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Foreword by the Governor

It is exactly five years since the National Bank of Serbia launched its Working Papers Bulletin, with the aim of further encouraging research activities within our institution and promoting them to the wider public. With this in mind, it gives me particular pleasure to note that the new, eleventh edition of the Bulletin contains the largest number of papers to date, covering a very broad range of topics and employing state-of-the-art quantitative techniques in their analyses.

The first paper addresses a topic of considerable importance to monetary policymakers – the persistence of inflation in Serbia, depending on the direction, magnitude and source of the shock. Using quantile analysis, the authors show that positive inflation shocks have a more persistent effect on inflation than negative, i.e. disinflationary, shocks, a finding similar to those obtained for other countries. The paper also shows that the prices of processed food and services, as well as core inflation, exhibit a higher degree of persistence than other consumer prices (e.g. fuel, fruit and vegetables). The greater persistence of positive inflation shocks indicates that a stronger monetary policy response is generally required during periods of rising inflation than during periods when inflation is declining.

The second paper analyses the determinants and dynamics of the conditional volatility of the National Bank of Serbia's gross foreign exchange reserves, with particular reference to institutional resilience to systemic risks. Econometric analysis shows that the most important determinants of foreign exchange reserve movements are the M3 money supply, the degree of dinarisation and foreign direct investment. The high level of foreign exchange reserves held by the National Bank of Serbia supports the resilience of domestic monetary policy and the preservation of relative exchange rate stability. Applying stress tests, the authors show that even under the most adverse assumed scenarios (which have not occurred in practice), gross foreign exchange reserves would remain at a level fully sufficient to preserve macroeconomic stability.

The next paper examines the potential use of deep machine learning (LSTM) to forecast currency in circulation, which is a highly important input for the operational conduct of monetary policy. While the standard ARIMAX models currently used by the National Bank of Serbia require explanatory variables to be specified in advance, LSTM models independently identify patterns in large volumes of historical data, without rules being predefined. Although LSTM models produced larger forecast errors than ARIMAX over the entire period analysed, once a single atypical month was excluded from the analysis, the LSTM models achieved better results. This suggests that, when trained on representative historical data, they have the potential to outperform the conventional approach.

In the following paper, the authors analyse labour market developments in Serbia in the period 2011–2025, supplementing official statistics with derived indicators. The authors demonstrate econometrically that labour market efficiency, measured by the residual of the Beveridge curve, and labour market tightness, measured as the ratio of vacancies to the number of unemployed persons, are, alongside productivity and inflation, important factors driving wage developments over the period observed. In addition, the paper estimates that fluctuations in unemployment during the period under review were driven to a greater extent by the job-finding rate (62%) and to a lesser extent by the job-separation rate (38%).

The Bulletin continues with a paper on the development of the digital euro project, which is relevant for Serbia owing to its links with the European payments market, its inclusion in the geographical scope of SEPA and the significant use of the euro. The Eurosystem would issue the digital euro and provide the core infrastructure and settlement, while banks and other payment service providers would continue to interact directly with users. In practical terms, households would transfer part of their bank deposits to an account with the central bank and then use those funds via mobile applications or a dedicated device, in both online and offline modes. The paper examines various implications of introducing the digital euro – for financial stability and the payment services market, as well as for the privacy, security and accessibility of transactions.

The next paper examines differences in the treatment of debt assumption in financial accounting and macroeconomic statistics, as well as their impact on government debt and fiscal indicators. Particular attention is devoted to the proper identification of the economic substance of transactions, the classification of institutional units and the avoidance of double-counting liabilities. The paper also highlights the importance of reconciling accounting and statistical data, particularly in periods of higher government capital expenditure, when timing differences in recording transactions may affect key macroeconomic indicators. The author concludes that higher-quality and more detailed financial statements contribute to more reliable and efficient macroeconomic statistics.

The Bulletin concludes with a paper on EURIBOR, the money market interest rate in the euro area, which is important for Serbia because of the still relatively high, albeit declining, degree of euroisation of the domestic financial system. The paper first presents the framework within which EURIBOR is determined and operates, its role in the monetary policy and banking system of the euro area, and the methodology used to calculate it for different maturities. The author then uses econometric methods to estimate the impact of the European Central Bank's key interest rates, as well as euro area inflation, on the formation of EURIBOR rates.

I consider the diversity of topics and the high professional standard of the papers in this edition of the Collection to be its greatest strengths, and I hope that readers will agree. The National Bank of Serbia will continue to strengthen its research capacities in the period ahead, mindful of their importance in these turbulent and uncertain times.

Dr Jorgovanka Tabaković, Governor

WORKING PAPERS:

Working Papers describe research in progress by the author(s) and are published to encourage discussion and suggestions for future work.

National Bank of Serbia

WORKING PAPER

ESTIMATION OF INFLATION PERSISTENCE IN SERBIA: RESULTS OF APPLYING QUANTILE AUTOREGRESSION ANALYSIS

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Available at www.nbs.rs

The views expressed in the papers constituting this series are those of the author(s), and do not necessarily represent the official view of the National Bank of Serbia.

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Estimation of inflation persistence in Serbia: results of applying quantile autoregression analysis

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Abstract: The aim of this paper is to analyse the persistence of inflation in Serbia and its main components, using a quantile autoregression model as the primary analytical method. The results indicate that, on average, inflation in Serbia is a stationary process, i.e. it fluctuates around its equilibrium level, but that there is asymmetry in inflation's response to positive and negative shocks, with positive shocks exerting a more durable effect on inflation. Looking at the individual inflation components, unprocessed food prices exhibit the lowest degree of persistence, followed by prices of non-food industrial products, while processed food prices and services show a higher degree of persistence.

Key words: inflation, persistence, quantile autoregression model, quantile unit root.
[JEL Code]: E31, E52, C22

Non-technical summary

The term inflation persistence, or inflation inertia, refers to the durability of inflation over time. The higher the degree of inflation persistence, the longer the effects of price shocks last and the more time inflation needs to return to its equilibrium level. A wide range of factors can contribute to greater inflation persistence and its slower return to a stable level or target. These include shocks originating from the international environment (heightened geopolitical tensions, wars, energy shocks, etc.), as well as unanchored inflation expectations, changes in the behaviour of economic agents, and other factors. The main concern associated with persistent inflation is that it reduces business certainty and may adversely affect business and investment confidence. From the perspective of monetary policy, this phenomenon implies higher costs of inflation stabilisation when inflation is elevated, i.e. a stronger monetary policy response is needed to achieve the desired effects.

Traditional studies of inflation persistence have generally assumed that inflation invariably behaves in the same way regardless of whether the economy is experiencing a crisis or not. In that case, the empirical assessment is typically based on conventional unit root tests used to examine the stationarity of inflation series, i.e. the property that inflation always returns to a stable level irrespective of the magnitude of the shock affecting it. In contrast, the quantile unit root approach makes it possible to analyse the stationarity of inflation under different scenarios (quantiles), capturing its asymmetric behaviour depending on its position in the distribution and the nature of the shocks driving its movements. Lower quantiles correspond to periods of very low inflation or deflation, when inflation is affected by negative shocks. Middle quantiles represent periods in which inflation remains stable around the target, while upper quantiles correspond to periods of elevated inflation driven by strong positive shocks. Non-stationarity typically occurs in the upper quantiles, where there is a risk that, once inflation has reached a high level, it tends to remain elevated for a prolonged period. This may result from rising inflation expectations and the emergence of an inflationary spiral.

Inflation persistence has significant implications for monetary policy. When inflation tends to remain elevated as a result of strong upward shocks, a stronger monetary policy response is needed to bring inflation back to a stable level or to the target.

We applied quantile unit root tests to headline inflation in Serbia and its key components: unprocessed and processed food, non-food industrial products, services, and core inflation (inflation excluding food, energy, alcohol and cigarette prices). Unlike conventional unit root tests based on the conditional mean, which confirmed the stationarity of these inflation indicators, i.e. their tendency to revert to a stable level, quantile unit root tests for the upper quantiles indicate that the null hypothesis of a unit root generally cannot be rejected. This is particularly the case for processed food prices, services, and core inflation.

The application of the quantile methodology revealed certain asymmetries in the mechanisms through which inflation adjusts to its equilibrium level, depending on both the magnitude and the direction of shocks. The results indicate that both the sign and the size of shocks have a significant impact on the speed at which inflation converges to its long-run equilibrium. In particular, negative inflation shocks tend to revert to the mean more rapidly, whereas strong positive shocks result in greater inflation persistence.

In the final part of the paper, we applied a methodology that allows us to examine the dynamic relationship between inflation persistence and its components (processed food prices, energy prices, and core inflation) across three dimensions: over time, across different observation horizons (short-term and long-term), and across different quantiles of the distribution. The results indicate that, for processed food prices and core inflation, the correlation with headline inflation is stronger in the upper quantiles, i.e. during periods of stronger positive inflation shocks, and that it is more pronounced over the long term than over the short term. The weakest degree of correlation was recorded during the 2017–2020 period. In the initial phase of the pandemic, namely in 2020, the correlation was even negative, whereas the strongest correlation was observed in the post-pandemic period, particularly during 2022–2024. The relationship between headline inflation and energy prices is less pronounced and exhibits a weaker association in the presence of positive shocks.

Contents

1 Introduction

Inflation persistence, or inflation inertia, commonly defined as the speed at which inflation returns to its equilibrium level (the target, stable level, or long-term average) following an economic shock, is an important concept for understanding inflation dynamics. A higher degree of inflation persistence implies that shocks have more long-lasting effects and that inflation requires a longer period to return to its equilibrium level. From the perspective of monetary policy, this phenomenon entails higher costs of inflation stabilisation when inflation is elevated, i.e. a stronger monetary policy response is needed to achieve the desired effects. This is important to bear in mind because an excessive monetary policy response may simultaneously lead to a slowdown in economic activity. As a result, monetary policy may face an unnecessary trade-off between containing higher inflation and avoiding a deceleration in economic growth.

To examine how the speed of inflation adjustment varies with the magnitude and direction of economic shocks, this paper employs a quantile autoregression analysis, which makes it possible to assess how the rate at which inflation returns to equilibrium changes depending on whether inflation is high, low, or moderate. While standard linear regression models measure average inflation persistence, assuming a uniform speed of reversion to the equilibrium level regardless of whether shocks are positive or negative, quantile regression models allow for the identification of asymmetries in the adjustment process by examining different parts (quantiles) of the inflation distribution.

Given the importance of this concept and its implications for monetary policy, as well as the fact that the NBS pursues an inflation-targeting monetary policy regime, this paper analyses the persistence of monthly inflation in Serbia and its main components using the quantile autoregression model proposed by Koenker and Xiao (2004). The core purpose of the analysis is to test whether the inflation series is characterised by a stationary process, i.e. whether it exhibits reversion to its conditional mean, or whether the assessment of a unit root depends on the particular segment of the inflation distribution being examined. An additional advantage of this approach is that quantile regression is less sensitive to violations of the assumption of normally distributed error terms, and to the presence of outliers (Koenker and Bassett, 1978).

We applied quantile unit root tests to monthly annualised rates of headline inflation and its key components: unprocessed and processed food, non-food industrial products, services, and core inflation (inflation excluding food, energy, alcohol and cigarette prices). The results indicate that, at higher quantiles, inflation tends to revert more slowly to its equilibrium level when exposed to strong upward shocks. A higher degree of persistence is observed for processed food prices, services, and core inflation. The application of the Bai and Perron (2003) test identified two structural breaks in the headline and core inflation series. The first, occurring in late 2012 and early 2013, separates the period of high and volatile inflation from the period of low and stable inflation that lasted until the outbreak of the COVID-19 pandemic. The second structural break occurred in mid-2021, when global inflation began to rise following the reopening of the world economy after the first wave of the pandemic. Once these structural breaks are taken into account, inflation exhibits stationarity across all quantiles of the distribution.

The paper is structured as follows. Section 2 provides an overview of the relevant empirical literature on measuring inflation persistence in other countries using various methodological approaches. Section 3 briefly presents the estimation methodology employed in this paper, while Section 4 presents the results of the analysis. The final section summarises the main findings of the analysis.

2 Overview of the empirical literature

The analysis of inflation persistence has been the subject of numerous empirical studies. Examples of such analyses for the USA include: Taylor (2000), Pivetta and Reis (2007), Stock and Watson (2007), Benati (2008), etc. A large body of research on inflation persistence has also been conducted for industrial economies and the euro area, including studies by: Levin and Piger (2003), Cecchetti and Debelle (2006), Altissimo, Ehrmann and Smets (2006), Meller and Nautz (2012), Lopez and Papell (2012), etc. Inflation persistence has likewise been a frequent topic of empirical research in the countries of Central and South-Eastern Europe [see, for example, Darvas and Varga (2014), Mladenović and Nojković (2012), Franta, Saxa, and Šmídková (2009)].

Several methodologies are used in the analysis of inflation persistence. Most empirical studies are based on autoregression models and standard unit root tests. A second group of approaches comprises reduced-form Phillips curve models or structural macroeconomic models that incorporate a broader set of factors estimated using the Kalman filter. More recent studies have employed quantile autoregressive analyses and fractionally integrated models, commonly referred to as ARFIMA models.

In a large number of empirical studies, both for advanced economies [Tillmann and Wolters (2014), Tsong and Lee (2011), Manzan and Zerom, (2015)] and for emerging economies [Phiri (2018), Çiçek and Akar (2013), Gaglianone, Guillén and Figueiredo (2018) …], quantile-based inflation analysis has been employed to assess inflation persistence. The findings generally suggest that, at higher levels of inflation, shocks tend to exert more persistent effects on inflation.

Tillmann and Wolters (2014) analysed inflation persistence in the United States using annualised monthly inflation rates based on the consumer price index and the personal consumption expenditures price index, as well as annualised quarterly inflation rates measured by the GDP deflator. The analysis covered the period from 1947 to 2013. The results identified a structural break in the early 1980s. Applying a quantile unit root test, the authors found that inflation persistence in the United States declined significantly after 1981, i.e. following Volcker's disinflation policies. In contrast to the preceding period, during which inflation reverted only slowly to its equilibrium level in the presence of large positive shocks – as evidenced by unit root tests for the higher quantiles – the post-1981 period is characterised by the rejection of the unit root hypothesis across all quantiles of the conditional distribution.

Following the methodology proposed by Koenker and Xiao (2004), Tsong and Lee (2011) analysed inflation dynamics in 12 OECD countries over the 1957–2010 period using quarterly data series on year-on-year inflation rates. Their findings point to the existence of asymmetry where large negative shocks tend to induce a return of inflation to its mean level, whereas this is generally not the case for large positive shocks.

Phiri (2018) employed quantile autoregression analysis to assess inflation persistence in the BRICS countries over the 1996–2016 period. The results indicate that, at higher quantiles, inflation series exhibit a unit root, implying that once inflation exceeds a certain threshold, shocks tend to have more persistent effects on inflation.

Çiçek and Akar (2013) examined the dynamics of inflation and its components in Turkey over the 1994–2012 period using quantile autoregression analysis. The results of their study indicate that inflation persistence in Turkey declined significantly after 2002, when an explicit inflation-targeting regime was adopted as the monetary policy strategy.

Gaglianone, Guillén and Figueiredo (2018) demonstrated that Brazilian inflation is generally stationary, though in 28% of the sample period (1995–2017), i.e. at higher quantiles, it exhibits non-stationary behaviour.

Using quantile autoregression, Aguilar, Garibay and Quineche (2026) showed that inflation in Chile, Colombia, and Peru does not exhibit a symmetric response; rather, its persistence and transmission of shocks vary depending on the level of inflation. Inflation persistence declined significantly as the process of macroeconomic stabilisation progressed in all three countries. Although all three countries display similar patterns of asymmetry, the intensity and form of inflation persistence differ across Chile, Colombia, and Peru, reflecting country-specific economic and institutional factors.

Ajit and Ghosh (2025) similarly examined changes in inflation persistence in India across different monetary policy regimes, including monetary aggregate targeting, a multiple-objective regime, and explicit inflation targeting. Their study shows that the adoption of inflation targeting in India significantly reduced inflation persistence before the COVID-19 pandemic. However, food price shocks that emerged during and after the pandemic continue to generate prolonged inflationary pressures that are difficult for monetary policy alone to contain.

Using the quantile autoregression method, Gbolonyo, Boyetey and Yang (2020) examined inflation dynamics in Ghana and showed that inflation in that country has been relatively well controlled in the long run, as it tends to revert to equilibrium following shocks. However, inflation dynamics are not uniform across all conditions, with inflation behaviour differing between periods of low and high inflation, which makes quantile models more suitable than standard econometric approaches for analysing inflation. The authors also emphasise the importance of monitoring food and non-food product prices, as they play a significant role in shaping headline inflation developments.

Gbolonyo, Zhang and Yang (2020) also examined the persistence of inflation in China, namely the extent to which the effects of inflation shocks remain after they occur. The results of traditional unit root tests indicate that, over the full sample period (January 1987–May 2019), inflation tends to revert to its long-run mean, suggesting that shocks are not permanent.

However, quantile unit root tests show that approximately 44.85% of observations exhibit locally non-stationary behaviour, implying that, during certain periods, the effects of shocks may persist for a very long period.

3 Methodological concept of quantile regression

This section will present a brief overview of the quantile autoregression analysis model and of the quantile unit root test proposed by Koenker and Xiao (2004).

We will first consider the autoregression model of order p, AR(p) represented in the following form:

$$y_t = \beta_1 y_{t-1} + \sum_{j=1}^{p} \beta_{j+1} \Delta y_{t-j} + \varepsilon_t \quad (1)$$

where in the specific case $y_t = \pi_t - \widehat{\mu_t}$, where π_t is the inflation rate, and $\widehat{\mu_t}$ its multiyear average or equilibrium level.

Parameter β_1 is the autoregression coefficient; if $|\beta_1| = 1$, the y_t process is non-stationary, whereas if $|\beta_1| < 1$, it is a stationary process.

The quantile representation of the previous model for quantile τ is:

$$Q_{yt}(\tau|\Omega_{t-1}) = Q_e(\tau) + \beta_1(\tau) y_{t-1} + \sum_{j=1}^{p} \beta_{j+1}(\tau) \Delta y_{t-j} \quad (2)$$

where Ω_{t-1} is the set of information available from the preceding period, $Q_e(\tau)$ denotes the τ-th quantile of the model error term, which captures the effects of unanticipated shocks of different magnitudes that lead to fluctuations in series y_t, and where $Q_{yt}(\tau|\Omega_{t-1})$ is the τ-th conditional quantile of series y_t on Ω_{t-1}.

If we make some substitutions: $\beta_0(\tau) = Q_e(\tau)$, $\beta(\tau) = \left(\beta_0(\tau), \beta_1(\tau) \ldots . \beta_{p+1}(\tau)\right)$, $x_t = \left(1, y_{t-1}, \Delta y_{t-1}, \ldots \Delta y_{t-p}\right)'$, the previous equation takes the following form:

$$Q_{yt}(\tau|\Omega_{t-1}) = x_t{}'\beta(\tau) \quad (3)$$

The estimation of the QAR model presented in equation (3) involves solving the following problem:

$$\min_{\beta} \sum_{t=1}^{n} \varphi_\tau |y_t - x_t{}'\beta(\tau)| \quad (4)$$

where $\varphi_\tau = \left(\tau - I(y_t - x_t{}'\beta(\tau) < 0)\right)$ and I is an indicator function that takes the value of one if $y_t - x_t{}'\beta(\tau) < 0$, and zero otherwise.

The estimation of the QAR model represents a variation of the LAD (least absolute deviation) method and can be expressed as follows:

$$\min_{\beta} \sum_{t:y_t \geq x_t{}'\beta(\tau)} \varphi_\tau (y_t - x_t{}'\beta(\tau)) + \min_{\beta} \sum_{t:y_t < x_t{}'\beta(\tau)} (\varphi_\tau - 1)(y_t - x_t{}'\beta(\tau)) \quad (5)$$

Koenker and Xiao (2004) proposed the use of a quantile unit root test, which enables testing the stationarity of inflation at each quantile, in contrast to standard unit root tests that assess stationarity only at the conditional mean. Applying this test for the τ-th quantile involves testing the null hypothesis that $\beta_1(\tau) = 1$ and calculating the corresponding test statistic, $t_n(\tau)$, in the following way:

$$t_n(\tau) = \frac{f\left(\widehat{F^{-1}(\tau)}\right)}{\sqrt{(1-\tau)\tau}} (\Pi'_{-1} P_x \Pi_{-1})^{\frac{1}{2}} \left(\widehat{\beta_1}(\tau) - 1\right) \tag{6}$$

where Π_{-1} is the vector of lagged values of the dependent variable y_{t-1}, P_x is the projection matrix onto the space orthogonal to $X = \left(1, \Delta y_{t-1}, \dots \Delta y_{t-p}\right)$, f and F denote the probability density function and the cumulative distribution function of the error term from equation (1).

The consistent estimate for $f(F^{-1}(\tau))$ is:

$$f\left(\widehat{F^{-1}(\tau)}\right) = \frac{\tau_i - \tau_{i-1}}{x_t'(\widehat{\beta}(\tau_i) - \widehat{\beta}(\tau_{i-1}))} \tag{7}$$

where $\tau_i \in \Gamma = [0{,}1; 0{,}2; \dots; 0{,}9]$.

Therefore, in order to analyse inflation persistence and differences in its dynamics depending on the occurrence of positive and negative shocks, the Koenker and Xiao (2004) unit root test can be applied over a range of quantiles. Furthermore, to examine inflation persistence over a broader range of quantiles, Koenker and Xiao (2004) and Galvao (2009) propose the use of the quantile Kolmogorov–Smirnov (QKS) test, which is obtained as follows:

$$QKS = sup|t_n(\tau)| \tag{8}$$

The test statistic $t_n(\tau)$ and QKS have non-standard distribution. According to Galvao (2009), the limiting distribution $t_n(\tau)$can be written as:

$$t_n(\tau) \xrightarrow{D} \delta \left(\int_0^1 \underline{W_1^2}(r)dr\right)^{-\frac{1}{2}} \int_0^1 \underline{W_1}(r)dW_1(r) + \sqrt{1-\delta^2} N(0,1) \tag{9}$$

where $\xrightarrow{D}$ denotes convergence in distribution, and where $W_1(r)$ is Brownian motion, $\underline{W_1}(r) = W_1(r) - \left[\int_0^1 (4-6s)W_1(s)ds - r\int_0^1 (6-12s)W_1(s)ds\right]$and $N(0,1)$ is standardised normal distribution of random variable independent from limiting distribution.

Let $\psi_\tau(x) = \tau - I(x < 0)$ and let $\varepsilon_{t\tau}$ denote the residuals from the regression equation (2). The weighting parameter δ is then defined as follows:

$$\delta = \frac{\sigma_{\varepsilon\psi}}{\sigma_\varepsilon \sqrt{\tau(1-\tau)}} \tag{10}$$

where σ_ε is the long-term variance of ε_t, and $\sigma_{\varepsilon\psi}$ is the long-term covariance of ε_t and $\psi_\tau(\varepsilon_{t\tau})$.

The approach proposed by Koenker and Xiao (2004) and Galvao (2009) is employed for the estimation of these nuisance parameters.

The limiting distribution for *QKS* may be obtained using the simulation strategy proposed by Galvao (2009) in the following way:

1. $\delta(\tau_i)$ is calculated for every $\tau_i \in \Gamma$;
2. for each $\delta(\tau_i)$, one realisation is independently simulated from the Dickey–Fuller and standard normal distributions, and the expression from equation (9) is calculated;

   $t_n(\tau_i) = \delta(\tau_i)\left(\int_0^1 \underline{W_1^2}(r)dr\right)^{-\frac{1}{2}} \int_0^1 \underline{W_1}(r)dW_1(r) + \sqrt{1-\delta(\tau_i)^2}N(0,1)$ and maximum absolute value for every τ_i is taken;
3. finally, by repeating the previous step a large number of times, the critical value at the 5% significance level can be calculated as the 0.95th quantile of the empirical distribution.

In our specific analysis of inflation persistence, the estimate $\beta(\tau)$ represents the persistence estimate for the τ-th quantile, conditional on past inflation values y_{t-1}, ..., y_{t-p}. In this way, the application of quantile analysis enables the assessment of inflation dynamics depending on the magnitude and direction of shocks. If inflation is high relative to its previous values, this indicates that a large positive shock has occurred, causing inflation to move above the conditional mean and into one of the upper conditional quantiles. Similarly, if inflation is lower than in the previous period, a negative shock has occurred, and inflation is located in one of the lower conditional quantiles.

To investigate the dynamic dependence of inflation persistence on its components across three dimensions – over time, across different observation horizons (short-term and long-term), and across different quantiles of the distribution – the Rolling Window Wavelet Quantile Correlation (RWWQC) methodology can be applied. This approach measures the correlation between two time series, X and Y, by combining wavelet transform, rolling-window method, and the quantile distribution structures. Rather than being calculated over the entire sample period, the correlation is estimated for a specific subsample (window), which is then moved forward through time while maintaining a constant window length for each calculation.

This indicator is calculated as follows:

$$RWWQC_t(s_d, w_i[X], s_d, w_i[Y]\ ) = \frac{q\delta_t(s_d, w_i[Y], s_d, w_i[X])}{\sqrt{\sigma^2\left(\phi_\tau\left(s_j, w_i[Y] - Q_{\tau, s_j, w_i[Y]}\right)\right)\sigma^2\left(s_j, w_i[X]\right)}}$$

where $q\delta_t(s_d, w_i[Y], s_d, w_i[X])$ is the covariance for the specific quantile τ of scale s_d and window w_i, $Q_{\tau, s_d, w_i[Y]}$ is the conditional quantile function for each window w_i, ϕ_τ is the quantile-specific transformation function that captures asymmetric dependence and where $\sigma^2(s_d, w_i[X])$ и $\sigma^2\left(\phi_\tau\left(s_d, w_i[Y] - Q_{\tau, s_d, w_i[Y]}\right)\right)$ are the wavelet variances of scale s_d within window w_i. Scale s_d refers to the D-th resolution level of the wavelet transform. Wavelet decomposition is performed using Maximal Overlap Discrete Wavelet Transform (MODWT) with the least asymmetric Daubechies wavelet filter of length L=8, employing four or five resolution levels, D=4, D=5 [for more detail, see Ghosh and Ajit (2025)].

Results of the analysis

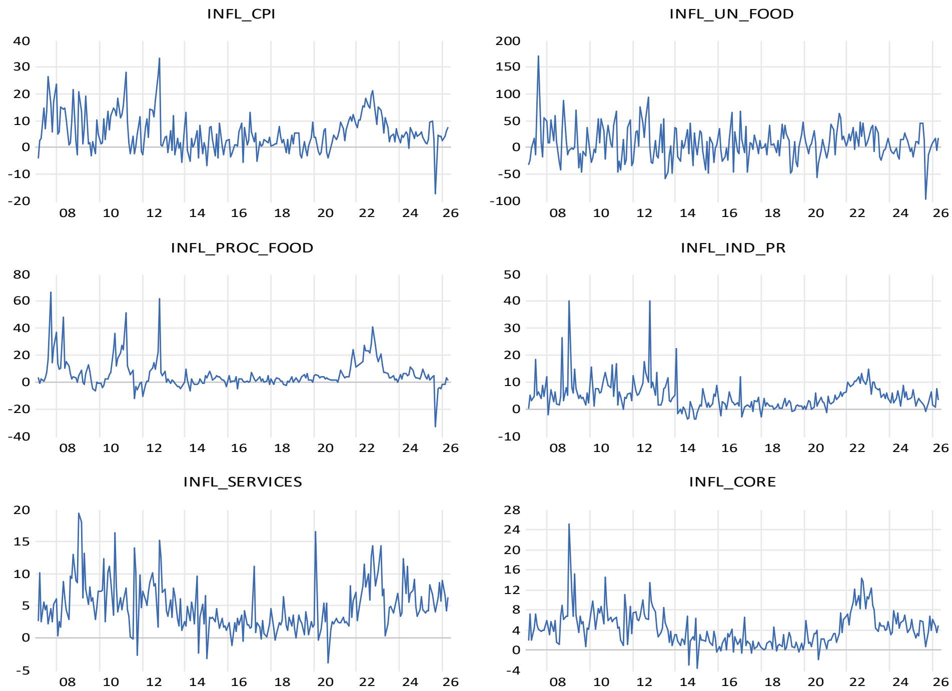
The analysis was conducted for the period from January 2007 (when the SORS began publishing consumer price index data) until and including April 2026. The analysis uses the headline consumer price index (index_cpi) and its most important price components: unprocessed food prices (index_un_food), processed food prices (index_proc_food), industrial non-food product prices (index_ind_pr), services prices (index_services), and the core inflation measure excluding food, energy, alcohol, and cigarettes (index_core). To eliminate the effects of seasonal factors that could obscure the assessment of inflation persistence, all inflation indicator series were first seasonally adjusted.

The analysis focuses on annualised monthly rates of inflation indicators. In the case of the headline consumer price index (infl_cpi), these rates were calculated using the following formula:

$$\pi_t = 1200 * \left(\frac{index\_CPI_t}{index\_CPI_{t-1}} - 1\right)$$

Price changes for the main inflation components – unprocessed food (infl_un_food), processed food (infl_proc_food), industrial non-food products (infl_ind_pr), services (infl_services), and core inflation (infl_core) – were calculated in the same manner.

Chart 1 **Monthly annualised growth rates of inflation indicators (seasonally-adjusted)**



The graphical presentation of the annualised monthly series of inflation indicators (Chart 1) shows that higher inflation rates were recorded at the beginning of the observed period (up to 2013), followed by a period of relatively low and stable inflation that lasted until 2021. The outbreak of the COVID-19 pandemic and the subsequent reopening of the global economy led to a significant increase in global demand which, together with rising world oil prices and disruptions in global supply chains, contributed to a surge in inflation worldwide. This was followed in 2022 by an energy crisis and a sharp increase in global prices of primary agricultural commodities triggered by the outbreak of the conflict in Ukraine. From mid-2023 onward, inflation gradually stabilised. In September 2025, a government regulation was adopted that capped wholesale and retail trade margins on food products and household chemicals at 20% for a period of six months, resulting in a significant monthly decline in food prices and headline inflation in that month. Excluding this effect, both headline and core inflation have exhibited relatively stable movements over the past two years, albeit at somewhat higher levels than those observed prior to the pandemic.

Based on the statistical indicators presented in Table 1, it can be observed that, over the period under review, unprocessed food prices recorded the highest average growth rates, while core inflation recorded the lowest. All the analysed series exhibit right-skewed distributions and higher-than-normal kurtosis, indicating heavier tails. The hypothesis of normality is rejected in all cases, while the results of the standard DF-GLS unit root test indicate that the inflation series is stationary, i.e. it returns to its equilibrium level. However, when an inflation time series departs from the normal distribution, i.e. exhibits a higher degree of skewness to the right or heavier tails, as is the case with the inflation indicators series analysed in this paper, conventional unit root tests may produce biased estimates.

Table 1 **Summary statistics for inflation indicators and results of the standard unit root test**

	Mean	Standard deviation	Skewness	Kurtosis	JB statistic	DF-GLS unit root test
infl_cpi	5.498	6.913	0.818	4.576	49.666***	2.122**
infl_un_food	7.075	31.594	0.636	5.708	86.144***	2.338**
infl_pr_food	5.784	10.85	2.317	12.437	1064.021***	4.152***
infl_core	4.32	3.572	1.361	7.539	269.574***	2.964***
infl_ind_pr	4.896	5.655	2.689	15.721	1836.014***	2.581***
infl_services	4.698	3.66	1.106	4.581	70.046***	2.317**

Note: *** denotes statistical significance at the 1% level; ** denotes statistical significance at the 5% level. JB test denotes the Jarque-Bera test statistic for assessing normality. The optimal lag length in the DF-GLS test was selected based on the Schwarz Information Criterion (SIC).

Table 2 shows, for each inflation indicator, the estimated values of the constants $\beta_0(\tau)$ and the autoregressive coefficient $\beta_1(\tau)$ across different quantiles, together with the results of the QKS test. The estimates of $\beta_0(\tau)$ capture systematic differences in the level of inflation across quantiles, i.e. the magnitude of the inflation shock at quantile τ. These estimates are negative up to the median (the 50th percentile), are close to zero around the median, and then increase with the quantiles, reaching their highest value at the uppermost quantile. This indicates a positive inflation shock at the highest quantile, whereas the negative values at the lowest quantile indicate a negative inflation shock. The estimates of $\beta_1(\tau)$, which measure inflation persistence, also increase across quantiles, indicating that inflation persistence is greater in the presence of larger positive inflation shocks. For the lower quantiles, the null hypothesis of a unit root is generally rejected, suggesting that, at lower inflation rates and under smaller positive and negative shocks, inflation tends to revert to its equilibrium level. This is not the case, however, when inflation is exposed to larger positive shocks.

Table 2 **Results of the quantile unit root test for different inflation indicators**

		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
infl_cpi	$\beta_0(\tau)$	-7.269***	-4.797***	-3.033***	-1,487***	-0.432	0.823*	2.407***	4.694***	7.554***
	$\beta_1(\tau)$	0.278***	0.250***	0.299***	0.499***	0.549***	0.632***	0.71*	0.773	0.692**
	QKS					6.971***				
infl_un_food	$\beta_0(\tau)$	-37.287***	-23.447***	-14.670***	-8.825***	-2.665	4.233*	10.481***	26.124***	37.311***
	$\beta_1(\tau)$	0.017***	0.085***	0.038***	0.101***	0.126***	-0.036***	0.143***	0.245***	0.257***
	QKS					12.28***				
infl_proc_food	$\beta_0(\tau)$	-5.483***	-3.755***	-2.815***	-1.441***	-0.608	0.204	1.812***	3.661***	6.446***
	$\beta_1(\tau)$	0.433***	0.453***	0.532***	0.663***	0.726**	0.772*	0.864	0.961	1.103
	QKS					10.77***				
infl_ind_pr	$\beta_0(\tau)$	-4.233***	-2.763***	-1.874***	-1.030***	-0.458*	0.259	1.188***	2.419***	4.562***
	$\beta_1(\tau)$	0.282***	0.375***	0.531***	0.592***	0.634***	0.672***	0.715***	0.76	0.791
	QKS					7.126***				
infl_services	$\beta_0(\tau)$	-3.500***	-2.509***	-1.772	-1.188***	-0.342	0.215	1.001***	2.309***	3.807***
	$\beta_1(\tau)$	0.269***	0.291***	0.442***	0.574***	0.664***	0.634***	0.666***	0.847	0.931
	QKS					8.75***				
infl_core	$\beta_0(\tau)$	-2.487***	-1.773***	-0.961***	-0.457***	0.020***	0.091***	0.644***	1.381***	3.196***
	$\beta_1(\tau)$	0.626***	0.663***	0.774***	0.752***	0.744***	0.745***	0.829	0.892	1.007
	QKS					4.831***				

Note: *** denotes statistical test significance at the 1% level; ** statistical significance at the 5% level, and * statistical significance at the 10% level. The significance of $\beta 0(\tau)$ is tested using the t test, while the significance of $\beta 1(\tau)$ is tested using t_n (τ).

