run phenomenon concerning the permanent or persistent effects of economic shocks over many years. Annual data, by smoothing out short-term fluctuations, is well-suited for investigating such low-frequency dynamics. Second, from a practical standpoint, annual data provides the longest and most consistent time series available for the CIVETS countries, a crucial factor for the statistical power and reliability of unit root tests that must account for structural breaks. While higher-frequency data (e.g., quarterly) could offer insights into seasonal patterns and the precise intra-year timing of shocks, it would come at the cost of a significantly shorter time span. Furthermore, using annual data avoids potential distortions from seasonal adjustment procedures and aligns with the FLSTAR test's strength in capturing smooth, long-term structural changes rather than seasonal cycles. Therefore, annual data are deemed most appropriate for investigating the long-run persistence of unemployment in this context.

A related consideration is the choice of the starting periods in the 1980s and 1990s and the inherent challenges of using long historical data. We acknowledge that the CIVETS economies and their labor markets have evolved significantly over these decades. Furthermore, official statistics are often subject to changes in definitions and survey methodologies, making perfect long-run harmonization difficult. However, this structural evolution is precisely the phenomenon our study seeks to address. A long time series is essential for the statistical power needed to test a long-run concept like hysteresis. Indeed, the very premise of employing a Fourier-based test is to formally account for such gradual, long-term evolution. The Fourier function is specifically included to capture smooth structural changes, which can arise from fundamental economic transitions, demographic shifts, policy reforms, or even implicitly from changes in data collection methodologies. Therefore, while we recognize the imperfections of historical data, we argue that using the longest available series and employing a methodology robust to structural breaks provides a more powerful and insightful analysis of long-run unemployment persistence than would be possible with a shorter, more recent dataset.

If the unemployment rates, when examined for stationarity using the FLSTAR unit root test, are found to possess a unit root, this indicates the validity of unemployment hysteresis in the respective country. Conversely, the rejection of the unit root null hypothesis suggests that unemployment rates can be modeled by a stationary LSTAR process. In such instances, the plucking model of unemployment is considered applicable. The "plucking model" posits that unemployment rises sharply during recessions but falls more slowly during expansions (Suah, 2024). In analyzing these unemployment rates, structural changes arising from factors such as labor market reforms, major recessions (e.g., the Global Financial Crisis), or demographic shifts will be accounted for using Fourier functions.

We applied the FLSTAR unit root test to the unemployment series of the CIVETS countries; the results are presented in Table 4.

Table 4 The results of FLSTAR Unit Root Test

Countries	Opt. frequency	F test	FLUR test stat.	Opt. lag length
Colombia	1	15.5782*	6.9871**	1
Egypt	4	16.2617*	0.1574	0
Indonesia	1	52.5740*	3.3190	0
South Africa	1	9.7971*	2.1501	0
Turkey	1	19.8331*	2.5861	1
Vietnam	1	69.0721*	2.4196	9

Note: *, **, and *** denote the statistics significance at the 1, 5, and 10% levels, respectively. The critical value at the 1% level for the F test is 6.730 (Becker et al., 2006).
Source: Author's own elaboration

The findings in Table 4 reveal a notable distinction for Colombia, where the FLSTAR unit root test led to the rejection of the unit root null hypothesis at the 5% significance level. Furthermore, the F test statistic for Colombia is also statistically significant. This suggests that Colombia's unemployment can be characterized by a stationary LSTAR process; consequently, the plucking model may be an applicable framework for understanding its dynamics. In contrast, for the remaining CIVETS countries – Egypt, Indonesia, South Africa, Turkey, and Vietnam – the FLSTAR test statistics were not significant. Therefore, the null hypothesis of a unit root could not be rejected for these nations, indicating the validity of unemployment hysteresis. The persistence of a unit root in these countries, even when analyzed with the flexible FLSTAR framework, points to deeper structural issues or stronger hysteresis effects in their labor markets. These divergent findings across the CIVETS group, obtained through a unified testing framework, highlight that a 'one-size-fits-all' approach to labor market policy in emerging markets is likely suboptimal. Furthermore, the FLSTAR test's ability to identify these nuances demonstrates its superior practical utility for policymakers and researchers analyzing complex macroeconomic time series. These results also imply that the shocks to unemployment rates in countries exhibiting hysteresis are likely to have lasting effects.

CONCLUSION

This study addressed a notable gap in the time series analysis literature by proposing and evaluating a novel two-stage unit root test, termed the Fourier-LSTAR (FLSTAR) test. Recognizing the limitations of traditional unit root tests in the presence of structural breaks and nonlinear dynamics, the FLSTAR test was designed to simultaneously account for multiple, potentially smooth, structural changes via Fourier approximation and LSTAR-type asymmetric nonlinearity. The first stage of the test removes deterministic components and adjusts for structural breaks in the series, while the second stage employs an LSTAR-based unit root test on the filtered residuals.

Main contribution of this paper is that it explicitly differentiates itself from and advances upon prior methodologies. While Enders and Lee (2012) pioneered the use of Fourier terms to accommodate smooth breaks, their test operated within a linear framework and may therefore overlook nonlinear mean reversion. Subsequent tests, such as Christopoulos and Leon-Ledesma (2010), and Ranjbar et al. (2018) incorporated symmetric ESTAR nonlinearity but could not capture asymmetric dynamics. The FLSTAR test uniquely synthesizes these developments by integrating Fourier terms into an LSTAR model, providing the first framework for testing unit roots against the alternative of stationarity with both smooth breaks and asymmetric adjustment. This is particularly relevant for economic phenomena – such as the "plucking" model of unemployment – in which behavior during recessions and expansions differs markedly.

The paper successfully derived new critical values for the FLSTAR test statistic across various sample sizes and Fourier frequencies. Subsequent simulation results indicate that the FLSTAR test exhibits no significant size distortions, demonstrating stable performance across different magnitudes of trigonometric term coefficients and sample sizes. The power of the test increases with higher Fourier frequency values and larger sample sizes. However, it decreases as the absolute value of the LSTAR location parameter increases or as the coefficients of the Fourier terms approach zero, suggesting reduced effectiveness in scenarios with weaker nonlinearity or less pronounced structural breaks.

An empirical application to unemployment rates in the CIVETS countries showcased the practical utility of the FLSTAR test. The results indicated that while Colombia's unemployment rate can be characterized by a stationary LSTAR process, supporting the plucking model, unemployment hysteresis appears valid for Egypt, Indonesia, South Africa, Turkey, and Vietnam. This heterogeneity underscores the necessity of advanced testing methods capable of handling both structural changes and nonlinear dynamics, particularly in developing economies where economic and demographic shifts are significant.

The study's results have important implications for economic policy and research. For countries exhibiting hysteresis, such as Egypt, Indonesia, South Africa, Turkey, and Vietnam, structural reforms may be necessary to address persistent unemployment, given the permanent impact of shocks. In contrast, for Colombia, where unemployment is found to be stationary, temporary measures might suffice to manage fluctuations, aligning with the plucking model.

Looking forward, several avenues for future research emerge from this study. The FLSTAR testing framework could be extended and applied to other key macroeconomic and financial time series where the interplay of structural changes and asymmetric nonlinearities is theoretically plausible, thereby broadening its empirical relevance. Additionally, comparative studies evaluating the performance of the FLSTAR test against other recently developed nonlinear and non-stationary testing procedures across a wider array of data generating processes would be a valuable addition to the literature, further elucidating its relative strengths and limitations.

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Statistics of a Lifetime – and beyond?

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Abstract

Official statistics are part of the infrastructure of democratic societies. As societies have changed statistics have changed accordingly, not so much in content but in ways of production and dissemination. This paper describes important trends in official statistics over approximately the last 50 years.

The trends considered comprise the general quality revolution in the last century and recognition of official statistics as a public good available for free. The Internet caused a shift in the way statistics were spread, while more use of secondary (non-statistical) input data has changed the way of producing statistics.

Some thoughts on the future development of official statistics are included. Now the data era threatens to replace statistics. Artificial intelligence will affect both the way statistics are produced, and not least how statistics are understood and used in society. Quality frameworks for official statistics may be changed, but the main principles or core values of such statistics should remain. Cooperation and statistical literacy are keys.[2]

Keywords	***DOI***	***JEL code***
Official statistics, quality, development trends	*https://doi.org/10.54694/stat.2025.30*	*C10*

INTRODUCTION

In the discussion on the future of official statistics it is useful to consider how such statistics have developed in the past. This covers how statistics have adapted to or taken benefit from developments in user needs, technology, and other relevant conditions. The paper considers developments in or affecting official statistics over about 50 years.