Based on the results reported in Table 2, the following conclusions can be drawn:

1. Unprocessed food prices exhibit the lowest degree of persistence. The null hypothesis of a unit root is rejected across all quantiles, indicating that unprocessed food prices revert to their average rate of increase even in the presence of large positive and negative shocks. Even at the highest quantile, the coefficient $\beta_1(\tau)$ is below 0.3. Unprocessed food prices mostly depend on the character of the agricultural season and market supply. When the agricultural season is favourable, prices can decline easily, whereas the opposite occurs when the season is unfavourable;

2. Unlike unprocessed food prices, processed food prices exhibit a higher degree of persistence. At the 5% significance level, the null hypothesis of a unit root can no longer be rejected from the 0.6 quantile onwards;

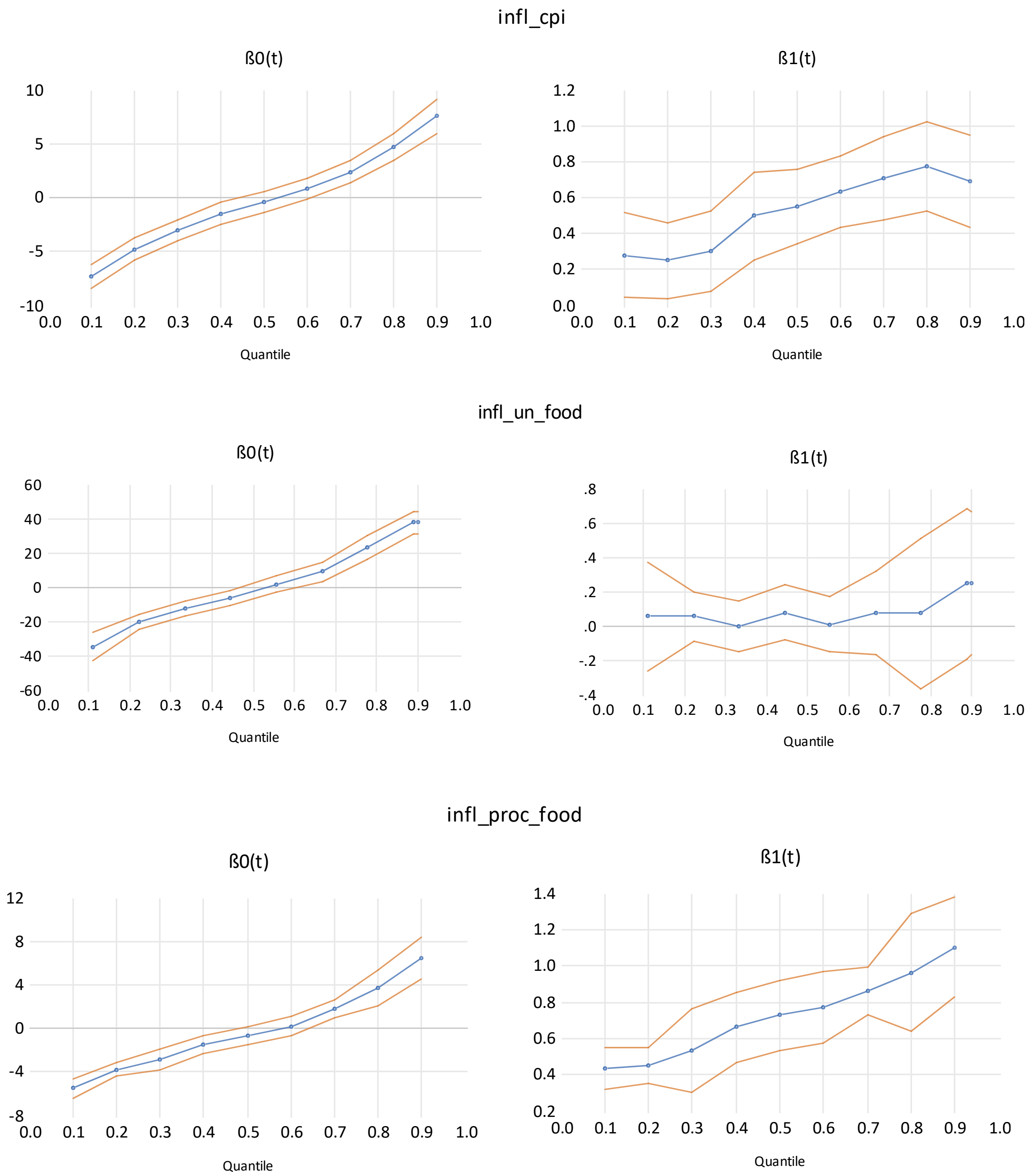
3. Core inflation exhibits a higher degree of persistence than headline inflation, with service prices displaying greater persistence than prices of non-food industrial products;

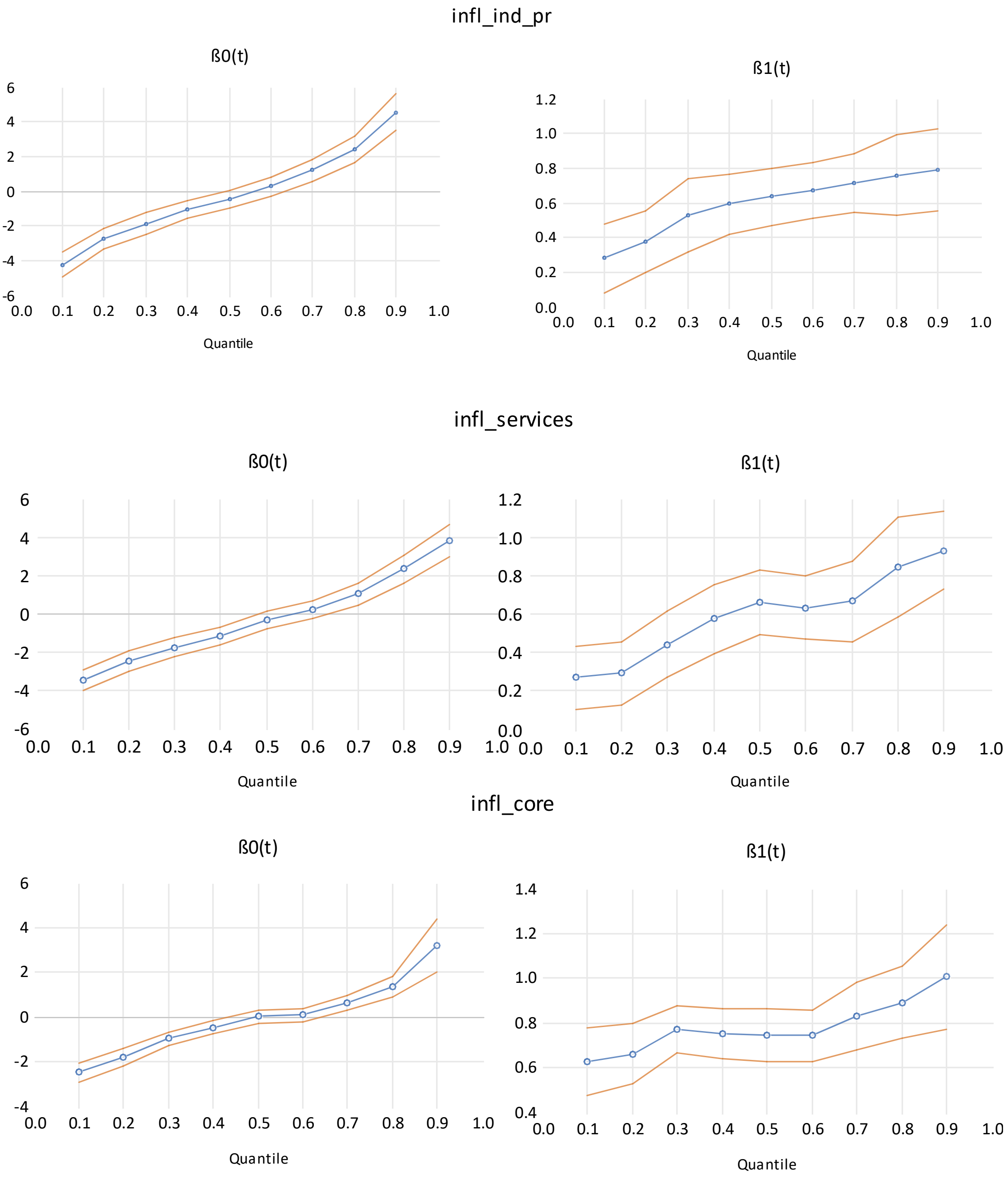
4. As regards headline inflation, as measured by the Consumer Price Index (CPI), the null hypothesis of a unit root cannot be rejected at the 5% significance level for the 0.7 and

0.8 quantiles. However, at very high inflation rates, headline inflation nevertheless reverts more rapidly to its equilibrium level;

5. The QKS test rejects the hypothesis of a unit root at the 1% significance level for all inflation indicators, indicating that all the series are stationary overall. This finding is consistent with the results of the DF-GLS test shown in Table 1.

Chart 2 **Estimated β_0 and β_1 parameters by quantile, with 95% confidence intervals**





We also calculated the speed of reversion of inflation and its components to the conditional mean for each quantile, denoted by HL, which is obtained using the following formula:

$$HL(\tau) = \frac{log(0,5)}{log(\beta_1(\tau))}$$

Table 3 **HL values by quantile for different inflation indicators**

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
infl_cpi	2.34	2.16	2.48	4.31	5.00	6.53	8.75	11.63	8.14
infl_un_food	0.74	1.22	0.92	1.31	1.45	***	1.54	2.13	2.20
infl_proc_food	3.58	3.78	4.75	7.29	9.36	11.58	20.49	75.31	***
infl_ind_pr	2.37	3.05	4.73	5.71	6.57	7.54	8.93	10.92	12.78
infl_services	2.28	2.43	3.67	5.40	7.32	6.57	7.37	18.04	41.90
infl_core	6.40	7.29	11.69	10.51	10.13	10.18	15.97	26.21	***

The results presented in Table 3 lead to the following conclusions:

1. The fastest mean reversion is observed at the 0.1 and 0.2 quantiles, approximately one month for unprocessed food prices, while it takes the longest – around six months – for core inflation;

2. Processed food prices and core inflation exhibit the slowest mean reversion. For the higher quantiles, it exceeds one year by a considerable margin, while at the highest (0.9) quantile, the reversion is undefined;

3. In the case of headline inflation, at the higher quantiles, inflation takes between 8 and 12 months to revert to its average level.

Since the presence of structural breaks may alter the dynamics of inflation, the analysis was extended by applying the Bai and Perron (2003) test, which allows for testing multiple structural breaks in a time series. The test identified two structural breaks in the headline inflation series in Serbia, occurring in November 2012 and March 2021. The first structural break marks the transition from a period of high and volatile inflation to a period of low inflation, supported by both subdued cost pressures from the international environment and the effects of relatively weak domestic demand, including the period of fiscal consolidation, underpinned by relative exchange rate stability and anchored inflation expectations. The second structural break relates to the period of rising inflation globally, driven by a sharp increase in demand following the reopening of economies after the initial phase of the COVID-19 pandemic, as well as by disruptions in global supply chains and increases in global energy and food prices, further exacerbated by the outbreak of the conflict in Ukraine. In the case of core inflation, two structural breaks were also detected – February 2013 and September 2021 – and they are, in principle, related to the same factors. However, headline inflation typically responds first, followed by core inflation.

The quantile unit root test is subsequently applied, allowing for the presence of these structural breaks, which are incorporated into the model through appropriate dummy variables. The headline inflation series is therefore adjusted as follows: $y_t = \pi_t - \widehat{\mu_t} - D_{2012M11} - D_{2021M}$, and core inflation series: $y_t = \pi_t - \widehat{\mu_t} - D_{2013M2} - D_{2021M}$.

Table 4 **Bai and Perron (2003) test for structural breaks in headline and core inflation**

infl_cpi			infl_core		
Structural break test	F-statistic	Critical value**	Structural break test	F-statistic	Critical value**
0 vs. 1*	11.44	8.580	0 vs. 1*	17.13	8.580
1vs. 2 *	15.89	10.130	1vs. 2 *	33.26	10.130
2 vs. 3	10.95	11.140	2 vs. 3	6.57	11.140
Structural break date:			Structural break date:		
1	2012M 11		1	2013M 02	
2	2021M 03		2	2021M 09	

* Significance at the 5% level, Newey-West estimator of variance was applied.

The results of the quantile unit root test indicate that, for all analysed quantiles and for both core and headline inflation, the null hypothesis of a unit root is rejected. Nevertheless, the results also confirm that larger positive shocks have a greater impact on the persistence of both headline and core inflation than negative shocks. However, the estimated autoregressive coefficients are lower than those obtained from the model that does not account for the effects of structural breaks. This clearly indicates that inflation persistence increased after the COVID-19 pandemic, while it was also higher during the initial years of the analysed period.

Table 5 **Results of the quantile unit root test for headline and core inflation adjusted for the effects of structural breaks**

		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
infl_cpi	$\beta_0(\tau)$	-6.416***	-5.096***	-3.013***	-1.551***	-0.566	0.840***	2.427***	4.509***	7.325***
	$\beta_1(\tau)$	0.071***	0.073***	0.226***	0.319***	0.401***	0.482***	0.553***	0.493***	0.65***
	QKS					11.44***				
infl_core	$\beta_0(\tau)$	-7.053***	-4.897***	-3.274***	-1.229**	-0.015	1.052**	2.871***	4.978***	6.865***
	$\beta_1(\tau)$	0.007***	0.134***	0.253***	0.376***	0.452***	0.508***	0.583***	0.552***	0.624***
	QKS	10.63***								

Note: *** denotes statistical test significance at the 1% level; ** statistical significance at the 5% level, and * statistical significance at the 10% level. The significance of β0(τ) is tested using the t test, while the significance of β1(τ) is tested using t_n (τ).

In the final step of the analysis, in order to examine the dynamic dependence of headline inflation persistence on its components, the correlation between headline inflation and its components – processed food prices, energy prices and core inflation – was estimated using the RWWQC method. The analysis employed a 48-month rolling window and four scales of the wavelet transformation, which separate short-term from long-term frequencies. Specifically, D1 corresponds to a period of one to two months, D2 to two to eight months, D3 to eight to 16 months, and D4 to a period of more than 16 months up to 32 months. The correlation was examined for $\tau = 0{,}1$, $\tau = 0{,}5$ and $\tau = 0{,}8$. The results are presented graphically using a so-called heat map.

The results show that the correlation between headline inflation and processed food prices is strongest at the higher quantiles of the distribution, i.e. when positive inflationary shocks are stronger. The correlation is also strongest at the D4 resolution level, i.e. when longer-term frequencies are considered. The lowest degree of correlation was recorded in the 2017-2020 period; notably, during the initial phase of the pandemic, i.e. in 2020, the correlation even became negative. By contrast, the strongest correlation was observed in the post-pandemic period, i.e. during 2022-2024.

Chart 3 **RWWQC results for headline inflation and changes in processed food prices**

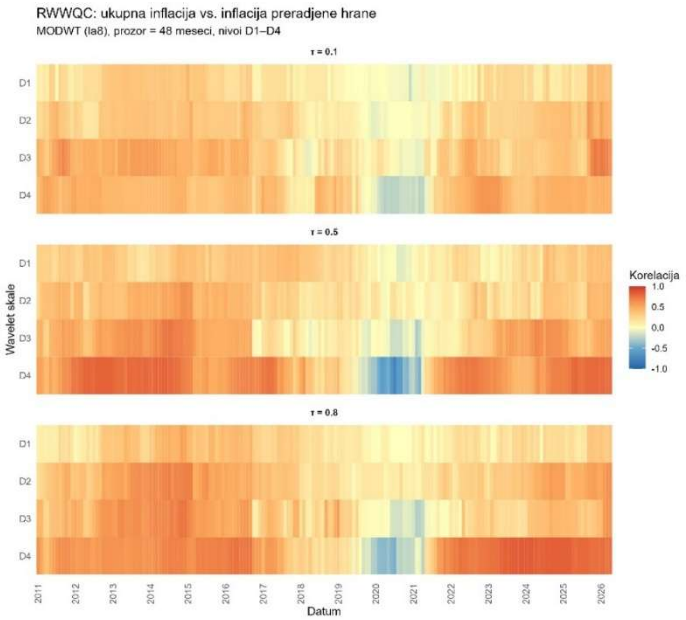


Chart 4 **RWWQC results for headline inflation and changes in energy prices**

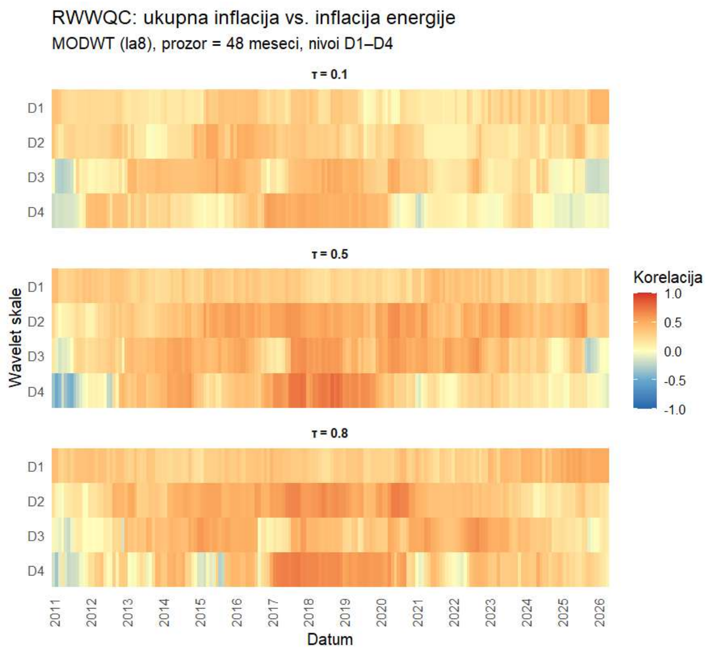
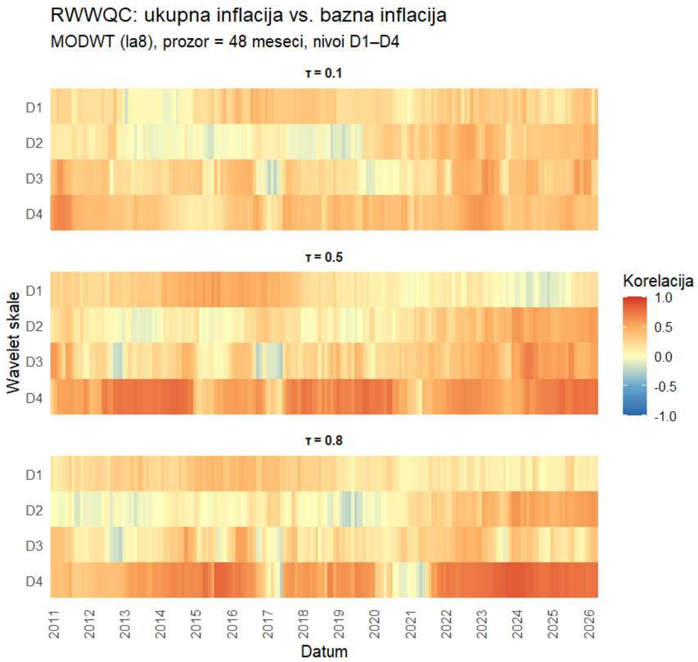


Chart 5 **RWWQC results for headline inflation and core inflation**



The correlation between headline inflation and energy prices (Chart 4) is lower than that observed with processed food prices. In this case, however, there is no pronounced asymmetry in the sense that the strongest correlation is associated with higher quantiles of the distribution, although the correlation is also stronger at longer-term than at shorter-term frequencies. For core inflation, a very similar pattern is observed as in the case of processed food prices: a higher correlation between headline and core inflation is recorded at higher quantiles of the distribution, as well as at longer-term frequencies. In addition, the highest degree of correlation is observed in the period after 2022.

4 Conclusion

This paper investigates the dynamics of inflation in Serbia over the period from January 2007 to April 2026, employing a quantile autoregression model and quantile unit root tests. This methodology identifies certain asymmetries in the mechanism of inflation adjustment towards its equilibrium level, depending on the intensity and direction of the underlying shock.

The analysis shows that both the sign and magnitude of shocks significantly affect the speed of inflation adjustment towards its long-run equilibrium level. Negative inflation shocks revert to the mean more quickly, whereas large positive shocks result in greater inflation persistence.

The analysis confirms that, in the case of Serbia over the observed period, inflation tended to revert to its equilibrium level, although the intensity of this adjustment differed across inflation categories. For example, unprocessed food prices exhibit the lowest degree of persistence, i.e. the period required for mean reversion is relatively short. By contrast, core inflation is characterised by a higher degree of persistence, particularly at the higher quantiles of the distribution. With regard to headline inflation, the null hypothesis of a unit root cannot be rejected for the 0.7 and 0.8 quantiles, whereas at the highest inflation rates inflation nevertheless reverts to its equilibrium level more quickly. This represents an important finding for monetary policy-makers in terms of determining the appropriate strength of the monetary policy response during periods of rising inflation.

The Bai and Perron test identified two structural breaks in the dynamics of headline inflation in Serbia – November 2012 and March 2021. The first structural break marked a transition from a period of high and volatile inflation to a period of low inflation, while the second break corresponds to a period of rising global inflation, driven by a sharp increase in demand following the reopening of economies after the initial phase of the COVID-19 pandemic. The results of the analysis indicate that inflation persistence increased after the COVID-19 pandemic.

The overall conclusion of the analysis of inflation persistence in Serbia using quantile autoregressive analysis is that inflation tends to revert to its equilibrium level, with the duration of this process depending on the magnitude of the inflation shock. At the same time, inflation persistence has increased in recent years, not only as a result of the crisis associated with the COVID-19 pandemic, but also due to a prolonged environment of global uncertainty, reflected in higher energy and primary commodity prices.

The importance of the findings of this analysis for monetary policy can be considered from several perspectives. The results confirm that the monetary policy response does not necessarily have to be the same in the case of positive and negative shocks. They indicate that a more forceful response is generally required when inflation is above the target, given the greater persistence of positive shocks. Therefore, central banks should also act pre-emptively in response to positive shocks, before risks materialise through higher inflation. Such a response does not necessarily have to take the form of interest rate increases, but may instead involve enhanced communication, highlighting risks and containing inflation expectations.

The particular importance of the model lies in its ability to demonstrate the persistence of an asymmetric pattern in inflation persistence, suggesting that such dynamics may represent an inherent feature of inflation. This finding is consistent with evidence from other studies conducted for various countries and regions. Consequently, the results add to the arguments in favour of considering an asymmetric monetary policy response depending on the nature and direction of the inflation shock.

The results of the correlation analysis based on one of the most advanced methods – the rolling-window wavelet quantile correlation (RWWQC) method – applied to monthly annualised headline inflation and monthly annualised changes in processed food prices and core inflation indicate that the correlation is stronger at higher quantiles, i.e. in the presence of larger positive inflation shocks, and that it is also stronger when longer-term rather than short-term changes are considered. The lowest degree of correlation was recorded in the 2017–2020 period; notably, during the initial phase of the pandemic, i.e. in 2020, the correlation even became negative, whereas the strongest correlation was observed in the post-pandemic period, i.e. during 2022–2024. The relationship between headline inflation and energy prices is less pronounced and does not display such a strong association with positive shocks.

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WORKING PAPER

ECONOMETRIC ANALYSIS OF DETERMINANTS OF THE NATIONAL BANK OF SERBIA’S FX RESERVES: IMPLICATIONS FOR THE PRESERVATION OF FINANCIAL STABILITY AND RESILIENCE TO EXTREME MACROECONOMIC SHOCKS

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Econometric analysis of determinants of the National Bank of Serbia's FX reserves: implications for the preservation of financial stability and resilience to extreme macroeconomic shocks

Đorđe Polomčić and Darko Kovačević

Abstract: The aim of this paper is to analyse the determinants and dynamics of the conditional volatility of the National Bank of Serbia's gross FX reserves, with a focus on institutional resilience to systemic risks. The applied methodological framework comprises linear and nonlinear autoregressive distributed lag models, which enable the simultaneous assessment of the long-run and short-run effects of key macroeconomic determinants, the M3 monetary aggregate, foreign direct investment, and the degree of dinarisation of receivables. The risk profile was analysed using a GARCH(1,1) specification assuming a Student's *t*-distribution, while institutional resilience was assessed using a conditional macroeconomic stress test based on extreme value theory and Monte Carlo simulations with 15,000 iterations. The bounds test confirms a stable cointegrating relationship. The M3 monetary aggregate channel exerts a dominant positive effect on the accumulation of FX reserves. The analysis of dinarisation dynamics confirms the effectiveness of the adopted Dinarisation Strategy, as an increase in the share of dinar receivables reduces exposure to FX risk and optimises the need for holding precautionary FX reserves. The analysis of conditional volatility indicates an absence of volatility clustering, confirming the effectiveness of liquidity sterilisation by the central bank. At the same time, the statistically significant use of the Student's *t*-distribution confirms the presence of "heavy tails" in the distribution of residuals, indicating the system's exposure to rare but severe extreme shocks. Simulations of extreme events show that, at a 99% confidence level, the maximum cumulative outflow would amount to EUR 5.27 bn, while the system would retain more than an adequate level of available liquidity. These findings unequivocally confirm the high resilience of the domestic monetary policy and the preservation of long-term exchange rate stability..

Key words: FX reserves, financial stability, ARDL/NARDL models, Student-t GARCH, macroeconomic stress testing.
[JEL Code]: C22, E58, F21, F31

Non-technical summary

This paper provides a systematic assessment of the determinants and adequacy of the National Bank of Serbia's (NBS) gross FX reserves, which, over the period under review, have proven to be a key pillar and safeguard of the country's macroeconomic stability. The analysis confirms that the sustained growth in FX reserves is directly associated with developments in the M3 monetary aggregate, the expansion of which the central bank has offset through timely and proactive interventions in the FX market. This strategic approach enabled the successful containment of speculative pressures and the preservation of dinar exchange rate stability, thereby transforming monetary expansion into enhanced defensive capacities across the financial system.

In addition to monetary factors, the dynamics of FX reserves are significantly shaped by foreign direct investment flows, whose cycles – ranging from import requirements in the initial stages to profit repatriation in the mature phase – necessitate the maintenance of higher levels of FX liquidity. On the other hand, empirical findings provide strong support for the rationale behind the Dinarisation Strategy. A higher share of dinar receivables fundamentally limits risks to the corporate and household sectors and reduces the need to accumulate excessive precautionary assets, thereby directly minimising the opportunity costs associated with holding such assets.

Finally, a quantitative assessment of the system's resilience, based on FX reserves of EUR 29.0 bn at end-2025 and record-high gold reserves of 52.5 tonnes, demonstrates the capacity of FX reserves to absorb extreme external shocks. The conducted stress testing, which simulates hypothetical crisis scenarios, shows that even in the event of extreme, synchronised and simultaneous shocks, the maximum cumulative outflow would amount to EUR 5.2 bn. The fact that, even after such a severe shock, the NBS would retain more than EUR 23.8 bn in available liquidity provides empirical confirmation that the level of FX reserves and exchange rate stability are sustainable over the long term and from an economic perspective..

Contents

1 Introduction

An analysis of the determinants and dynamics of FX reserves represents one of the fundamental issues of macroeconomic stability in a small, open economy, particularly under conditions of high import dependence and a high degree of euroisation. The current macroeconomic environment in the Republic of Serbia is characterised by a dynamic setting marked by global geopolitical tensions, fragmentation of supply chains, and restrictive monetary policy adjustments by major central banks. Under such circumstances, increased investor risk aversion and volatility in commodity prices are testing the flexibility of the domestic economic system (Calvo, 1998). **In the conditions of heightened global uncertainty, FX reserves are not merely a conventional indicator of external liquidity, but rather a primary macroeconomic shield against external shocks, a safeguard of financial stability, and a key instrument for maintaining confidence in the national currency.** Guided by the principles of liquidity and safety, the NBS uses FX reserves as one of the key mechanisms for maintaining the relative stability of the dinar exchange rate, meeting external obligations, and cushioning systemic balance-of-payments imbalances in the event of potential crises. **At end-2025, the NBS's gross FX reserves stood at a very high level of EUR 29.0 bn (or EUR 24.6 bn net), supported by record-high gold reserves of 52.5 tonnes (equivalent to EUR 6.2 bn, accounting for 21.4% of total gross assets).**

A comprehensive assessment of FX reserves adequacy based on traditional and composite indicators confirms that the NBS's gross FX reserves fully support the macroeconomic environment and the stability of the domestic financial system, as the value of each individual indicator exceeds all established international reference minimums and optimal adequacy thresholds. The specifically designed internal indicator, the "right measure for Serbia," further confirms the system's high resilience to shocks that directly reflect the domestic structure of debt and potential outflows of FX and dinar deposits of the corporate and household sectors. At the same time, the **Jeanne–Rancière stress-testing model** (Jeanne & Rancière, 2006) **empirically demonstrates that the country's external position is highly resilient to the simultaneous impact of multiple factors and a sudden stop in capital inflows, ensuring the preservation of financial stability, even under the assumptions of the most conservative stress scenarios and the risk of extreme, low-probability events**, **in the sense of the black swan concept** (Taleb, 2007; National Bank of Serbia, 2025).

However, although these traditional models provide quantitative confirmation of reserve adequacy, by their nature they offer a predominantly static picture, as they rely on pre-calibrated parameters and do not capture dynamic, nonlinear adjustments in real time, which fully justifies the application of more advanced dynamic econometric models. The aim of the research is to precisely quantify, based on empirical monthly data for the period from January 2008 to December 2025, the nature of the long- and short-run relationships between gross FX reserves and their main macroeconomic determinants. The empirical focus is placed on the dynamic impact of three key transmission channels: the M3 monetary aggregate; foreign direct investment (FDI), expressed as a share of gross domestic product (GDP); and the degree of dinarisation of household and corporate receivables – **the evaluation of which also provides**

direct empirical confirmation of the long-term success of the NBS's Dinarisation Strategy (National Bank of Serbia, 2025), **given that an increase in the share of dinar deposits and receivables systematically mitigates the exposure of the corporate and household sectors to FX risk.**

To address the issue of non-stationarity in the series (Dickey & Fuller, 1979; Zivot & Andrews, 1992) and avoid the phenomenon of spurious regression, while at the same time preserving long-run information on equilibrium levels, the paper employs a modern econometric approach based on the linear (Pesaran et al., 2001) and nonlinear autoregressive distributed lag (NARDL) models (Shin et al., 2014). In addition to examining the long-run cointegrating relationship, which was further validated by applying equation-based cointegration tests (Banerjee, Dolado & Mestre, 1998), the conditional volatility and risk profile of FX reserves was analysed using a Student-t GARCH (1,1) specification (Danielsson, 2011). Furthermore, with a view to macroeconomic stress testing of resilience to systemic risks arising from extreme events, the paper conducts a conditional macroeconomic stress test based on the extreme value distribution (EVT-GEV), using 15,000 stochastic Monte Carlo simulations (McNeil and Frey, 2000; Coles, 2001) over a twelve-month projection horizon. In this way, the study provides a comprehensive empirical analysis of the effectiveness of monetary policy and the NBS's Dinarisation Strategy.

The structure of the paper is organised as follows. Following an introductory discussion of the importance of FX reserves, the second section provides a detailed overview of the methodological framework for econometric modelling, including testing the properties of the time series and the specification of the baseline ARDL model. The third section is devoted to cointegration analysis and the bounds test, with a focus on estimating long-run multipliers and short-run dynamics through an error correction model. The fourth section examines the structural stability of the parameters. The fifth section analyses the nonlinear (asymmetric) effects of the dinarisation strategy and monetary shocks using the NARDL model. The sixth section models the conditional volatility of FX assets using a GARCH(1,1) specification, incorporating the assumption of a Student's *t*-distribution, together with diagnostic testing of the normality of residuals (Jarque & Bera, 1987). The seventh section presents the results of the macroeconomic stress testing based on the GEV distribution and stochastic Monte Carlo simulations of extreme risks. The paper concludes with synthesised conclusions and a review of the literature used.

2 Methodological econometric modelling framework and baseline ARDL model specification

2.1 Testing the properties of time series

Prior to specifying the dynamic ARDL model, it is methodologically imperative to formally determine the order of stationarity of each individual series in order to rule out the presence of $I(2)$ processes. To accurately determine the order of integration of the variables, the Augmented Dickey–Fuller (ADF) unit root test was applied (Dickey & Fuller, 1979). For the level variables exhibiting a pronounced time trend (gross FX reserves and the M3 monetary aggregate), the test was conducted with a constant and deterministic trend included, while for the other level series (FDI as a share of GDP and the dinarisation of receivables), as well as for all variables in first differences, a specification with a constant included was used. The optimal number of lags was determined automatically based on the Bayesian Information Criterion (BIC).

The empirical results of the ADF test, presented in Table 1, reveal distinct stochastic properties across the analysed macroeconomic series. **FDI is the only variable that achieves full stationarity already in its original levels**, as evidenced by its very low *p*-value. This finding indicates that the FDI series follows an $I(0)$ integration process, reflecting the relatively rapid reversion of the series to its long-run mean after temporary shocks.

In contrast, gross FX reserves, the M3 monetary aggregate, and the degree of dinarisation of receivables exhibit pronounced non-stationarity in levels, implying a strong persistence component and a long-run trend in their movements. However, following the application of the first-difference operator, all three variables become stationary, confirming that they are processes integrated of order one, i.e. $I(1)$ series.

Table 1 **Results of the Augmented Dickey-Fuller unit root test**

Variable	Series form	Model specification	ADF statistics	*p*-value
Gross FX reserves	Level	Constant+deterministic trend	-1.7237	0.7375
	First difference	Constant	-11.6504	0.0000***
M3 monetary aggregate	Level	Constant+deterministic trend	-1.5535	0.8079
	First difference	Constant	-15.6178	0.0000***
FDI	Level	Constant	-6.0808	0.0000***
Dinarisation of receivables	Level	Constant	-0.9038	0.7857
	First difference	Constant	-6.5889	0.0000***

Note: *** indicates rejection of the null hypothesis of a unit root and the presence of stationarity at the 1% significance level.
Source: Authors' calculation based on NBS data.

These consistent diagnostic results confirm that the key variables are integrated of order zero or one, thereby definitively ruling out the presence of second-order integrated processes in the system and confirming the full methodological appropriateness of employing the ARDL/NARDL methodology and the bounds testing approach.

2.2 Specification of the baseline ARDL model and empirical results of the primary regression

Following confirmation of the appropriate order of integration of the time series through the diagnostic tests presented above, the general linear ARDL model is specified in levels. This baseline dynamic model is specified as follows:

$$\ln(FXR_t) = c + \sum_{i=1}^{p} \phi_i \ln(FXR_{t-i}) + \sum_{j=0}^{q_1} \beta_{1,j} \ln(M3_{t-j}) + \sum_{k=0}^{q_2} \beta_{2,k} FDI_{t-k} + \sum_{m=0}^{q_3} \beta_{3,m} DIN_{t-m} + \varepsilon_t$$

where the defined symbols denote:

- $\ln(FXR_t)$ – the natural logarithm of the monthly level of the NBS's gross FX reserves at time *t* (dependent variable);
- c – model constant;
- $\ln(M3_t)$ – the natural logarithm of the monthly level of the M3 monetary aggregate;
- FDI_t – share of monthly net FDI inflow in monthly GDP;
- DIN_t – share of dinar-denominated household and corporate receivables in total household and corporate receivables on a monthly level;
- i, j, k, m – optimal lags for the dependent and independent variables, respectively;
- ϕ_i, $\beta_{1,j}$, $\beta_{2,k}$, $\beta_{3,m}$ – short-run dynamic coefficients capturing the effects of the lags;
- ε_t – white noise.

Since official GDP data are published on a quarterly basis, whereas the econometric model requires all analysed variables to be available at a monthly frequency, quarterly GDP was disaggregated to a monthly frequency using the standard Chow–Lin method (Chow & Lin, 1971). The monthly industrial production index was used as the high-frequency indicator (auxiliary series) in the interpolation procedure, as it represents the most reliable monthly indicator of economic activity in the Republic of Serbia. This approach ensures full accounting consistency, whereby the sum of the three disaggregated monthly values equals the official quarterly GDP, while preserving the actual monthly dynamics of the business cycle. Finally, the variable was defined as the ratio of monthly net FDI inflows to the monthly GDP obtained in this manner, thereby normalising inflows relative to the size of the economy and eliminating the scale effect.

A key step in the construction of this model is the precise determination of the optimal number of lags for each variable individually. To this end, a systematic search algorithm was conducted across the space of possible lag combinations (grid search), guided by rigorous minimisation of the Bayesian Information Criterion (BIC) (Wooldridge, 2021). This criterion was selected because it imposes a stronger penalty on models with a large number of parameters than other information criteria, thereby ensuring parsimony and mitigating the risk of overfitting the model to the sample.

The aforementioned *BIC* criterion identified ARDL(1, 1, 1, 0) as the optimal specification. This result indicates that the current level of gross FX reserves contains a pronounced inertia component (dependence on the previous month), while also responding promptly to one-month lags in the money supply and FDI, as well as to current changes in the degree of dinarisation of receivables. The model specification is presented as follows:

$$\ln(FXR_t) = \beta_0 + \beta_1 \ln(FXR_{t-1}) + \beta_2 FDI_{t-1} + \beta_3 \ln(M3_t) + \beta_4 \ln(M3_{t-1}) + \beta_5 DIN_t + \varepsilon_t$$

The empirical results of estimating the baseline ARDL(1, 1, 1, 0) regression using the ordinary least squares (OLS) method are systematically presented in Table 2. The high adjusted coefficient of determination, which is common for dynamic ARDL models in levels with a lagged dependent variable, confirms that the selected system of variables explains **as much as 99.3% of the variability in the NBS's gross FX reserves**, while the overall statistical significance of the regression is confirmed by the *F*-statistic at the 1% significance level.

The high coefficient on the first lag of FX reserves indicates a pronounced autoregressive component and strong inertia in the dynamics of FX assets. This is fully consistent with the macroeconomic nature of FX reserves as a systemic safeguard, the level of which is characterised by a high degree of accumulation and gradual adjustment over time.

The current level of the M3 monetary aggregate exhibits a positive and statistically significant coefficient, while its first lag has a negative sign. The combined effect of these coefficients reflects the dynamic response of FX reserves to net changes in the money supply, confirming that monetary expansion in the short run is directly associated with an increase in the NBS's FX reserves due to foreign exchange purchases in the interbank market aimed at maintaining the relative stability of the dinar exchange rate.

Table 2 **Results of the ARDL(1, 1, 1, 0) model**

Independent variable	**Coefficient**	***p*-value**
Constant	-0.1387	0.0424**
$\ln(FXR_{t-1})$	0.9703	0.0000***
$\ln(M3_t)$	0.6545	0.0000***
$\ln(M3_{t-1})$	-0.6040	0.0000***
FDI_{t-1}	-0.0017	0.0017***
DIN_t	-0.0028	0.0205**
Statistical and diagnostic model indicators		
Determination coefficient	0.9934	
Adjusted determination coefficient	0.9932	
F-statistics (*p*-value)	6,252.439 (0.000***)	
Durbin-Watson statistics	1.7711	

Note: ** and *** denote statistical significance at the 5% and 1% levels, respectively.
Source: Authors' calculation based on NBS data.

The exclusion of the contemporaneous FDI term and the retention of only its first lag has a clear economic and operational rationale. FDI inflows do not translate immediately into the central bank's FX reserves, as some time is required for the funds to pass through the interbank market and the payment system. In addition, the initial capital inflow in the same month is often accompanied by imports of equipment or raw materials required for the investment, temporarily offsetting the initial positive effect on FX reserves. Consequently, the actual net impact of FDI on the accumulation of FX reserves is recorded only with a one-month lag, as also empirically confirmed by the information criteria used in model selection.

The statistically significant negative coefficient on the degree of dinarisation of receivables reflects the effects of implementing the Dinarisation Strategy, whose key objective is to reduce the impact of euroisation on domestic economic flows. By reducing reliance on foreign currency funding, the economy becomes less dependent on FX interventions, thereby reducing the need for the central bank to maintain high levels of FX reserves. In this way, pressure on the FX balance is effectively eased, confirming the positive effect of dinar flows on macroeconomic stability.

Standard diagnostic tests indicate that the model residuals exhibit neither serial correlation nor conditional heteroskedasticity. The Box–Ljung test confirms the absence of autocorrelation and partial autocorrelation, indicating the robustness and efficiency of the estimated model. Accordingly, the estimated parameters are statistically valid for the subsequent stages of the analysis, including the cointegration analysis and the bounds testing procedure.

3 Cointegration analysis and bounds testing

3.1 Bounds testing

Once the high quality of the baseline regression has been confirmed, the next methodological step is to examine whether a long-run cointegration relationship exists among the economic variables under consideration. To formally verify cointegration, the bounds test is conducted within the framework of an Unrestricted Error Correction Model (UECM). This model represents a dynamic reparameterisation of the baseline ARDL equation *(Pesaran et al.,* 2001) and is specified as follows:

$$\begin{aligned}\Delta\ln(FXR_t) = c &+ \rho\ln(FXR_{t-1}) + \lambda_1\ln(M3_{t-1}) + \lambda_2 FDI_{t-1} + \lambda_3 DIN_{t-1}\\ &+ \sum_{i=1}^{p-1}\gamma_i\,\Delta\ln(FXR_{t-i})\\ &+ \sum_{j=0}^{q_1}\alpha_j\,\Delta\ln(M3_{t-j}) + \sum_{k=0}^{q_2}\psi_k\Delta FDI_{t-k} + \sum_{m=0}^{q_3}\phi_m\Delta DIN_{t-m} + \varepsilon_t\end{aligned}$$

where the delta operator denotes the first difference of the variables, capturing their short-run dynamics. Within this framework, testing for long-run cointegration amounts to examining the joint statistical significance of the coefficients on the lagged level variables. Accordingly, the null hypothesis is formulated to rule out the existence of a long-run cointegration relationship among the variables under consideration, while the alternative hypothesis assumes that at least one of the coefficients is different from zero, indicating the existence of a long-run cointegration relationship:

$$H_0 : \rho = \lambda_1 = \lambda_2 = \lambda_3 = 0$$

H_1 : at least one of the coefficients is different from zero.

Table 3 **Results of the Pesaran bounds test**

	Value		
Calculated *F*-statistic	4.6572		
p-value of linear restriction	0.0013***		
Number of independent variables (*k*)	3		
Model specification	Case III (unrestricted constant, no trend)		
Critical values (Pesaran, Shin & Smith, 2001 – Case III, k=3)			
Level of significance (α)	**Lower bound *I*(0)**	**Upper bound *I*(1)**	**Test result**
0.10	2.72	3.77	Cointegration exists
0.05	3.23	4.35	Cointegration exists
0.01	4.29	5.61	Test is inconclusive

Note: *** denotes statistical significance at the 1% level.
Source: Authors' calculation based on NBS data and critical values (*Pesaran et al.*, 2001).

The test is conducted by calculating a joint *F*-statistic, the empirical value of which is compared with the non-standard critical values (Pesaran et al., 2001). These tabulated values are defined by the lower bound *I*(0), which assumes that all variables are stationary in levels, and the upper bound *I*(1), which assumes that all variables are stationary in first differences. If the calculated *F*-statistic exceeds the upper critical bound *I*(1), the null hypothesis is rejected in favour of the existence of cointegration. If the calculated *F*-statistic falls below the lower critical bound *I*(0), the null hypothesis is not rejected, and the conclusion is that there is no cointegration relationship. In contrast, an *F*-statistic value falling between the two critical bounds renders the test inconclusive. The empirical results of the bounds test conducted in this study are summarised in Table 3.

Model results show that the calculated *F*-statistic (4.6572) exceeds the critical value of the *I*(1) upper bound at the standard 5% significance level, as well as at the 10% significance level. Accordingly, the null hypothesis is rejected with a high degree of statistical confidence, providing **evidence of a strong, stable and economically justified long-term relationship among FX reserves, the M3 monetary aggregate, the share of FDI in GDP, and the degree of dinarisation of receivables**. The very low *p*-value of the linear restriction provides additional mathematical confirmation of the stability and high statistical significance of the specified long-run restrictions.

3.2 Long-run dynamics and multipliers

Once cointegration has been confirmed, the next step is to reparametrise the model into an error correction form in order to analyse short-run dynamics:

$$ln(FXR_t) = \beta_0 + \beta_1 ln(M3_t) + \beta_2 FDI_t + \beta_3 DIN_t + \varepsilon_t$$

where coefficients $\beta_1, \beta_2, \beta_3$ represent the long-run elasticities or semi-elasticities of the variables. The estimated long-run coefficients, which quantify the effects of the independent variables on gross FX reserves, are presented in Table 4.

In analysing the estimated long-run equilibrium coefficients, the M3 monetary aggregate emerges as a key determinant of gross FX reserves. With a positive coefficient of 1.7027, which is statistically highly significant at the highest 1% level, **this monetary aggregate implies that a 1% increase in the money supply is associated, in the long term, with an approximately 1.70% increase in gross FX reserves**. This finding is consistent with the economic rationale underlying the regime of a relatively stable dinar/euro exchange rate. In the presence of appreciation pressures on the domestic currency arising from capital inflows, the central bank engages in net FX purchases in the interbank FX market. Through these interventions, the NBS simultaneously accumulates FX assets and generates dinar liquidity. Consequently, an increase in the M3 monetary aggregate is accompanied by a corresponding increase in the level of FX reserves, thereby contributing to the mitigation of pressures on the dinar exchange rate.

Table 4 **Overview of long-run cointegration coefficients**

	Coefficient	***p*-value**
Long-run impact of M3 monetary aggregate (in %)	1.7027	0.1294
Long-run impact of FDI (in pp)	-0.0589	0.0010***
Long-run impact of the degree of dinarisation of receivables (in pp)	-0.0938	0.0670*

Note: * and *** denote statistical significance at the 10% and 1% levels, respectively.
Source: Authors' calculation based on NBS data.

Directly structurally linked to the dynamics of domestic monetary aggregates is the process of dinarisation, which is quantified in the model by the degree of dinarisation of household and corporate receivables. The estimated negative long-run coefficient amounts to -0.09 and is statistically significant at the 10% level, providing empirical support for the rationale underpinning the objectives set out in the Dinarisation Strategy consistently pursued by the NBS. Since the dinarisation variable is expressed in levels as a percentage share, this coefficient represents the semi-elasticity of the model, implying that **each 1 pp increase in the degree of dinarisation of the financial system leads to a structural reduction in the underlying need for FX reserves by approximately 0.09%**. From a macroprudential policy perspective, a sustained increase in the share of dinar loans in total receivables reduces the banking sector's systemic exposure to foreign currency-indexed credit risk, i.e. the risk of a deterioration in the solvency of unhedged borrowers due to exchange rate fluctuations. As this systemic risk is mitigated, the central bank's need to accumulate high precautionary foreign exchange buffers (Jeanne & Rancière, 2006), maintained through the reserve requirement imposed on commercial banks, is also reduced. In this way, a higher degree of long-run dinarisation facilitates the NBS's balance sheet assets optimisation and reduces the opportunity costs associated with holding excessive FX reserves.

In contrast to the monetary channels, the long-run effect of FDI is associated with specific and moderate structural pressures, with a cointegrating coefficient estimated at -0.06; however, the coefficient is not statistically significant at conventional significance levels. Since, in the absence of statistical significance, the estimated coefficient cannot be reliably distinguished from zero, these results do not provide a basis for drawing robust conclusions about the long-run effect of FDI on the level of FX reserves. In econometric practice, interpreting the economic significance of the sign and magnitude of a statistically insignificant parameter lacks empirical support. Therefore, within the given specification, this factor cannot be regarded as a statistically relevant long-run determinant of FX reserves.

3.3 Short-run dynamics and the error correction model

To examine short-run adjustments and the operational responses of the monetary system at the monthly frequency, the model is transformed into its final restricted error correction form by introducing a lagged error correction term (ECT_{t-1}).

$$\Delta ln(FXR_t) = \alpha_0 + \sum_{i=1}^{p} \gamma_i \, \Delta ln(FXR_{t-i}) + \sum_{j=0}^{q_1} \delta_j \, \Delta ln\big(M3_{t-j}\big) + \sum_{k=0}^{q_2} \phi_k \, \Delta FDI_{t-k} + \sum_{m=0}^{q_3} \psi_m \, \Delta DIN_{t-m} + \theta ECT_{t-1} + \varepsilon_t$$

where delta denotes the first-difference operator, while ECT_{t-1} denotes the error correction term, defined as follows (Pesaran, Shin & Smith, 2001):

$$ECT_{t-1} = ln(FXR_{t-1}) - (\beta_0 + \beta_1 ln(M3_{t-1}) + \beta_2 FDI_{t-1} + \beta_3 DIN_{t-1})$$

This term quantifies the deviation of the dependent variable from the long-run equilibrium path established in the previous period. The short-run dynamic model is estimated using the ordinary least squares (OLS) method, and the obtained results of the short-run dynamics are presented in Table 5.

Table 5 **Overview of short-run cointegration coefficients**

	Coefficient	***p*-value**
Error correction term	-0.033	0.0000***
Monthly change in M3 monetary aggregate	0.681	0.0000***
Monthly change in FDI	-0.001	0.312
Monthly change in degree of dinarisation of receivables	-0.014	0.002***

Note: *** denotes statistical significance at the 1% level.
Source: Authors' calculation based on NBS data.

Turning to the analysis of current short-run dynamics within the error correction model, the key empirical indicator of the financial system's dynamic stability is found in the error correction term. The estimated coefficient on $ECT_{t-1}$is -0.0331, has the theoretically consistent, strictly negative sign, and is highly statistically significant at the 1% level. This finding provides unequivocal empirical evidence of the existence of a functional selfcorrecting mechanism in the financial system of the Republic of Serbia (Banerjee et al., 1998). **In a monthly interval, 3.31% of the deviation of gross FX reserves from their long-run equilibrium path** (caused by sudden external shocks, geopolitical tensions or speculative pressures) **is systematically neutralised over the long term**. Such a moderate speed of adjustment indicates that the system has the capacity to gradually absorb shocks, which is often associated in the economic literature with the concept of precautionary FX reserve holdings aimed at safeguarding against long-term macroeconomic disturbances (Jeanne & Rancière, 2006). Although the statistical properties of the error correction term alone do not allow definitive conclusions to be drawn regarding FX market interventions, this convergence parameter indicates the absence of abrupt, procyclical depletion of FX reserves and primarily reflects a stable and controlled process of returning to the long-run equilibrium.

In the context of current monthly changes, the short-run impact of the M3 monetary aggregate amounts to 0.6811 and is highly statistically significant. At the monthly level, this coefficient directly reflects the primary channel through which domestic liquidity is created under a managed floating exchange rate regime. When there is a net inflow of foreign currency into the interbank FX market (through exports, remittances or foreign capital inflows), pressures for short-term appreciation of the domestic currency arise. To preserve exchange rate stability and price competitiveness, the NBS enters the FX market as a net buyer of foreign currency. Through these operational interventions, the central bank acquires foreign exchange assets and directly increases gross FX reserves, while simultaneously injecting primary dinar liquidity into the banking system, thereby leading to a parallel increase in the M3 monetary aggregate. Accordingly, **for every 1% increase in the M3 monetary aggregate, gross FX reserves increase by an average of 0.68% in the same month**, providing empirical evidence that short-run money supply creation is fully backed by the accumulation of FX assets.

In contrast to monetary developments, the short-run dynamics of the degree of dinarisation of receivables have a statistically significant negative impact on monthly changes in gross FX reserves, with an estimated coefficient of -0.0142. Since the dinarisation variable is expressed as a percentage, this coefficient represents a semi-elasticity of the model, meaning that **a 1 pp increase in the degree of dinarisation of receivables in the current month results in an average short-run decrease in gross FX reserves of 1.42%**. The above finding precisely quantifies the operational effects of tactical balance-sheet restructuring by commercial banks and their short-run interactions with the central bank. In the context of stronger demand for dinar-denominated loans, commercial banks adjust their liquidity positions by releasing the FX reserve requirement held with the NBS, which is maintained against FX funding sources, thereby freeing up lending capacity in domestic currency. From the perspective of systemic stability, this short-run decline in gross FX reserves does not represent a destabilising factor, but rather an expected second-round effect within the operational framework that supports the achievement of a higher strategic objective – stable dinarisation of the domestic financial system.

Finally, short-run changes in FDI with an estimated coefficient of -0.001, are not statistically significant at any of the conventional significance levels. This finding conveys an important macroeconomic message: current monthly fluctuations and short-run informational noise in the initial stages of FDI inflows do not warrant operational interventions in the FX market. The process of deploying foreign capital is characterised by a pronounced time lag and phased implementation, as the FX funds initially remain deposited in companies' FX accounts with commercial banks and only gradually affect official FX reserves through subsequent import transactions, purchases of capital equipment, and international payment flows. The absence of short-run statistical significance confirms that FDI operates through a delayed transmission channel and provides the NBS with considerable room to plan its operational actions strategically and over the longer term, without the need for *ad hoc* responses to monthly fluctuations.

4 Testing the structural stability of parameters

One of the most common methodological challenges in econometric modelling of macroeconomic time series over a long period is the potential presence of structural breaks (Zivot & Andrews, 1992). Given that the sample covers a period of more than 17 years, the historical horizon is marked by pronounced global and domestic economic shocks. This period was characterised by the global financial crisis, significant domestic fiscal reforms and consolidation, the COVID-19 pandemic, as well as energy shocks accompanied by inflationary pressures (Krugman, Obstfeld & Melitz, 2012). If the estimated coefficients of the dynamic ARDL model were found to be unstable and to vary significantly over time, all conclusions and recommendations derived from the model would lose their scientific credibility and practical relevance for economic policymaking.

To address this concern and assess the robustness of the results, two complementary tests of structural stability based on recursive regression residuals were conducted: the CUSUM (Cumulative Sum) test and the CUSUM Squares (Cumulative Sum of Squares) test (Brown, Durbin & Evans, 1975). The CUSUM test primarily focuses on detecting gradual, systematic changes in the parameters, particularly in the model constant, whereas the CUSUM Squares test is particularly sensitive to sudden, sharp structural breaks affecting the conditional variance of the error term.

Mathematically, the CUSUM statistic is constructed as the cumulative sum of recursive residuals standardised by the estimated standard deviation of the model:

$$W_t = \frac{1}{\hat{\sigma}_w} \sum_{r=k+1}^{t} \omega_r \ , \qquad t = k+1, \dots, T$$

where ω_r represents the recursive residual at time r (based on the model estimated up to time $r-1$), while $\hat{\sigma}_w$ is the estimated standard deviation of the residuals over the entire sample, calculated as:

$$\hat{\sigma} = \sqrt{\frac{\sum_{t=1}^{T} (\omega_t - \overline{\omega})^2}{T-k-1}}$$

The stability of the model parameters is statistically and visually confirmed if the empirical cumulative sum line W_t remains within the strictly defined critical bounds throughout the entire observation period, at a 5% level of statistical significance. The critical bounds evolve linearly over time in accordance with the methodology of Brown, Durbin and Evans (1975) and are symmetrically defined as:

$$\pm\left[a\cdot\sqrt{T-k}+\frac{2\cdot a\cdot(t-k)}{\sqrt{T-k}}\right]$$

where parameter a = 0.948 represents the critical value corresponding to the significance level of 5%.

In the case of the CUSUM Squares test, the S_t test statistic is based on the cumulative squares of the recursive residuals and is mathematically defined as:

$$S_t=\frac{\sum_{j=k+1}^{t}\omega_j^2}{\sum_{j=k+1}^{T}\omega_j^2}\,,\qquad t=k+1,\dots,T$$

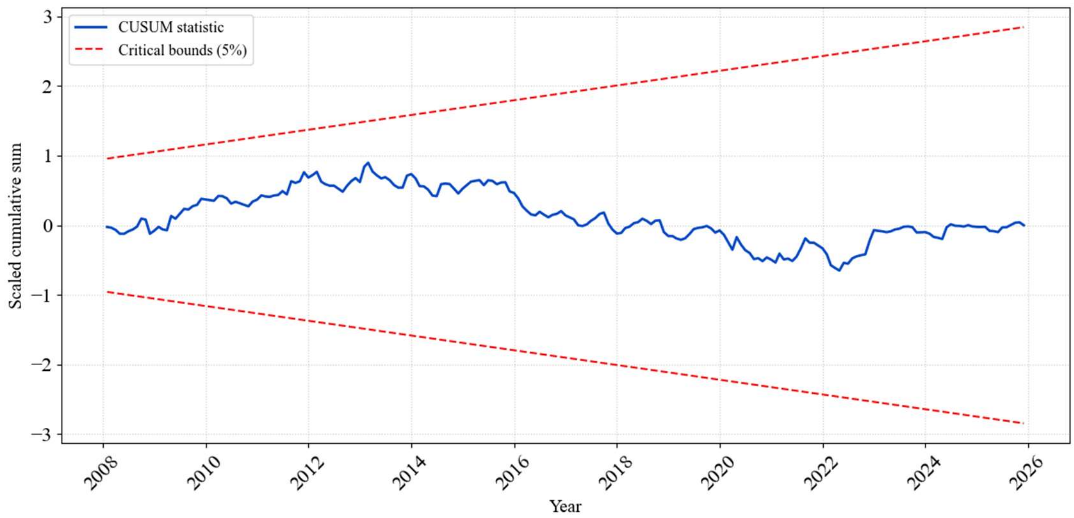
The critical bounds for the S_t statistic are defined as a parallel corridor around the expected mean: $E(S_t)=\frac{t-k}{T-k}$ in form $E(S_t)\pm c_{0,05}$, where critical value $c_{0,05}$ for significance level of 5% equals: $c_{0,05}=\frac{1,358}{\sqrt{T-k}}$.

The empirical results of the CUSUM test unequivocally confirm the high methodological stability of the estimated model. The test generated a high empirical p-value of 0.4025, whereby the null hypothesis H_0 regarding the structural stability of the parameters cannot be rejected at any standard significance level.

The maximum amplitude of the dynamic deviation was recorded in March 2013. At this point, the scaled maximum CUSUM value stands at 0.8405, which is significantly below the then-permissible critical boundary of ±1.4948. This result indicates that the recorded deviation does not constitute a structural break in the model's parameters. The recorded maximum amplitude is econometrically entirely valid and reflects a short transitional period of consolidation in the domestic FX market, following the implementation of the new monetary policy framework and the stabilisation of the exchange rate in the second half of 2012. It was precisely during that period that the foundations of the new, proactive FX intervention regime were laid, which enabled the absorption of external shocks and calmed the volatility of the domestic financial market. Chart 1 clearly shows that the cumulative sum line does not leave the symmetric confidence interval at any single point of the observed sample.

On the other hand, the results of the CUSUM Squares test (Chart 2) provide a more detailed insight into the dynamics of the conditional variance of the residuals. The calculated maximum deviation of the cumulative sum of squared residuals from the theoretical trajectory amounts to 0.1066, which slightly exceeds the critical threshold of ±0.0939 at the 5% significance level. This spike was recorded in January 2023, when the empirical S_t statistic line briefly moved above the upper critical bound.

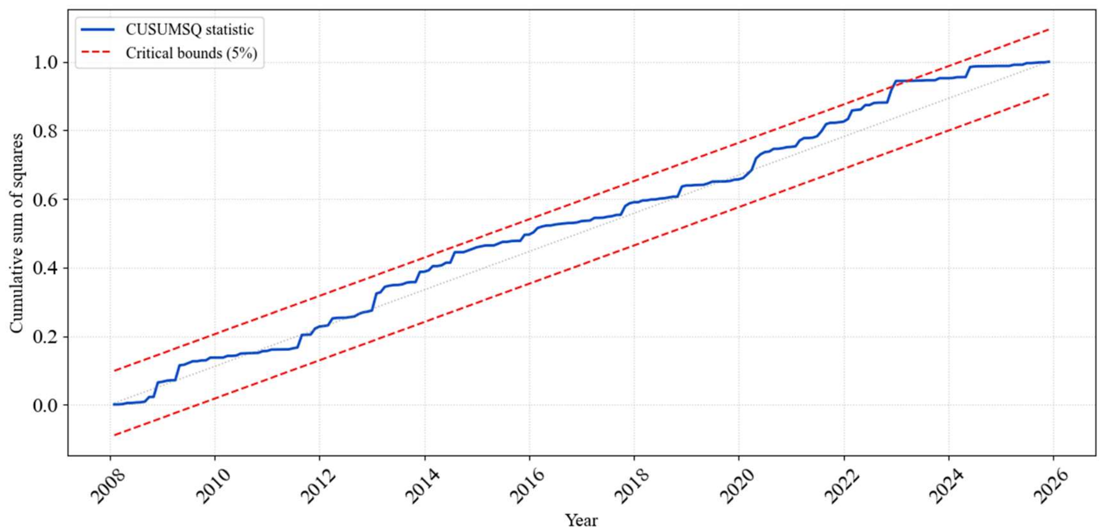
Chart 1 **Cumulative sum of recursive residuals**



Source: Authors' calculation based on NBS data.

The aforementioned temporary increase in residual variability is econometrically entirely justified and directly reflects the cumulative effect of strong exogenous shocks from early 2023. During that period, the peak of the spill-over from the global energy crisis, record imported inflation in Europe, and intensive FX market intervention by the NBS to preserve the relative stability of the domestic currency were recorded. It is important to emphasize that after the brief peak, the CUSUM Squares statistic fully returned within the permissible confidence interval already during 2024, confirming that no permanent destabilisation of systemic risks occurred.

Chart 2 **Cumulative sum of squared recursive residuals**



Source: Authors' calculation based on NBS data.

A synthesis of the results of both tests leads to the key methodological conclusion. Since the CUSUM test confirms that all model coefficients are structurally stable over time, and the CUSUM Squares test shows rapid dissipation and a return of the variance to the control corridor after a short-lived external shock, the estimated ARDL model possesses high analytical robustness. The results provide strong empirical evidence that the NBS's monetary policy and the Strategy of Dinarisation of the Financial System have been consistent, and that the long-term relationships between gross FX reserves, the monetary aggregate M3, FDI and the degree of dinarisation of receivables are highly resilient to geopolitical and macroeconomic shocks.

5 Nonlinear ARDL (NARDL) model and asymmetric effects of the dinarisation strategy

Traditional linear econometric models rest on the rigid and often unrealistic assumption that economic variables respond symmetrically. This would imply that shocks of the same magnitude, but opposite sign (positive and negative) would produce effects of identical strength. However, in the real world of financial markets, the behaviour of economic agents is strongly influenced by psychological factors, risk aversion and institutional asymmetries. To overcome these linear limitations and more realistically model the dynamics of the Serbian financial system, the research introduces the **nonlinear ARDL (NARDL) model**, developed by Shin, Yu & Greenwood-Nimmo (2014). The primary focus of this model is directed at examining the potential presence of an asymmetric response of gross FX reserves to positive and negative changes in the degree of dinarisation of receivables, as well as in the monetary aggregate M3.

To this end, the total degree of dinarisation of receivables (DIN_t) and the broad money supply ($M3_t$) have been decomposed into two separate cumulative partial sums that track positive and negative shocks in isolation. For the dinarisation variable, the decomposition is formally written as:

$$DIN_t = DIN_0 + DIN_t^+ + DIN_t^-$$

where DIN_0 denotes the initial value of the series at the beginning of the observed period, which is absorbed within the constant term of the model in the econometric estimation, while DIN_t^+ and DIN_t^- are the cumulative sums of positive (increase in dinarisation and strengthening of confidence in the domestic currency) and negative changes (decline in dinarisation, i.e. return to euroisation due to heightened risk perception):

$$DIN_t^+ = \sum_{i=1}^{t} \Delta DIN_i^+ = \sum_{i=1}^{t} \max(\Delta DIN_i\,, 0)$$

$$DIN_t^- = \sum_{i=1}^{t} \Delta DIN_i^- = \sum_{i=1}^{t} \min(\Delta DIN_i\,, 0)$$

In the same manner, the total broad money supply ($M3_t$) is decomposed within the nonlinear specification by the following equation:

$$\ln(M3_t) = \ln(M3_0) + \ln(M3_t^+) + \ln(M3_t^-)$$

where $\ln(M3_0)$ denotes the initial logarithmic value of the series at the beginning of the observed period, which is absorbed into the constant term of the model in the econometric estimation, while $\ln(M3_t^+)$ and $\ln(M3_t^-)$ are the cumulative sums of positive (monetary expansion and growth of liquidity in the system) and negative changes (monetary contraction and withdrawal of dinar liquidity):

$$\ln(M3_t^+) = \sum_{i=1}^{t} \Delta \ln M3_i^+ = \sum_{i=1}^{t} \max(\Delta \ln(M3_i)\,, 0)$$

$$\ln(M3_t^-) = \sum_{i=1}^{t} \Delta \ln M3_i^- = \sum_{i=1}^{t} \min(\Delta \ln(M3_i),0)$$

By incorporating these decomposed series, the final regression specification of the asymmetric NARDL model takes the following structural form:

$$\Delta \ln(FXR_t) = c + \gamma \ln(FXR_{t-1}) + \beta_{FDI} FDI_{t-1} + \alpha^+ \ln(M3_{t-1}^+) + \alpha^- \ln(M3_{t-1}^-) + \beta^+ DIN_{t-1}^+ + \beta^- DIN_{t-1}^- + \sum_{i=1}^{P} \phi_i \Delta \ln(FXR_{t-i}) + \varepsilon_t$$

Table 6 **Empirical results of the estimate of the asymmetric *NARDL* model**

	Coefficient	***p*-value**
Constant	0.523	0.027**
Gross FX reserves, lagged by one period	0.941	0.000***
FDI as a share of GDP, lagged by one period	-0.001	0.024**
Cumulative positive shock of the monetary aggregate M3, lagged by one period	0.106	0.017**
Cumulative negative shock of the monetary aggregate M3, lagged by one period	0.098	0.458
Cumulative positive shock of dinarisation of receivables, lagged by one period	-0.004	0.047**
Cumulative negative shock of dinarisation of receivables, lagged by one period	-0.002	0.462

Note: ** and *** denote a statistical significance at the levels of 5% and 1%, respectively.
Source: Authors' calculation based on NBS data.

The model was optimised according to the BIC criterion and estimated using the ordinary least squares method. Its empirical parameters and accompanying significance statistics are presented in detail in Table 6.

In order to calculate the actual long-run elasticities of positive and negative shocks on gross FX reserves, a normalisation of the estimated coefficients on the lagged level variables was performed with the pair of lagged dependent variables. The speed of adjustment of the model towards equilibrium is first defined ($\theta = \gamma_1 - 1$ = –0,0591). The formula for calculating the long-run asymmetric multipliers is as follows:

$$\delta^{+} = -\frac{\beta^{+}}{\theta}, \quad \delta^{-} = -\frac{\beta^{-}}{\theta}$$

By applying this mathematical matrix to the estimated values from Table 6, the following long-run effects are obtained:

- **Long-run effect of M3 growth ($\boldsymbol{\delta^{+}_{M3}}$):** 0.1063/0.0591= 1.799
- **Long-run effect of M3 decline ($\boldsymbol{\delta^{-}_{M3}}$):** 0.0978/0.0591= 1.655
- **Long-run effect of dinarisation growth ($\boldsymbol{\delta^{+}_{DIN}}$):** -0.0036/0.0591= -0.061
- **Long-run effect of dinarisation decline ($\boldsymbol{\delta^{-}_{DIN}}$):** -0.0020/0.0591= -0.034

In order to determine whether the observed differences between the positive and negative multipliers are statistically significant (i.e. whether formal long-run asymmetry exists), a **Wald test of linear restrictions** was conducted. Two separate null hypotheses of complete equality of the long-run effects were tested:

1. **For the monetary aggregate M3 ($\boldsymbol{H_0: \alpha^{+} = \alpha^{-}}$):**
   - Empirical value of the Wald *F*-statistic: **0.0042**
   - Corresponding significance level (*p*-value > *F*-statistic): **0.9486**
   - Given the high *p*-value, the null hypothesis of coefficient equality is not rejected. The long-run impact of the monetary aggregate M3 on gross FX reserves, viewed through the formal Wald test, is symmetric.
2. **For the degree of dinarisation of receivables ($\boldsymbol{H_0: \beta^{+} = \beta^{-}}$):**
   - Empirical value of the Wald *F*-statistic: **0.2648**
   - Corresponding significance level (*p*-value > *F*-statistic): **0.6074**
   - The null hypothesis of coefficient equality cannot be rejected at standard significance levels. Viewed through the strict statistical test, the effects of changes in the degree of dinarisation behave symmetrically in the long run.

However, although the Wald test, in a purely mathematical sense of coefficient equality, does not reject the null hypothesis of multiplier symmetry, economic logic and the matrix of statistical significance of the estimated parameters from Table 6 reveal a substantive asymmetry in the significance of the transmission:

- **Monetary aggregate M3 channel:** An increase in the money supply generates a long-run multiplier of **1.799**, which is statistically significant at the 5% level (p = 0.017). This result confirms that systemic expansion of liquidity and economic activity naturally leads to a cumulative easing and strengthening of the central bank's foreign assets through net FX purchases. By contrast, a decline in the monetary aggregate M3 has a long-run coefficient of **1.659**, but it is not statistically significant (p = 0.456). **This disparity in statistical significance clearly indicates that, through successful monetary policy, the NBS's gross FX reserves have been largely insulated from negative shocks to domestic monetary liquidity**.

- **Dinarisation of receivables to the household and corporate sector channel:** An increase in the degree of dinarisation produces a statistically significant long-run effect of -0.061 ($p = 0.047$), confirming a structural release of FX assets. A systemic increase in the share of dinar loans reduces FX exposure and the structural risk of banks, thereby reducing the need for a precautionary maintenance of a high level of mandatory FX reserves. By contrast, a decrease in the degree of dinarisation, with a coefficient of -0.034, is not statistically significant (p = 0.462), demonstrating that **episodes of a temporary decline in dinarisation do not cause permanent or significant consequences for the level of the NBS's FX reserves**.

6 Modelling conditional volatility

A comprehensive assessment of the stability and resilience of the domestic financial system requires, in addition to level analysis, precise modelling of the risk profile, i.e. the dynamics of conditional volatility of FX reserves (Danielsson, 2011). Prior to the specification of nonlinear conditional volatility models, a diagnostic check of the residuals of the baseline regression was performed. Testing for normality of the error distribution was conducted using the Jarque–Bera (JB) test (Jarque & Bera, 1987), which simultaneously uses information on skewness and kurtosis of the distribution to examine the null hypothesis that the residuals are normally distributed. The results are as follows:

- **Jarque–Bera statistic (JB):** 24.4445 (with an accompanying *p*-value of 0.000)
- **Skewness coefficient:** 0.4813 (positive skewness)
- **Kurtosis coefficient:** 4.3425

The extremely low p-value of the Jarque–Bera test (0.000) implies that the null hypothesis of normally distributed residuals is explicitly rejected at all levels of statistical significance. The obtained skewness coefficient of 0.4813 indicates a right-skewed distribution, while the kurtosis coefficient of 4.3425 (>3) clearly signals a leptokurtic distribution, i.e. a pronounced presence of a fat-tailed distribution, meaning an increased probability of extreme deviations relative to the standard Gaussian distribution (Coles, 2001; McNeil & Frey, 2000).

Nevertheless, from the standpoint of statistical inference, it is important to emphasize that given the relatively large sample (N = 216), the central limit theorem guarantees the unbiasedness and asymptotic validity of ordinary least squares estimation. Therefore, the absence of strict normality does not impair statistical inference, nor does it undermine the reliability of the estimated long-run and short-run ARDL coefficients. The residuals still display strong accumulation around zero and are well dispersed along the tails of the distribution (Verbeek, 2017). However, although the lack of normal distribution does not invalidate the level estimates in the ARDL model, the presence of leptokurtosis and time-varying dispersion within the tails raises the diagnostic suspicion that the residuals may potentially exhibit characteristics of conditional heteroskedasticity with volatility clustering.

As an appropriate methodological framework for modelling the conditional variance, the paper proceeds to advanced **nonlinear modelling of conditional volatility through the specification of a GARCH(1,1) model with the assumption of a Student's *t*-distribution**

(Danielsson, 2011). This approach simultaneously optimises the mean equation and the conditional variance equation, using the standardised Student's *t*-distribution of the error terms precisely in order to mathematically absorb and precisely quantify the characteristic fat tails of macroeconomic series.

Mean Equation:

$$\ln(FXR_t) = \mu_t + \varepsilon_t$$

where the stochastic disturbance ε_t follows a standardised Student's *t*-distribution with ν degrees of freedom: $\varepsilon_t = \sigma_t \cdot z_t,\ z_t \sim t_\nu(0,1,\nu)$

Conditional Variance Equation: $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

where the parameter ω defines the constant component of variance, the ARCH parameter (α_1) measures the reaction of volatility to current short-run shocks, while the GARCH parameter (β_1) quantifies the degree of persistence of conditional volatility from previous periods. The parameters were estimated using the maximum likelihood estimation (MLE) method, and the results are systematised in Table 7.

Table 7 **Parameter estimates of the Student-t GARCH(1,1) model**

	Coefficient	***p*-value**
Constant	0.000	0.440
ARCH effect	0.0603	0.491
GARCH effect	0.4264	0.570
Student's shape parameter	3.8627	0.000***

*Note: *** denotes statistical significance at the 1% level.
Source: Authors' calculation based on NBS data.

The estimated ARCH parameter (α_1 = 0.0603) and GARCH parameter (β_1 = 0.4264) are not statistically significant at any conventional significance level. This empirical outcome indicates that the potential diagnostic suspicion of volatility clustering has not been confirmed in the final model, i.e. that there is no significant temporal risk accumulation or autoregressive spillover of volatility over time in the residuals. From a macroeconomic perspective, this confirms that the NBS's proactive interventions successfully neutralise the transmission of short-run volatility shocks over time.

Unlike the variance coefficients, the Student's shape parameter (ν = 3.8627) exhibits exceptionally high statistical significance. Such a low value of the degrees of freedom parameter (ν < 5) formally verifies that the residuals are burdened with pronounced fat tails, thereby fully justifying the Student's *t*-distribution specification. This finding provides a crucial methodological insight that the deviation from the normal distribution identified by the Jarque–Bera test is not a consequence of time-varying conditional volatility, but rather the presence of rare but strong economic shocks in the tails of the distribution, which the specified model has fully captured through the Student's *t*-distribution.