The trends considered include the recognition of official statistics as a public good, systematic quality work in statistics and the development of Internet in addition to more use of secondary data and coordination of the statistical system. The most recent developments affecting official statistics are linked to the so-called data era. Most of the trends originated 50 years or earlier as ideas, though materialised fully during the last 30 years.

Some thoughts on the future of official statistics are included in the paper. This regards further developments of the trends described but also new issues such as the use of artificial intelligence (AI).

Aspects linked to the development of European and Norwegian statistics are briefly described. Examples referring to Statistics Norway are believed to be valid beyond the national level.

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[2] The paper is based on a presentation at the *European Conference on Quality in Official Statistics* (Q2024) in Estoril, Portugal, 4–7 June 2024.

1 SETTING THE TABLE

Svein Nordbotten gave a speech at the European Conference on Quality in Official Statistics Q2012 in Athens, looking back and forward (Nordbotten, 2012). He started with the punched cards used for censuses at the end of the 19th century. Other main shifts comprised the use of sampling theory 100 years ago, and the introduction of electronic processing in the 1950s. He mentioned that automatic editing really took off in the 1990s when computers had become important tools for simulating the human brain by means of artificial neural networks. An example relevant before its time!

A former Director General of Statistics Norway, Petter Jakob Bjerve, wrote a paper on international trends in official statistics for a lecture presented to the Statistical Council of Portugal (Bjerve, 1980). He noted that the use of official statistics was expanding rapidly. On data collection he noticed the international trend in increasing use of administrative data.

Bjerve was concerned with quality before this became a pronounced focus for the National Statistical Institutes (NSIs). He also advocated analyses to satisfy user needs.

An interesting aspect of the period up to the late 1970s was according to Bjerve that more and more countries planned their economies, following the development of national accounts after the second world war. Related to this he advocated analyses based on official statistics including projections. Statistics Norway has since 1950 had a department of research. One example of the planning trend was the development of natural resource accounts within Statistics Norway around 1980, where use of natural resources was linked to the national accounts. However, the planning trend was broken during the 1980s, though national accounts are central in most countries. Today, the need to control emissions damaging the climate is central, and linking emissions and environment to the economy and more central planning is on the agenda.

Bjerve considered the need to coordinate production of official statistics. He mentioned that the NSIs have been given greater and greater professional independence.

2 MAIN TRENDS IN OFFICIAL STATISTICS

Some of the trends described in the following are mentioned by Sæbø and Hoel (2023).

2.1 Official statistics as a public good

The understanding that official statistics are a public good, available for free to all users, is relatively new. The UN Fundamental Principles of Official Statistics (UNFPOS) first adopted by the Statistical Commission in 1994 and reaffirmed in 2014, state that "official statistics provide an indispensable element in the information system of a democratic society, serving the Government, the economy, and the public with data about the economic, demographic, social and environmental situation" (UNFPOS, 2014). The Fundamental Principles of Official Statistics were endorsed by the General Assembly in 2014.

UNFPOS is a basis for quality frameworks such as the European Statistics Code of Practice (ESCoP, 2017) and the UN National Quality Assurance Framework (UN NQAF, 2019). These frameworks elaborate how to secure official statistics as a public good. Official statistics as a public good is also included in new statistical legislation.

Official statistics available for everyone should in principle be free of charge. Free statistics contribute to goodwill and increased trust.

Production of some statistics may involve an extra use of resources and costs beyond governmental grants. In this case most NSIs receive payment corresponding to marginal costs (in practice often average costs including necessary overhead linked to support, equipment, and offices). Statistics Norway's budget today is for example based on about 25 percent "market funding" of which most comes from public institutions such as ministries. Some such funding is useful to provide user feedback, too much might involve a risk of less professional independence. It could at least be perceived as such. However, this should not be a problem regarding official statistics as a common good. In Norway the results of all production of statistics or analyses are available for free simultaneously for all. This is part of all contracts with funding partners.

2.2 Professional independence

The recognition of the professional independence of the producers of official statistics has emerged in parallel with the understanding of these statistics as a public good. But what does professional independence mean? UNFPOS does not mention independence specifically, but states that "to retain trust in official statistics, the statistical agencies need to decide according to strictly professional considerations, including scientific principles and professional ethics, on the methods and procedures for the collection, processing, storage and presentation of statistical data".

The indicators in ESCoP mention the responsibility of the NSIs and Eurostat for ensuring that statistics are developed, produced and disseminated in an independent manner, in other words *how* statistics are produced and disseminated, but not *what* or *which statistics* should be produced. What statistics should describe depends on the user needs, both the needs of the decision makers and the public.

However, even if professional independence is recognised as a precondition for producing official statistics today, there are several examples where this principle is not followed. Some of these are mentioned by Sæbø and Holmberg (2019), who also discuss how professional independence may be challenged by availability or lack of resources.

2.3 Quality

A quality revolution took place worldwide during the last half of the 20th century. This had a great impact on the production of statistics. This revolution is often associated with professor W. Edwards Deming and his advisory activities in Japan from 1950 (Deming, 1975), which provided the basis for Total Quality Management (TQM). Important principles in TQM comprise customer or user orientation, understanding variation and its causes, teamwork, and continuous improvement. Statistical methodology was applied as a basis for improvements controlling processes.

Quality was not new to statistical organisations. However, at least until the end of the century the concept was almost solely associated with accuracy. Total quality thinking points at a wider content of the quality concept, covering the needs of different users for products, as well as requirements to the underlying production processes as the key to improvements.

In Europe, a milestone in the development of a systematic quality work within official statistics was the Leadership Expert Group (LEG) on Quality which published a comprehensive report on quality in the European Statistical System (Eurostat, 2002). The report is inspired by TQM philosophies. It refers to the quality definition given by the International Standardisation Organisation (ISO) which in its later version specifies: "Quality is the degree to which a set of inherent characteristics of an object fulfils requirements" (ISO 9001: 2015). A simple version of this is „fit for use". Different users may have different needs that must be balanced to give the quality concept a concrete content.

The LEG report states that quality can be defined along several dimensions which constitute the product quality of statistics: Relevance, accuracy, timeliness and punctuality, accessibility and clarity, comparability, coherence and completeness. These dimensions are largely identical with the principles for quality of statistical output in the ESCoP that was originally adopted in 2005.

The LEG on quality developed a list of recommendations on quality work in the European Statistical System. One of them was to organise a biennial conference covering methodological and quality-related topics. The first such conference took place in Stockholm in 2001. The Q-conferences have been held regularly except for the pandemic year of 2020.

The UNFPOS has had a great impact on the work in statistical organisations worldwide. It was originally developed under the leadership of the United Nations Economic Commission for Europe (UNECE) following the need for a set of principles governing official statistics when countries in Eastern Europe began to change from centrally planned economies to market-oriented democracies. It was adopted by the UNECE in the Conference of European Statistics (CES) in 1992. Statisticians in other part of the world soon realised that the principles were of much wider global significance. Hence the process towards the UN Statistical Commission adoption of UNFPOS in 1994 started. Its rather short and simple formulation structured as 10 commandments is one of its strengths. UNFPOS itself does not say much about how to live up to its principles. However, as mentioned it has been the basis for the more recent quality frameworks, the global UN NQAF (2019) and regional frameworks such as ESCoP (2017).

The IMF Data Quality Assessment Framework (2012) should also be mentioned. In fact, the IMF was one of the first organisations promoting official statistics as a common public good and the importance of equal and simultaneous access to such statistics for everyone.

In the EU and the European Economic Area including Norway, the ESCoP is the basis for the quality requirements for official statistics. These requirements are reflected in new statistical legislation.

In Norway, the requirements for official statistics are given in the new Statistics Act (2019). Professional independence and impartiality are pillars in this act.

A quality framework is not much worth if not used for improvements. It can be the basis for self-assessments, audit-like reviews and peer reviews identifying improvement points to be followed up. In Europe, peer reviews based on ES CoP have been carried out for the whole European Statistical System three times. All countries had to set up improvement plans which have been followed up by Eurostat annually.

After each round of European peer reviews the ESCoP has been revised. The current issue from 2017 was strengthened by including a principle on coordination and cooperation.

There has been work in the international statistical community on core values for official statistics. The aim of selecting and communicating core values is to promote trust in official statistics. The Conference of European Statisticians session in 2022 endorsed a set of 6 core values for official statistics or their producers (CES, 2022).

Relevance of official statistics is the first core value. Other values *are impartiality, transparency, professional independence and protection of privacy* which are largely specific for official statistics. The last value is *collaborative* which points at the direction producers of official statistics should go. The core values can be looked upon as a superstructure over the UNFPOS, and hence over the main principles in the quality frameworks as well.