Although the sum of the point estimates of the ARCH and GARCH coefficients amounts to 0.4867, which mathematically satisfies the condition of covariance stationarity ($\alpha_1 + \beta_1 < 1$), the absence of statistical significance of the individual parameters prevents the conditional variance from possessing a strong mean-reverting property. More precisely, the conditional variance of FX reserves behaves as a stable, essentially constant unconditional variance with pronounced Student's tails, without autoregressive accumulation of volatility shocks over time. From a macroeconomic perspective and from the standpoint of monetary policy makers, the obtained results provide strong confirmation of the structural stability of the domestic financial system.

The absence of statistically significant ARCH and GARCH effects demonstrates that the movement of the NBS's gross FX reserves is not subject to persistent volatility nor to systemic risk accumulation. Through timely and measured interventions in the interbank FX market, the central bank effectively sterilises external disturbances, allowing all initial shocks to be rapidly absorbed, thereby preserving long-term exchange rate stability and overall macro-financial stability.

7 Macroeconomic stress testing and quantification of extreme event risk

7.1 Construction of stress scenarios and the Monte Carlo simulation methodological framework

Although the previously specified and estimated linear and nonlinear ARDL models provide empirically consistent insight into long-run cointegration relationships and the short-run dynamics of FX reserve determinants, their projection capacity is structurally limited under conditions of extreme macroeconomic disruptions. Classical linear models are based on the assumption of symmetry of shocks and normal distribution of error terms, which *a priori* renders them inadequate for modelling nonlinear systemic crisis periods. In the real economic environment, the distribution of extreme FX reserve outflows exhibits pronounced asymmetry and leptokurtosis. Given that the previous empirical analysis of the residuals of the primary ARDL specification confirmed the strong presence of fat tails and a high Jarque–Bera statistic value, the institutional standard in systemic risk analysis requires the abandonment of the normality assumption and the implementation of the conceptual framework of Extreme Value Theory (EVT) (Coles, 2001).

In this context, this paper develops a conditional forecasting system that methodologically integrates three complementary econometric segments within the so-called Conditional EVT approach (McNeil and Frey, 2000):

1. An **ARDL(1,1,1,0) conditional mean model**, which filters deterministic trends, temporal interdependence and long-run structural influences of macroeconomic variables on the level of gross FX reserves;

2. A **GARCH(1,1) conditional volatility model with a Student's *t*-distribution**, which dynamically filters time-varying volatility and provides standardisation of residuals;

3. A **Generalised Extreme Value (GEV) distribution of the Fréchet type**, which is applied to the standardised residuals in order to perform an asymptotic approximation of the behaviour of the left tail of the distribution, i.e. the quantification of the most severe systemic risks.

The forecasting horizon is set to a dynamic period of 12 months, up to and including December 2026. As a reference starting point, the model uses the end of the analysed sample, i.e. December 2025, with the initial level of gross FX reserves defined at EUR 29,008.30 mn.

In order to generate a complete empirical density distribution of future FX reserve levels and eliminate the statistical error characteristic of small samples at the extreme tails, the algorithm was run through 15,000 independent stochastic Monte Carlo simulations. The introduction of such a high number of iterations represents a key methodological turning point in the paper for two reasons:

- **First**, it enables asymptotic convergence of the GEV distribution parameters in the most critical domains (above the 95^{th} and 99^{th} percentiles), thereby reducing the standard error of the estimated FX Reserve-at-Risk (FX RaR) indicators to a statistically negligible level;
- **Second**, it ensures the complete insensitivity of the results to random fluctuations in the stochastic process, providing a methodologically sound and reliable basis for decision-making in the domain of preserving macro-financial stability.

The systemic shock is constructed as a coherent scenario of the simultaneous manifestation of three independent, but economically connected, transmission channels which jointly exert a systemic shock on the central bank's liquidity:

- **Monetary channel (domestic liquidity expansion)**: Within this channel, a continuous and relatively aggressive growth of the monetary aggregate M3 is modelled at a fixed rate of 1.2% per month (which cumulatively represents an annual monetary expansion of over 15.3%). In accordance with the portfolio balance theory and the monetary approach to the exchange rate (Krugman, Obstfeld & Melitz, 2012), the continuous generation of excess dinar liquidity exceeds real money demand defined by economic activity. Amid heightened macroeconomic uncertainty, economic agents seek to optimise the structure of their financial assets. In order to protect the purchasing power of capital from potential inflationary pressures, they initiate a process of currency substitution, channelling excess dinar funds into the purchase of foreign currency. This portfolio reallocation exerts direct pressure on the interbank FX market through a sharp increase in FX demand. To prevent the depreciation of the domestic currency and preserve the relative stability of the exchange rate as an anchor for inflation expectations, the NBS acts reactively as a net FX seller. Through FX interventions, the central bank absorbs excess dinar liquidity, but this directly causes an outflow of gross FX reserves.
- **External channel (balance of payments shock)**: Within this channel, an extreme negative shock is modelled through the phenomenon of a "sudden stop" of capital inflows (Calvo, 1998). This scenario assumes a sudden and complete halt in net FDI inflows, with their value set to zero throughout the entire 12-month projection horizon, with the possibility of slightly negative net values due to capital repatriation. From an economic perspective, FDI represent a key inflow for covering the current account deficit, whereby, in addition to equity components, they partly include debt instruments, such as intercompany loans. Their sudden absence prevents the

conventional financing of the foreign trade deficit. Since FX demand for settling goods and services import and servicing foreign liabilities remains high, while the inflow of foreign capital from FDI is drying up, a sharp financing gap and a significant narrowing of FX liquidity supply occur in the interbank FX market. The resulting shortage of FX funds directly spills over to the central bank, which is forced to compensate for the missing foreign capital through the continuous sale of FX from its reserves in order to maintain the regular settlement of the country's international obligations and prevent uncontrolled disruptions in the FX market.

- **Systemic stability channel (currency substitution in the banking sector)**: Within this channel, the impact of an intensive systemic disruption is quantified through a continuous decline in the degree of dinarisation of total receivables at a rate of 0.50 pp per month (which cumulatively represents a reduction of 6.0 pp on an annual basis). This trend reflects a sharp increase in the perception of systemic risk and the erosion of market participants' confidence in the domestic currency, triggering a process of re-euroisation of the banking sector's balance sheets. During the massive shift of dinar deposits into FX deposits, commercial banks face serious mismatches in the currency structure of their sources of funds and receivables. In order to maintain the regulatory minimums for net open FX positions and meet increased demands for FX liquidity, commercial banks withdraw FX funds from their clearing and ring-fenced accounts with the central bank, or convert excess dinar reserves into FX assets. This structural turn of the entire banking sector towards foreign currency creates additional pressure on the NBS's primary liquidity, causing a direct and rapid outflow of funds from FX reserves.

The mathematical implementation of the stochastic simulation is carried out recursively over time for a 12-month ahead horizon. At each individual step, within each of the 15,000 iterations, a stochastic increment is generated from the previously estimated GEV distribution. This asymmetric shock is then scaled by the current value of conditional volatility derived from the GARCH equation, and implemented into the ARDL structure. The resulting dynamic model does not simulate a passive decline in FX assets, but actively quantifies the real volume of net outflows through which the NBS, via FX interventions in the interbank FX market, sterilises excess dinar liquidity and successfully preserves the relative stability of the exchange rate under the most severe conditions of extreme event risk. The core dynamic equation modelling the movement of gross FX reserves over the projection period is as follows:

$$FXR_{t+h}^{(i)} = c + \sum_{j=1}^{p} \phi_j \, FXR_{t+h-j}^{(i)} + \sum_{m=0}^{q} \beta_m \, X_{t+h-m}^{(i)} + \left(\sigma_{t+h|t} \cdot \eta_{t+h}^{(i)}\right)$$

where the conditional volatility within the innovation is updated through the accompanying GARCH(1,1) structure:

$$\sigma_{t+h|t}^2 = \omega + \alpha \varepsilon_{t+h-1}^2 + \beta \sigma_{t+h-1|t}^2$$

and the stochastic shock is generated from the extreme value distribution:

$$\eta_{t+h}^{(i)} \sim \mathrm{GEV}(\mu, \psi, \xi)$$

- $FXR_{t+h}^{(i)}$ – simulated value of gross FX reserves for each individual month of the projection horizon h ($h = 1,2,\dots,12$), within each individual Monte Carlo iteration i ($i = 1,2,\dots,15{,}000$),
- c – constant term estimated from the long-run ARDL specification,
- ϕ_j – autoregressive forecasting coefficients for the lags of gross FX reserves ($j = 1,\dots,p$),
- β_m – coefficients of long-run and short-run multipliers for the accompanying macroeconomic determinants,
- $X_{t+h-m}^{(i)}$ – vector of simulated values of selected macroeconomic determinants (monetary aggregate M3, FDI and the degree of dinarisation of receivables) over the projection horizon,
- $\sigma_{t+h|t}$ – dynamic conditional standard volatility derived from the GARCH(1,1) specification, incorporating the Student's t-distribution, which quantifies current market uncertainty at time $t + h$ based on information available at time t,
- ω, α, β – GARCH parameters: the constant variance term (ω), the ARCH parameter for short-run shocks (α) and GARCH parameter for volatility persistence (β),
- ε_{t+h-1} – the residual or shock from the previous projection period,
- $\eta_{t+h}^{(i)}$ – stochastic increment (random variable) generated from the empirically estimated GEV distribution,
- μ, ψ, ξ – GEV distribution parameters: the location parameter (μ), the scale parameter (ψ) and the shape parameter (ξ), which directly measures the fat tails and the probability of the occurrence of extreme shocks.

7.2 Empirical results of stochastic simulations and valorisation of FX reserve resilience

Following the execution of 15,000 stochastic simulations over a twelve-month horizon under the constructed extreme systemic stress scenario, the final empirical density distribution of future FX reserve levels was generated. The comprehensive numerical results of the FX Reserve-at-Risk (FX RaR) indicators for various statistical confidence levels are systematised in Table 8.

The FX RaR indicator represents the key methodological framework for the quantitative assessment of the systemic vulnerability of the FX balance under conditions of extreme macroeconomic disruptions. Based on the principles of the Value-at-Risk concept, this indicator enables the estimation of the maximum expected decline in the level of FX reserves at a given level of statistical confidence (Danielsson, 2011).

Table 8 **Quantification of extreme event risk and projected outflow of FX reserves in the conditional Monte Carlo model (December 2026)**

Indicator of simulated systemic stress	Indicator value (in EUR mn)	Quantified maximum decline in FX reserves
Starting level (December 2025)	29,008.3	Starting point of the econometric model
Expected value after 12 months	28,218.21	790.09
Critical value at 90% confidence level	25,436.64	3,571.66
Critical value at 95% confidence level	24,846.47	4,161.83
Critical value at 99% confidence level	23,742.41	5,265.89

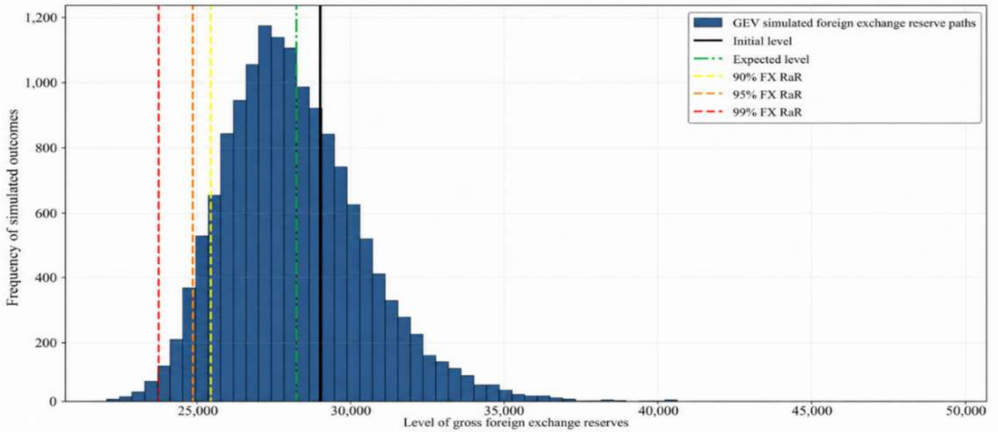
Source: Authors' calculation based on the conditional ARDL-GARCH-GEV Monte Carlo model with 15,000 iterations.

The expected value of gross FX reserves after one year of continuous exposure to combined systemic pressures amounts to EUR 28.22 bn. This result implies a moderate, gradually distributed and entirely controllable average outflow of only EUR 0.8 bn (i.e. a decline of just 2.72% relative to the initial level). Econometrically speaking, such stability at the central point of the distribution is a direct consequence of the exceptionally high value of the autoregressive parameter of the initial ARDL specification ($\phi_1 = 0.9717$). This coefficient quantifies the high temporal persistence and inertia of the NBS's FX reserves, confirming that the available defence mechanisms are sufficiently strong to absorb and neutralise the initial shock waves of a crisis. At the same time, the property of gradual decay of conditional volatility over time ensures that temporary volatility spikes are of a limited nature. This eliminates the possibility of uncontrolled outflows and guarantees the stability of the central bank's balance sheet.

If the analysis shifts from average values towards the left tail of the empirical distribution, the econometric model, by identifying quantiles at the 90% and 95% confidence levels, delineates the frameworks of possible but extreme macroeconomic shocks. As Chart 2 illustrates, in these scenarios – encompassing episodes such as capital outflows, adverse movements in the terms of trade or FX speculation – the value of FX reserves declines to EUR 25.44 bn (at 90% confidence) and EUR 24.85 bn (at 95% confidence). In practice, this means that the maximum cumulative outflow of funds would range between EUR 3.57 bn and EUR 4.16 bn.

From the standpoint of external economic stability assessment, these results confirm that the NBS possesses substantial levels of FX reserves. Even in the event of materialisation of serious market pressures, the system retains strong defence capacities. The available FX mechanism enables the uninterrupted neutralisation of adverse outflows without undermining the fundamental equilibrium in the market, which testifies to the long-run resilience of the domestic financial framework to external shocks.

Chart 3 **Empirical distribution of the NBS's FX reserves**



Source: Authors' calculation based on NBS data.

The position at the far left tail of the empirical distribution (99% confidence level) represents a scenario of extremely low probability of materialisation, but with serious macroeconomic consequences (a black swan scenario) (Taleb, 2007). Thanks to the implementation of 15,000 stochastic iterations, the estimate of this quantile is fully stabilised, thereby eliminating the high-variance problem characteristic of standard non-parametric methods. At this critical point, a simultaneous interaction of shocks occurs: accelerated growth of the monetary aggregate M3 creates a significant excess of dinar liquidity that exerts pressure on the FX market, which coincides with a decline in market participants' confidence (reflected through a 0.50 pp monthly decline in the degree of dinarisation) and a sharp slowdown in FDI inflows.

Under these circumstances, the GEV distribution precisely estimates the asymmetry of the left tail of the distribution and projects a decline in FX reserves to a critical minimum of EUR 23.74 bn at the 99% confidence level. The numerical calculation shows that the central bank, in the event of highly unfavourable macroeconomic developments, would have to spend a maximum of EUR 5.17 bn of gross FX reserves for the complete neutralisation of depreciation pressures and the preservation of exchange rate stability. Although this amount represents a significant expenditure (around 17.8% of initial assets), the fact that even in this scenario the system retains over EUR 23.8 bn in liquidity represents a strong confirmation of overall stability. The model empirically confirms that the existing defence mechanisms are sufficiently robust to absorb even the most severe extreme shocks, thereby ensuring the long-term credibility of monetary policy and the stability of the domestic exchange rate.

8 Conclusion

The empirical analysis conducted in this paper unequivocally confirms the high resilience, structural stability and methodological robustness of the NBS's macroeconomic framework. By applying advanced linear and nonlinear econometric specifications (ARDL/NARDL) on a sample from January 2008 to December 2025, it has been demonstrated that gross FX reserves have evolved from a passive indicator of external liquidity into a key instrument of macroeconomic stability of the domestic financial system.

The results of the bounds test confirm the existence of a stable long-run cointegration relationship within the system, in which the monetary aggregate M3 plays a dominant role. With a long-run coefficient of 1.70, this aggregate represents the key pillar of stability, implying that the expansion of domestic liquidity has been consistently supported by adequate FX assets through **successful interventions in the interbank market, thereby timely neutralising speculative pressures on the dinar exchange rate**.

The estimation of long-run multipliers provides strong empirical evidence of the justification of the Dinarisation Strategy. The statistically significant negative coefficient on the degree of dinarisation of receivables (-0.09) indicates that an increase in the share of dinar loans substantially limits the systemic risk of exchange rate exposure, thereby reducing the need to hold excessive preventive FX assets. The findings of the NARDL model further confirm the resilience of the system: FX reserves are successfully insulated from negative monetary shocks, as the central bank, through effective interventions, rapidly absorbs short-run currency shocks, preventing their spill-over into long-run imbalances.

Risk profile management, tested through the GARCH(1,1) specification with the assumption of a Student's *t*-distribution, reveals the high operational efficiency of the domestic monetary system. The absence of statistically significant ARCH and GARCH parameters demonstrates that shocks do not cause long-run accumulation or persistence of volatility. In other words, external pressures are efficiently absorbed through the central bank's actions, thereby preventing the spread of instability and maintaining a high degree of predictability of the macroeconomic environment. Methodologically, the centrepiece of the paper is the conditional macroeconomic stress test with 15,000 stochastic Monte Carlo simulations, which provides the final institutional confirmation of the high resilience of the domestic monetary framework. The analysis of the extreme black swan scenario, which simultaneously activates a sharp increase in M3, a complete halt in FDI inflows and a steep decline in the degree of dinarisation, shows that at a 99% confidence level, the maximum cumulative outflow would amount to EUR 5,166.42 mn. The fact that even after such a shock, gross FX reserves retain over EUR 23.8 bn in available liquidity represents the key proof that the credibility of the domestic monetary anchor is long-term secured and sustainable.

With a view to further strengthening macro-financial stability and optimising the monetary policy framework, the presented results impose two key recommendations for economic policy makers, relating to: the continuation of the practice of timely and measured two-way interventions in the interbank FX market for the effective mitigation of short-run liquidity shocks; and the further strengthening and institutional support of the dinarisation process through the development of dinar instruments.

Finally, the conducted diagnostic tests of parameter stability confirm the absence of structural breaks and the stability of the estimated parameters throughout a seventeen-year sample marked by numerous global crises. These findings indicate that the **NBS's policy is grounded in a consistent institutional framework. The accumulated FX reserves and efficient transmission mechanisms transcend the traditional role of a mere shock absorber, representing a key pillar for the preservation of financial stability and long-term economic growth of the Republic of Serbia in conditions of pronounced global uncertainty**.

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DEEP LEARNING-BASED FORECASTING OF CURRENCY IN CIRCULATION

Ivan Popović

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Deep Learning-Based Forecasting of Currency in Circulation

Ivan Popović

Abstract: To improve the quality of daily forecasts of currency in circulation (CIC), four deep learning models were developed. The performance of these models was systematically compared with that of the existing ARIMAX (65,1,65,18) model, adjusted through expert judgment. The analysis covers the period from January 2025 to March 2026 and is based on a time series comprising 5,497 daily observations. The results indicate that the ARIMAX model achieved superior forecasting performance over the analysed period. However, the LSTM model with L1+L2 ElasticNet regularisation (Model 3) attained a higher coefficient of determination when January 2025 was excluded from the analysis. This period was characterised by an unforeseen change in pension disbursement dynamics. The paper presents the mathematical foundations of both modelling approaches, provides a detailed description of the developed model architectures, and investigates the phenomenon of overfitting.

Key words: LSTM, ARIMAX, currency in circulation, machine learning, deep learning, overfitting, regularisation, ElasticNet
[**JEL Code]:** C22, C45, C53, E41, E51.

Non-technical summary

The subject of this study is the forecasting of currency in circulation (CIC), one of the key autonomous factors influencing the liquidity of the banking sector. Demand for cash exhibits predictable patterns, typically increasing ahead of weekends, at the beginning of each month, and during holiday periods. However, it is also susceptible to sudden and difficult-to-predict surges, triggered by events such as changes in the timing of pension or social benefit disbursements introduced by government authorities.

The traditional statistical approach to forecasting CIC, based on the ARIMAX model, requires the analyst to specify in advance all factors considered relevant to cash demand dynamics, drawing on prior experience. Such factors typically include public holidays, payment schedules, seasonal patterns, and similar. This approach is well established, transparent, and capable of producing forecasts that are readily interpretable.

Deep learning models based on Long Short-Term Memory (LSTM) neural networks operate differently – they independently learn patterns from large volumes of historical data, without predefined rules. Their principal advantage lies in the ability to capture complex dependencies that may not be readily identifiable by the analyst. However, a key question remains whether such models can maintain robust predictive performance when confronted with previously unseen events – changes they were unable to learn from historical data.

The traditional statistical model incorporates the previous 65 days of currency-in-circulation dynamics and relies on 18 predefined factors identified as significant by the analyst. These include payment dates, public holidays, beginning-of-month effects, and similar.

Four neural network models were designed with progressively more stringent safeguards against overfitting, a common limitation of AI models whereby a model achieves excellent performance on the historical training data but exhibits poor generalisation when exposed to previously unseen situations. Each successive model incorporated additional mechanisms aimed at mitigating this phenomenon, ranging from a baseline to the most complex architecture featuring nine safeguards.

The traditional forecasting model, supplemented by analysts' adjustments, proved to be the most reliable over the evaluation period. The neural network models gravely underperformed in January 2025, when the pension disbursement schedule was modified – an unforeseen event which could not be anticipated by the models. When this period is excluded from the evaluation, the neural network models achieve better predictive performance, suggesting that, given sufficiently representative historical data, they have the potential to outperform the conventional approach.

Particular attention should be given to Model 3, the neural network architecture that incorporated additional mechanisms to prevent overfitting. As a result, the model demonstrated a greater capacity to generalise to previously unseen situations rather than merely fitting patterns observed in historical data.

Contents

1 Introduction

The management of daily banking sector liquidity is one of the core operational responsibilities of every central bank. Within the framework of autonomous factors, CIC is assessed on a daily basis to enable timely responses to changes in banking sector liquidity.

The time series of daily changes in CIC exhibits three structural characteristics that make it particularly challenging to model: (1) pronounced multi-scale seasonality, including weekly, monthly, and annual cycles; (2) the presence of impulse shocks associated with public and religious holidays; and (3) occasional structural changes driven by changes in fiscal and social policies, such as modifications to pension disbursement schedules, unexpected economic shocks, and shifts in household behaviour.

Traditional econometric models of the ARIMA class, and especially their extended ARIMAX variants incorporating exogenous variables, have long represented the standard approach to forecasting cash flows in central banking operations. Advances in machine learning, particularly the development of deep learning architectures for time-series analysis, have raised the question of whether Long Short-Term Memory (LSTM) models can match or outperform conventional econometric approaches in this specific forecasting task.

The LSTM deep learning models were developed in the Python programming language. Artificial intelligence tools, including Claude and ChatGPT, were utilised as coding assistants.

The present study has three main objectives: (1) to develop and systematically evaluate four LSTM-based models tailored to forecasting daily changes in CIC; (2) to compare their performance with that of the ARIMAX (65,1,65,18) model currently employed in operational forecasting; and (3) to formulate practical recommendations regarding model selection for CIC forecasting based on the empirical findings. Particular attention is devoted to the problem of overfitting – a phenomenon in which a model fits the training data extremely well but exhibits poor generalisation to unseen data – which represents a key factor in assessing the practical applicability of LSTM models. The structure of the paper is as follows: Section 2 presents the theoretical framework and a review of the relevant literature; Section 3 describes the mathematical formulations of both approaches; Section 4 presents the developed models and empirical results; Section 5 provides a comparative analysis; and Section 6 concludes the study.

2. Theoretical framework and review of relevant literature

2.1 Liquidity forecasting in central banking

Since the mid-1990s, central banks have intensively developed quantitative models for forecasting autonomous liquidity factors, including currency in circulation. Pioneering studies by Bindseil et al. (2002) and Whitesell (2006) systematised approaches to liquidity forecasting in the euro area, identifying seasonality and calendar effects as the dominant sources of predictable variability.

In the context of autonomous factors, seasonality in CIC is particularly pronounced. The end of December and the beginning of January, coinciding with pension disbursements, generate fluctuations in CIC that can be an order of magnitude larger than typical daily variations. Modelling this effect requires either explicitly defined artificial variables or model architectures capable of automatically identifying multiple seasonal cycles.

2.2 ARIMA and ARIMAX models in time series forecasting

Box and Jenkins (1970) laid the foundations of the modern approach to time series modelling through the ARIMA (AutoRegressive Integrated Moving Average) framework. The model combines an autoregressive component, differencing to achieve stationarity, and a moving average component, forming a flexible tool for linear modelling of stochastic processes.

The extension to ARIMAX (ARIMA with exogenous variables), formalised by Hamilton (1994), enables the incorporation of deterministic seasonal effects and exogenous shocks directly into the model structure. This feature makes ARIMAX particularly well suited for CIC forecasting, where the influence of holidays and calendar-related factors is dominant and can be precisely quantified through statistical testing of the coefficients associated with exogenous variables.

Studies by Brockwell and Davis (2002) and Lütkepohl (2005) document that ARIMAX models achieve high predictive accuracy on seasonal macroeconomic time series when exogenous variables are appropriately specified. The main limitation of this approach lies in its assumption of linear relationships and the requirement that all relevant variables be manually specified.

2.3 LSTM networks in economic time series forecasting

Hochreiter and Schmidhuber (1997) introduced the LSTM architecture as a solution to the vanishing gradient problem in conventional recurrent neural networks. The gating mechanisms of the LSTM cell enable selective retention of long-term dependencies, which is crucial for economic time series with long memory.

Fischer and Krauss (2018) showed that LSTM networks outperform classical statistical models in forecasting S&P 500 stock returns, particularly during periods of market turbulence. However, Makridakis et al. (2018), in the fourth international forecasting competition (M4), documented that hybrid approaches combining statistical models and machine learning consistently outperform both methods when used individually.

In the context of central bank cash flow forecasting, Papadimitriou et al. (2019) applied an LSTM model to daily liquidity flows of the European Central Bank and reported improvements over ARIMA models for forecasting horizons shorter than five days. Huang et al. (2020) showed that regularisation techniques – particularly Dropout and L2 regularisation

– have a critical impact on the generalisation performance of LSTM models when applied to short financial time series.

The key open research question is the extent to which LSTM models can robustly generalise in the presence of structural breaks in the time series – a setting in which classical econometric models with expert adjustments have demonstrated advantage in empirical studies.

2.4 Overfitting and regularisation in deep learning

Overfitting – a situation in which a model fits the training data too closely, including random noise, while performing poorly on new observations – is a fundamental challenge in applying deep neural networks to economic time series with limited numbers of observations. Srivastava et al. (2014) introduced Dropout regularisation as an effective mechanism for mitigating overfitting, while Ioffe and Szegedy (2015) developed Batch Normalisation, which stabilises the distribution of activations across layers.

Zou and Hastie (2005) formalised Elastic Net regularisation as a combination of L1 (Lasso) and L2 (Ridge) penalties. L1 regularisation promotes sparse solutions by eliminating irrelevant parameters, whereas L2 regularisation prevents parameter explosion. The combination yields a model that is simultaneously parsimonious, stable, and robust to multicollinearity in the input variables.

3. Mathematical formulation of the model

3.1 ARIMAX model

3.1.1 Basic structure

Let y_t denote the daily change in CIC at time t. The ARIMAX (p,d,q) model with exogenous variables X_t is defined as follows:

$$\Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t + \beta' X_t \quad (3.1)$$

where:

$\Phi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \ldots - \varphi_p L^p$ – is the autoregressive (AR) polynomial of order p in the lag operator L, representing the dependence of the process on its own lagged values;

$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q$ – is the moving average (MA) polynomial of order q, which captures dependence on past forecast errors;

$(1-L)^d$ – is the differencing operator of order (d), which transforms the time series into a stationary process;

$\varepsilon_t \sim WN(0, \sigma^2)$ – is a white noise process with zero mean and constant variance;

X_t – denotes the vector of exogenous variables (artificial seasonal variables, holidays);

β' – the vector of coefficients associated with the exogenous variables.

3.1.2 Stationarity and identification

The stationarity condition of the ARIMAX model requires that all inverse roots of the polynomial Φ(z) lie inside the unit circle in the complex plane, i.e. $|z| < 1$ for all z such that $\Phi(z) = 0$. Similarly, invertibility requires that all inverse roots of the polynomial Θ(z) lie inside the unit circle.

The ARIMAX (65,1,65,18) model was selected based on a comparative analysis of the coefficient of determination and the AIC/BIC criteria across a range of competing models with different orders of the AR and MA components. For the ARIMAX (65,1,65,18) model analysed in this study, d=1 implies that daily changes in CIC are modelled (first differences), rather than the level of the series. This is consistent with the empirical finding that CIC is an integrated process of order one, I(1), as confirmed by the Augmented Dickey-Fuller (ADF) test. The autoregressive component (p=65) and the moving average component (q=65), together with 18 exogenous variables, provide the model with sufficient capacity to capture seasonal dynamics extending up to a three-month horizon.

$$\Delta y_t = (1-L)y_t = y_t - y_{t-1} \quad (3.2)$$

where Δy_t represents the daily change in CIC, measured in millions of dinars.

3.1.3 Exogenous variables

In the ARIMAX (65,1,65,18) model, the following categories of exogenous variables are included:

- Weekly effects (week-of-year, four binary variables): W1, W6, W10 and W48, where $W_j = 1$ if it is the first week of the year;
- Monthly effects (one binary variable): Secondw, indicating the second week of the month;
- Holiday effects (13 variables): binary variables for national and religious holidays;

$$X_t = [W1, W6, W10, W48, SECONDW, NY\_1A, NY\_4A, NY\_5A, CHR\_2A, EH\_1A, EH\_2A, TW1, TW4, WT1, WT4, MT2, MT3, MT4] \quad (3.3)$$

A total of 18 statistically significant exogenous variables were selected based on a p-value threshold of ≤ 0.10 (10% significance level), ensuring that each variable contributes to explaining the variance of the dependent variable.

The selection of exogenous variables was performed in multiple iterations. In the first step, each candidate variable was tested for statistical significance within a simple regression model. In the second step, variables were included sequentially according to their level of statistical significance, with multicollinearity assessed using the Variance Inflation Factor (VIF) test. In the third step, the final specification was evaluated using the Akaike Information Criterion (AIC) and the Bayesian Schwarz Criterion (BIC):

$$AIC = -2\ln(L) + 2k \quad (3.4)$$

$$BIC = -2\ln(L) + k\ln(n) \quad (3.5)$$

where L is the maximum value of the likelihood function, k is the number of parameters, and n is the number of observations. Minimisation of the AIC/BIC criteria ensures an optimal balance between model fit and model simplicity (parsimony).

3.1.4 Residual diagnostics of the ARIMAX model

The validity of the ARIMAX model is assessed through a series of diagnostic tests applied to the residuals $\hat{\varepsilon}_t = y_t - \hat{y}_t$:

Durbin-Watson test: This test examines the presence of first-order autocorrelation in the residuals. A value of $DW \approx 2$ indicates no autocorrelation; $DW < 2$ suggests positive autocorrelation, and $DW > 2$ indicates negative autocorrelation. For the ARIMAX (65,1,65,18) model, DW = 2.02, indicating satisfactory residual properties.

Ljung-Box Q test: This tests H_0: $\rho_1 = \rho_2 = ... = \rho_m = 0$ for all lags up to m. Failure to reject H_0 confirms that the residual white noise and in fact all seasonal structure are adequately captured by the model.

Jarque-Bera test: The normality of the residual distribution is assessed based on skewness and kurtosis coefficients. Mild deviations from normality are typical for high-frequency financial time series.

ARCH test: The ARCH test examines the presence of conditional heteroskedasticity, a situation in which the variance of the error terms is not constant over time. The presence of ARCH effects may require extending the model with a GARCH component.

All diagnostic tests confirm the adequacy of the ARIMAX (65,1,65,18) model specification: DW = 2.02 (no autocorrelation), the Q test fails to reject the null hypothesis (H_0) up to lag 100, and the residual distribution is approximately symmetric. These results suggest that the model adequately captures the seasonal structure of CIC.

The ARCH test confirms statistically significant presence of conditional heteroskedasticity in the residuals ($F - statistic = 2.39$, $p = 0.0049$), although its practical impact on model reliability is limited. This is further supported by the sample size of 711 observations, which provides sufficient asymptotic justification for absorbing the observed form of conditional heteroskedasticity.

3.2 LSTM model

3.2.1 Architecture of the LSTM cell

The LSTM cell is the fundamental building block of recurrent deep neural networks equipped with gating mechanisms. At time step t, given the input vector x_t and the previous hidden state h_{t-1}, the LSTM cell computes the following (see Diagram 1):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3.4)$$

Input gate determines which new information is written into the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3.5)$$

Forget gate: determines the proportion of the previous cell state that is retained.

$$g_t = \tanh(W_g \cdot [h_{t-1}, x_t] + b_g) \quad (3.6)$$

New cell state: new candidate values used for updating the memory.

$$C_t = f_t \odot C_{t-1} + i_t \odot g_t \quad (3.7)$$

Cell state update: a combination of retained past information and newly proposed candidate values.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3.8)$$

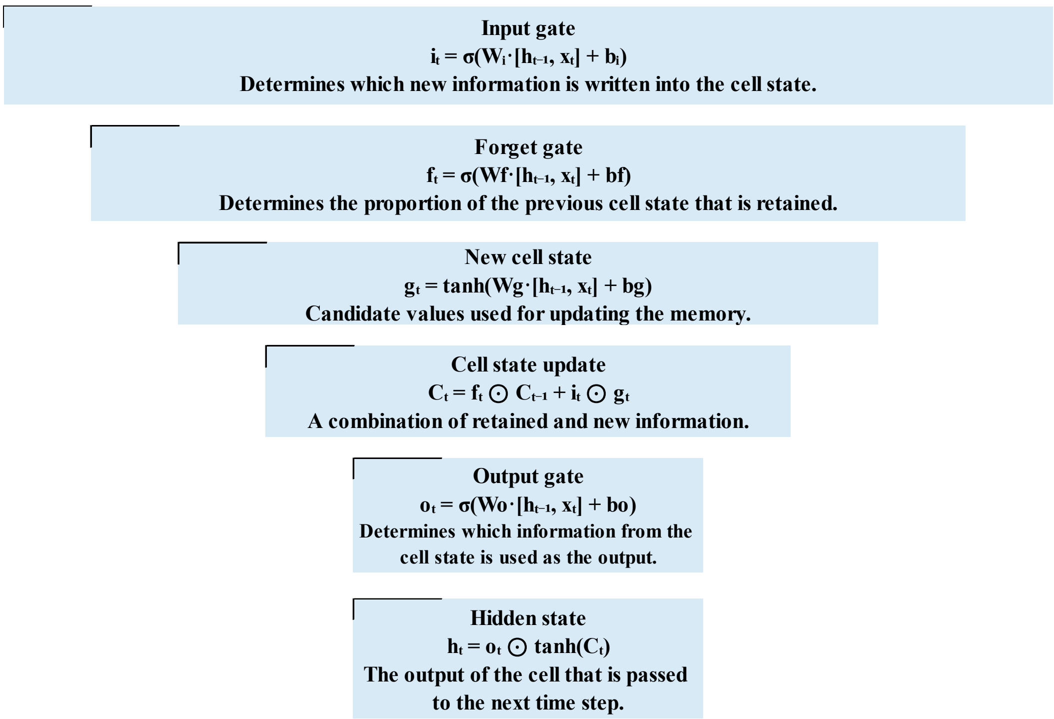
Output gate: determines which information from the cell state is used as the output.

$$h_t = o_t \odot \tanh(C_t) \quad (3.9)$$

Hidden state: the output of the cell that is passed to the next time step.

where: **$\sigma(\cdot)$** – denotes the sigmoid function; **$\tanh(\cdot)$** – the hyperbolic tangent function; $\odot$ – element-wise (Hadamard) multiplication; **W_f, W_i, W_g, W_o** – the weight matrices of the gates; **b_f, b_i, b_g, b_o** – bias vectors.

Figure 1 **Architecture of the LSTM cell**



3.2.2 Dense layers and activation functions

The LSTM layers are followed by fully connected (Dense) layers, which perform non-linear transformations of the extracted representations:

$$a^{(l)} = f^{(l)}(W^{(l)} \cdot a^{(l-1)} + b^{(l)}) \quad (3.10)$$

where **$f^{(l)}$** denotes the activation function of layer l. For the hidden Dense layers, the ReLU (Rectified Linear Unit) is used:

$\mathrm{ReLU}(z) = \max(0, z)$ *(3.11)*

The ReLU activation introduces non-linearity while avoiding the vanishing-gradient problem for positive input values. For the final output layer, which forecasts changes in CIC – a variable that is not restricted in sign – a linear activation function is employed:

$f^{(exit)}(z) = z$ *(3.12)*

3.2.3 ElasticNet regularisation

L1+L2 ElasticNet regularisation modifies the loss function by adding penalty terms on the network weights:

$L_{total} = L_{MSE} + \lambda_1 \Sigma|w_j| + \lambda_2 \Sigma w_j^2$ *(3.13)*

where **$L_{MSE} = (1/n)\Sigma(y_t - \hat{y}_t)^2$** is the Mean Squared Error (MSE), **$\lambda_1 = 0.0001$** is L1 (Lasso penalty coefficient) and **$\lambda_2 = 0.001$** is the L2 (Ridge penalty coefficient). The L1 penalty promotes sparse solutions by driving unimportant parameters to zero, whereas the L2 penalty reduces the magnitudes of all parameters, thereby improving model stability.

3.2.4 Sliding window mechanism and iterative forecasting

LSTM models employ a sliding window of length T_w to structure the input data:

$X_t^{(window)} = [x_{t-T_w+1}, x_{t-T_w+2}, \ldots, x_t]$ *(3.14)*

where $T_w = 30$ business days for Models 1–3, and $T_w = 20$ for Model 4. Each sample in the training set consists of a sequence of T_w consecutive observations, with the corresponding output being a one-step-ahead forecast.

For long-term forecasting, an iterative (recursive) forecasting strategy is employed:

$\hat{y}_{t+k} = f_{LSTM}([\hat{y}_{t+1}, \ldots, \hat{y}_{t+k-1}, x_{t+k}])$ *(3.15)*

where the forecast generated at the previous step is fed back as the input to the subsequent step. This strategy is necessary for producing forecasts up to the end of 2035, but it is susceptible to the accumulation of forecast errors over long horizons.

3.2.5 Performance metrics

The performance of the models was evaluated using the following standard metrics:

- The coefficient of determination R^2, which indicates the percentage of the variation in changes in CIC explained by the model.

$R^2 = 1 - \Sigma(y_t - \hat{y}_t)^2 / \Sigma(y_t - \bar{y})^2$ *(3.16)*

- Mean Absolute Error (MAE) = $(1/n)\, \Sigma|y_t - \hat{y}_t|$ *(3.17)*

- Root Mean Squared Error (RMSE) = $\sqrt{[(1/n)\, \Sigma(y_t - \hat{y}_t)^2]}$ *(3.18)*

- Direction Accuracy of CIC Change Forecasts = $(1/n)\ \Sigma\ 1[\mathrm{sgn}(y\_t - y\_{\{t-1\}}) = \mathrm{sgn}(\hat{y}\_t - y\_{\{t-1\}})]$ *(3.19)*

The evaluation metrics are computed during both the model training and model testing phases. During the training phase, the model automatically identifies 80 candidate time windows that may be statistically significant for forecasting daily changes in CIC. During the testing phase, model selection is performed by choosing the time window that yields the lowest forecast errors. The training period spans from 31 December 2004 to 31 December 2024, while the testing period covers the year 2025.

The MAE gap and RMSE gap are indicators of how well the model generalises to the testing period. As measures of overfitting, the MAE gap and RMSE gap are defined as the relative differences between the training and testing metrics:

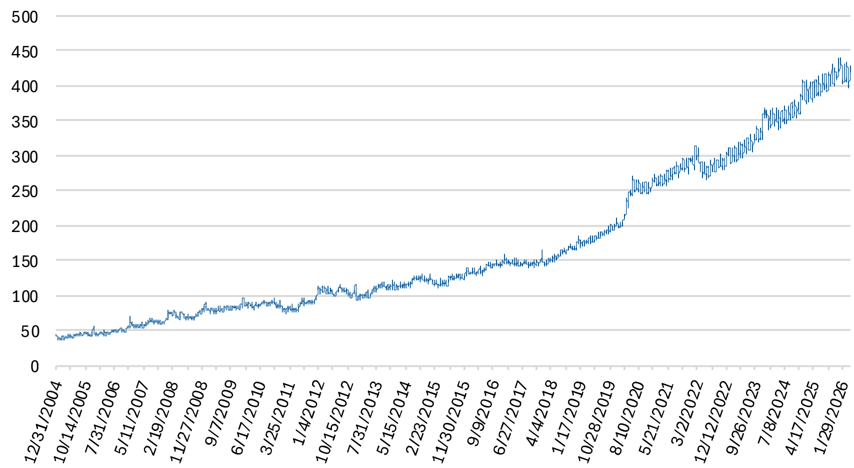
$\mathrm{MAE\_gap} = (\mathrm{MAE\_test} - \mathrm{MAE\_train}) / \mathrm{MAE\_train} \times 100\%$ *(3.20)*

4. Developed models and empirical results

4.1 Data preparation for analysis

The analysis is based on a time series of daily changes in CIC covering the period from 31 December 2004 to 26 January 2026, comprising a total of 5,497 business days (observations).

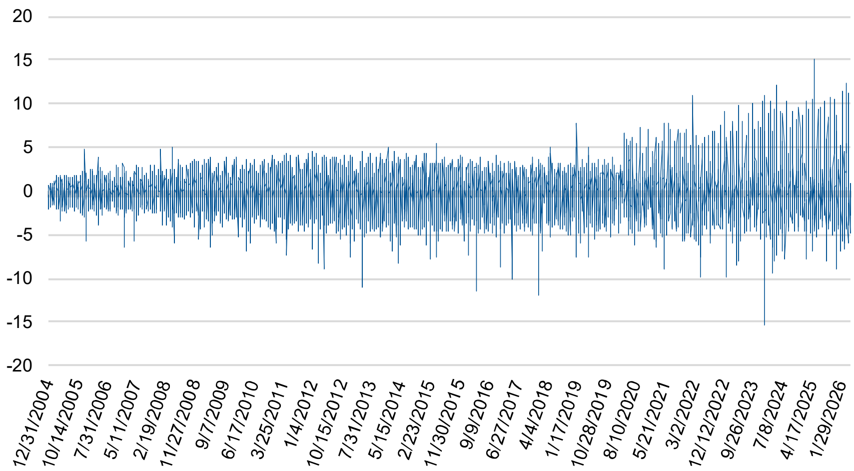
Chart 1 **Cash in circulation (daily volumes)**
in RSD bn



Source: NBS.

The CIC series exhibits the following statistical properties: a mean daily change close to zero, a standard deviation on the order of 2–3 billion Serbian dinars, pronounced positive skewness resulting from asymmetric December and January effects, and the presence of multiple seasonal cycles (5-day, ~22-day, ~65-day, and 260-day cycles).

Chart 2 **Cash in circulation (daily changes)**
in RSD bn



Source: NBS.

The results of the ADF test confirmed that the daily changes in CIC (Δy_{t}) are stationary ($p < 0.01$), whereas the level of CIC follows an integrated process of order one, I(1). In all LSTM models, the dependent variable was standardised (mean=0, std=1) prior to training and transformed back to its original scale (denormalised) for model evaluation.

4.2 Model 1: LSTM (128→64→16→*1*)

4.2.1 Architecture and parameters

Model 1 is a deep LSTM neural network with a four-layer funnel architecture, comprising a total of 200,500 trainable parameters. The input space consists of 164 variables: 129 exogenous variables, 34 automatically generated seasonal variables, and lagged values of the target variable. The 30-business-day sliding window implies that each observation in the training set is represented by an input tensor – i.e. a data structure passed to the model for processing and learning – of dimension [30 × 164] (Table 1).

Table 1 **Model 1 Architecture and hyperparameters**

Parameter	Value	Note
Layer Architecture	128→64→16→1	Funnel architecture; LSTM+Dense
Number of parameters	200,500	74.8% in the first layer
Window mechanism	30 business days	Sliding window
Dropout	0.30	Between LSTM layers
Optimizer	Adam	lr = 0.001 (default)
Batch size	16	Lower value → better generalization
EarlyStopping patience	10 epochs	Monitoring: val_loss, indicating model error on new data

Parameter	Value	Note
Training period (optimal)	2.3.2006 – 31.12.2024	4,914 observations
Regularisation	Dropout only	Without L1/L2

During the training process, using a 30-business-day sliding window, the model automatically identified 80 candidate periods that could be statistically significant for forecasting changes in CIC. Among all analysed periods, the model selected as optimal the one in which forecasting errors on the test set (year 2025) were the lowest, i.e. where the coefficient of determination (R^2) was the highest. Model 1 identifies the period starting on 2 March 2006 as optimal, with $R^2 = 0.9019$ on the training set.

4.2.2 Results and diagnostics

On the test set (261 observations, 2025), Model 1 achieves an R^2 of 0.7745 and an MAE of RSD 1,329 mn, with a Direction Accuracy of 82.3% – demonstrating that the model accurately predicts the direction of daily CIC changes in more than four out of five cases (82% of cases). This is also the highest level of Direction Accuracy for daily CIC changes among all tested models.

However, the overfitting analysis reveals a significant gap between training and test performance: the MAE gap amounts to +162.5%, which by far exceeds the threshold level of 20%. The model has memorised historical patterns, including the specific noise characteristics in the training set, which makes it potentially unstable in long-term projections.

A detailed look at monthly performance reveals an interesting heterogeneity: in eight out of the 15 analysed months, Model 1 achieves an R^2 above 0.75, while in the remaining seven months (mainly January and December), it records a significant drop. This is consistent with a known characteristic of LSTM models – good performance under regular conditions, but increased sensitivity to structural anomalies.

The finding related to direction error is also interesting: out of 261 forecasted days, Model 1 incorrectly identifies the direction of change in only 47 cases (17.7%). Of those 47 cases, 31 (66%) occur in January and December – which once again confirms that holiday and seasonal periods are the key source of errors for all models (Table 2).

Table 2 **Model 1 – Key parameters**

🔍 TRAINING vs TEST — OVERFITTING ANALYSIS						
Parameter	**Training value**	**Test value**	**Difference (Test–Train)**	**Difference %**	**Status**	**Interpretation**
R²	0.9019	0.7745	-0.1273	-14.12	**OVERFIT**	Lower gap = better model
MAE	506.2555	1328.7652	822.5097	162.47	**OVERFIT**	Higher MAE test = normal below 20%
RMSE	709.5949	1764.4323	1054.8375	148.65	**OVERFIT**	Higher RMSE test = normal below 20%
Direction Accuracy (%)	84.5177	82.3077	-2.21	-2.61	**OK**	Difference < 5pp = OK
Durbin-Watson	1.9565	1.7673	-0.1892	-9.67	**OK**	Both should be close to 2.0
Mean bias	35.037	-213.7663	-248.8033	-710.12	**CAUTION**	Both should be close to 0
Residual Std	708.7294	1751.4353	1042.7059	147.12	**CAUTION**	Std test higher by max 30%

🔍 TRAINING vs TEST — OVERFITTING ANALYSIS						
Parameter	Training value	Test value	Difference (Test–Train)	Difference %	Status	Interpretation
Pearson r	0.9531	0.8827	-0.0704	-7.39	CAUTION	Difference < 0.05 = OK
Theil U	0.1672	0.2566	0.0895	53.51	OK	Both should be < 0.5
CONCLUSION: ✗ SIGNIFICANT OVERFITTING – the model is too adjusted to the training set						

4.3 Model 2: LSTM (128→64→16→1) – second overfitting criterion

Model 2 shares an identical architecture with Model 1 and achieves almost the same numerical performance. The only difference lies in the criterion for overfitting classification: instead of the MAE gap ≥ 20% which categorically classifies the model as overfitted, Model 2 applies a threshold of $\Delta R^2 < 0.15$ (Table 3).

Table 3 **Model 2 – Overfitting criterion**

Criterion (ΔR^2)	Lower threshold	Upper threshold	Overfitting level	Description	Result (0.127)
$\Delta R^2 < 0.05$	0.00	< 0.05	Mild overfitting	The model generalises well, with a minimal difference between the training and test sets.	—
$\Delta R^2 < 0.15$	0.05	< 0.15	Moderate overfitting	Acceptable difference; the model has a certain tendency towards overfitting.	✓ 0.127
$\Delta R^2 \geq 0.15$	0.15	1.00	Significant overfitting	Large difference; the model overfits the training data excessively, resulting in poor generalisation.	—

CONCLUSION
$\Delta R^2 = 0.127$ → Moderate overfitting ($0.05 \leq \Delta R^2 < 0.15$) → The model is acceptable, but there is room for improvement through regularisation.

Since $\Delta R^2 = 0.127 < 0.15$, Model 2 is classified as moderate overfitting – which indicates that the choice of parameters for measuring overfitting has a substantial impact on the interpretation of the results (Table 4).

Table 4 **Model 2 – Key parameters**

🔍 TRAINING vs TEST — OVERFITTING ANALYSIS						
Parameter	Training value	Test value	Difference (Test–Train)	Difference %	Status	Interpretation
R²	0.9019	0.7745	-0.1273	-14.12	OVERFIT	Lower gap = better model
MAE	506.2555	1328.7652	822.5097	162.47	OVERFIT	Higher MAE test = normal below 20%
RMSE	709.5949	1764.4323	1054.8375	148.65	OVERFIT	Higher RMSE test = normal below 20%
Direction Accuracy (%)	84.5177	82.3077	-2.21	-2.61	OK	Difference < 5pp = OK
Durbin-Watson	1.9565	1.7673	-0.1892	-9.67	OK	Both should be close to 2.0
Mean bias	35.037	-213.7663	-248.8033	-710.12	CAUTION	Both should be close to 0
Residual Std	708.7294	1751.4353	1042.7059	147.12	CAUTION	Std test higher by max 30%
Pearson r	0.9531	0.8827	-0.0704	-7.39	CAUTION	Difference < 0.05 = OK
Theil U	0.1672	0.2566	0.0895	53.51	OK	Both should be < 0.5
CONCLUSION: ✗ MODERATE OVERFITTING – the model is more adapted to the training set						

4.4 Model 3: LSTM (128→64→16→1) with ElasticNet regularisation

Model 3 introduces L1+L2 ElasticNet regularisation (λ_1 = 0.0001, λ_2 = 0.001) on the densely connected layers (dense layers), shares the identical architecture of Models 1 and 2, and the same sliding window mechanism of 30 business days. The regularisation reduces the weight amplitudes, particularly on dense layers, which directly suppresses the tendency towards overfitting.

The regularisation alters the optimal training period length: Model 3 identifies the period from 12 June 2012 (3,276 observations) instead of 2006 to 31 December 2024. This is consistent with theoretical expectations – a regularised model can learn effectively even from a shorter but richer period, without excessive reliance on distant history.

The effects of regularisation are measurable and statistically significant: ΔR^2 falls from 0.127 (Model 1) to 0.056 (Model 3), while the MAE gap decreases from 162.5% to 73.9%. Model 3 achieves an R^2 = 0.7344 and Direction Accuracy = 78.9% on the test set, along with an improved Durbin-Watson coefficient of 1.829 and a more symmetric residual distribution (skewness = -0.100 compared to +0.283 for Model 1), indicating higher-quality modelling of residual noise (Table 5).

Table 5 **Model 3 – Key parameters**

🔍 TRAINING vs TEST — OVERFITTING ANALYSIS						
Parameter	Training value	Test value	Difference (Test–Train)	Difference %	Status	Interpretation
R²	0.7899	0.7344	-0.0556	-7.03	CAUTION	Lower gap = better model
MAE	804.5368	1399.2087	594.6719	73.91	OVERFIT	Higher MAE test = normal below 20%
RMSE	1145.2979	1915.1021	769.8043	67.21	OVERFIT	Higher RMSE test = normal below 20%
Direction Accuracy (%)	83.1433	78.8462	-4.2971	-5.17	OK	Difference < 5pp = OK
Durbin-Watson	1.9466	1.8291	-0.1175	-6.03	OK	Both should be close to 2.0
Mean bias	-317.6571	-438.2904	-120.6333	-37.98	OK	Both should be close to 0
Residual Std	1100.3641	1864.2741	763.91	69.42	CAUTION	Std test higher by max 30%
Pearson r	0.8978	0.8655	-0.0323	-3.6	OK	Difference < 0.05 = OK
Theil U	0.2396	0.2787	0.0391	16.33	OK	Both should be < 0.5
CONCLUSION: ✗SIGNIFICANT OVERFITTING – the model is too adapted to the training set						

A particularly valuable finding is that Model 3, despite its slightly lower overall R^2 compared to Models 1 and 2, achieves a higher average R^2 = 0.805 during the February–March 2026 period. This indicates that regularisation improves generalisation precisely where it matters most – on the latest, previously unseen data. This characteristic makes Model 3 the most suitable LSTM candidate for future operational testing (Table 10).

4.5 Model 4: LSTM (64→32→8→1) – anti-overfitting architecture

Model 4 represents a fundamental architectural redesign aimed at eliminating overfitting through the application of nine concurrent anti-overfitting strategies. The reduced network (64→32→8→1) has only 71,300 parameters – three times fewer than the previous models.

Each of the nine strategies contributes to reducing overfitting at a different level (Table 6): (1) reduced architecture 64→32→8→1, (2) Batch Normalisation after both LSTM layers, (3) increased Dropout to 0.45 (standard) and 0.10 (recurrent), (4) Dense Dropout of 0.20, (5) enhanced L1+L2 regularisation (ten times stronger than the previous model), (6) Gradient Clipping (clipnorm=1.0), (7) Weight Decay in the Adam optimiser (AdamW effect), (8) larger batch size (32 neurons instead of 16 neurons), and (9) smaller window size of 20 instead of 30 days.

Model selection introduces a filter: out of 80 tested configurations, only 13 pass the MAE gap ≤ 20% filter. The optimal training period length is from 19 May 2021 to 31 December 2024.

Table 6 **Model 4 – Anti-overfitting strategies**

9 Anti-Overfitting Strategies		
1 ARCHITECTURE	**2 NORMALISATION**	**3 REGULARISATION**
Reduced Architecture 64 → 32 → 8 → 1 Reducing network capacity limits its ability to memorise noise.	Batch Normalization After both LSTM layers BatchNorm returns values to the normal range (~0). More stable training, with a lower risk of overfitting.	Increased Dropout 0.45 std · 0.10 rec Standard and recurrent dropout for the LSTM layers.
4 REGULARISATION	**5 REGULARISATION**	**6 OPTIMISATION**
Dense Dropout p = 0.20 Additional regularisation of the dense layers. More aggressive dropout would destroy the weak signal.	L1 + L2 Regularisation 10× stronger than before Stronger penalisation of large weights. Stronger regularisation → a simpler model.	Gradient Clipping clipnorm = 1.0 Prevents exploding gradients. Never change weights by more than 1.0 in a single step.
7 OPTIMISATION	**8 DATA**	**9 DATA**
Weight Decay (AdamW) Adam + decay Directly reduces weights. The model remains simple, improving generalisation.	Larger Batch Size 32 instead of 16 Larger batch → a more stable gradient and less noise. Effect: the model fluctuates less → less overfitting.	Smaller Window Size 20 instead of 30 days Smaller window → less information → less chance of memorising specific noise.

The selected configuration achieves $R^2 = 0.6651$ with $\Delta R^2 = +0.033$ and an MAE gap = +26.2% – confirming that the anti-overfitting strategy achieves its goal (Table 7).

Table 7 **Model 4 – Key parameters**

TRAINING vs TEST — OVERFITTING ANALYSIS						
Parameter	**Training value**	**Test value**	**Difference (Test–Train)**	**Difference %**	**Status**	**Interpretation**
R²	0.6979	0.6651	-0.0328	-4.7	OK	Gap < 0.05 = excellent
MAE	1251.4888	1579.8329	328.3441	26.24	CAUTION	MAE test ≤ 20% > Train = OK
RMSE	1758.9828	2150.2113	391.2285	22.24	CAUTION	RMSE test ≤ 20% > Train = OK
Pearson r	0.857	0.8366	-0.0203	-2.37	OK	Difference < 0.05
Dir. acc. (%)	74.026	70.7692	-3.2567	-4.4	OK	Difference < 5pp

🔍 TRAINING vs TEST — OVERFITTING ANALYSIS						
Parameter	Training value	Test value	Difference (Test–Train)	Difference %	Status	Interpretation
Residual Std	1758.9741	2131.5099	372.5358	21.18	OK	Std test ≤ 30% > Train
Durbin-Watson	2.0616	1.6716	-0.39	-18.92	OK	Both ≈ 2.0
Theil U	0.3295	0.3454	0.016	4.85	OK	Both < 0.5
CONCLUSION: ⚠ MILD OVERFITTING – the model works somewhat better on the training set						

Unfortunately, reducing the network capacity degraded predictive performance: Model 4 is consistently the weakest across all forecast accuracy parameters (Table 10).

4.6 ARIMAX (65,1,65,18) model

The ARIMAX model was developed based on the series of daily CIC changes from 3 January 2022 to 23 September 2024 period (711 observations), which has the highest statistical significance in forecasting daily CIC changes. The choice of this period reflects the assessment that CIC dynamics since 2022 are structurally more stable and more relevant for short-term forecasting compared to older data that cover the COVID period (Table 3 in the annex).

The model specification is the result of an iterative testing process. The starting point was the identification of stationarity – the ADF test confirms that daily CIC changes (first difference) are stationary. Autocorrelation (ACF) and partial autocorrelation (PACF) plots suggest the presence of significant autocorrelations at lags up to 65 working days. By specifying AR(65) and MA(65) components with first-order differencing, the ARIMAX (65,1,65,18) model was obtained.

The final model achieves Adjusted $R^2 = 0.76$, a Durbin–Watson statistic of 2.02, and a standard error of regression significantly below the standard deviation of the dependent variable – confirming high predictive power (Table 8).

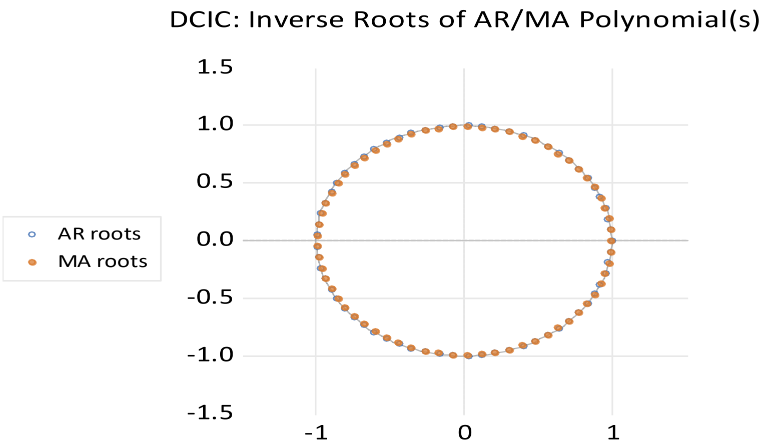
Table 8 **ARIMAX (65,1,65,18) – Summary indicators of model quality**

Statistics	Value	Interpretation
Adjusted R^2	0.76	76% of CIC variance explained
Standard error of regression	< S.D. of dependent variable	Good predictive power
Durbin–Watson	2.02	No residual autocorrelation
Stationarity (AR inverse roots)	Within the unit circle	Model is stable
Invertibility (MA inverse roots)	Within the unit circle	Model is invertible
Number of parameters	18 exogenous + AR/MA	Simple model

Although the ARCH test confirms the statistically significant presence of conditional heteroskedasticity in the residuals (F-statistic = 2.39, p = 0.0049), its practical impact on the model's reliability is limited in scope. This is indicated by the low coefficient of determination of the ARCH test regression ($R^2 = 0.04$), which shows that only 4% of the variability in the squared residuals can be statistically explained, while the remaining part represents a random component that the model objectively cannot capture. Given that the primary goal of the model is forecasting, not statistical inference (i.e. drawing conclusions about the entire population based on a sample), the presence of heteroskedasticity does not cause the parameter estimates obtained by the maximum likelihood method to become systematically biased; as the number of observations increases, they converge to the true parameter values. The sample size of 711 observations provides a sufficient asymptotic basis to absorb the observed form of conditional heteroskedasticity (Table 4 in the annex).

All AR and MA inverse roots lie within the unit circle, guaranteeing the stationarity and invertibility of the model (Chart 3).

Chart 3 **ARIMAX (65,1,65,18) – Plot of AR and MA inverse roots within the unit circle**



5. Comparative performance analysis

5.1 Metrics

The performance of all models is compared based on monthly R^2, MAE and RMSE values for the period January 2025 – March 2026. Each model is also assigned an overfitting category based on ΔR^2 and the MAE gap, which quantify the difference between training and test performance (Table 9).

Table 9 **Summary performance metrics of all models – test period (2025)**

Model	R^2 test	MAE test (RSD bn)	ΔR^2	MAE gap	Dir. acc.	Overfitting
ARIMAX (65,1,65,18) + expert	0.790	1.353	N/A	N/A	N/A	N/A
Model 1: LSTM 128→64→16→1	0.7745	1.329	0.127	+162.5%	82.3%	High
Model 2: LSTM 128→64→16→1 (alt.)	≈ Model 1	≈ Model 1	0.127	+162.5%	≈ Model 1	Moderate

Model	R^2 test	MAE test (RSD bn)	ΔR^2	MAE gap	Dir. acc.	Overfitting
Model 3: LSTM 128→64→16→1 + ElasticNet	0.7344	1.399	0.056	+73.9%	78.9%	Moderate
Model 4: LSTM 64→32→8→1 (anti-OF)	0.6651	Highest	0.033	+26.2%	Lowest	Low

Note: N/A – not applicable in the same manner; Dir. Acc. – Direction Accuracy; OF – overfitting.

The ARIMAX (65,1,65,18) model, adjusted by expert judgement, gives the best CIC forecast results for the period January 2025 – March 2026 compared to the other tested models. The coefficient of determination R^2 is the highest, and the mean absolute error (MAE) is the lowest compared to all models, indicating that the forecasted values are close to the actual ones.

Table 10 **A comparative overview of the performance of all models**

Month	ARIMAX*			Model 1			Model 2			Model 3			Model 4		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
Jan 25	0.698	1,634	1,263	0.000	3,119	2,013	0.014	3,048	1,968	0.045	3,162	1,980	0.007	2,937	2,122
Feb 25	0.766	2,107	1,666	0.851	1,723	1,505	0.851	1,727	1,507	0.841	1,740	1,457	0.789	2,219	1,579
Mar 25	0.812	1,601	1,173	0.832	1,539	1,260	0.832	1,540	1,258	0.882	1,198	877	0.791	1,672	1,249
Apr 25	0.828	1,658	1,297	0.865	1,546	1,203	0.864	1,549	1,205	0.868	1,483	1,237	0.839	1,754	1,322
May 25	0.851	1,978	1,470	0.919	1,523	1,194	0.920	1,519	1,191	0.830	1,994	1,300	0.771	2,795	1,801
Jun 25	0.748	1,906	1,564	0.874	1,397	1,145	0.875	1,395	1,142	0.830	1,632	1,301	0.825	1,793	1,449
Jul 25	0.757	1,859	1,319	0.854	1,461	1,171	0.854	1,462	1,173	0.880	1,321	1,066	0.884	1,513	1,256
Aug 25	0.811	1,615	1,239	0.820	1,457	1,107	0.795	1,490	1,151	0.799	1,549	1,220	0.772	1,696	1,318
Sep 25	0.685	2,130	1,364	0.854	1,504	1,045	0.854	1,503	1,045	0.846	1,683	1,186	0.819	1,859	1,245
Oct 25	0.828	1,696	1,375	0.844	1,746	1,358	0.844	1,746	1,358	0.844	1,810	1,531	0.847	1,947	1,643
Nov 25	0.921	1,130	874	0.774	1,836	1,449	0.774	1,836	1,449	0.700	2,095	1,642	0.725	2,040	1,549
Dec 25	0.779	2,005	1,632	0.781	2,145	1,779	0.781	2,145	1,779	0.838	2,042	1,645	0.771	2,363	1,839
Jan 26	0.343	2,524	1,692	0.249	2,705	1,887	0.249	2,705	1,887	0.536	2,296	1,636	0.202	2,660	2,052
Feb 26	0.862	1,714	1,363	0.727	2,282	1,747	0.727	2,282	1,747	0.755	2,171	1,668	0.748	2,314	1,685
Mar 26	0.774	2,120	1,531	0.908	1,424	1,130	0.908	1,424	1,131	0.825	1,899	1,408	0.727	2,498	1,901
Average Feb 25–Mar 2	**0.769**	**1,860**	**1,397**	**0.797**	**1,735**	**1,356**	**0.795**	**1,737**	**1,359**	**0.805**	**1,780**	**1,370**	**0.751**	**2,080**	**1,563**
Average Jan 25–Mar 2	**0.764**	**1,845**	**1,388**	**0.744**	**1,827**	**1,400**	**0.743**	**1,825**	**1,399**	**0.755**	**1,872**	**1,410**	**0.701**	**2,137**	**1,601**

**ARIMAX model adjusted by expert judgement   Green = best value in the row   Red = weakest value in the row*

The LSTM models record weaker performance, primarily due to the unforeseen change in the pension payment schedule in January 2025, since this change was not represented in the training set and the models could not learn it (Table 10).

If January 2025 is excluded from the forecast period and the period February 2025 – March 2026 is observed, all LSTM models except Model 4 have better performance compared to ARIMAX (65,1,65,18). Model 3 (LSTM 128→64→16→1 with ElasticNet L1+L2 regularisation) has the highest coefficient of determination R^2. This shows that the additional L1+L2 ElasticNet regularisation succeeded in reducing overfitting and improving generalisation, i.e. the model's ability to perform well on new, unseen data, not just on the data it was trained on (Table 10).

5.2 Monthly performance analysis

An analysis of monthly R^2 values (Table 10) reveals significant performance variations across all models during the tested period. Three characteristic behavioural patterns can be observed:

January 2025 (structural break): All LSTM models record a drastic drop in performance ($R^2 \approx 0.3$–0.5) due to the unforeseen change in the dynamics of pension payments. The ARIMAX model, thanks to expert adjustment, shows greater resilience ($R^2 = 0.698$), although it also records weaker performance than in other months.

February 2025 – October 2025 (stable period): LSTM models 1, 2 and 3 achieve performance comparable to the ARIMAX model adjusted by expert judgement, and in certain months (March, June, September) even better.

November 2025 (special period): The ARIMAX model adjusted by expert judgement achieves by far the best coefficient of determination, $R^2 = 0.921$. LSTM models ($R^2 \approx 0.75$–0.80) lag behind because it is more difficult for them to forecast without explicit exogenous variables.

5.3 Error analysis

Across all models, RMSE is significantly higher than MAE, which indicates the presence of occasional large errors that are disproportionately penalised by the RMSE metric (Table 10). These extremes are primarily related to:

– Pension and salary payment days – when cash flow can be several times higher than the average;

– Extended holiday periods – especially the Christmas celebrations;

– Unexpected changes in fiscal policy – such as the alteration of the pension payment calendar in January 2025.

A common feature across all models is a skewed distribution of residuals with positive skewness coefficients – the models more frequently underestimate CIC growth than overestimate it.

For all models, the autocorrelation structure of the residuals was also analysed using the Durbin–Watson statistic. The ARIMAX model adjusted by expert judgement achieves DW = 2.02 – a practically ideal result. The LSTM models record DW values between 1.77 and 1.83, which indicates mild positive autocorrelation of residuals (Table 2 in the annex).

Table 11 **Advantages and disadvantages of ARIMAX and LSTM models**

Aspect	ARIMAX model	LSTM model
Interpretability	High: coefficients on exogenous variables directly quantify the effects of holidays and seasonality	Low: "black box"; relationships between variables are implicitly encoded in the weight matrices
Seasonality	Explicit: requires all relevant dummy variables to be defined in advance	Automatic: the model itself identifies seasonal patterns from the data

Aspect	ARIMAX model	LSTM model
Structural changes	Requires manual adjustment and expert judgement; responds faster with intervention	Responds slowly – a new change must be in the training set for the model to learn it
Long-term forecasting	Limited – parameters do not evolve automatically; periodic re-estimation is required	Risky for horizons > 2 years due to the accumulation of errors in iterative forecasting
Computational requirements	Minimal – rapid estimation and evaluation, suitable for operational use	Substantial – training requires GPU resources; evaluation is fast
Overfitting risk	Low – the model is simple by construction; statistical variable selection	High on short series – requires careful regularisation and a validated training process
Development and maintenance	Standardised process; available literature; supported in Eviews/R/Python	Requires specialised knowledge in deep learning; more complex adjustment process

6. Conclusion

This paper presents a systematic comparative analysis of four LSTM deep machine learning models and the ARIMAX (65,1,65,18) econometric model, adjusted by expert judgement, for forecasting daily changes in CIC. The analysis is based on a time series of 5,497 daily observations from 2004 to 2026, with the analysed period being January 2025 – March 2026. The research generated five key findings.

Finding 1 – Superiority of the ARIMAX model over the entire period. The ARIMAX model adjusted by expert judgement achieves superior performance in the observed period: the lowest MAE, the highest overall R^2, and robustness, with good forecasting in January 2025 – a period marked by a structural change in the pension payment dynamics.

Finding 2 – Competitiveness of regularised LSTM in stable periods. LSTM Model 3 with ElasticNet regularisation achieves an average $R^2 = 0.805$ in the period February 2025 – March 2026 – higher than the coefficient of determination (R^2) of the ARIMAX model. In the absence of structural changes, regularised LSTM Model 3 provides very good forecasting without expert adjustment. Recommendation: Model 3 is the most promising candidate for operational testing in the parallel monitoring phase.

Finding 3 – Effectiveness of regularisation in controlling overfitting. ElasticNet regularisation reduces ΔR^2 from 0.127 (Model 1) to 0.056 (Model 3) and improves the Durbin-Watson coefficient from 1.77 to 1.83. The aggressive anti-overfitting architecture (Model 4) eliminates overfitting ($\Delta R^2 = 0.033$), but at the cost of predictive power ($R^2 = 0.6651$). There is an optimal level of regularisation between these two extremes that should be systematically explored.

Finding 4 – Criticality of defining overfitting parameters. Models 1 and 2, identical in architecture and numerical performance, are classified differently depending on whether overfitting is measured through the MAE gap (Model 1: high overfitting) or ΔR^2 (Model 2:

moderate overfitting). This classification difference can be crucial for the decision on the operational application of the model.

Finding 5 – Complementarity of approaches and hybrid potential. ARIMAX and LSTM models are not competitors – they are complementary approaches with different strengths and weaknesses. The ARIMAX model provides interpretability, transparency, and resilience to structural changes. The LSTM model provides automatic learning of non-linear patterns and potential for adaptability, i.e. the ability to adjust to new conditions, changes, or different situations.

Increasing the number of observations, assuming the absence of significant structural changes, could further improve the performance of LSTM models.

Annex: Detailed comparison of model architectures

The annex provides a more detailed technical overview of all five models, with complete hyperparameter specifications, the results of the optimal training period search, and summarised diagnostic indicators. This information is intended for technical users who wish to reproduce or adapt the developed models.