2.4 WWW

A major shift affecting official statistics came with the Internet. Several NSIs including Statistics Norway reacted quickly to the new possibilities and launched their first websites early in 1995. In the annual plan for Statistics Norway written during the autumn 1994 this was not foreseen. About 10 years later, the Internet was the main channel for disseminating statistics, such as news, tables and publications, in addition to databases where users could specify their own tables and download statistics.

Today, statistics can be transferred in different formats and by machine-to-machine transfer through the application programming interface (API). It has improved transfer of data between systems, and this has had a great significance for statistics as open data. The NSIs' use of social media for spreading or referring to statistics is common.

Technology has also facilitated electronic data collection by the NSIs.

2.5 Use of secondary data

During the last 30 years there has also been a shift in data sources for statistics, first from statistical sources (data collected for the purpose of statistics) to administrative sources (data registers developed for public administration), then to other sources including what is denoted as new sources including big data. Sæbø (2016) notes that while the first Q conference in 2001 treated quality of administrative registers only in a session on business registers and macroeconomics, there were 5 sessions devoted to this in Q2014. Now most sessions treating data collection focus on utilising new data sources, in addition to administrative data. New data sources dominate the discussion on development in different working groups in the international statistical community, though this has not resulted in many official statistics yet.

Recently, several countries have amended their statistical legislation with greater emphasis on access to privately held data on third parties.

In Norway, official statistics are largely based on administrative data systems. Statistics Norway has established a system for cooperation on quality with holders of administrative data to be used for official statistics. The system involves the signing of cooperation agreements. There are currently around 30 of such agreements. The agreement terms state that Statistics Norway is to produce yearly quality reports for each administrative data system, also for the use of the data holder to improve the data quality. There are about 100 such reports today.

2.6 From NSIs to statistical systems

NSIs are not sole producers of official statistics, but the NSIs normally have a coordination role that comprises quality assurance. The European Statistical System currently consists of Eurostat, 31 NSIs and currently 290 other national statistical authorities.[3] In the recent round of European peer reviews coordination has been a main issue.

According to the Norwegian Statistics Act (2019), Statistics Norway shall coordinate all development, production, and dissemination of official statistics in Norway, and produce an annual public report to the Ministry of Finance on the quality of official statistics. The Ministry has appointed a Committee for Official Statistics, led by Statistics Norway. The members mainly represent authorities who are responsible for official statistics or hold administrative data systems that are important for official statistics. The Committee shall contribute to the quality of official statistics and an effective national statistical system. Based on the Statistics Act, Norway has a national programme that defines and delimits official statistics. The programme is drawn up by Statistics Norway in consultation with the Committee for Official Statistics. The current programme covers the period 2024–2027 (Statistics Norway, 2024). Statistics Norway and 15 other public authorities have the responsibility for official statistics.

2.7 Data era replaces statistics

Data is not the same as statistics, though statistics are also data. Statistics based on aggregated data are normally closer to decisions than data. However, today the concept of data is widened and dominates the public discourse. The age of statistics is being replaced by the data era as expressed by Radermacher (2021).

Statisticians and data scientists cooperate and participate at the same international fora. In their communication, it is important to use a clear language to avoid misunderstandings. Open data is an advantage for use and reuse of data in the society. What is sometimes not communicated in their discussions is that official statistics as a public good today are open almost by definition.

[3] According to Eurostat website: <*https://ec.europa.eu/eurostat/web/european-statistical-system*>.

The request for more open data may indicate a need for more relevant and disaggregated statistics. Access to source data used in the production of official statistics can normally not be open to all because of necessary confidentiality rules. They may be accessible, with specific restrictions, for research or other specified purposes. A lot of work is going on to improve access to more data by anonymization and advanced technical solutions.

Reister (2023) addresses the assurance of quality in the new data ecosystem and warns to mind the gap between data and statistics. One of his points is the need to distinguish between the quality of data for different purposes including the quality of source data used to produce statistics, and the quality of output statistics. Distinguishing data in general from statistics can help bring clarity to the discussion of the role of official statistics in the data ecosystem.

3 WHAT NOW?

Many working groups or task forces are considering todays' challenges to official statistics and how to meet these. Challenges comprise competition from new producers of data and statistics, also by using artificial intelligence (AI), the difficulties for the public to differentiate the continuous data flow through the society from official statistics with specific quality requirements, access to privately held data and possible lack of funding because of easy access to data from other sources than the NSIs.

What from the past can contribute to new solutions? A few thoughts based on the trends considered above follow; new developments linked to data stewardship and AI are considered in separate chapters.

As a prerequisite for a democratic society, *official statistics as a public good must be promoted and defended*. Far from all countries in the world are democratic, and there is probably a way to go for all official statistics in practice to serve as a basis for a public debate. The work of international statistical organisations to promote quality frameworks based on UNFPOS is crucial since they contain principles and requirements supporting this and assuring the professional independence of producers of official statistics. The core values are also important in this context.

There is a discussion within the international statistical community about the quality of source data, in particular new, often denoted big data. Do we need to develop new quality frameworks for such data? Some of these discussions are based on misunderstandings about the difference between quality of produced statistics and quality of source data. The quality frameworks for statistics are geared towards the users of statistics, to ensure that statistics are fit for use. Statistics are based on source or input data that are fit to produce statistics, which in principle is different from requirements to output statistics for their users. This means that there may be different quality dimensions and requirements for such data, though some of the concepts used for characterizing the quality of statistics are suited for source data as well. What might be added in future revisions of quality frameworks for statistics is a requirement to systematic assessment of source data quality following checklists adapted to the type of data.

Gomez et al. (2023) address the overlap between ethical codes or assessment tools, legislation and the ESCoP. Discussions on new roles of official statistics and access to and use of new input data such as big data have triggered even more work on developing ethical and other principles and requirements for official statistics, possibly overlapping existing codes and frameworks. The paper argues that most of new proposals are already covered by existing codes/frameworks, and even statistical legislation. But what might be missing is highlighting and communicating what particularly applies to ethics in data collection.

There is a tendency to reinvent the wheel when developing frameworks, beyond what can be justified, e.g. to assure ownership. New data sources may imply a need for modifications and revisions of existing quality frameworks. However, that is different from developing new frameworks overlapping the existing.

4 DATA STEWARDSHIP?

There is a discussion in the international statistical community on the role of NSIs as data stewards. Several working groups and meetings have had this on the agenda.

UNECE (2024) has published a comprehensive report on Data stewardship and the Role of National Statistical Offices. Here "data stewardship means ensuring the ethical and responsible creation, collection, management and reuse of data so that they are used for public good and benefit the full community of data users". In brief, data stewardship implies the responsibility to manage a data ecosystem. The objective is to improve the use of data and statistics in society.

While few NSIs have the full responsibility for all public data as a national data steward, many hold this role for data used for official national statistics, including access to administrative data, sharing of data given privacy protection and coordination of the national statistical system. Almost all European NSIs collaborate extensively with other government bodies on issues related to data and information management processes. This may be prescribed in the statistical legislation, but it varies between countries.

This is in line with the experiences and plans for Statistics Norway, see Sæbø (2024). Statistics Norway has collaborated with other public authorities to develop solutions which have simplified the employers' communication with the different authorities, but which has also benefitted the production of official statistics.

To take a more active role in such collaboration, quality assurance, data sharing, teaching, and explaining statistical literacy in the society is natural for the NSIs. Most of these extensions of the role of an NSI are relevant regardless of the legislative basis.

Data stewardship roles may involve promotion of data exchange that go beyond the main NSI role of producing official statistics and sharing of microdata under specific conditions. This involves a risk of reducing trust, even if trust may also be an argument for extending the NSI role. An example is the efforts to utilise privately held data on third parties for official statistics in Statistics Norway, see Sæbø and Dimakos (2023). The statistics act authorizes such access. However, in a project to use bank transaction data linked to receipts from grocery stores as a basis for a new household budget survey, there has been protests both from data holders and the public. The Data Protection Agency has decided to forbid this because of possible privacy implications with reference to the Personal Data Act/GDPR. Statistics Norway decided to postpone the project while developing more methodology on data minimisation and offers a cooperation with the Data Protection Agency. It is a challenge to explain that data will only be used for official statistics describing groups and not individuals. The public debate focuses on surveillance.

The conflation of data and statistics is probably one of the reasons why it is challenging to explain that official statistics do not threaten privacy. An extended role for the NSI as national data steward might not make tasks like this easier.

5 ARTIFICAL INTELLIGENCE

Artificial intelligence (AI) and machine learning (ML) are often mentioned in connection with new developments in data science and statistics. Statistics might be considered a core element of AI (Friedrich et al., 2022).

Use of AI is not new, and machines have taken over manual operations for centuries. But as normal applications follow some years after theory. From the beginning of the 1990s, AI has been developing with major breakthroughs and practical applications such as automatic face recognition, speech recognition, translation, autonomous driving, and games such as chess. This is partly linked to an explosion in available open data, code and in particular computing capabilities. Today, machines can learn from data and information in amounts far beyond what humans can manage, but they still depend on human teaching. The development of AI is expected to expand dramatically in the years to come. We might be witnessing a shift comparable with the development of Internet 30 years ago.

AI has already affected the production of official statistics. Examples comprise programming, automatic classifications and editing. However, many new activities within statistics in this area can mainly be classified as research and development. The most relevant areas for implementation in the first round seem to be further automatization of editing to improve effectiveness and timeliness. Dissemination, including the development of chatbots is also a relevant area for new developments.

Challenges are linked to possible biases in the training material, necessary protection of privacy and false news also based on statistics. The results of using AI must be validated. Tools that can contribute to modify results in desirable directions are under development. One example is the so-called constitution,[4] named after the legal constitutions. By comparing statistical results with given laws/regulations (such as GDPR) and guidelines, possibly also quality frameworks, they may be modified in a specific and ethical direction.

However, another side of the coin is how statistics are used and tools applied by our users. Will official statistics be recognized as trusted compared to an increasing amount of false and misused information also based on statistics? The concept "AI hallucinations" refers to AI produced outputs that are factually incorrect, fabricated or misleading, which follow biased or outdated training data. But even if such data in the form of statistics are correct, machines may not distinguish between the correlation between two data series and causality. Treatment of uncertainty (e.g. in small samples) is also an issue in this context. Promoting statistical literacy will be even more important for statistical institutions.

Recently, much attention has been devoted to chat robots such as ChatGPT and Copilot. An example particularly interesting for statisticians is Google's Data Commons,[5] a system for presenting graphics including maps with data and statistics. These statistics are from open sources, mainly international organisations including UN and Eurostat but also from some NSIs. The sources are referred to, but there might still be a challenge regarding the visibility of official statistics compared to other statistics, and hence the quality of data in the system.

So far, the AI systems are a bit immature. They are very impressive when used for the purposes they are trained for, but other purposes humans take for granted like ethical principles may be missing. Validation and quality control are crucial.

CONCLUSIONS

Official statistics have developed greatly during the last 50 years. This has not so much applied to the content of such statistics, but to systematic quality work and the technological developments affecting their production and dissemination. Major developments are linked to the recognition of official statistics as a public good, available for free simultaneously for everyone in line with the development of quality frameworks for statistics, use of administrative and other data sources, the development of Internet and the following data revolution.

The last chapter in this development is probably the exploding use of artificial intelligence. This will affect both the production and use of official statistics positively, but it also represents a challenge for official statistics. Will such statistics be visible and perceived as relevant compared to the access to other data, including misuse of statistics and fake news? Availability of information of sources for statistics and data may not be granted.

Quality control and promotion of statistical literacy are important tasks for an NSI which may go beyond its own statistics.

Keeping and developing the statistical infrastructure in line with developments in the society and technology will be crucial also in the future. Reserving enough resources for research and development

[4] *<https://www.anthropic.com/news/claudes-constitution>*.
[5] *<https://datacommons.org>*.

of new technical solutions and data to produce statistics is necessary. International cooperation is important in this context. A key concept linked to innovation is *curiosity,* an attitude that should pervade any statistical organization.

The NSIs should stick to the core values of official statistics, and extending their roles should not compromise this. Collaboration is probably the main answer to the discussion on extended roles. Official statistics must continue to be associated with trusted institutions.

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Different Approaches to Volunteering in the Official Statistics

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Abstract

Volunteer work constitutes an important input into the activities of non-profit institutions and for society as a whole. Volunteering is a beneficial activity, for which no wage or remuneration is obtained, namely not even in the form of a service in return or in kind.

There are two main sources of the data on volunteer work, the data from Satellite Account of Non-profit institutions and the data from the Sample survey on volunteer work by Labour force survey. Both data sources provide a basis for valuation of volunteer work.

The article represents methodology of Satellite Account of Non-profit institutions, which presents basic information about volunteers and valuation of volunteer work organized by non-profit organizations. The article also presents methodology of the Sample survey on volunteer work by Labour Force Survey, which provides a comprehensive overview of organized and unorganized (direct) volunteering in Czechia. Based on the data from these two sources, the article also presents a methodology for estimation of the value of volunteer work and compares the specific values of these estimates.

Keywords	***DOI***	***JEL code***
Volunteer, volunteering, satellite account of non-profit institutions, labour force survey, valuation	*https://doi.org/10.54694/stat.2025.20*	*E23, E24, J30*

INTRODUCTION

In recent years, attention has been focused on the role of volunteers in society. Volunteering is an unpaid, non-compulsory activity, for which no wage or remuneration is obtained, namely not even in the form of a service in return or in kind.

For analytical purposes two kinds of volunteer work can be separately identified:
1) organization-based volunteering – volunteer work performed formally for or through organizations, community groups or any platform that allocates support;

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2) direct volunteering – volunteer work performed informally as part of everyday activities to help other people, directly for other households, excluding the household of the volunteer or of family members living in other households.

The intensity of volunteer engagement can be episodic, involving short-term, emergent, sporadic engagement of volunteers and may even be a one-off event. Volunteering can also be more regular and long-term activity, with fixed patterns.

Volunteering can be performed online, also known as virtual or digital volunteering, which has boomed especially during the Covid-19 pandemic. In the Sample survey on volunteer work, this type of volunteering turned out to be a minority, only 5.1% (130.2 thousand) of volunteers reported that their volunteer activity was conducted online (or at least partially online).

In 2023, the Czech Statistical Office conducted two surveys on volunteering, each of them with a different approach. The first is a survey of non-profit institutions, which is carried out annually. The output is The Satellite Account of Non-profit Institutions (hereinafter „SANPI") complements and extends the national accounts. It both unifies all the data for all non-profit institutions into one sequence of accounts and extends the statistical monitoring by indicators that are characteristic for non-profit institutions. Non-profit institutions are all the institutions that meet specified conditions, regardless of the institutional sector under which they are classified according to the System of National Accounts. An important contribution of the SANPI is the representation of voluntary work and inclusion of its value in the national accounts. The next benefit of SANPI is distribution of current transfers for Non-profit institutions serving households according to institutional sectors as payers of these transfers. The article also presents specific attributes by type of units and special classification CZ-COPNI used for Non-profit institutions. This classification is intended for the monitoring of the purpose which the funds of a non-profit institution were spent on. A non-profit institution is included in one or more of the sectors according to the shares of resources spent by it. Here is the difference from the CZ-NACE sectoral classification, where a non-profit institution is included in one sector according to its prevailing activity.

The second volunteer survey – Sample survey on volunteer work – was an add-on module of questions attached to the Labour Force Survey (LFS). It was conducted in the second half-year of 2023 as a one-time survey with possible repetition until 2030. Since 2002 LFS questionnaire has been fully harmonized with the Eurostat survey and corresponds to Council Regulation (EU). All sample data are recalculated to the age structure of the population according to population aggregates from demographic statistics, which takes into account the 2021 census. LFS allows making expert estimates of employment in organizations and companies, including activities of self-employed persons in business under the Trade Licensing Act and other legal regulations. The LFS examines the current structure of employment by gender, age group and educational attainment level, CZ-NACE activity and respondents' employment status. Also, data on total unemployment, unemployment pattern, structure of unemployed persons. Together with data on economically inactive population, LFS allows for quantifying the level and structure of disposable labor force, combining a wide range of social and demographic indicators on the respondents and their households.

There are not many countries in Europe which have annual survey of volunteering. Some of them has it as part of Labor Force Survey or other surveys in households once a few years (for example Poland in 2022, Austria in 2025), some of them held one-time survey focused on special type of organizations in rural areas (Germany – Thewes, 2024) and some of them held survey in nonprofit organizations (Italy).

1 SATELLITE ACCOUNT OF NON-PROFIT INSTITUTIONS

1.1 Methodology of SANPI

To begin with, we present the relevant definitions and the classification issue. The restated structural-operational definition of non-profit institutions is used for the purposes of statistical monitoring of non-profit institutions in the Satellite Account of Non-profit Institutions. According to this definition from the handbook of Non-Profit institutions (UN, 2018), institutions should meet the following five structural or operational criteria to fall within the scope of the non-profit institutions:

1. They must fulfil the defining characteristics of being organizations, that is, be institutionalized to some extent;
2. They must be completely (NPI) or significantly (cooperatives, mutual societies and social enterprises) limited in their capacity to distribute any profit they might generate to members, directors or investors;
3. They must be self-governing;
4. They must engage people on the basis of free choice; and
5. They must be private (not controlled by government).