Table 1 **Complete hyperparameter specification of all LSTM models**

Hyperparameter	Model 1	Model 2	Model 3	Model 4
Architecture (LSTM→Dense→out)	128→64→16→1	128→64→16→1	128→64→16→1	64→32→8→1
Total parameters	200,500	200,500	200,500	71,300
Dropout (standard)	0.30	0.30	0.30	0.45
Recurrent dropout	–	–	–	0.10
Dense dropout	–	–	–	0.20
L1 regularisation	–	–	0.0001	0.001
L2 regularisation	–	–	0.001	0.01
Batch Normalisation	No	No	No	Yes
Gradient Clipping	–	–	–	1.0
Window size (days)	30	30	30	20
Batch size	16	16	16	32
Optimiser	Adam	Adam	Adam	AdamW
EarlyStopping patience	10	10	10	10
OF filters at selection	MAE gap ≤ 20%	$\Delta R^2 < 0.15$	MAE gap ≤ 20%	MAE gap ≤ 20%
Optimal training start	2.3.2006	2.3.2006	12.6.2012	19.5.2021
Number of training observations	4,914	4,914	3,276	945

Table 2 **Results of the optimal training period search – summary statistics**

Search statistics	Model 1	Model 2	Model 3	Model 4
Number of tested configurations	80	80	80	80
Passed through the OF filter	N/A	53 ($\Delta R^2 < 0.15$)	N/A	13 (MAE ≤ 20%)
R^2 training (selected model)	0.9019	0.9019	0.8618	0.6984
R^2 test (selected model)	0.7745	0.7745	0.7344	0.6651
ΔR^2 (training – test)	0.127	0.127	0.056	0.033
MAE gap (%)	+162.5%	+162.5%	+73.9%	+26.2%

Search statistics	Model 1	Model 2	Model 3	Model 4
Durbin-Watson (residual test)	1.774	1.774	1.829	1.801
Residual skewness	+0.283	+0.283	-0.100	+0.147

Table 3 **ARIMAX (65,1,65,18)**

Dependent Variable: DCIC
Method: ARMA Maximum Likelihood (BFGS)
Date: 02/21/25 Time: 13:46
Sample: 1/03/2022 9/23/2024
Included observations: 711
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
W10	-622.8686	259.1914	-2.403122	0.0165
TW1	10127.95	1636.893	6.187302	0.0000
MT3	1948.424	755.0318	2.580585	0.0101
MT2	4584.982	837.0957	5.477250	0.0000
EH_2A	-2478.763	571.2319	-4.339329	0.0000
W48	3460.174	561.9205	6.157764	0.0000
EH_1A	-6688.144	2641.319	-2.532123	0.0116
MT4	-9082.940	1516.119	-5.990914	0.0000
W1	-1141.472	550.1693	-2.074765	0.0384
SECONDW	572.8555	348.7151	1.642761	0.1009
NY_1A	-7287.528	949.1455	-7.677988	0.0000
WT1	2641.636	1284.037	2.057289	0.0400
WT4	-3694.829	1686.075	-2.191378	0.0288
TW4	-6157.223	3678.150	-1.674000	0.0946
NY_4A	-2478.705	769.3149	-3.221965	0.0013
NY_5A	-3411.392	1460.454	-2.335844	0.0198
CHR_2A	3358.348	1512.940	2.219749	0.0268
W6	1052.604	277.8336	3.788614	0.0002
AR(45)	0.169553	0.015234	11.12981	0.0000
AR(65)	0.777811	0.017361	44.80256	0.0000
AR(1)	0.077832	0.015160	5.134141	0.0000
AR(2)	-0.109737	0.014551	-7.541568	0.0000
AR(22)	0.081253	0.013115	6.195303	0.0000
MA(64)	-0.073675	0.030963	-2.379487	0.0176
MA(65)	-0.586921	0.034954	-16.79116	0.0000
MA(43)	0.076906	0.028518	2.696732	0.0072
MA(44)	0.130228	0.029151	4.467349	0.0000
SIGMASQ	2539056.	102895.7	24.67600	0.0000

R-squared	0.765310	Mean dependent var	101.6203
Adjusted R-squared	0.756032	S.D. dependent var	3291.504
S.E. of regression	1625.775	Akaike info criterion	17.72566
Sum squared resid	1.81E+09	Schwarz criterion	17.90551
Log likelihood	-6273.474	Hannan-Quinn criter.	17.79513
Durbin-Watson stat	2.021595		

Table 4 **Heteroskedasticity test: ARCH**

Heteroskedasticity Test: ARCH

F-statistic	2.392522	Prob. F(12,686)	0.0049
Obs*R-squared	28.07917	Prob. Chi-Square(12)	0.0054

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 06/20/26 Time: 17:01
Sample (adjusted): 1/19/2022 9/23/2024
Included observations: 699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2314059.	342482.5	6.756722	0.0000
RESID^2(-1)	0.145720	0.038164	3.818236	0.0001
RESID^2(-2)	0.075450	0.038568	1.956270	0.0508
RESID^2(-3)	-0.032200	0.038671	-0.832683	0.4053
RESID^2(-4)	-0.031701	0.038596	-0.821363	0.4117
RESID^2(-5)	-0.007807	0.038605	-0.202229	0.8398
RESID^2(-6)	0.034927	0.038599	0.904868	0.3659
RESID^2(-7)	0.019319	0.038600	0.500481	0.6169
RESID^2(-8)	0.021279	0.038609	0.551134	0.5817
RESID^2(-9)	-0.069998	0.038598	-1.813531	0.0702
RESID^2(-10)	-0.012271	0.038666	-0.317374	0.7511
RESID^2(-11)	-0.016229	0.038564	-0.420839	0.6740
RESID^2(-12)	-0.029133	0.038162	-0.763406	0.4455

R-squared	0.040170	Mean dependent var	2564340.
Adjusted R-squared	0.023380	S.D. dependent var	5099925.
S.E. of regression	5039953.	Akaike info criterion	33.72211
Sum squared resid	1.74E+16	Schwarz criterion	33.80673
Log likelihood	-11772.88	Hannan-Quinn criter.	33.75483
F-statistic	2.392522	Durbin-Watson stat	1.997415
Prob(F-statistic)	0.004949		

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Abbreviations

Abbreviation/term	Definition
CIC	Currency in circulation – the total value of banknotes and coins in circulation
ARIMAX	*AutoRegressive Integrated Moving Average with exogenous variables – an extended ARIMA model incorporating exogenous variables*
LSTM	*Long Short-Term Memory – a type of recurrent neural network using gating mechanisms to retain long-term dependencies*
ReLU	*Rectified Linear Unit – activation function: f(x) = max(0,x)*
Dropout	Regularisation technique: randomly disabling neurons during training to prevent overfitting
ElasticNet	Combined L1 + L2 regularisation that simultaneously promotes sparse solutions and reduces parameter magnitudes
Overfitting	Overfitting of the model to the training data; the model describes historical data well but generalises poorly to new data
R^2	Coefficient of determination: the proportion of variance in the dependent variable that is explained ($0 \leq R^2 \leq 1$)
MAE	*Mean Absolute Error – the mean absolute forecast error*
RMSE	*Root Mean Squared Error – the square root of the mean squared error; it penalises larger errors, meaning that larger errors have a greater impact, i.e. large deviations are penalised more heavily*
Direction Accuracy	The proportion of cases in which the model correctly forecasts the direction of change (increase/decrease)
Batch Normalization	Normalisation of activations by mini-batch (a smaller group of data); stabilises the training of deep neural networks
EarlyStopping	A mechanism for stopping training early when the error on the validation set does not improve over a specified number of patience epochs. It indicates how many epochs the model may go without improvement before training is stopped.
Window size	Length of the sliding window (number of consecutive days) used as input to the LSTM model
Dense layer	Densely connected neural-network layer (Fully Connected Layer) This means that each neuron is connected to all neurons in the preceding layer.

WORKING PAPER

ANALYSIS OF LABOUR MARKET EFFICIENCY AND WAGE DYNAMICS IN SERBIA, 2011–2025

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Analysis of labour market efficiency and wage dynamics in Serbia

Konstantin Sorak and Nevena Stošić

Abstract: In this paper, we analyse the dynamics of Serbia's labour market over the period 2011–2025 and their implications for wage developments. Using administrative data from the National Employment Service and the Statistical Office of the Republic of Serbia, we constructed a Beveridge curve for Serbia. In the initial period, movements along the Beveridge curve were recorded, driven by cyclical labour market tightening. From 2022 onwards, however, a shift in the curve became apparent, reflecting substantially higher vacancy rates at comparable unemployment rates than the historical pattern would suggest. The observed shifts were quantified using two measures of the matching efficiency between labour supply and demand: the residual from the Beveridge curve equation and matching function efficiency. In the next stage of the analysis, the Beveridge curve residual is incorporated into the estimation of a wage equation. The estimated coefficients have the expected signs: labour market tightness has a positive effect on wage growth, while the coefficient on the Beveridge curve residual has the expected opposite sign, since negative residual values indicate an improvement in labour market matching efficiency. As an indicative measure of the strength of the effects of these factors on wage developments, we decomposed the contributions of deviations of these variables from their respective long-run averages to the deviation of wages from their long-run average. The contribution decomposition implies that the effect of labour market tightness dominates over most of the period. Its negative contribution in the first part of the period gradually weakens as vacancies rise and unemployment falls. From 2022 onwards, matching becomes less efficient and works in the opposite direction to tightness, consistently with the shift in the Beveridge curve, with the effect peaking at the end of 2024. As a result, record labour market tightness is transmitted to wages only partially. During 2025, matching efficiency gradually improves. The findings suggest that measures of matching efficiency can provide additional insight into wage pressures beyond that offered by standard labour market indicators.
рада**.**

Keywords: unemployment rate, Beveridge curve, matching efficiency, wage Phillips curve.
[JEL Code]: C22, E24, J31, J63, J64

Non-technical summary

Serbia's labour market has changed substantially over the past fifteen years. The number of unemployed persons has fallen markedly, employment has increased and wages have recorded strong growth, which continued even after inflationary pressures eased. This raises the question of whether such developments reflect the recovery in economic activity or structural changes in the functioning of the labour market.

To address this question, we use the Beveridge curve, which depicts the relationship between the number of unemployed persons and job vacancies. The relationship between these two variables is normally negative: stronger economic activity increases labour demand and hence the number of vacancies, while the number of unemployed persons declines. It is possible, however, for a large number of vacancies and a large number of jobseekers to coexist. Such a situation suggests a structural mismatch between employers' needs and jobseekers. Sources of such mismatches may include unemployed persons having qualifications that do not correspond to employers' needs or difficulties with labour mobility.

The analysis is based on data from the National Employment Service and the Statistical Office of the Republic of Serbia for the period 2011–2025. Over the period observed, there was stable movement along the Beveridge curve, reflecting a continuous decline in the unemployment rate and an increase in the vacancy rate. A departure from the previous pattern emerges from 2022 onwards, when, at unemployment levels similar to those recorded in earlier years, the vacancy rate rises above its historically usual level. In other words, employers find it more difficult to fill vacancies even though the number of jobseekers has not changed significantly. The results also show that the decline in unemployment over the period as a whole was attributable primarily to unemployed persons finding jobs more quickly, and to a lesser extent to a lower incidence of job loss.

These changes also had implications for wages. Wage growth is shown to be faster when demand for workers is high relative to the number of unemployed persons, owing to workers' stronger bargaining power. This effect, however, also depends on the success with which vacancies are filled. During most of the period, wage growth is supported by a rising vacancy rate accompanied by a declining unemployment rate. From 2022, the gradual increase in the vacancy rate above its usual level began to exert a negative effect on wage developments. This effect peaked in 2024, when, despite the larger number of vacancies relative to unemployed workers, the effect of workers' bargaining power was only partially transmitted to wages precisely because of the weaker compatibility between labour supply and demand. Matching efficiency gradually improved during 2025.

The main conclusion of the paper is that standard labour market indicators, such as the unemployment rate, do not provide a complete picture of labour market dynamics. Monitoring the relationship between unemployed persons and vacancies, together with the effectiveness with which they are matched, provides a more detailed view of labour market developments and a more comprehensive assessment of wage pressures.

Contents

1 Introduction

The unemployment rate is one of the key macroeconomic indicators and one of the most frequently studied variables in economics. Among the best-known methodological frameworks for analysing unemployment dynamics is the Phillips curve, i.e. the relationship between unemployment and inflation. Another equally important relationship is represented by the Beveridge curve, i.e. the relationship between vacancy and unemployment rates. In this paper, we use both frameworks to provide a more detailed explanation of labour market dynamics in Serbia between 2011 and 2025.

The original Phillips curve depicts a negative relationship between the growth rate of nominal wages and the unemployment rate. More recent versions of the wage Phillips curve, however, have sought to broaden this framework because nominal wage developments are determined by numerous factors and the unemployment rate alone is not a sufficient determinant of their dynamics (Gali, 2011). The limited informational content of the unemployment rate has raised the question of which measures can supplement this framework; inflation expectations, labour productivity and indicators of labour market tightness have most commonly been used for this purpose.

A detailed analysis of unemployment dates back to Keynesian theory, in which unemployment was interpreted as a consequence of insufficient aggregate demand. One question nevertheless remained unresolved: why can a large number of unemployed persons and a large number of unfilled vacancies coexist? Search-and-matching models were developed precisely to address this issue (Diamond, 1982; Mortensen and Pissarides, 1994). These models place the relationship between vacancies and unemployment, described by the Beveridge curve, at the centre of the analysis. The curve depicts a negative relationship between the two variables, while movements along it reflect cyclical changes in aggregate demand that lie at the heart of the Keynesian interpretation. Shifts in the curve itself, by contrast, point to structural changes, primarily in the efficiency with which labour supply and demand are matched (Petrongolo and Pissarides, 2001). Consolo and Dias da Silva (2019) introduce measures derived from such shifts into a wage Phillips-curve equation, showing that matching efficiency may provide some additional explanatory power for nominal wage developments beyond standard indicators of labour market tightness.

Serbia's labour market has undergone a pronounced transformation over the past decade. According to the National Employment Service, the registered unemployment rate fell from 25.3% in 2011 to 10.8% in 2025,[1] with wages and total employment rising at the same time. The question addressed in this paper is what drove this transformation, i.e. to what extent it resulted from cyclical labour market tightening and to what extent from structural changes in the process of matching labour supply and demand.

This paper follows the approach of Consolo and Dias da Silva (2019), and the analysis is conducted in four steps. First, we construct a Beveridge curve using data for Serbia's labour

[1] According to data from the SORS Labour Force Survey, the unemployment rate fell from 24.9% in 2011 to 8.9% in 2025.

market. We then apply the decomposition of unemployment fluctuations proposed by Shimer (2012) to determine how much of the change in the unemployment rate depended on hiring dynamics and how much on the frequency of job separations. Next, we construct two measures quantifying the effectiveness of labour supply-demand matching – the residual from the Beveridge equation and matching function efficiency – and examine these results alongside movements in the Beveridge curve. Finally, we use the resulting Beveridge-equation residual to estimate a Phillips-curve wage equation and determine the extent to which labour market tightness and matching efficiency affect wage dynamics.

The results show that, in the initial period, the Beveridge curve was characterised by a high unemployment rate and a low vacancy rate, i.e. a slack labour market. In 2015–2019, movement along the Beveridge curve reflected cyclical labour market tightening, while the curve itself remained stable, as indicated by a residual fluctuating around zero; the matching efficiency measure points to a slight improvement in the matching process. During the pandemic, the unemployment rate remained almost unchanged while vacancies declined slightly, against the background of government job-retention measures. From 2022 onwards, the Beveridge curve shifted: at comparable unemployment rates, the vacancy rate was substantially higher than the historical relationship would imply, pointing to structural changes in labour supply-demand matching and a decline in efficiency. The decomposition of unemployment fluctuations implies that movements in unemployment over the entire period were primarily driven by hiring dynamics rather than by the frequency of job separations. Estimation of the wage equation shows that labour market tightness has a positive effect on wage growth, while the coefficient on the Beveridge curve residual is statistically significant and has the opposite sign because negative residual values indicate higher efficiency, which has a positive effect on wages. The decomposition of contributions to deviations of wage growth from its long-run average shows that the negative contribution of low labour market tightness dominated in the first part of the sample and gradually weakened as the labour market tightened. From 2022, matching efficiency gradually deteriorated, consistently with the shift in the Beveridge curve, and these adverse effects peaked in 2024. The decline in efficiency partly dampened the impact of high labour market tightness on wage growth, while the effect of the efficiency measure began to improve gradually from mid-2025.

2 Data and methodology

The analysis is based on quarterly administrative data from the National Employment Service (NES) on registered unemployment and reported labour demand. Since the NES register does not contain data on total employment, quarterly Labour Force Survey (LFS) data from the Statistical Office of the Republic of Serbia (SORS) are used as an indicator of the number of employed persons. The analysis covers 2011–2025. Before all measures are calculated, the underlying series are seasonally adjusted using the X-13 ARIMA-SEATS method.

Since all measures are constructed from administrative data, the results relate to the formal segment of the labour market, i.e. the part of labour supply and demand in which the NES acts as intermediary. There are therefore limitations on both the supply and demand sides. On the supply side, the register covers only registered unemployment and excludes work in the informal sector. A significant proportion of unemployed persons also use alternative job-search channels (such as online platforms and informal contact networks), making the NES register incomplete. On the demand side, employers also use other recruitment channels, so the number of vacancies recorded in the register is lower than the actual number. In recent years, there has also been a noticeable change in the composition of registered unemployed persons and reported vacancies, as those registering are predominantly lower-qualified persons and employers tend to report vacancies for lower-qualified workers. The constructed measures should therefore be regarded as an approximation of conditions in the formal segment of the labour market rather than in the labour market as a whole. These limitations do not invalidate conclusions regarding the direction and drivers of developments, but they do call for additional caution when interpreting the levels themselves. Changes in the composition of the register over time are not merely a limitation, but the subject of the analysis considered below.

The main variables in the empirical analysis are the number of registered unemployed persons in quarter t (U_t), the number of reported vacancies in quarter t (V_t), the number of employed persons in quarter t (E_t) from the SORS Labour Force Survey, the number of newly employed persons – i.e. persons from the unemployment register who found employment in quarter t (h_t) – and the number of newly registered unemployed persons in the quarter (n_t). The registered unemployment rate in quarter t (u_t) is calculated as the ratio of unemployed persons to the labour force $\left(\frac{U_t}{U_t+E_t}\right)$, which differs from the SORS Labour Force Survey unemployment rate as it is based on NES data. The vacancy rate in quarter t (v_t) is defined as the ratio of vacancies to total jobs, comprising vacancies and filled jobs represented by the number of employed persons $\left(\frac{V_t}{V_t+E_t}\right)$. Based on these variables and the standard labour market flow framework (Pissarides, 2000; Elsby, Michaels and Solon, 2009; Shimer, 2012), three key indicators are defined: the job finding rate, the job separation rate and labour market tightness. The job finding rate identifies the proportion of persons unemployed in period t-1 who become employed in period t.

$$F_t = \frac{h_t}{U_{t-1}}$$

The job separation rate measures the inflow into unemployment in the current quarter originating from persons employed in the previous period.

$$S_t = \frac{n_t}{E_{t-1}}$$

Labour market tightness is defined as the ratio of vacancies to unemployed persons. A higher value of θ indicates a tighter labour market, characterised by stronger labour demand relative to supply, whereas a lower θ indicates that a large number of unemployed persons face relatively few available opportunities.

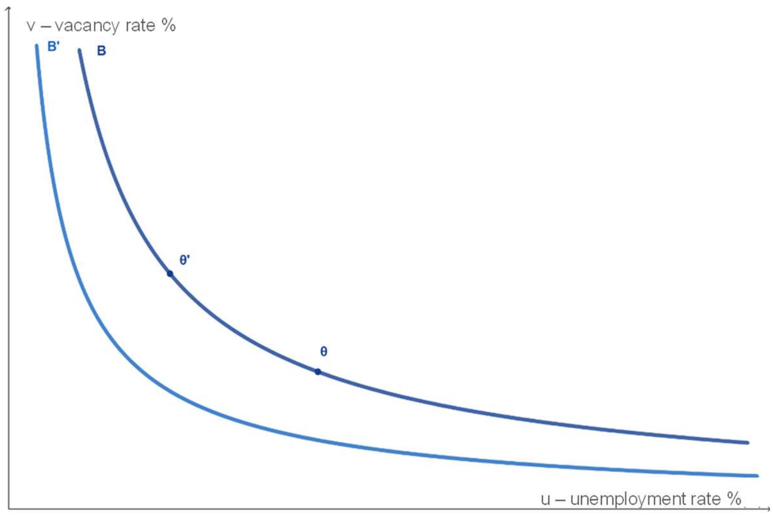
$$\theta_t = \frac{V_t}{U_t}$$

For estimation of the wage equation, we also use the average nominal net wage series and the Consumer Price Index (CPI), published by the SORS, together with a measure of labour productivity per person taken from the Eurostat database.

2.1 Beveridge curve

The Beveridge curve is an analytical framework for assessing labour market conditions and depicts a negative relationship between the unemployment rate (u_t) and the vacancy rate (v_t). This negative relationship is theoretically grounded in the search-and-matching model (Diamond, 1982; Mortensen and Pissarides, 1994), in which the curve represents a set of labour market equilibria. Two types of change are distinguished when interpreting labour market developments. Movements along the curve reflect cyclical aggregate demand shocks, i.e. changes in labour market tightness. If economic activity increases, labour demand rises and unemployment falls. Such developments raise our measure of labour market tightness θ, i.e. move it from θ to θ'. Shifts in the curve itself, by contrast, indicate structural changes, primarily in the efficiency of matching unemployed persons to vacancies, but also structural reforms and demographic changes (Petrongolo and Pissarides, 2001). A shift of the curve towards the origin, from B to B', indicates an improvement in matching efficiency because, for the same vacancy rate, the unemployment rate is lower, and vice versa. The observed shifts are formally quantified below using the Beveridge curve residual.

Chart 1 **Beveridge curve**



Source: Authors' illustration produced using GeoGebra.

2.2 Shimer decomposition

We apply the decomposition proposed by Shimer (2012) to identify the drivers of changes in the unemployment rate over the period observed. Under the Shimer decomposition, unemployment fluctuations can be described by the contributions of the job finding rate (F_t) and the job separation rate (S_t). Discrete quarterly probabilities are transformed into instantaneous (hazard) rates to correct for time-aggregation bias, since discrete measures do not capture changes of status within a quarter.

$$f_t = -\ln(1 - F_t), \quad s_t = -\ln(1 - S_t)$$

The starting point of the decomposition is the construction of the steady-state unemployment rate (u_t*) towards which the market converges under the influence of these two rates. The steady-state unemployment rate equals the share of the job-separation rate in the sum of the job separation and job finding rates $\left(u_t^* = \frac{s_t}{s_t+f_t}\right)$. Since convergence towards the steady state is rapid at quarterly frequency, the actual unemployment rate closely tracks the steady-state rate ($u_t^* \approx u_t$), allowing fluctuations in the latter to be used as an approximation of fluctuations in the actual unemployment rate.[2]

The contribution of each channel is determined by comparing the steady-state unemployment rate with two counterfactual scenarios: one in which only the job finding rate varies while the job separation rate is fixed at its full-sample average:

$$u_t^{*,f} = \frac{\bar{s}}{\bar{s} + f_t}$$

and a scenario in which only the job separation rate varies, while the job finding rate is fixed at its full-sample average:

$$u_t^{*,s} = \frac{s_t}{s_t + \bar{f}}$$

The steady-state unemployment-rate series and both counterfactual series are log-transformed and decomposed into trend and cyclical components using the Hodrick-Prescott filter (Hodrick and Prescott, 1997), with smoothing parameter λ = 1600. Contributions are calculated from the cyclical component because the purpose of the decomposition is to explain fluctuations. In the subperiod decomposition, cyclical components are estimated over the full sample and then extracted for each subperiod, so the contributions for individual phases are expressed relative to a unique reference trend and average.

To calculate the relative contribution of each channel to total fluctuations in the steady-state unemployment rate, we use the ratio of the covariance between the relevant counterfactual and steady-state unemployment to the variance of steady-state unemployment,

$$\beta_f = \frac{Cov\left(u_t^{*,f}, u_t^*\right)}{Var(u_t^*)}, \quad \beta_s = \frac{Cov(u_t^{*,s}, u_t^*)}{Var(u_t^*)}$$

where the condition is satisfied that $\beta_f + \beta_s \approx 1$ over the full sample. The paper also presents an analysis by subperiods, in which the sum of β_f and β_s need not satisfy this condition, since

[2] The correlation coefficient between the registered and steady-state unemployment rates is 0.95, indicating that the approximation is adequate.

the equilibrium unemployment rate is a non-linear function of two flow rates, whose average values are calculated over the entire sample.

2.3 Measures of labour market efficiency

Movements along the Beveridge curve and structural shifts in the curve can be approximately quantified using measures of labour supply-demand matching efficiency. The first is estimated as the deviation from the long-run relationship between the vacancy and unemployment rates, i.e. as the residual from the Beveridge-curve equation, while the second is estimated from the matching function described below.

2.3.1 Beveridge curve residual

The efficiency measure based on the Beveridge curve residual (εBC) is constructed in two steps. In the first step, a linear regression is estimated in which the vacancy rate (v_t) is the dependent variable and the unemployment rate (u_t) is the explanatory variable:

$$v_t = \beta_0 + \beta_1 \cdot u_t + \varepsilon BC_t \tag{1}$$

over the period Q1 2011 – Q4 2019. In the second step, the estimated coefficients $\widehat{\beta_0}$ and $\widehat{\beta_1}$ are applied to the full sample and the residual is calculated as

$$\widehat{\varepsilon BC_t} = v_t - \widehat{\beta_0} - \widehat{\beta_1} \cdot u_t \tag{2}$$

The estimation window ends in Q4 2019, thereby excluding both the temporary disruption during the pandemic and the persistent structural shift from 2022 onwards, described in Section 3.1. These two issues were tested separately. The Quandt-Andrews structural-break test (Andrews, 1993; Hansen, 1997) rejects the hypothesis of no persistent break and locates the break in Q3 2022 ($p < 0.0001$). The temporary deviation during the pandemic is confirmed by estimation over an extended 2011 – Q2 2022 window, in which a dummy variable for 2020–2021 is significant ($p < 0.001$).

The curve is estimated in linear form using rates. It is also tested in an alternative non-linear, log-log form implied by the steady state of the matching function. The estimated elasticity is -1.06 (standard error 0.27), and the tested value of -1 cannot be rejected, which is consistent with a hyperbolic curve. Since the curve is estimated over a relatively narrow range of unemployment rates, the linear and log-log forms yield similar estimates. This is also supported by the Ramsey RESET test, which does not indicate omitted curvature within the estimation window. The residuals from the two specifications are strongly correlated over the full sample (0.884), while their correlation within the estimation window is 0.974. Unit roots are tested using the augmented Dickey-Fuller test with a constant; the unit-root hypothesis cannot be rejected for either the unemployment rate or the vacancy rate, so both series behave as integrated of order one. The Engle-Granger test is used to test for a cointegrating relationship between the unemployment rate and the vacancy rate, with the latter as the dependent variable. It rejects the hypothesis of no cointegration ($\tau = -3.58$, $p = 0.044$) implying that the estimated residual series is stationary, a finding also confirmed by the Johansen trace test with one lagged difference. The hypothesis of no cointegrating relationship is also rejected for the log-log specification, although only at the 10% significance level (τ = -3.24, p = 0.087).

A positive residual (εBC) indicates a deterioration in matching efficiency: at a given unemployment rate, there are more vacancies than the equilibrium relationship would suggest, implying that firms find it more difficult to recruit suitable workers. Negative residual values imply the opposite.

2.3.2 Matching function efficiency (A)

The second measure, matching function efficiency (A), is derived from a Cobb-Douglas matching function:

$$h_t = A_t \cdot U_{t-1}^{\alpha} V_t^{1-\alpha} \tag{3}$$

where h_t is the number of new hires, U_{t-1}^{α} the total number of unemployed persons in the previous period, $V_t^{1-\alpha}$ the number of vacancies, α[3] the matching elasticity and A_t matching function efficiency. Dividing function (3) by the number of unemployed persons in the previous quarter transforms the left-hand side of the equation into the job finding rate from Section 2.2 $F_t = \frac{h_t}{U_{t-1}}$, which can be calculated as $F_t = A_t \cdot \left(\frac{V_t}{U_{t-1}}\right)^{1-\alpha}$, from which matching function efficiency can be calculated inversely

$$A_t = \frac{F_t}{\left(\frac{V_t}{U_{t-1}}\right)^{1-\alpha}} \tag{4}$$

as the rate of successful hiring for given stocks of vacancies and unemployed persons in the previous period. A higher value of the efficiency function (4) indicates that the market matches workers and employers more effectively, increasing the probability of finding a job and, analogously to the first measure, strengthening the bargaining position of unemployed persons.

2.4 Wage equation

In the next step of the analysis, following the approach adopted in the study published in the ECB proceedings (Consolo & Dias da Silva, 2019), we estimated a wage equation (w_t) using the ordinary least squares method, with annualised quarterly nominal growth in the average wage over the period Q1 2013 – Q4 2025 as the dependent variable, and the lagged logarithm of the labour market tightness measure (θ_{t-1}) and the lagged Beveridge curve residual (εBC_{t-1}) as a measure of the efficiency of the matching process in the labour market. Inflation expectations were approximated by the four-quarter moving average of the y-o-y inflation rate ($\bar{\pi}_t$), reflecting the predominantly adaptive formation of expectations among market participants in the wage-bargaining process. The equation also includes the y-o-y

[3] The matching elasticity with respect to unemployment, $\alpha = 0.5$, was calibrated following Petrongolo and Pessaries (2001).

growth rate of real productivity per person ($prod_t$), measured as real GDP per employed person.

$$w_t = \beta_0 + \beta_1 \cdot \bar{\pi}_t + \beta_2 \cdot log\theta_{t-1} + \beta_3 \cdot \varepsilon BC_{t-1} + \beta_4 \cdot prod_t + u_t \qquad (5)$$

An increase in labour market tightness in the previous quarter translates into wage growth, as it implies greater bargaining power for workers, while a higher ratio of job vacancies to unemployment provides workers with a wider range of options and greater flexibility in finding employment. A positive Beveridge curve residual indicates structural skills mismatch: if job vacancies and unemployed persons remain unmatched, the labour market generates weaker wage pressures. Conversely, a negative residual indicates that matching is taking place successfully and that workers have genuine opportunities to change jobs.

3 Empirical analysis of labour market efficiency and wage dynamics

3.1 Beveridge curve in Serbia's labour market

The Beveridge curve for the Serbian labour market was constructed using the unemployment rate and the job vacancy rate defined in Section 2, for the period from 2011 to 2025. The period under review was divided into four subperiods: post-crisis stagnation (2011–2014), the period of recovery and fiscal consolidation (2015–2019), the pandemic crisis (2020–2021), and the post-pandemic period (2022–2025).

The first subperiod is characterised by simultaneously high unemployment (an average of 25.1%) and a low vacancy rate (0.18% on average). The Beveridge curve for this subperiod is located in the lower-right part of the coordinate system, with average labour market tightness of 0.005. This points to a very slack labour market in which a large number of unemployed persons compete for very few vacancies.

During the second subperiod, the labour market tightened markedly: the average unemployment rate fell to 19.8%, while the average vacancy rate increased to 0.25%. This can be characterised as movement along the Beveridge curve driven by cyclical labour market tightening, as explained in greater detail in Section 2.1. Aggregate demand increased during this period as economic activity recovered both in the broader euro-area environment and in the domestic economy. Together with fiscal consolidation and the introduction of a range of active labour market measures, these developments increased labour demand and reduced unemployment.

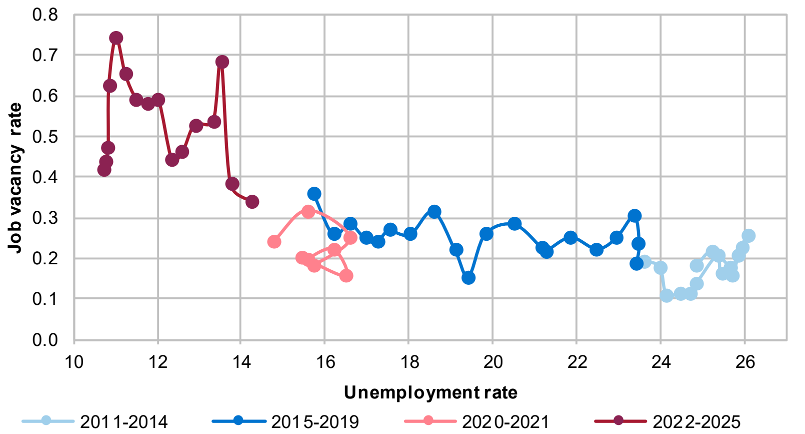
During the pandemic subperiod, the deviations that might have been expected given the nature of the shock were not recorded. The unemployment rate remained stable during the crisis at 15.8%, while the vacancy rate declined slightly to 0.22%. The absence of dramatic changes can largely be attributed to government job-retention measures characteristic of this period; consequently, the crisis was reflected primarily in employers' caution when hiring new workers.

The final subperiod displays the most pronounced differences relative to the rest of the sample. The unemployment rate continued to decline, to 12.1%, while the vacancy rate rose severalfold relative to its pre-crisis level, to 0.53%. Labour market tightness was consequently at its highest in this subperiod, at 0.04. The observations lie in the upper-left part of the coordinate system and clearly depart from the pattern seen in the rest of the sample, as the vacancy rate is substantially higher than the historical relationship would suggest. In other words, the Beveridge curve itself shifted, in contrast to the earlier movement along it.

The Beveridge curve for Serbia's labour market, shown in Chart 2, supports the descriptive analysis of these developments. The following sections introduce quantitative measures of the efficiency with which unemployed persons and vacancies are matched in order to explain these trajectories.

Chart 2 **Beveridge curve for Serbia**

(%)



Source: SORS, NES and authors' calculations.
Note: The unemployment rate is calculated as the ratio of the number of registered unemployed persons (NES) to the sum of registered unemployed persons (NES) and employed persons (Labour Force Survey, SORS). The job vacancy rate is calculated analogously, as the ratio of registered job vacancies (NES) to the sum of job vacancies (NES) and filled jobs, i.e. employed persons (Labour Force Survey, SORS).

3.2 Decomposition of unemployment fluctuations

The period observed as a whole is characterised by an almost uninterrupted decline in the unemployment rate. To identify the drivers of this movement, we apply the Shimer decomposition described in Section 2.2.

The average steady-state unemployment rate is 28.5%, substantially above the average registered unemployment rate of 18.6%. This is because it is calculated from flow rates (the job finding and job separation rates), which cover only two formal channels, inflows into the register and outflows through employment, while other forms of exit from the NES register are not included. The steady-state unemployment rate is therefore used solely to analyse fluctuations (dynamics). The correlation coefficient between the steady-state and registered unemployment rates is 0.95, indicating that the steady-state rate is an adequate approximation of the actual unemployment rate for this purpose.

Applying the Shimer decomposition to the period observed shows that the job finding rate explains 62% of fluctuations in the steady-state unemployment rate, while the remaining

38% is explained by the job separation rate. In other words, unemployment developments in Serbia are determined primarily by the speed at which unemployed persons find jobs rather than by the frequency with which existing jobs are lost. Sensitivity to the choice of smoothing parameter was tested by repeating the decomposition with $\lambda = 400$ and $\lambda = 6400$. The alternative parameter values changed the contribution of the job finding rate by less than 1 pp both for the full sample and across subperiods, indicating that the results are not dependent on the parameter choice.

Table 1: **Contributions to fluctuations in the steady-state unemployment rate**

Period	β_f	β_s	Total	Observations
2011–2025	**0.62**	**0.38**	**1.00**	**59**
2011–2014	0.80	0.31	1.11	15
2015–2019	0.89	0.10	0.99	20
2020–2021	0.04	0.92	0.96	8
2022–2025	0.60	0.32	0.92	16

Source: NES and authors' calculations.

Note: The sum of βf and βs in individual subperiods need not equal one because the steady-state unemployment rate is a non-linear function of the two flow rates, whose average values are calculated over the full sample.

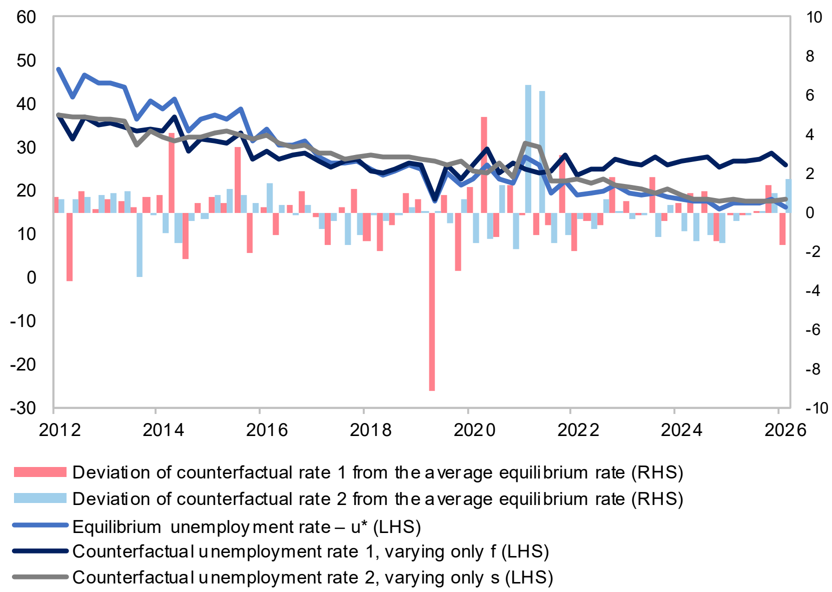
Table 1 shows that this relationship is relatively stable over time, with the exception of the pandemic shock. The job finding rate is the dominant channel in the first two subperiods and its contribution tends to increase, indicating that the pronounced decline in unemployment was almost entirely attributable to job finding, while the frequency of job separations played only a minor role. This finding is consistent with the movement of the Beveridge curve in the second subperiod, which was driven by stronger economic activity.

A reversal occurs during the pandemic, when the contribution of the job finding rate falls to only 4%, while the job separation rate explains 92% of fluctuations in steady-state unemployment. Caution in interpreting this subperiod is warranted for two reasons. It comprises only eight observations and was characterised by exceptionally strong government intervention through a broad range of measures. Nevertheless, the direction of the change is unambiguous. During this shock, labour-market measures helped preserve jobs by limiting dismissals. At the same time, employment relationships were terminated in segments not covered by these measures, such as the informal sector. In addition, the crisis brought a decline in new hiring, i.e. weaker labour demand.

In the final subperiod, the pre-pandemic pattern re-emerges and the job finding rate once again becomes the dominant contribution channel, albeit with reduced importance (60%). This finding points to a partial recovery of the labour market after the crisis, as unemployment dynamics are no longer driven exclusively by employment opportunities. The reduced importance of the job finding channel suggests possible difficulties in filling vacancies, consistent with the shift in the Beveridge curve observed in the same subperiod. The next section introduces measures of the efficiency with which jobseekers and employers are matched, in order to examine whether lower efficiency accounts for this change.

Chart 3 shows the movement of the steady-state unemployment rate. The series in which only the job finding rate varies, while the job separation rate is held fixed, tracks the steady-state unemployment curve almost completely. The exception is the Covid-19 crisis, when steady-state unemployment is better captured by the series based on variation in the job separation rate.

Chart 3 **Decomposition of fluctuations in the equilibrium unemployment rate**



Source: NES, NBS calculations using the Shimer (2012) decomposition.

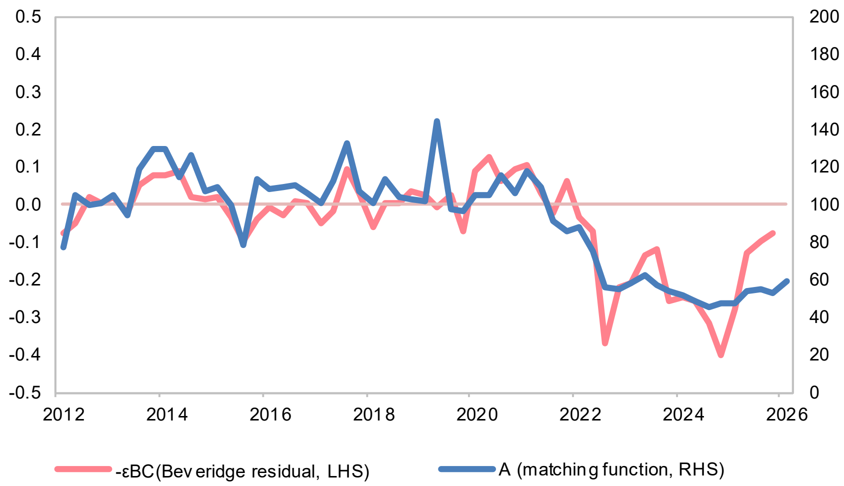
3.3 Developments in labour market matching efficiency measures

Consistent with movements in the Beveridge curve, up to 2019 the residual from Beveridge equation (2) fluctuated around zero, while matching efficiency (4) remained close to its historical average; the matching function measure points to a gradual improvement in job finding during this period. During the coronavirus pandemic the measures diverged: the residual indicates an improvement, reflecting weaker labour demand rather than a genuine increase in efficiency, while the second measure remains unchanged owing to job-retention measures. From 2022 onwards, both measures point to a deterioration in matching efficiency. In the case of the Beveridge curve residual, this can be linked to a substantially higher vacancy rate than would normally be associated with the prevailing unemployment rate, potentially indicating a shift in the curve and structural mismatch between employers and unemployed persons. The matching efficiency measure reaches a minimum value of 45 in Q3 2024, while the residual reaches its highest value (0.400) at the end of 2024. Both measures improve gradually during 2025, although efficiency has not yet returned to the historical curve.

The matching function efficiency measure A (4), however, is sensitive to changes in recruitment channels. The numerator of the job finding rate includes only hires achieved through the National Employment Service. When recruitment shifts to alternative channels such as online platforms, referrals or direct recruitment of students and graduates without formal entry in the register, the number of hires through the NES falls even if total hiring remains unchanged. The measure therefore records a decline in efficiency that does not necessarily reflect actual labour market conditions. The Beveridge residual does not depend on the recruitment channel because it uses stocks of unemployed persons and vacancies – the same rates shown in Chart 2 – which are formed independently of the way in which vacancies are ultimately filled. The residual therefore captures all factors affecting the position of the curve, including skills mismatch, demographic changes such as emigration and structural reforms, and thus provides a more informative approximation of overall market efficiency. For this reason, the wage-equation estimation presented below uses the Beveridge residual as the measure of efficiency.

The two efficiency measures are strongly negatively correlated (correlation coefficient -0.84 over the full sample). The sign is as expected, since a higher matching function efficiency value and a lower Beveridge curve residual both indicate more successful matching of labour supply and demand. The correlation is also negative within the stable 2011–2019 period (-0.64), indicating that the measures correspond even apart from the common structural shift.

Chart 4 **Measures of matching efficiency in the labour market**



Source: NES and NBS calculations.
Note: Beveridge residual is shown with the opposite sign, so that an increase in either measure indicates an improvement in matching efficiency in the labour market.

3.4 Effects on wage dynamics

In the next step of the analysis, following Consolo and Dias da Silva (2019), we estimated the wage equation (5) to examine whether the labour market measures constructed in the preceding sections contain information relevant to wage dynamics. The estimated coefficients are presented in Table 2. The results should be interpreted as indicative, given that the NES data do not cover the labour market in its entirety.

Table 2: **Estimated wage equation**

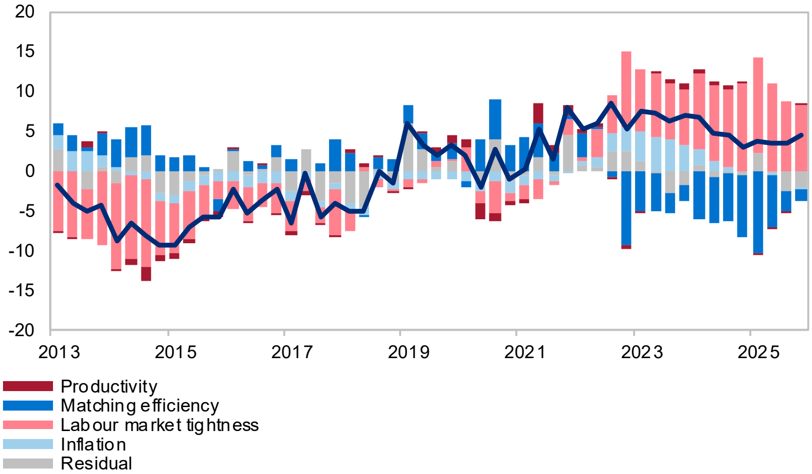
Dependent variable: annualised quarterly nominal wage growth		
Estimation period:	Q1 2013 – Q4 2025 (n=52)	
Explanatory variable	**Coefficient**	**Standard error**
Constant	41.39^{***}	(3.83)
Four-quarter moving average of y-o-y inflation– $\bar{\pi}$	0.41^{***}	(0.09)
Labour market tightness – $\log\theta(-1)$	8.01^{***}	(0.81)
Beveridge curve residual– $\varepsilon BC(-1)$	-28.79^{***}	(5.12)
Y-o-y productivity growth– prod	0.25^{**}	(0.12)
	R^2=0.82	Adj. R^2=0.81
	Standard error of regression = 2.30	DW=1.69

Source: Authors' calculations in EViews.
*** Denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level.
The Breusch-Godfrey test does not reject the absence of serial correlation up to four lags (p = 0.135), while the Jarque-Bera test does not reject normality of the residuals (p = 0.76).

The estimated coefficients have the expected signs. Adaptive inflation expectations, labour market tightness (measured by the vacancy-to-unemployment ratio) and productivity contribute positively to wage growth, while the coefficient on the Beveridge curve residual is negative because positive residual values represent labour market matching inefficiency. A one-standard-deviation change in the residual corresponds to a change in wage growth of around 4 pp, while the comparable magnitude for labour market tightness is around 6 pp.

In the next step, we assess the strength of the effects of these explanatory variables on wage dynamics using historical data. This is done by calculating the contribution of each variable's deviation from its own long-run average to the deviation of annualised quarterly nominal wage growth from its long-run average. Since contributions are expressed relative to the 2013–2025 sample average, a positive contribution from efficiency in the earlier period does not necessarily indicate an improvement in matching at that particular time; rather, it reflects relatively more favourable residual values compared with the end of the sample. The decomposition of contributions to the deviation of wage growth from its long-run average (Chart 5) points to the dominant influence of labour market tightness. Although the decomposition depends on the estimated coefficients and therefore inherits the limitations already noted, it illustrates the relative strength of labour market tightness and matching efficiency across subperiods. In 2013–2014, the negative effect of low labour market tightness on wages dominates, during a period in which the number of unemployed persons was relatively high compared with vacancies, implying weaker worker bargaining power. Thereafter, the negative contribution of low tightness gradually weakens as the labour market tightens, from -7.7 pp in 2013 to -0.2 pp in 2019, accounting for almost the entire change over that period. The contribution of matching efficiency (measured by the Beveridge curve residual) remains approximately constant and positive over the same period. This reflects residual values below the sample average – an average heavily influenced by the marked deterioration in matching after 2022 – rather than necessarily an improvement in matching at the time, since the measure itself fluctuates around zero without a systematic deviation. In 2022–2023, both increasing labour market tightness and inflationary pressures contribute to above-average wage growth, while the adverse effect of the Beveridge curve residual already partly dampens the impact of tightness. In 2024, labour market tightness contributes an average of 10.0 pp above the long-run average, of which matching inefficiency absorbs around two thirds, leaving a substantially smaller net effect on wages than tightness alone would imply. In 2025, the share absorbed by matching inefficiency falls from around 85% in Q1 to around 17% in Q4, allowing tightness to exert increasingly strong pressure on wage growth. This interpretation should be viewed as a complement to, rather than a substitute for, standard labour market indicators, consistently with Consolo and Dias da Silva (2019), who conclude that matching efficiency adds a qualitative dimension to the analysis but that its quantitative implications for wages do not differ substantially from the standard approach.

Chart 5 **Contributions to the deviation of wage growth from its long-term average**
(contributions to annualised quarterly growth, pp)



Source: SORS, NES and authors' calculations.
Note: Contributions are calculated as the product of the estimated coefficient and the deviation of the corresponding variable from its average over the estimation sample. The residual captures the entire unexplained component.

3.5 Alternative specification of the wage equation

Table 3: **Wage-equation estimates using alternative efficiency measures**

	Linear residual	Log–log residual
Sample	2013Q1–2025Q4	2013Q1–2025Q4
Constant	41.39 (3.83)***	31.79 (2.97)***
Four-quarter moving average of y-o-y inflation ($\bar{\pi}$)	0.41 (0.09)***	0.31 (0.10)***
Labour market tightness $log\theta(-1)$	8.01 (0.81)***	6.05 (0.63)***
Beveridge curve residual $\varepsilon BC(-1)$	−28.79 (5.12)***	−7.42 (1.61)***
Y-o-y productivity growth prod	0.25 (0.12)**	0.41 (0.13)***
R^2	0.82	0.80
Standard error of regression	2.30	2.47
DW	1.69	1.23
BG(4), F form	0.135	0.006
BG(4), χ^2 form	0.104	0.006
VIF: ln θ / residual	3.99 / 4.08	2.09 / 1.92
Effect of 1 s.d. of residual	−3.66 pp	−2.21 pp
Effect of 1 s.d. of tightness	+6.36 pp	+4.81 pp
Ratio of 1 s.d. residual effect to 1 s.d. tightness effect	0.58	0.46

Source: Authors' calculations in EViews.
*** Denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level.
The one-standard-deviation effect is calculated as the product of the estimated coefficient and the standard deviation of the relevant variable over the estimation sample of the equation concerned. Since the two variables are correlated, this is a descriptive comparison of relative importance rather than a decomposition of contributions.

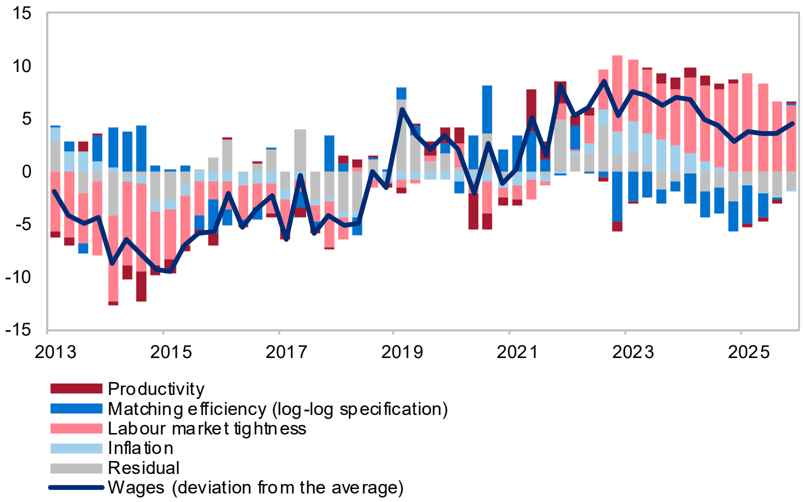
Section 2.3.1 describes two functional forms of the Beveridge curve. All results presented thus far have been obtained using the linear form, whereas in this section we consider the measure of matching efficiency based on the Beveridge curve residual derived from the log-log specification. Table 3 presents the same equation as in Section 3.4, but using the residual from the log-log form of the Beveridge curve. The equation is estimated over the same sample using the ordinary least squares method. In both specifications, all coefficients retain the expected sign and statistical significance. The coefficients on the Beveridge curve residual are not directly comparable, since the measures are expressed in different units. The coefficients on the labour market tightness measure are 8.01 in the linear specification and 6.05 in the log-log specification. The difference arises because both residual measures are correlated with the labour market tightness measure, although the correlation coefficient is lower in the log-log specification (0.67) than in the linear specification (0.84). This means that, in the linear specification, part of the shared variance is distributed between the two variables in a way that increases both coefficients. This is also supported by the centred variance inflation factor for the labour market tightness measure and the Beveridge curve residual, which indicates the extent to which the variance of an estimated coefficient is increased owing to the correlation of the respective variable with the other variables in the equation. Its values are approximately half the size in the log-log specification. Nevertheless, all values remain below the conventional threshold of 5 across in both specifications.

The linear equation is adopted as the baseline specification owing to its more favourable diagnostic properties, with the Durbin-Watson statistic standing at 1.69 in the linear specification and 1.23 in the log-log specification. The linear specification passes the test for serial correlation, as the Breusch-Godfrey test with four lags yields $p = 0.135$, whereas this is not the case for the non-linear specification ($p = 0.006$). In addition, the equation using the residual from the linear Beveridge curve exhibits a somewhat better fit, as reflected in a slightly higher coefficient of determination and a lower standard error of the regression.

Given that the coefficients are not comparable, their relative importance is assessed by comparing the effects of a one-standard-deviation change. A one-standard-deviation increase in the residual from the linear Beveridge curve results in annualised wage growth that is 3.66 pp lower, while the corresponding effect of an increase in the residual from the log-log curve is 2.21 pp. Similarly, a one-standard-deviation increase in labour market tightness raises annualised wage growth by 6.36 pp in the former case and by 4.81 pp in the latter. The ratio of these two effects is 0.58 in the linear specification and 0.46 in the log-log specification. Both channels operate in the same direction, although the alternative specification attributes a somewhat smaller role to matching efficiency.

Chart 6 shows the contribution decomposition obtained using the coefficients from the equation with the log-log residual, constructed in the same manner as Chart 5. The direction and timing of the changes are consistent with the baseline version: the contribution of tightness is negative until 2019, becomes positive in 2022 and continues to rise thereafter, while over the same period the contribution of matching efficiency changes sign, peaks in 2024 and recedes during 2025. Differences are apparent in the magnitude of the contributions, particularly that of matching efficiency, with the result that in the post-pandemic period the effects of labour market tightness are less strongly dampened by the adverse effects of

Chart 6 **Contributions to the deviation of wage growth from its long-term average (alternative specification)**
(contributions to annualised quarterly growth, pp)



Source: SORS, NES and authors' calculations.
Note: Contributions are calculated as the product of the estimated coefficient and the deviation of the corresponding variable from its average over the estimation sample. The residual captures the entire unexplained component.

matching inefficiency. It is important to note that the alternative specification contains a larger unexplained contribution, reflecting serial correlation in this equation.

4 Conclusion

The Serbian labour market over the period 2011–2025 was characterised by an almost continuous decline in unemployment accompanied by rising wages. In this paper, we sought to examine the extent to which these developments were attributable to cyclical labour market tightening and the extent to which they reflected structural changes in the matching of labour supply and demand. Following Consolo and Dias da Silva (2019), the analysis combines the Beveridge curve, the Shimer decomposition of unemployment fluctuations, two measures of matching efficiency and an augmented wage equation.

The measures employed provide a relatively consistent picture of labour market dynamics over the past fifteen years. The decline in unemployment was driven primarily by faster job finding, which accounts for 62% of fluctuations in the equilibrium unemployment rate. The analysis of movements in the Beveridge curve points to a gradual movement along the curve over the period 2015–2022, driven by cyclical labour market tightening, while matching efficiency remained stable. From 2022 onwards, the Beveridge curve itself shifted, with the job vacancy rate at a given unemployment rate becoming considerably higher than suggested by the historical relationship, indicating reduced matching efficiency between employers and jobseekers, especially towards the end of 2024 before gradually subsiding during 2025. The results obtained from the measures of matching efficiency are broadly consistent with these dynamics, although matching function efficiency is less reliable owing to its methodological properties and greater sensitivity to changes in recruitment channels. For this reason, in estimating the wage equation we used the Beveridge curve residual as a rough measure of matching efficiency in the labour market. The coefficients obtained from the estimated wage equation were in line with expectations: labour market tightness exerts upward pressure on wages, while the coefficient on the Beveridge curve residual has the opposite sign, as negative residual values imply an improvement in matching efficiency, with a favourable effect on wages. An examination of the contributions of the explanatory variables to the deviation of wage growth from its long-term average shows that the negative contribution of low labour market tightness gradually diminished over the period 2015–2019, accounting for almost the entire change during this part of the sample. From 2022 onwards, matching becomes less efficient and acts counter to labour market tightness, with the most pronounced negative effect occurring towards the end of 2024. As a result, record-high labour market tightness was only partially transmitted to wages, after which matching gradually improved during 2025.

Nevertheless, the conclusions should be interpreted in light of the data limitations and regarded only as an approximation of labour market dynamics, particularly since measures of matching efficiency are themselves inherently only rough approximations. The measures are constructed using NES administrative records and relate to the formal segment of the labour market. Unlike Consolo and Dias da Silva (2019), who use harmonised survey data, our analysis combines two data sources (NES and the Labour Force Survey). Furthermore, the measures constructed do not allow individual causes of changes in matching efficiency – such as skills mismatch, emigration or structural changes in recruitment channels – to be disentangled. Consequently, conclusions regarding the direction and drivers of developments are more robust than those concerning the levels themselves. With these caveats in mind, the findings suggest that measures of matching efficiency can provide additional insight into wage pressures beyond that offered by standard labour market indicators.

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WORKING PAPER

DIGITAL EURO: DEVELOPMENT, DESIGN AND IMPLICATIONS FOR THE PAYMENT AND FINANCIAL SYSTEMS

Ivan Radanović

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Digital euro: development, design and implications for the payment and financial systems

Ivan Radanović

Abstract: The paper analyses the development of the digital euro project, its main features and its potential implications for the European payment and financial systems. The digital euro would be a digital form of central bank money intended for households and businesses, existing alongside cash and private money issued by commercial banks. Its development is driven by the digitalisation of payments, the declining relative importance of cash, the need to preserve direct access to public money, and efforts to strengthen the resilience and strategic autonomy of the European payment system. The paper is based on an analysis of documents issued by the European Central Bank and other European Union institutions, the proposed legislative framework, and relevant professional literature. Particular attention is paid to the phased development of the project, the legal and institutional framework, the two-tier distribution model through private intermediaries, online and offline functionality, holding limits, the fee model, privacy protection, and accessibility. The analysis indicates that the digital euro could broaden access to public money and contribute to the integration of the European payments market, while at the same time affecting competition, costs and the business models of existing payment service providers. The envisaged non-interest-bearing design, individual holding limits and automatic transfer mechanisms should mitigate potential risks to bank intermediation and financial stability. The ultimate effects will depend on the legal and technical design, user acceptance, and the way in which usability, privacy, competition and financial stability are balanced. For Serbia, the development of the digital euro is particularly relevant due to its integration with the European payments market, inclusion in the SEPA geographical scope and the widespread use of the euro.

Key words: digital euro, digital central bank currency, public money, payment system, payment services, financial stability.
[JEL Code]: E42, E58, G21, G28

Non-technical summary

An increasing number of everyday payments is made using cards, mobile applications and other digital means, while cash is practically the only form of central bank money that citizens can use directly. Although users perceive the money held in a bank account as being the same as the euros they keep in their wallet, it represents the liability of a commercial bank. It is precisely this distinction that underpins the digital euro project: the aim is to ensure that central bank money remains directly accessible to the public in the digital environment as well. The digital euro would not be a new currency or a replacement for cash, but an additional form of the existing euro intended for everyday payments.

The project, however, extends beyond the question of the form of money itself. The European digital payments market remains fragmented, while a significant share of card payments relies on non-European international card schemes. The digital euro is therefore also viewed as a common European payments infrastructure that would be available throughout the euro area, including the possibility of making payments without an active internet connection. The Eurosystem would issue the digital euro and provide the underlying infrastructure and settlement, while banks and other payment service providers would continue to interact directly with users. Basic services for citizens would be free of charge, while private intermediaries could develop additional services.

Such a model also raises the question of the relationship between public infrastructure and the private market. Regardless of its intention to complement existing forms of payment, the digital euro would compete at the individual transaction level with cards and other private payment instruments. One of the main challenges will therefore be to ensure that the common infrastructure contributes to the integration of the European payments market and reduces dependence on non-European networks, while at the same time preserving incentives for banks and other private-sector participants to invest in and develop new services. The ultimate market impact will depend on the rules governing access, the level of fees, interoperability and the actual level of use of the digital euro.

A particular issue concerns the potential implications for banks and financial stability. If significant amounts of bank deposits were transferred into digital euros, banks would lose a part of their funding base. This risk could be more pronounced during periods of financial uncertainty, when a central bank liability may become more attractive than a bank deposit. Therefore, the digital euro is designed to be non-interest-bearing, the amount that an individual can hold on a permanent basis would be subject to a limit, and funds exceeding that limit would be automatically transferred to a linked bank account. The ECB's analyses to date do not indicate that the digital euro would necessarily jeopardise the stability of the banking system under the scenarios considered, but the effects could vary significantly across individual banks. This conclusion therefore depends on the final level of the holding limit, user behaviour, and the economic and financial conditions prevailing at the time of any potential issuance.

Privacy, security and accessibility are also essential to the success of the project. Online payments would not be anonymous vis-à-vis the bank or other intermediary, but the Eurosystem should not directly link payment data to the identity of users. Offline payments should provide a higher level of privacy and, in this respect, be closer to cash. At the same time, the use of the digital euro should not depend on owning a smartphone or having a high level of digital skills. Therefore, alternative access methods and institutional assistance are envisaged for users who need them.

For Serbia, the digital euro does not imply the automatic introduction of a new means of payment. Its potential availability to Serbian residents will depend on the future legal framework and specific international and operational arrangements. Nevertheless, the development of the project is important given Serbia's close economic ties with the EU, its inclusion in the SEPA geographical scope, the significant use of the euro, and the potential impact of the new European infrastructure on cross-border payments. It is therefore appropriate for domestic payment service providers and the National Bank of Serbia to monitor the development of technical standards and future rules, without prejudging future access to the digital euro system or the need for a domestic central bank digital currency..

Contents

1 Introduction

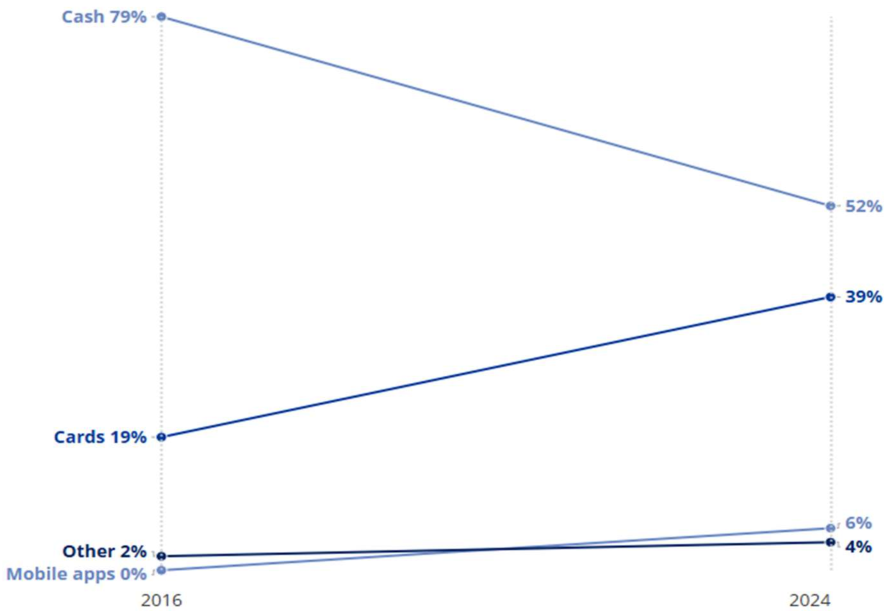
The accelerated digitalisation of economic activity over recent decades has changed the way households and businesses access and use money and make payments. Though cash continues to play an important role, particularly as a universally accepted means of payment and a form of central bank money that is directly accessible to the public, an increasing share of everyday transactions is carried out using payment cards, credit transfers, mobile applications and other privately provided digital payment solutions. Against this background, the question arises as to whether central bank money, directly available to the public through banknotes and coins, should also be offered in digital form.

One response by central banks – and the subject of this paper – is the development of central bank digital currencies (CBDCs). These are digital payment instruments denominated in the official unit of account that represent a direct liability of the central bank, rather than a claim on a private issuer. The digital euro would be a general-purpose, retail CBDC, available to individuals and legal entities and used alongside cash and existing private means of payment (BIS, 2020: 3–4; ECB, 2023a: 10–11).

The digital euro project was launched against a backdrop of the declining relative importance of cash payments, the growth of e-commerce, the expansion of private digital payment instruments, and the increasingly prominent role of large international companies in the payments and high-technology sectors (Big Tech) (Figure 1). The ECB justifies the project by the need to preserve direct access to public money in the digital economy, provide a universally accepted digital means of payment throughout the euro area, strengthen the resilience of the European payment system, and reduce dependence on non-European solutions. The digital euro is therefore envisaged not merely as a technologically modernised form of the euro, but as a monetary, infrastructure and market project that could affect the relationship between public and private money, the role of intermediaries, the fee structure, and competition in the payments market (ECB, 2023a: 4; ECB, 2025c: 6–8).

The project is developed in several successive phases. Following the investigation phase (2021–2023) and the preparation phase (2023–2025), the ECB Governing Council announced on 29 October 2025 that it is advancing the project to its next phase of technical readiness, focused on capacity building, piloting and cooperation with market participants. This decision does not mean that the digital euro has already been approved: the Governing Council can take a final decision on its issuance only after the EU's legal framework has been adopted. At the time of writing, the legislative process had not yet been completed; on 9 July 2026, the European Parliament approved the opening of interinstitutional negotiations with the Council (ECB, 2023a: 42; ECB, 2025c: 5, 33–34; European Parliament, 2026a).

Figure 1 **Payments for goods and services in the euro area, by payment instrument** (in %)



Source: European Council, according to ECB data.
Note: Due to rounding, the sum of the percentage shares exceeds 100%.

The subject of this paper are the key features, development and the envisaged operating model of the digital euro, with a particular emphasis on the outcomes of the investigation and preparation phases and the technical readiness phase launched at the end of 2025. **The aim of the paper is to provide a clear overview of the key design decisions concerning the digital euro** and to analyse its potential implications for the payment services market, bank intermediation, financial stability, consumer privacy and European payments infrastructure.

The starting premise of the paper is that the digital euro should not be viewed solely as a new electronic payment instrument, but rather as an attempt to adapt public money and public payments infrastructure to the digital economy. Its impact will be determined not only by its technical features but, perhaps even more importantly, by the way in which the relationship between the Eurosystem and private market participants (intermediaries), holding limits, the fee model, acceptance requirements, privacy protection and access for users outside the euro area are structured. The success of the project will depend on its ability to reconcile usefulness for users, a sustainable business model for payment service providers and the preservation of financial stability.

Although the digital euro is primarily intended for the euro area, its development is also relevant for Serbia given its strong economic ties with the EU, the significant use of the euro, and Serbia's inclusion in the SEPA geographical scope. **Any potential availability of the digital euro to residents of Serbia would depend on the final EU legal framework and specific international and operational arrangements.** For the domestic payment system, the main areas of relevance are therefore the potential implications for cross-border payments, the operations of payment service providers, and the easier use of the euro in digital form (European Commission, 2023a: Art. 19; NBS, 2025).

The paper is based on an analysis of documents issued by the ECB and other EU institutions, the proposed legislative framework, technical reports produced during the various phases of the project, and other relevant sources. Following a conceptual definition of CBDCs and a discussion of the rationale for developing the digital euro, the paper presents the various phases of the project, followed by an examination of the legal and institutional framework, the envisaged operating model, the implications for the payment services market, the banking sector and financial stability, as well as issues relating to privacy, security and accessibility. The conclusion identifies the conditions that will determine the future role of the digital euro and briefly considers its significance for Serbia.

2 The digital euro – a new form of central bank money

This section first defines the digital euro conceptually as a distinct form of central bank money and then examines its place in the modern monetary system. Particular attention is devoted to the distinction between public and private money, the monetary anchor function, and the key reasons for developing the digital euro.

2.1 Concept and main characteristics of central bank digital currencies

It is more precise to define a CBDC as a digital form of central bank money, rather than as a separate currency existing in parallel with the euro. The BIS defines a CBDC as "a digital payment instrument, denominated in the national unit of account, that is a direct liability of the central bank" (BIS, 2020: 1). In its initial report of October 2020, the ECB likewise emphasized that it would not constitute a parallel currency, but rather a complement to the existing euro, convertible at par into cash and other forms of the euro. As a direct liability of the Eurosystem, **the digital euro would not be exposed to the credit risk** of a private issuer and **would represent the safest form of digital money** available to end users (ECB, 2020: 7–8). These definitions point to three fundamental characteristics of a CBDC: it exists in digital form, its value is denominated in an existing unit of account, and the user's claim is directly against the central bank.

Based on the user base, CBDCs are most commonly divided into general-purpose instruments (retail CBDCs), available to households and businesses for everyday payments, and instruments intended for a limited group of financial institutions (wholesale CBDCs), used primarily for interbank settlement and transactions in financial markets. **The digital euro** would belong to the first category: **it would be intended for payments by individuals, businesses and public authorities** and would be used alongside cash and existing private means of payment (ECB, 2023a: 11–12).

The position of the digital euro can best be understood by comparing it with existing forms of money. Cash and the reserves that commercial banks hold with the central bank are liabilities of the central bank. Cash is available to the public but exists in physical form, whereas reserves are "digital" but accessible only to financial institutions. By contrast, deposits held with commercial banks and electronic money represent liabilities of private issuers (BIS, 2020: 3–4). The digital euro would fill the space between cash and reserves: it would be digital like reserves, but accessible to the public like cash. The difference between the digital euro and a payment card or mobile banking application is that the latter are payment instruments, whereas the digital euro represents monetary value.

2.2 Public and private money and the monetary anchor function

The modern monetary system is based on the coexistence of public and private money. Central bank money comprises cash available to the public and the reserves of financial institutions, while private money used in everyday transactions consists largely of deposits held with commercial banks. Although a euro in cash and a euro held in a bank account are claims on different institutions, users treat them as equivalent because they are convertible at par. This convertibility rests on institutional arrangements, while central bank money serves as the monetary anchor: the ultimate public form of money into which privately issued money can be converted. Highlighting the fact that "people's trust that private money can always be converted into central bank money could be jeopardised" (Lagarde and Panetta, 2022), the **ECB's leadership argues that the digital euro would preserve confidence in the singleness of the currency, the payment system, financial stability, and even private money itself.**

This is important in the context of the declining use of cash, whose scope of use has been narrowing significantly in the digital environment (e-commerce). The purpose of the digital euro project is therefore not to "pre-empt" the disappearance of cash, as the ECB remains committed to ensuring its availability. **The key objective is to ensure, through the digital euro, that central bank money remains accessible to the public in a cashless environment as well.**

2.3 Why the digital euro? Key reasons

The above gives rise to the first reason for developing the digital euro: **preserving access to public money in the context of digitalisation of payments**. It would enable households to use, including for electronic transactions, a means of payment that represents a liability of the central bank. In this way, public money would remain accessible not only in physical but also in digital form. **The second reason concerns the absence of a single electronic payment solution for all euro area countries.** The existing European solutions are generally limited to individual national markets or specific types of transactions. According to ECB data, nearly two-thirds of card-based transactions in the euro area are carried out by non-European companies, while thirteen euro area countries depend entirely on international card schemes for point-of-sale payments (Cipollone, 2026). This raises the question of operational resilience and strategic autonomy. The digital euro would therefore be the first pan-European payment instrument operating under EU rules and on infrastructure whose key components are under the remit of the Eurosystem (ECB, 2023b: 4). The third reason is **to strengthen the resilience of the payment system**. The digital euro would provide an additional payment channel, thereby reducing dependence on a limited number of private providers and technical systems. In this context, the envisaged possibility of offline payments is particularly important, as it would enable certain transactions without an active internet connection and even without holding a bank account (Ibid.: 13).

The ECB's Chief Economist Philip Lane similarly views the rationale for introducing the digital euro, particularly in the broader context of preserving the two-tier monetary system, in which public central bank money and private bank money are available to the public alongside each other. In his view, prudence calls for preserving the public's direct access to central bank money even as the digitalisation of payments advances. He sees the rationale in the fact that there is no guarantee that confidence in the convertibility of private money would be maintained if cash were to lose its practical significance without a corresponding digital form of public money being made available. In addition, **the digital euro would constrain the market power of private payment infrastructures, provide a backup payment channel, and help overcome the fragmentation that still exists.** Lane also attributes political and institutional significance to the digital euro: by preserving a direct monetary link between public authorities and citizens, the digital euro would be a potent symbol of the economic and political unity of the European Union (Lane, 2025).

3 Development of the digital euro project: from investigation to technical readiness

The development of the digital euro project is a multi-phase process in which the rationale for the project, the main design options, technical feasibility and the conditions for potential deployment are examined separately. Moving to the next phase does not mean that a decision on issuance has already been taken; rather, investigation and preparatory activities continue, with **the ECB Governing Council retaining the option to take a final decision only after the relevant** EU **legislative framework has been adopted**.

The ECB published its first comprehensive report on the digital euro in October 2020, with the aim of examining the rationale for its potential issuance, the key design requirements, and the potential implications for monetary policy, financial stability and the payment system. The starting point was that it was first necessary to identify the scenarios in which the issuance of a digital euro would be justified, as well as the requirements that such a form of money would have to meet (ECB, 2020: 9–14).

On 14 July 2021, the ECB Governing Council decided to launch a two-year investigation phase for the project. Its objective was to examine key design and distribution issues and determine whether a digital euro could be developed that would meet users' needs without undermining financial stability or facilitating illicit activities. It was emphasized at the time that the launch of the project did not constitute a final decision on issuance.

3.1 Investigation phase (2021–2023)

The investigation phase ran from October 2021 to October 2023. During this phase, conceptual analyses and prototyping examinations were conducted, user needs were examined, and consultations were held with payment service providers, merchants and EU institutions. The main use cases were identified – person-to-person payments, payments at brick-and-mortar points-of-sale, e-commerce, and transfers to and from the public sector – as well as the need for the digital euro to be available in both online and offline modes (ECB, 2023a: 3, 15–17).