The main reason for establishing non-profit institutions is either voluntary or charitable activity, or the effort to support certain groups of people in business, politics, or other areas of social life.

There is newly defined Third or Social Economy sector (TSE), that includes not only non-profit institutions but also other related institutions as cooperatives, mutual societies and social enterprises in Handbook of National Accounting: Satellite Account on Non-profit and Related Institutions and Volunteer Work (UN, 2018). The definition is very similar, the biggest change is about distributing profit to members, directors, or investors. Related Institutions must be completely (NPIs) or significantly limited in their capacity to distribute any profit they might generate. Even, there are Mutual societies in Czechia, they don´t have any limit to distribute their profit, that´s why these units are not included in the Satellite Account. Social enterprises also exist in Czechia, although there is no specific legislation for them. Instead, they are defined by guidelines of the Ministry of Labour and Social Affairs and included in the national registry named CESOP. They can take various legal forms (non-profit, non-financial institution or self-employed person) and are therefore classified across different sectors of the national accounts. Although they are not systematically identified by the CZSO in the core national accounts, their activities can be partially captured through satellite accounts or administrative registries.

Compilation of national accounts requires working with a number of classifications in the Business Register such as sector classification, classification of branches or, most importantly, so-called legal forms. Legal forms reflect the mode of operational functioning of different kinds of units. The delimitation of the sphere composed of NPI is thus based on the legal forms' codes. In 2023, the definition of non-profit institutions meets the following legal forms (see Table 1).

Table 1 Number of NPI included into satellite account by legal form for the year 2023

Code [1]	Title	NPI	NPI in S.11 and S.12 [2]	NPISH
	Total	**146 653**	**837**	**145 816**
	from this active units	***115 591***	***776***	***114 815***
117	Foundation	**598**		598
118	Endowment fund	**2 679**		2 679
141	Public service company	**2 424**	127	2 297
161	Institute	**1 620**	38	1 582
641	School legal entity	**371**	8	363

Table 1 (continuation)

Code[1]	Title	NPI	NPI in S.11 and S.12[2]	NPISH
704	Special organization for representation of Czech interests in international non-governmental organizations	**16**		16
706	Society	**96 227**	162	96 065
	from this active units	***67 720***	*108*	*67 612*
707	Trade union	**7 199**		7 199
708	Employers' organization	**79**	79	0
711	Political party, political movement	**276**		276
721; 722; 723	Church organization	**3 976**		3 976
734	An organizational unit of a special organization for representation of Czech interests in international non-governmental organization	**0**		
736	Branch of society	**25 510**	20	25 490
	from this active units	***22 955***	*13*	*22 942*
741	Professional organization/chamber	**22**		22
745	Other chamber (excl. professional ones)	**206**	206	
751	Association of legal persons	**1 028**	197	831
761	Hunting community	**4 210**		4 210
907	International trade union	**2**		2
921	International non-governmental organization (NGO)	**177**		177
922	An organizational unit of a international NGO	**21**		21
936	Foreign branch of society	**12**		12

Note: [1] legal form of organization, [2] S.11 means sector of non-financial institutions, S.12 means sector of financial institutions.
Source: CZSO, SANPI

Societies and branches of societies represent the largest group of non-profit institutions. For the year 2022, the CZSO received the first updated database from the Ministry of Justice, when those associations that have not fulfilled the obligation to send a notification of their establishment/activity to the registry court are considered inactive. There is 31 thousand of inactive units in 2023 that represents 25% of societies and Branch of societies.

Following the System of National Accounts, the SANPI presents NPI classified by individual institutional sectors according to the producer type, and by individual industries according to the product type. As shown in Table 1, non-profit institutions are included not only in the sector of Non-profit institutions serving households (S.15 – thereinafter "NPISH") but a number of them is included in the institutional sector of nonfinancial corporations (S.11) and financial corporations (S.12).

In 2024, an audit of the methodology and data processing within SANPI was carried out. Based on the recommendations from the audit, units of international non-governmental organizations operating in Czechia were included into SANPI, which have not yet been comprehensively surveyed and data for 2022 are available for the first time. Also based on the audit, the Public Universities and other units (Associations of health insurance companies) in the general government sector were excluded from SANPI during publication for 2023. These units and Public Universities were considered as borderline cases; the main discussion was about the fulfilment of the condition of separation from government institutions.

Concerning the data sources for the NPI, an exhaustive annual statistical survey is conducted for units with 10 or more employees. Units with 0–9 employees are surveyed once in five years, whereas each year a certain legal form is picked to be the subject of survey (or group of legal forms). Data for units with 0–9 employees which are not surveyed in given year are grossed up.

1.2 Funding of NPISH and volunteer work

NPI are usually funded differently from other economic sectors. Since the relevant breakdown is available for the NPISH sector only, let´s focus on this sector for now. Though the explanatory power is not much undermined by doing so, because the NPISH sector plays a crucial role in the SANPI.

NPISH, as well as NPI in their entirety, are funded differently from other economic sectors. NPISH can similarly as other sectors raise revenues from selling its own products or from property income, it represents only 11% of total income. Part of revenues NPISH sells for economically insignificant prices that are lower than market prices (22% of income). About 58% of the total income comes from other sectors in the form of current transfers.

These transfers are recorded under the item D.751 (Current transfers to NPISH); for other sectors, the given transfers are covered by the item D.759 (Other current transfers). The largest transfers came from the general government sector (about 64%), subsidies from the EU also contributed (another 8%). The contribution of households to non-profit institutions reached 17% in 2022. On the top of these, the NPISH collect membership fees and they normally receive donations from other economic sectors, including non-financial and financial corporations (11%). NPISH may obtain funds from non-profit organizations themselves (especially foundations). Because the sector is consolidated, the amount of these revenues cannot be determined.

A very specific source of input into operation of NPI recorded on the resources side is a contribution of volunteering. Volunteering concerns not only households, but also corporations. Mentioning the work of volunteering brings us to the key question, how the work of volunteers should be valued? The evaluation of volunteer work and its inclusion into the accounts represents an important step beyond the standard framework of national accounts. Unpaid volunteer work does not fall within the production border as defined by the methodology; however, it is unquestionably an important input into the activities of non-profit institutions. Disregarding volunteer work leads to underestimation of the actual contribution of non-profit institutions to the welfare of society.

Here, the term volunteer means a person who is not in an employment relationship with an economic entity as regards the respective voluntarily done activity and performs his or her activity without any financial or other remuneration or legal entitlement (including any entitlements arising from obligations of the entity's members according to the statutes or other resolutions adopted by the economic entity). Voluntary workers may be volunteers performing work for an economic entity, on volunteer service, as well as other persons performing work in an organization without entitlement to remuneration (unpaid members of administrative and control bodies, members of an economic entity and other persons).

It remains valid that it is not possible to establish the number of inhabitants of Czechia performing volunteer work for non-profit institutions on the basis of source data. This is due to the fact that one person can perform volunteer work for several non-profit institutions. Therefore, the number of volunteers is given as a number of natural persons converted on the basis of the number of hours worked by volunteers (full-time equivalent approach, thereinafter "FTE"), it means 20 810 FTE in 2023.

Table 2 shows the number of volunteers in natural persons by legal form in the years when the legal forms were surveyed. International non-profit organizations operating in Czechia were surveyed in 2022 for the first time. As can be seen, the number of volunteers involved in non-profit institutions is around 1 million people.

Table 2 Number of volunteers and hours worked in particular kind of NPI (2019–2023)

		Year	Number of volunteers	Hours worked (in thousand of hours)	Average of hours worked per person/year
0–9 employees	Foundation/endowment fund	2019	12 215	463.7	38
	Trade union	2019	4 843	260.0	54
	Other	2020	11 583	270.3	23
	Church organization	2021	11 451	880.5	77
	Society	2022	393 670	18 593.4	47
	Branch of society	2022	407 321	14 134.0	35
	International NPI in the CR	2022	1 880	50.8	27
	Public service company/institute	2023	10 769	405.3	38
More than 10 employees	Foundation/endowment fund	2023	117	2.3	19
	Trade union	2023	10	0.8	82
	Other	2023	492	23.6	48
	Church organization	2023	14 956	489.8	33
	Society	2023	182 178	2 900.7	16
	Branch of society	2023	1 823	110.5	61
	International NPI in the CR	2023	15	525.0	35
	Public service company/institute	2023	7 975	256.2	32
	Total		1 061 298	39 366.9	42

Source: CZSO, SANPI

From the survey of non-profit institutions, we can also get information about what kind of work volunteers do. The first part is focused on how often volunteers come to NPI. Irregular work is occasional unpaid work performed by one volunteer, e.g. 5 times a year, regular work means fixed-scheduled work. The second part is about which kind of work volunteers do. The categories are defined similarly to the classification of occupation (CZ-ISCO).

Table 3 Volunteer work according to kind of work (Survey NI 1-01)

		2023	
Hours worked by volunteers (thousands)		36 962	
Of which	One-time work	5 027	11%
	Irregular work	18 702	41%
	Regular work	13 196	29%
According to the nature of the work	Management and professional mental work	7 731	17%
	Lower administrative work, operational work, craft and qualified production work	22 769	50%
	Work in operating machines, auxiliary and unskilled work	6 390	14%

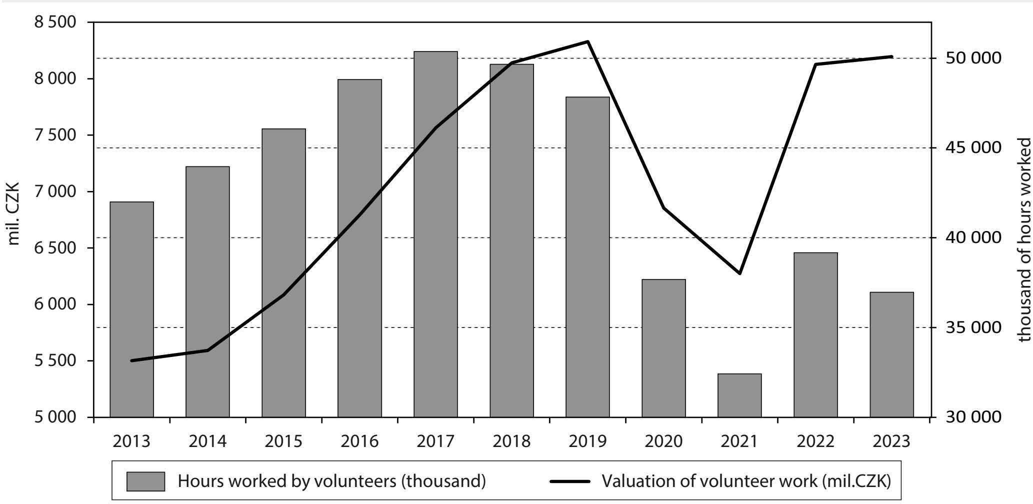
Source: CZSO, SANPI

1.3 Valuation of Volunteer work

The method of valuation by means of the median determined on the basis of the results obtained from the Average Earnings Information System (ISPV, which is the national realization of the Structure of earnings survey) is used for valuation of volunteer work at SANPI. The Average Earnings Information System (ISPV) is carried out by the Statistical Services Department of the Ministry of Labour and Social Affairs according to Act No. 43/1992 Coll., on salary and remuneration for stand-by duty in budgetary and certain other organizations and bodies.

For the year 2023, the median value of salaries in Czechia according to ISPV reached 221.79 CZK/hour. The number of hours worked by volunteers, that the Czech Statistical Office obtained from the statistical surveys by means of questionnaires NI 1-01 (a), was multiplied by this median. To illustrate, the median in 2013 was 126.42 CZK/hour. The following graph shows the valuation of volunteer work for non-profit institutions in Czechia for the years 2013 to 2023.

Figure 1 Hours worked by volunteers and the valuation of volunteer work for non-profit institutions (NPI) in total from 2013 to 2023



Source: CZSO, SANPI

The evaluated volunteer work still enters the Satellite Account of Non-profit Institutions as part of the Wages and Salaries (D.11) item. The increase in item D.11 is reflected in the change to the total remuneration of employees (D.1). For NPISH, the non-market output (P.132), which is calculated using the cost method, will increase in addition. There is no impact to balancing items (the operating surplus, disposable income, net savings, net loans, and others) as the evaluated volunteer work is added also into the item Current transfers to NPISH (D.751).

2 SAMPLE SURVEY ON VOLUNTEER WORK BY LFS

2.1 Methodology of the sample survey on volunteer work

In the second half-year of 2023, the Czech Statistical Office carried out a survey with the topic of volunteering, which was an add-on module of questions attached to the Labour Force Survey (LFS). Interviewers in all Regions of Czechia addressed respondents aged 15+ years. This survey on the initiative of the Office of the Government of the Czech Republic was financed by the Ministry of the Interior of the Czech Republic.

In the survey, volunteering was defined as a beneficial activity, for which no wage or remuneration is obtained, namely not even in the form of a service in return or in kind. Activities resulting from an obligation (e.g. to an employer, a school, etc.) or activities only aimed at family members were not considered volunteering. This definition is based on a definition of volunteering as it was determined by the International Labour Organization (ILO).

Making financial donations alone was not considered a volunteering activity in the survey, because it is usually a one-time aid, which lies in sending a donation SMS, bank payment, or a donation in cash. For the purposes of this survey, neither blood donation was considered volunteering, namely because more precise statistics can be obtained from administrative sources, which are available for blood donation.

Respondents were first answering three basic filtering questions that were to select from the population those who in the last 12 months participated in a volunteering activity, which they carried out for at least 1 hour; for those respondents, details were further examined. However, when respondents gave negative answers to all of the three filtering questions, the module ended up for them.

A direct link to the LFS allows us to obtain detailed information about respondents such as gender, age, educational attainment level, economic activity, employment status etc.

2.2 Basic characteristics of the volunteers and types of volunteering in the sample survey on volunteer work

One of the key tasks of the survey on volunteer work was to quantify the number of volunteers involved and their share in the adult population – i.e. the volunteering rate. In total 19.2% of the respondents were involved in volunteering, which represents 1 662.3 thousand inhabitants of Czechia aged 15 years and over. Women predominated among the volunteers, numbering 947.5 thousand, the volunteering rate of women (21.4%) was higher than the volunteering rate of men (16.9%), but on the other hand men reported a greater number of hours devoted to volunteering.

The biggest proportion of volunteers was in the age group of 25–44 years (36.3%) and 45–64 years (36.2%). There were 18.0% of volunteers aged 65+ years and the smallest proportion belonged to volunteers aged 15–24 years (9.5%). Females were considerably prevailing among volunteers in the age group of 65+ years, they made 64.3%.

The largest share of volunteers consisted of people with secondary education with A-level examination (35.2%) followed by those with higher education (28.8%), secondary vocational education (27.9%), and the lowest number of volunteers was among those with primary education (8.1%).

Over two thirds of volunteers were working persons (68.4%), the inactive (students, the retired, etc.) made up 30.1% of volunteers, and 1.5% were unemployed. Among both the inactive and the unemployed volunteers, females were significantly prevailing.

Volunteering is divided into organized, where activities are organized by an umbrella institution (a company, an association, a club, a state, a municipality, a community, etc.) and unorganized (direct), where activities are managed and coordinated directly by an individual.

Organized volunteering was prevailing, 941.1 thousand (56.6%) volunteers were organized by some institution. The volunteer activity was organized most often by a non-profit, charitable or a church organization, by an association, a club, a health or social establishment (502.7 thousand, 30.2% from the total number of volunteers), by a state or municipal organization (249.7 thousand, 15.0%), by an informal community (95.0 thousand, 5.7%), other organization (47.0 thousand, 2.8%) or by a workplace of a respondent (46.6 thousand, 2.8%).

As for unorganized (direct) volunteering, the volunteer activity was most often organized directly by the respondent (455.0 thousand, 27.4%), by a person helped by the respondent (213.8 thousand, 12.9%), or another person (45.9 thousand, 2.8%).

Because SANPI captured organized volunteers, in the sample survey on volunteer work we present not only the results for the total number of volunteers, but also for the part of volunteers which is made up of the organized volunteers.

Table 4 Volunteers in total and organized volunteers by age, education, economic activity (in thousands of people)

Classification	Total number of volunteers	In which		Organized volunteers	In which	
		Males	Females		Males	Females
Age groups (years)						
15–24	157.5	59.5	98.0	103.3	39.7	63.7
25–44	603.8	279.7	324.1	346.6	158.1	188.5
45–64	602.6	269.2	333.4	352.2	160.3	191.9
65+	298.4	106.4	192.0	139.0	47.6	91.4
Education						
Primary education	135.0	41.4	93.6	65.9	19.4	46.6
Secondary education without A-level examination	463.4	253.2	210.3	246.7	136.6	110.1
Secondary education with A-level examination	585.7	228.6	357.1	333.4	134.5	198.9
Higher education	478.2	191.6	286.6	295.1	115.1	180.0
Economic status						
Working person	1 137.1	554.5	582.6	677.5	326.7	350.9
Unemployed	24.6	8.1	16.5	12.4	4.5	7.9
Inactive	500.6	152.2	348.5	251.2	74.5	176.7
Total	1 662.3	714.8	947.5	941.1	405.6	535.5

Source: CZSO, sample survey on volunteer work

2.3 Volunteering activities by classification of occupations (CZ-ISCO)

The range of volunteer activities is very wide, and the activities are similar to occupations, therefore the CZ-ISCO classification was used to classify the volunteer activities. CZ-ISCO is a national version of the International standard classification of occupations.

Generally, it is not surprising that the most frequently reported volunteer activities were included in the main class of Elementary occupations, which included 611.5 thousand (36.8%) volunteers. Volunteers were also engaged in qualified activities, a large proportion of volunteers were in the main class of Technicians and associate professionals (382.7 thousand, 23.0%), where they were most often in a subclass of Professional workers in the business sector and public administration, this activity was reported by 86.6 thousand men and 222.7 thousand women.

Organized volunteers were more often engaged in qualified activities, e.g. all volunteers in the main class of Managers were organized, a large proportion of organized volunteers also were in the main class of Clerical support workers were organized volunteers and in the main class of Professionals.

Table 5 Volunteers and organized volunteers by main classes of CZ-ISCO (in thousands of people)

CZ-ISCO	Total number of volunteers	In which		Organized volunteers	In which	
		Males	Females		Males	Females
1 Managers	4.7	3.9	0.8	4.7	3.9	0.8
2 Professionals	113.5	45.2	68.3	67.8	27.0	40.8
3 Technicians and associate professionals	382.7	133.1	249.6	206.5	78.1	128.5
4 Clerical support workers	20.5	7.5	13.0	17.4	6.1	11.3
5 Service and sales workers	312.8	134.1	178.7	184.9	109.3	75.6
6 Skilled agricultural, forestry and fishery workers	53.4	31.5	21.9	30.0	18.4	11.6
7 Craft and related trades workers	98.8	63.2	35.6	35.8	14.7	21.1
8 Plant and machine operators and assemblers	64.4	46.4	17.9	19.1	13.1	6.1
9 Elementary occupations	611.5	249.8	361.7	374.9	135.2	239.7
Total	1 662.3	714.8	947.5	941.1	405.6	535.5

Source: CZSO, sample survey on volunteer work

2.4 Valuation of volunteer work in total in the sample survey on volunteer work

In the sample survey on volunteer work, there were two different methods used to estimate the financial value of volunteer work, both of them on the basis of the results obtained from the Average Earnings Information System (ISPV). The first method used the basic framework for calculating the hourly rate of volunteering. The framework is appropriate to the principles for determining the value of volunteer work based on the median gross monthly wage and the median average hours worked in the wage sector according to the results of the Average earnings information system (ISPV) for the given year (2023). The first method is more general, does not take into account the type of volunteer work and it is the same method that was used to evaluate the volunteer work in SANPI. The only difference is in the rounding, because in the sample survey on the volunteer work were used the principles for determining the value of volunteer activities, which follows from the government resolution and recommend rounding down to the nearest whole CZK.

The median gross monthly wage according to ISPV was 38 236 CZK. The median average monthly hours worked according to ISPV was 172.4 hours. By dividing these two values, we obtain an hourly rate, which rounded down to the nearest whole CZK was 221 CZK. The number of volunteers according to the results of the survey was 1 662.3 thousand people. The average number of hours worked by volunteers according to the results of the survey was 9.8 hours in the last 4 weeks. Converting to a whole year (i.e. multiplying by the corresponding number of weeks according to the calendar) we obtain a value of 128.4 hours per volunteer.

The final estimate of the financial value of volunteer work in the sample survey on volunteer work in 2023 was obtained by multiplying the number of volunteers (1 662 300 people) by the annual number of worked hours per person (128.4 hours) and the hourly rate (221 CZK), which comes out to 47 170.1 million CZK. Using the first method, the total financial value of volunteer work in Czechia in 2023 according to the sample survey on volunteer work was estimated for more than 47 billion CZK.

The second method of valuation is more detailed, takes into account the types of volunteer work, and it is based on the average wages for the main CZ-ISCO classes according to ISPV. The determined average number of hours spent volunteering in the last 4 weeks was divided by 4 to obtain the average weekly numbers of hours spent volunteering and multiplied by the number of volunteers to obtain the annual number of hours worked per volunteer. To obtain the annual volume of hours, the annual number of hours per volunteer is multiplied by the number of volunteers in each CZ-ISCO class. The hourly average wage was obtained by dividing the monthly average wage by the number of paid hours. By multiplying the annual volume of working hours by the hourly average wage (according to ISPV), we obtain an estimate of the valuation of volunteer work in individual CZ-ISCO classes, which in total is almost 43 billion CZK. If these activities were not carried out by volunteers, the state or local governments would have to pay this amount.

Table 6 Estimated financial value of volunteer work based on average wages for the main CZ-ISCO classes according to ISPV

CZ-ISCO	Number of people (thousand)	Average number of volunteering hours in the last 4 weeks	Annual number of hours per person	Annual number of hours	Monthly average salary (ISPV, CZK)	.. by number of paid hours	Average hourly wage (ISPV, CZK)	Value (CZK million)
1 Managers	4.7	17.0	222.8	1 051 834	102 316	172.0	595	625.5
2 Professionals	113.5	15.4	201.4	22 852 932	66 207	173.2	382	8 733.6
3 Technicians and associate professionals	382.7	7.1	92.7	35 460 397	49 200	172.0	286	10 144.7
4 Clerical support workers	20.5	11.1	145.1	2 978 256	36 842	172.1	214	637.5
5 Service and sales workers	312.8	11.3	148.2	46 361 180	32 275	172.2	187	8 687.5
6 Skilled agricultural, forestry and fishery workers	53.4	10.3	134.5	7 177 123	33 440	179.1	187	1 339.9
7 Craft and related trades workers	98.8	9.8	128.2	12 668 924	38 890	172.7	225	2 853.0
8 Plant and machine operators and assemblers	64.4	8.0	104.8	6 746 982	37 186	173.0	215	1 449.9
9 Elementary occupations	611.5	6.9	90.2	55 187 574	26 499	173.1	153	8 447.4
Total	1 662.3			190 485 202				42 919.1

Source: CZSO, sample survey on volunteer work 2023, ISPV

2.5 Valuation of volunteer work of organized volunteers in the sample survey on volunteer work

In the Sample survey on volunteer work, we can divide organized and unorganized volunteers. Volunteer activities of organized volunteers in the sample survey of volunteer work were organized by a company, association, club, state, municipality, community, charitable or church organization, association, club or medical or social institution etc., we can therefore assume, that the range of the institutions includes a non-profit organizations, but not only them. In order to get closer to the range of volunteers who are monitored by the satellite account of non-profit institutions, we are taking a closer look at the organized volunteers. According to the sample survey on volunteer work, there were 941.1 thousand of organized volunteers (56.6% of the total number of volunteers). In this group women significantly predominated (535.5 thousand, 56.9%).

To estimate the financial value of the work of the organized volunteers, there were used the same two methods as in the total estimation of the value of the volunteer work. In the first method, the median gross monthly wage according to ISPV (38 236 CZK) was used again. The median average monthly hours worked according to ISPV were 172.4 hours, hourly rate was 221 CZK. The number of organized volunteers according to the results of the survey was 941.1 thousand people. The average number of hours worked by organized volunteers according to the results of the survey was 10.6 hours in the last 4 weeks. Converting to a whole year we obtain a value of 139.4 hours per volunteer.

The final estimate of the financial value of volunteer work of organized volunteers in 2023 was obtained by multiplying the number of volunteers (941 100 people) by the annual number of hours per person (139.4 hours) and the hourly rate (221 CZK), which comes out to 28 992.8 million CZK. According to the first method, the financial value of organized volunteer work in Czechia in 2023 was estimated for nearly 29 billion CZK.

The second method based on average wages for the main CZ-ISCO classes according to ISPV provided the result of 31 030.6 million CZK. If the activities were not carried out by volunteers, the state or local governments would have to pay more than 31 billion CZK.

Table 7 Estimated financial value of organized volunteer work based on average wages for the main CZ-ISCO classes according to ISPV

CZ-ISCO	Number of people (thousand)	Average number of volunteering hours in the last 4 weeks	Annual number of hours per person	Annual number of hours	Monthly average salary (ISPV, CZK)	.. by number of paid hours	Average hourly wage (ISPV, CZK)	Value (CZK million)
1 Managers	4.7	21.0	275.2	1 299 324	102 316	172.0	595	772.7
2 Professionals	67.8	26.8	350.6	23 771 265	66 207	173.2	382	9 084.5
3 Technicians and associate professionals	206.5	11.3	148.3	30 630 359	49 200	172.0	286	8 762.8
4 Clerical support workers	17.4	17.0	222.8	3 882 250	36 842	172.1	214	831.0
5 Service and sales workers	184.9	10.8	140.9	26 043 577	32 275	172.2	187	4 880.2
6 Skilled agricultural, forestry and fishery workers	30.0	13.8	180.9	5 423 474	33 440	179.1	187	1 012.5
7 Craft and related trades workers	35.8	9.6	126.0	4 505 029	38 890	172.7	225	1 014.5
8 Plant and machine operators and assemblers	19.1	12.8	167.5	3 206 663	37 186	173.0	215	689.1
9 Elementary occupations	374.9	5.3	69.4	26 021 493	26 499	173.1	153	3 983.0
Total	941.1	10.6		124 783 435				31 030.6

Source: CZSO, sample survey on volunteer work 2023, ISPV

3 COMPARISON OF SANPI AND SAMPLE SURVEY ON VOLUNTEER WORK

Comparing volunteers and the value of their work from the sample survey on volunteer work by LFS and the SANPI survey is challenging due to differences in scope and methodology. Even SANPI and Sample survey on volunteer work focus on volunteering at the different groups of volunteers and take volunteering from a different perspective, both of these sources are valuable for observation the situation of volunteers in Czechia. The sample survey on volunteer work includes volunteers in a much broader sense than SANPI. According to the sample survey on volunteer work, 1 662.3 thousand inhabitants of Czechia aged 15 years and over in total were involved in volunteering in 2023. The sample survey on volunteer work also provides other information on the classification of volunteers, such as gender, age, employment status, level of education etc. On the other hand, the biggest advantage of the survey for SANPI is a continuous time series from 2009, when the new system was held. Trends in volunteering involvement in non-profit institutions can be traced there.

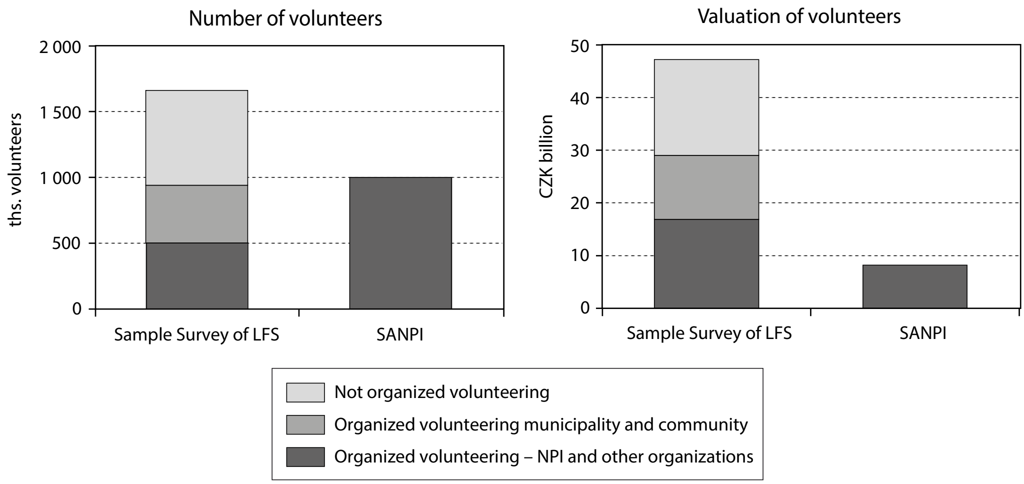
If we compare a number of organized volunteers that more or less correspond to itself in both data sources, we obtain similar numbers. The sample survey on volunteer work by LFS includes not only non-profit institutions but also volunteer activities organized by other types of institutions (company, association, club, state, community, municipality, charitable, or church organization). In the sample survey on volunteer work, there were 941 thousand such volunteers, of which only 502 thousand volunteers worked directly in NPI. In total, it corresponds to the data for natural persons in SANPI, which was around 1 million.

The difference can be explained by the different approach to counting volunteers. In SANPI, some volunteers can be counted more than once if they work for more than one organization. On the other hand, in the sample survey a volunteer is counted only once, even if he works for more than one organisation, whether NPI or other.

The biggest discrepancy in the estimated value of volunteer work comes from the very different number of hours worked by volunteers per year in each data source. In the long-term SANPI data, the average annual working time is relatively low, between 35–50 hours per year, and in the recent years a decrease has been seen. In contrast, in the sample survey on volunteer work, the number of hours worked in the last 4 weeks ranges around 10 hours, thus on average more than 120 hours per year. In addition, organized volunteers in the sample survey reported a greater number of hours dedicated to volunteering, on average nearly 140 hours of volunteering per year. This is also related to the estimated value of volunteer work, which is much greater for volunteers from the sample survey on volunteer work than from SANPI, even though the methodology for valuing volunteer activities is the same in both surveys. With such a difference in hours worked, it is self-evident, that the estimates of the value of volunteer work in both data sources differs greatly. In 2023 in SANPI the value of volunteer work in non-profit organization was estimated for 8.2 billion CZK and in the sample survey the total value of volunteer work was estimated for 47.2 billion CZK. From that 29.0 billion CZK was the value of organized volunteer work in the sample survey, as also not NPI organizations are included. If only volunteers in NPI and other organizations (could be political parties or other legal forms considered as NPISH in SANPI) were considered in the sample survey, the estimate of valuation would take 58% of the 29.0 billion CZK, that is 16.9 billion CZK. Even this value of volunteer work in the sample survey is twice as large as the value of volunteer work in SANPI. These estimates are based on a similar methodology, the only difference being in the hours worked and in the rounding process.

The sample survey on volunteer work also provides a second estimate, which takes into account the type of volunteer work according to CZ-ISCO. Based on this method, the total value of volunteer work was estimated at 42.9 billion CZK. Within that, the value of organized volunteer work was estimated at 31.0 billion CZK, of which 18.0 billion CZK was attributed to volunteers in non-profit institutions and other organizations. One of the major challenges in estimation of the value of volunteer work therefore remains in a more accurate recording of the hours worked by volunteers. Estimating the number of hours worked by volunteers is complicated, as volunteers often do not track the hours, they simply help when they can, without remembering or writing down the number of hours worked. Therefore, in the sample survey on volunteer work some volunteers did not report the number of volunteering hours at all, some volunteers gave only a rough estimate of volunteering hours in the survey.

Figure 2 Comparison of the number of volunteers and the volunteer work valuation (2023)



Source: CZSO, sample survey on volunteer work, SANPI, ISPV

CONCLUSION

Volunteering is a great way to help those in need, support the community and contribute to solving various social problems, moreover the volunteer work plays a key role in the functioning of non-profit institutions. This paper presented two major data sources for measuring and valuing volunteer work in Czechia: the Satellite Account of Non-profit Institutions (SANPI) and the sample survey on volunteer work by LFS. While both sources offer valuable insights, they differ in scope, methodology, and focus.

SANPI provides consistent time series data specific to volunteers within non-profit institutions and is based on data from national accounts, offering a macroeconomic view over time. In contrast, the sample survey on volunteer work captures a broader spectrum of volunteer activities – including direct, unorganized volunteering – and offers more detailed demographic and occupational data.

Regarding the number of volunteers, the results do not differ substantially. SANPI reports around 1 million volunteers in NPI, the sample survey has 1.6 million volunteers in total, of which 941 thousand works as volunteers in organizations. And 502 thousand of these volunteers works directly in NPI. The divergence in total numbers can be explained by different approach in surveys, as NPISH don´t monitor if their volunteers work for another organization or not.

Despite methodological alignment in the valuation of volunteer work, the estimated financial contributions differ substantially due to discrepancies in reported hours and coverage. While SANPI reports lower average annual hours per volunteer, the sample survey on volunteer work suggests significantly higher involvement, highlighting the challenges inherent in accurately capturing volunteer activity.

Both SANPI and the sample survey on volunteer work contribute to a better understanding of the scope, structure, and value of volunteer work in Czechia. Together, they provide a robust basis for policy development, support for the non-profit sector, and recognition of the substantial economic and social value generated by volunteers.

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