This phase also saw the adoption of a **two-tier distribution model**, whereby the Eurosystem would issue the digital euro, provide settlement and manage the core components, while supervised payment service providers would establish relationships with end users. At the same time, the need to limit the amounts that individuals could hold was identified, so that the digital euro would not become a significant store of value. These decisions represented high-level design options, which were subsequently elaborated during the preparation phase (Ibid.: 12–13, 18–30).

The investigation phase concluded with the assessment "that it would be possible to develop a digital euro that, from a product design and distribution perspective, meets users' needs and the Eurosystem's requirements" (Ibid.: 42). The Governing Council then decided to move to a two-year preparation phase, which began on 1 November of the same year.

3.2 Preparation phase (2023–2025)

The preparation phase, from November 2023 to October 2025, was tasked with establishing the operational and technical foundations for a potential digital euro. This included developing the draft scheme rulebook, selecting potential providers of technical components and services, conducting experiments with market participants, and further analysing offline functionality, accessibility, architecture, and the methodology for determining holding limits.

One of the main outcomes of this phase was the **development of the digital euro scheme rulebook**. It sets out the common rules, standards and procedures that participants would apply to ensure consistent basic services and user experience throughout the euro area. The provisional draft rulebook, prepared in 2024 by the Rulebook Development Group (RDG), was subsequently expanded to include rules on minimum user experience, dispute and risk management, testing and certification. In parallel, an innovation platform was established to assess design elements and the potential for innovation, with around 70 banks, fintech companies, merchants and non-bank payment service providers testing selected payment flows and conditional functionalities (ECB, 2025a: 5–7, 22; ECB, 2025c: 1–2, 9–12, 14).

Research on the future user base, conducted to better understand the preferences and behaviour of end users of payment services, showed that different groups do not place the same value on the features of the new means of payment. More vulnerable users emphasized universal acceptance, simple design, direct support and the possibility of offline use, while small merchants highlighted low costs, easy integration into existing payment processes and the existence of genuine consumer demand. These findings were used in developing minimum user experience and accessibility requirements (ECB, 2025c: 26–27).

Although the ECB assessed the objectives of the preparation phase as having been achieved, its completion did not constitute a final decision on the issuance of the digital euro. **The outcome of the preparation phase was a more developed, although still evolving, draft rulebook, the selection of potential technical partners, and a body of analyses and experimental findings that can serve as a basis for the next phase of the project**, in which the Eurosystem will "build the necessary technical capacity ahead of a possible decision to issue" the digital euro (ECB, 2025c: 34–35).

3.3 Technical readiness phase (from 2025)

Following the Governing Council's decision of 29 October 2025, the project entered the technical readiness phase. Work is focused on developing and testing technical capabilities, deepening cooperation with payment service providers, merchants and user representatives, and supporting the legislative process. The Eurosystem emphasizes that preparations will follow a modular approach, so that the project can align with the final legal and functional framework (Ibid.: 35). This modular approach also implies flexibility, meaning that the focus will be on enhancing technical readiness, deepening communication with the market and supporting the legislative process.

During 2026, work on the scheme rulebook continued. Version 0.91 of the rulebook, published on 2 July, contains expanded requirements for user flows, testing and certification, risk management and technical specifications, but remains preliminary and non-binding. Nevertheless, **a pilot test of the digital euro is planned for the second half of 2027**, in order to assess technical stability, operational procedures, scalability and user experience in a controlled environment. **In July 2026, the ECB selected 36 payment service providers to participate in the pilot**;[4] the value used in this environment will not have legal tender status (ECB, 2026a; ECB, 2026b; ECB, 2026c). From a regulatory perspective, given the absence of final legislation on the digital euro, the relevant framework will be the PSD2 – Second Payment Services Directive (ECB, 2023a: 18).

Assuming that the legislative framework is adopted in a timely manner, **the Eurosystem aims to achieve technical readiness for a potential first issuance in 2029**. This is a conditional timeline, meaning that the final decision remains within the remit of the ECB Governing Council and will depend on the adopted legal and functional design, the results of the pilot, and the prevailing economic and financial conditions.

4 Legal and institutional framework

It is important to note that, although they are proceeding in parallel, **the legal and technical development of the digital euro are separate processes**. The Eurosystem is developing the design and ensuring the technical readiness of a potential digital euro, while the European Parliament and the Council of the European Union, under the regular legislative procedure, are establishing the framework within which this digital currency would be issued and used. Accordingly, progress on the technical project does not, in itself, create a legal basis for the launch of the digital euro, just as the adoption of the regulation would not oblige the ECB to issue it.

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[4] Among the banks in the region with subsidiaries in the Republic of Serbia, the 36 payment service providers include Raiffeisenbank Austria d.d. in Croatia and Nova Ljubljanska banka d.d. in Slovenia.

The institutional framework is based on a **division of responsibilities**. The provisions governing the tasks of the Eurosystem and the issuance of money, including Articles 127 and 128 of the Treaty on the Functioning of the European Union (TFEU) and Articles 17 and 22 of the Statute of the ECB, provide the basis for the ECB's role in the areas of money and payment systems. However, the general rules governing the use of the digital euro are established by the European Parliament and the Council on the basis of Article 133 of the TFEU. The ECB is therefore not the legislator in this process, but retains the exclusive competence to authorise the issuance of the digital euro (Grünewald, 2023: 17–20).

On 28 June 2023, the European Commission presented a package on the single currency. Its central element is the Proposal for a Regulation on the establishment of the digital euro,[5] based on Article 133 of the TFEU. The package also includes a proposal on the provision of digital euro services by providers in member states that have not adopted the euro, as well as a proposal to safeguard the status and availability of euro cash. The choice of the regulation is intended to ensure direct and uniform application throughout the euro area, while at the same time emphasizing that the digital euro should complement, rather than replace, banknotes and coins (European Commission, 2023a; European Commission, 2023b; European Commission, 2023c).

The proposed regulation defines the digital euro as a digital form of the single currency available to individuals and legal entities. The ECB would have the exclusive right to authorise its issuance, while the digital euro would be issued by the ECB and the national central banks of the euro area. Following the adoption of the regulation, the Governing Council would decide whether, when and in what form the digital euro would be issued (European Commission, 2023a: Articles 3–4).

For practical implementation, it is important to distinguish between the role of the issuer of the digital euro and that of the institution providing payment services to the end user – the intermediary. **The digital euro would represent a liability of the Eurosystem, while the payment service user would establish a contractual relationship with a bank or another authorised payment service provider.** Intermediaries would open and maintain accounts or digital wallets, carry out customer identification, execute payments and provide customer support – but, unlike the case with "ordinary" money held in an account, they would not be the issuers of the monetary value itself (ECB, 2023a: 18–27). This means that **the end user would not interact directly with the ECB or a national central bank**, even when using its front-end interface through which the digital euro is accessed.[6] **Article 6 provides that supervision of payment service providers would be carried out by national competent authorities in cooperation with the ECB** (European Commission, 2023a: Arts. 6, 13 and 28).

The proposed Regulation also provides for the digital euro to have the status of legal tender. This (envisaged) measure would entail an obligation to accept it at full face value, meaning that its use by the payer would discharge the monetary obligation (Arts. 7 and 9).

[5] Proposal for a Regulation of the European Parliament and of the Council on the establishment of the digital euro.

[6] Articles 25–33 of the proposed Regulation also provide for the possibility for a commercial bank itself to develop a similar interface, allowing payment service users to choose which interface they wish to use.

Nevertheless, **the obligation to accept the digital euro would not be universal**: among others, individuals engaged in personal activities at household level, as well as micro enterprises and non-profit legal entities that do not accept comparable cashless means of payment, would be exempt from this obligation.

Distribution of the digital euro would be entrusted to banks, payment institutions and other authorised payment service providers. **Credit institutions that already provide basic services in connection with payment accounts would be required, at the request of their customers, to also offer basic digital euro services.** In accordance with Directive (EU) 2019/882, Article 14 of the proposed Regulation provides that, where a person does not have or does not wish to have a payment account, member states must ensure access to digital euro services through public authorities or postal offices. A support scheme is also envisaged for older persons, persons with disabilities and users with limited digital skills. Basic services for individuals, including opening and managing an account or wallet and making payments, would be provided free of charge.

Access for persons outside the euro area would not be automatic. Under Article 18 of the proposed Regulation, **payment service providers would be able to make the digital euro available to residents of EU member states that are not part of the euro area** only where a separate arrangement has been concluded between the relevant national central bank and the ECB. This would require the national central bank to first submit a request and undertake to abide by "any rules, guidelines, instructions or requests" issued by the ECB in relation to the digital euro, including those concerning supervision. **In the case of "third countries"** that are neither EU member states nor part of the euro area, similar rules would apply, except that a separate arrangement would first have to be concluded between the third country and the European Union, followed by an arrangement between the ECB and the national central bank. Distribution of the digital euro in such a country – including Serbia – would require the national central bank to provide all necessary information concerning the use of the digital euro within its territory that the ECB might request. As regards cross-currency payments between the digital euro and other currencies, the applicable arrangements would be those previously concluded between the ECB, on the one hand, and the national central banks of EU Member States whose currency is not the euro and third countries, on the other. To ensure interoperability between payments in digital euros and other currencies, Article 21 provides for cooperation between the ECB and national central banks.

At the time of writing, the legislative process had not yet been completed. On 19 December 2025, the Council of the European Union adopted its negotiating position, supporting a legal framework for the online and offline use of the digital euro, free basic services, and its status as legal tender. Among other things, the Council's position provides for the ECB to determine individual holding limits within an overall maximum set by a Council decision, with a view to balancing the ECB's responsibilities with broader considerations of financial stability and monetary sovereignty (Council of the European Union, 2025a).

The European Parliament adopted its position in the competent committee on 23 June 2026 (European Parliament, 2026b), and on 9 July approved the opening of interinstitutional negotiations with the Council (European Parliament, 2026a). **The Parliament supported online and offline use, free basic services, privacy protection and limits on individual**

digital euro holdings. Interestingly, the issue of strategic autonomy is becoming increasingly prominent in the positions of the legislators as well. Both the Council and the European Parliament link the digital euro to strengthening the resilience of the European payment system and reducing dependence on providers from outside the European Union (Council of the European Union, 2025b; European Parliament, 2026b). According to ECB data, international card schemes processed 64% of all electronically initiated transactions made with cards issued in the euro area in 2023 (ECB, 2025b: 11).

5 Design and functioning

The final design of the digital euro will depend on the outcome of the legislative process and the subsequent decision of the ECB Governing Council on issuance. Nonetheless, the investigation and preparatory phases have shaped a sufficiently clear operational model: the digital euro would be a direct liability of the Eurosystem, but would be distributed to end users through banks and other authorised payment service providers. It would be intended for retail payments, available in both online and offline modes, and accompanied by mechanisms that limit its use as a store of value.

5.1 Issuance, distribution and user access

The Eurosystem would issue the digital euro and provide the core infrastructure, while supervised payment service providers would carry out most of the operations in direct contact with users. Their functions would include user identification and onboarding, opening and managing accounts or wallets, loading and withdrawing funds, initiating payments and providing customer support. Intermediaries would provide the payment service, but would not be issuers of the monetary value, which would represent a claim on the central bank (ECB, 2023a: 18–30; European Commission, 2023a: Art. 13). **Users would access the digital euro through the applications and electronic channels of their intermediaries, or through a dedicated Eurosystem interface**; even in the latter case, there would be no contractual relationship between the user and the ECB or the national central bank (European Commission, 2023a: Art. 28; ECB, 2023a: 19–20).

To ensure that access does not depend on owning a modern smartphone or a high level of digital literacy, **the use of a physical card or other suitable device is also foreseen** (ECB, 2025c: 21–22). In Article 31 of the proposed Regulation, the European Commission has provided for easy switching of payment service providers, while retaining the digital euro account identifier, which, it is considered, would facilitate service portability and reduce dependence on a single intermediary.

5.2 Use cases, account top-up and conditional payments

The digital euro would be intended for basic forms of payment: transfers between natural persons, payments in shops, e-commerce, and payments to and from public authorities, such as taxes, fees, subsidies and social benefits. The specific standards and user flows would be set out in the scheme rulebook, and **the technical solutions under consideration include QR codes, NFC, hyperlinks and digital euro account numbers** (DEAN) (ECB, 2023a: 15–17; 2023b: 10).

Depending on the scope of services that banks and other credit institutions will provide, funds could be transferred into digital euro from a payment account or by depositing cash, and the same would apply in the reverse direction. Digital means of topping up and withdrawing funds should be available on a continuous basis, while cash-related transactions would depend on the available infrastructure and the times at which the intermediary otherwise provides cash-desk-related services (ECB, 2023a: 22–23). The **so-called conditional payments** are also envisaged, **in which the transfer of funds is executed automatically upon a pre-defined condition**. Funds could be temporarily reserved and then transferred to the payee following, for example, the confirmation of a delivery of goods or performance of a service. Activities relating to these conditions would be carried out by payment service providers within a separate conditionality layer, while the Eurosystem would provide the back-end layer for settlement and funds reservation purposes (ECB, 2025c: 21). It should be noted that this conditionality of payment is not the same as programmable money – a type of digital money with separate built-in logic and restrictions on the type, recipient, timing of execution and other features of transactions. Article 24 of the proposed Regulation explicitly states that **the digital euro would not be programmable money**; conditions may determine the moment of the execution of a specific transaction, but not the general usability of the digital euro held by the user (ECB, 2023b: 24).

5.3 Online and offline mode of operation

According to the Commission's proposal, online and offline modes should be available from the initial issuance. The online mode would cover payments at brick-and-mortar points-of-sale, e-commerce and transfers between remote users. If the user has previously linked the digital euro account to a payment account (or to one of the payment accounts) and activated the corresponding function, the missing amount could be automatically withdrawn from the linked account, therefore it is not necessary to hold the full payment amount in digital euro in advance (European Commission, 2023a: Art. 23; ECB, 2023a: 13–17, 23).

The offline mode would be intended for payments between devices in close proximity,[7] without an active internet or telecommunications connection and without forwarding each transaction to an online system. Funds would be transferred in advance to a protected element[8] on the phone, card or other device, and the payment would be executed by directly updating locally stored balances, without data storage or validation by payment service providers. For topping up or withdrawing funds for offline use – as well as for periodic checks of security

[7] Art. 23 of the proposed Regulation envisages that close proximity payment can be executed online as well, of which payment service users would be informed in advance.

[8] This refers to protection against unauthorised physical modifications (tamper-proof chip) with pre-embedded software capable of storing confidential and cryptographic data and running secure applications.

functions – the device would need to connect to the system (ECB, 2023a: 13–14, 22; ECB, 2025c: 16–17).

The offline mode would enable payments during internet and telecommunications service outages, and would **provide a higher degree of privacy, closer to cash payments**. Data on individual offline transactions would not be available to intermediaries or the Eurosystem. Locally stored funds would be exposed to a risk similar to that of cash: if the device is lost or stolen, recovery of the funds would not be possible, nor would it represent an obligation of the intermediary or the Eurosystem (ECB, 2023a: 14, 38).

5.4 Holding limits and fund management

The digital euro is not intended as an investment asset or a means of saving. Funds held by natural persons would not bear interest and would be subject to an individual holding limit, the final amount of which has not yet been determined. The main task during the project's preparatory phase was to develop a methodology for calibrating the digital euro holding limit. The purpose of this methodology, which is being developed in cooperation with the national central banks and relevant institutions of the euro area member states, is to **maintain a balance between ensuring the usefulness of the digital euro as a means of payment, the effectiveness of monetary policy, and financial stability**; the purpose of the holding limit would be to mitigate the risk of excessive and persistent shifts of deposits from commercial banks into central bank money (ECB, 2023a: 12–13, 33; ECB, 2025c: 23; European Commission, 2023a: Arts. 15–16). In 2025, at the request of the legislators, the ECB analysed hypothetical limits ranging from EUR 500 to EUR 3,000 per natural person; the appropriate amount would be determined closer to the possible issuance date and in light of the economic and financial conditions at that time.

The practical impact of the limit would be mitigated by waterfall and reverse waterfall mechanisms. If a received payment increases the balance above the limit, the surplus would be automatically transferred to the linked payment account. If the user wishes to pay more than their available digital euro balance allows, the difference would be automatically withdrawn from the linked account. Account linking and the activation of these functions would be voluntary and would require the user's prior consent (ECB, 2022: 10; ECB, 2023a: 14–15, 23). These mechanisms would apply to online funds; offline funds would need to be topped up in advance and would have a separate limit per device, as part of the overall individual limit.

In the model developed during the investigation phase, corporates and public authorities could receive and execute payments, but could not permanently accumulate online funds. For them, a zero online holding limit is foreseen: received amounts would be automatically transferred to a bank account, while funds needed for a payment would be withdrawn immediately before the transaction. Limited funds received offline could temporarily remain on the acceptance device until the connection is re-established; the final parameters of this exception have not yet been determined (ECB, 2023a: 12–13, 23–24).

5.5 Settlement and technical architecture

With regard to the settlement of digital euro payments, final settlement for online and offline payments would occur at different times. For online payments, final settlement would take place when the transfer is recorded in the Eurosystem infrastructure, and for offline payments, after the local updating of balances on the payer's and payee's devices (European Commission, 2023a: Art. 30).

According to the technical concept developed during the preparatory phase, **the continuity of the online digital euro service would rest on a centralised ledger, distributed across a multi-regional infrastructure with servers on multiple physically separated sites**. In this way, business continuity would be ensured even in the event of a collapse of the data-processing infrastructure – because transactions would be redirected to servers in regions where there are no disruptions. The centralised ledger was chosen because holding a digital euro means holding a direct liability of the central bank, which means that the Eurosystem must be able to correctly record, and thus verify, all settlements relating to those liabilities (ECB, 2025c: 17–19).

It follows from the above that the envisaged digital euro model seeks to combine the security of central bank money with the existing network of private intermediaries and user interfaces. Its practical usability will depend on the ease of switching between digital euro, bank deposits and cash, the quality of the online and offline user experience, and the calibration of the holding limits so as to protect the financial system without diminishing the usefulness of the payment instrument.

6 Impact on the payment services market

The above exposition of the features and functionalities of the digital euro, at least according to the current decisions of the competent institutions, has shown that the introduction of the digital euro would not, by its effects, be limited solely to the emergence of a new payment instrument, but would partially rearrange the institutional and economic structure of retail payments in the euro area. The Eurosystem would provide the monetary value, common rules, central infrastructure and settlement, while banks and other payment service providers would retain direct relationships with users and merchants. The digital euro is therefore conceived as a public infrastructure layer embedded in the existing payment ecosystem, but its introduction would inevitably affect the costs, revenues and market position of existing intermediaries (ECB, 2025b: 3–5, 30).

6.1 Impact on banks and other payment service providers

Banks would have a central role in the distribution of the digital euro. Credit institutions that already provide payment account services would be obliged to offer clients, upon their request, basic digital euro services, while other authorised payment service providers could participate at their own commercial discretion. Articles 14 and 17 of the proposed Regulation provide for **free basic services for natural persons, with intermediaries being able to**

develop and charge for additional services, including certain forms of conditional payments (European Commission, 2023a: 24, 26).

An important advantage for intermediaries would be the ability to integrate the digital euro into their existing mobile phone applications, e-banking and wallets, thereby maintaining a direct relationship with clients. **At the same time, a dedicated Eurosystem interface is foreseen, which would provide a uniform fallback access option and thus reduce the development costs borne by smaller institutions**. There is no consensus regarding the mandatory support for this interface: the ECB, consumer representatives and merchants emphasize resilience, inclusion and a consistent user experience, while intermediaries cite additional costs and a possible weakening of client relationships. The final solution will depend on the legislative process (ECB, 2025b: 25–28).

The introduction of the digital euro would require significant initial investments in user interfaces, user identification and onboarding, liquidity management, limit controls, fraud prevention and customer support. The ECB estimates that the total investment by the euro area banking sector could amount to between EUR 4 bn and EUR 5.8 bn, i.e. between EUR 1 bn and EUR 1.44 bn per year over four years. This level of costs is "comparable to the costs of initiatives such as the introduction of PSD2 and lower than the investments for SEPA harmonisation" (ECB, 2025c: 32).

The costs would not be evenly distributed. Fixed investments could be spread across a wider customer base by large banks, while for smaller banks and payment institutions they would represent a relatively greater burden. **For this reason, the option of "digital euro as a service" is being developed**, whereby an intermediary would procure part of the necessary functions from a specialised technical provider or processor, rather than developing the entire system independently. Such a model could reduce investment and maintenance costs, particularly for smaller intermediaries, but would require managing the risks of outsourcing, business continuity and concentration of services with a limited number of providers (ECB, 2025b: 30, 35–37). In addition, a common infrastructure could create scope for new services that could be charged (Ibid: 10, 30–31).

The net impact on intermediaries' revenues cannot be unambiguously determined. Part of existing electronic payments could shift to the digital euro, while free basic services and the limitation of fees would narrow certain sources of revenue. Conversely, intermediaries would be compensated for distribution, the Eurosystem would not charge them for the bulk of its own costs, and they could develop additional services. The final effect will depend on the degree of usage, the fee model and the ability of institutions to leverage the new infrastructure (ECB, 2023c: 12; ECB, 2025b: 30–33).

6.2 Fee model and merchant position

The proposed fee model seeks to balance three objectives: free basic use for natural persons, an appropriate fee structure for intermediaries, and protection of merchants from excessive costs. Since basic services would not be charged to natural persons, **an intermediary fee is foreseen, which would be paid by the merchant's payment service provider to the payer's payment service provider, while the merchant would pay a**

merchant fee to its acquirer. Both fees would be capped at the lower of two amounts: the relevant costs with a reasonable profit margin, or the fees for comparable private cashless payment instruments. **The cost-based limit would be based on the costs of the most efficient providers** that together distribute one-quarter of the digital euro in the euro area (European Commission, 2023a: Art. 17; ECB, 2023c: 12).

The fee cap is linked to the envisaged status of the digital euro as legal tender. If intermediaries had full freedom to set the price of accepting digital euro payments, merchants, who are in principle obliged to accept digital euro, would be in a weak negotiating position. At the same time, intermediaries require adequate compensation to have an incentive to actively distribute the digital euro and provide a quality service. A certain advantage for merchants would be the simpler cost structure: the Eurosystem would not charge fees related to scheme or processing operations, although acceptance would not be free, as merchants would still pay for the services of their intermediaries (ECB, 2023c: 12; ECB, 2025b: 30–31, 41–42).

As banks and other payment service providers warn, it has been observed that a single upper fee cap may not sufficiently reflect differences between national markets, cost structures and the allocation of responsibilities in cases where payment accounts and digital euro accounts are held with different institutions. Merchants, by contrast, consider the cap necessary and expect lower and more transparent costs than existing comparable payment instruments. The economic sustainability of digital euro distribution will, accordingly, depend on the final solution reached by the European legislative bodies (ECB, 2025b: 30–33).

6.3 Competition, interoperability and market structure

The digital euro could simultaneously be both a competitor to existing payment instruments and an infrastructure on which private providers develop their own solutions. Common standards and a broad acceptance network could create a common acceptance layer for account-to-account (A2A) payments, available at brick-and-mortar points-of-sale and in e-commerce. European payment solutions could thus expand their geographical reach without having to independently establish an acceptance network in each country (ECB, 2025b: 3, 10–13; ECB, 2025c: section 6.2.1).

Nevertheless, the objective on which European institutions insist – that the digital euro should not crowd out private payment instruments – has an objective limit: in each transaction, the user chooses only one payment instrument. This means that the digital euro inherently competes with private solutions. Hence, the more interesting question is whether the digital euro can be calibrated so as to help reduce the fragmentation of the European payments market, without distorting incentives for innovation in the private sector.

The ECB emphasizes that the digital euro can make a difference, given that there is currently no pan-European market solution that satisfies the use cases at which the digital euro is aimed, namely person-to-person (P2P) payments, online payments and payments at brick-and-mortar points-of-sale. Nonetheless, **the possibility is foreseen of voluntary co-badging of the digital euro and a domestic or regional payment scheme on the same physical card**. The private scheme could be used where it already has an acceptance network, with the digital euro as a fallback solution in the rest of the euro area. This could enable certain European schemes to achieve pan-European reach, although some intermediaries remain sceptical due to technical complexity, costs and branding concerns (ECB, 2025b: 28–29).

The impact on competition would not be automatically positive. A common infrastructure could lower barriers to cross-border expansion and increase the negotiating power of European intermediaries and merchants, but high fixed costs, integration complexity and reliance on a limited number of technical providers could also favour the largest companies, i.e. financial institutions. Existing global operators would still possess strong brands, large user bases and established merchant relationships, so the mere existence of a public infrastructure does not guarantee a significant shift in market shares. Hence, it can be concluded that the final effect on market structure will be influenced by access rules, interoperability, the level and structure of fees, and the roll-out schedule of functionalities. A successful model will require common public standards, broad acceptance and low barriers to entry, but also sufficient scope and economic incentive for the private sector to differentiate and innovate. Failing that, the digital euro could increase costs without materially weakening the existing market concentration; if the balance is struck, it could contribute to market integration and reduce dependence on non-European networks – an emphasis that has become increasingly noticeable, particularly in recent years.

7 Impact on the banking sector and financial stability

The most important risk associated with the introduction of the digital euro arises from the possibility that households may convert part of their commercial bank deposits into a direct liability of the central bank. If this shift were large or sudden, it could change the funding structure of banks, increase their costs and indirectly affect loan supply and financial system stability. This means that the risk depends not only on the existence of the digital euro, but also on the demand for it, the level of the holding limit and the general conditions in the banking system. For this reason, a distinction should be made between the effects under normal circumstances and the possible consequences during periods of financial stress.

7.1 Impact on banking intermediation under normal circumstances

Converting cash into digital euro would not, in itself, have significant consequences for banking intermediation, as one form of central bank liability would merely be exchanged for another. The significant effect comes from topping up the digital euro with funds from a bank account, as this reduces the deposit liability of the commercial bank and its reserves with the central bank, while the corresponding amount appears as a liability of the Eurosystem. The bank then loses part of its funding sources and may use available liquidity, obtain funds on the market or from the central bank, offer more favourable terms to depositors, or adjust its assets and lending policy (Adalid et al., 2022: 15–28; BIS, 2021: 6–11). This means that, **at this point, it is not possible to determine the impact of the issuance of the digital euro on bank operations**, given that this impact depends on banks' business models, their deposit structure, available collateral and access to market funding.

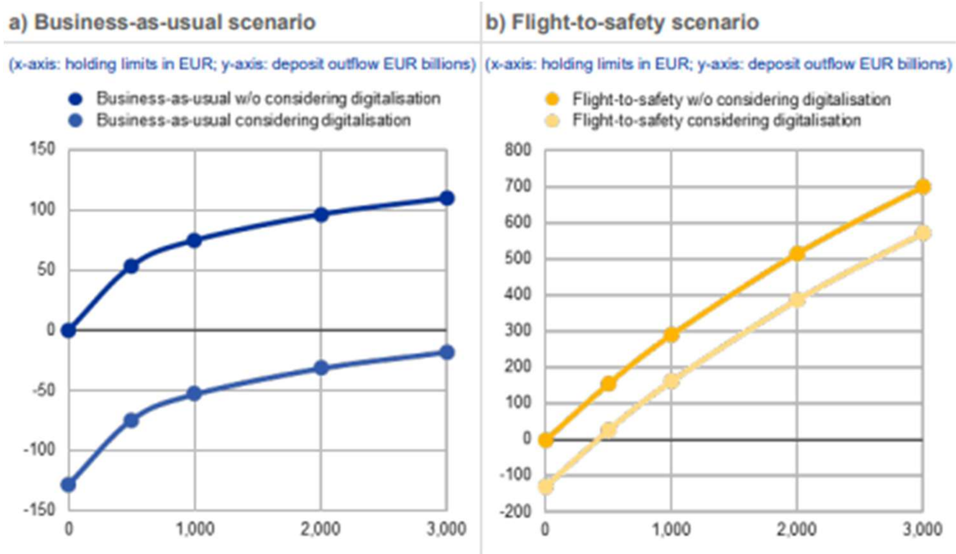
In the ECB's analysis, the consequences of various digital euro holding limits were examined, based on data obtained from the supervision of 2,025 banks. The analysis covered a) a business-as-usual scenario, and b) a conservative (flight-to-safety) scenario in which users prefer to hold the maximum possible amount of the digital euro (Figure 2). In both scenarios, the hypothetical effects of different holding limits were considered in two situations – the first, with the then-current level of digitalisation, and the second, assuming a continued trend of further digitalisation up to 2034.[9] In the business-as-usual scenario, if the existing trend of digitalisation continues, **no aggregate net outflow of deposits is expected under limits of up to EUR 3,000**. This result is based on the estimated inflow of EUR 127 bn, the distribution of which among banks is uncertain. When this compensating trend is excluded, under a hypothetical limit of EUR 3,000, the aggregate Liquidity Coverage Ratio (LCR) declines from 166% to 163%, and the Net Stable Funding Ratio (NSFR) from 128% to 127%.[10] The authors of the analysis note, however, that the results should be treated with caution, as they are not methodologically fully developed forecasts, particularly not on a bank-by-bank basis (ECB, 2025e: 1–4, 8–17).

Risks would be mitigated by the mechanisms described in the fifth chapter; the absence of interest would diminish the attractiveness of the digital euro as a savings instrument, the individual holding limit would directly constrain the amount that could be permanently shifted out of the banking system, while the waterfall and reverse waterfall mechanisms would enable payments without the need for a high digital euro balance. As regards business users and public authorities, the zero online holding limit would prevent a more permanent shift of their liquidity, with a limited technical exception for funds received offline (European Commission, 2023a: Arts. 15–16; ECB, 2023a: 12–15, 23–24).

[9] Digitalisation of payment products and services implies a reduction in the use of cash, which in turn leads to higher levels of deposit inflows into accounts (negative values on the x-axis in Figure 2).

[10] The LCR and NSFR are regulatory indicators introduced by the Basel III regulatory framework from 2010.

Figure 2 **Estimated impact of digital euro holdings on bank deposit outflows**



Source: ECB (2025e), p. 7.

7.2 Risk of accelerated deposit outflows and protection mechanisms

The digital euro could be particularly attractive during a period of loss of confidence in the banking system, as it would represent an easily accessible liability of the central bank which, unlike the assets of private issuers, is not exposed to the credit risk of the private issuer. An unlimited ability to instantly transfer deposits into such a form of money could increase the speed and scale of withdrawals. Modelled analyses show that unlimited demand for retail central bank digital currency could amplify a "run on banks," while a firm individual holding limit would significantly constrain that channel. However, the digital euro would not be the cause of the initial loss of confidence, but rather one of the possible forms of assets into which funds are transferred after a crisis has occurred (Adalid et al., 2022: 35–40; BIS, 2021: 8–9).

At the request of European legislators, the ECB examined an extremely conservative "flight-to-safety" scenario, in which every individual with sufficient funds simultaneously seeks to reach the full digital euro limit, with no assumed monetary policy reaction. In this scenario, a net outflow of deposits, as expected, occurs at a limit level of around EUR 400, under the situation of continued further digitalisation. In a situation without noticeable progress in digitalisation, household deposit outflows would amount to EUR 156 bn at a limit of EUR 500 and EUR 699 bn at a limit of EUR 3,000 (Figure 2, panel b); the latter amount corresponds to 2.2% of total banking sector assets and 8.2% of covered sight deposits. Aggregate liquidity indicators would remain above the prescribed minimums, but thirteen out of the 2,025 analysed banks would reach a Liquidity Coverage Ratio of 100%, while nine would be at risk of falling below this level due to insufficient eligible collateral (ECB, 2025e: 5–13).

In addition to the holding limit and the interest-free design, the available liquidity of the Eurosystem would also mitigate the risk. If the conversion of deposits reduced banking sector reserves, banks could use their own reserves, the interbank market and standard Eurosystem operations, provided they have adequate collateral. This would not automatically resolve the problem for each individual bank, but it would enable the mechanical decline in reserves caused by the conversion of deposits into digital euro to be mitigated at the system-wide level (Adalid et al., 2022: 15–20; ECB, 2025e: 11–13).

Overall, the analyses considered do not indicate that the digital euro, in its envisaged transactional form, would necessarily threaten financial stability. This conclusion is conditional upon effective holding limits, the interest-free design, banks' access to liquidity and the gradual introduction of the digital euro itself. In this sense, the calibration of the digital euro so that it is a usable means of payment, rather than a significant store of value or a channel for uncontrolled deposit outflows, is seen as the real task ahead.

8 Privacy, security and accessibility of the digital euro

The uptake of the digital euro will depend not only on functionality and costs, but also on user confidence that their data are protected, that the system is resilient to disruptions and abuse, and that it is accessible to individuals with varying levels of technical capability. Privacy, security and accessibility are therefore interconnected design requirements. Achieving them requires a balance between data protection and the prevention of illicit activities, high security standards and ease of use, as well as digitalisation and inclusiveness.

In the literature of pan-European institutions, it is emphasized that, **in the case of the online digital euro, the user would not be anonymous vis-à-vis the bank** or other payment service provider. The intermediary would carry out identification and process the data necessary for the execution of payments, the application of limits, fraud prevention, and the fulfilment of obligations in the area of anti-money laundering and counter-terrorist financing. The intermediary must do so in accordance with AML/KYC procedures, as well as the General Data Protection Regulation (GDPR). The transaction would be processed within the **Digital Euro Service Platform** (DESP), to which intermediaries would send, for settlement, data protected by pseudonymisation and encryption, so that the user's identity is separated from the payment data. In this way, **the Eurosystem is prevented from directly linking a transaction to a specific individual** (European Commission, 2023a: Arts. 34–36; ECB, 2025c: 18). This solution does not imply anonymity of online payments: intermediaries would still know the identity of their payment service users and would apply regulatory obligations. The aforementioned proposed Regulation, in Articles 34, 35 and 36, specifies the purposes and categories of data that may be processed by payment service providers, the ECB, national central banks and providers of ancillary services, with the application of technical and organisational measures that prevent the direct identification of users in the central infrastructure.

The offline mode would be significantly closer to the privacy of cash payments. The data necessary for the execution of the transaction would be processed locally and remain in the secure components of the payer's and payee's devices. Details of an individual payment would not be transmitted to intermediaries or the Eurosystem, while intermediaries would process data on the topping up and withdrawal of funds from the device on which digital euros are held for offline use, but not data on specific offline transactions. The higher degree of privacy would, therefore, relate to the use of locally stored funds, rather than to the complete absence of user identification (European Commission, 2023a: Art. 37; ECB, 2025c: 18).

The European Data Protection Board and the European Data Protection Supervisor have positively assessed the embedding of the principles of data protection by design and by default, particularly in the offline mode. At the same time, they have called for a clearer determination of the legal basis for processing, the allocation of responsibilities and the types of data that each participant may process. **They have also proposed that the obligation of pseudonymisation of data available to the Eurosystem be explicitly included in the normative part of the Regulation**, and that the common fraud detection mechanism be more precisely regulated (EDPB-EDPS, 2023: 3–4). This proposal, like the other features presented in this paper, must be understood as preliminary and not as matters on which a definitive decision on the design of the digital euro has been taken.

As regards security, it implies protection against unauthorised access and fraud, but also the ability of the system to continue operating during technical failures, cyber-attacks and other disruptions (business continuity). The envisaged approach of the ECB and other relevant institutions is based on data minimisation and separation, multi-layered risk management, cryptographic protection, regular security testing and geographically separated processing capacities. In the event of a failure of part of the infrastructure, processing should be redirected to the available capacities, thereby preserving the continuity of core payment services (ECB, 2025c: 17–18).

Offline payments pose a particular security challenge, as the transaction is executed without real-time verification in the central system. The offline environment would need to enable cryptographic operations, secure key storage and the integrity of payment execution, so that in the event of an interruption the operation is either completed in full or not executed at all. The secure components of the phone, card or other device would need to be resistant to unauthorised physical modifications and other forms of attack (ECB, 2025d: 6; ECB, 2025c: 16–17).

As availability cannot be reduced to the formal right to open an account or a digital wallet, **the digital euro service would need to be accessible regardless of age, physical abilities and level of digital literacy**. The accessibility strategy encompasses physical and cognitive accessibility, a simple interface and multiple means of accessing the service, including direct assistance. Access should not depend on owning a smartphone, and the proposed Regulation foresees institutional support for persons without a payment account, persons with disabilities, and users with insufficient digital skills (ECB, 2025c: 21–22; European Commission, 2023a: Art. 14).

Given the above, privacy, security and accessibility cannot be viewed in isolation. Broader data processing may facilitate fraud detection, but diminish privacy; more complex security procedures may increase protection, but make use more difficult; a fully digital approach may lower costs, but exclude part of the population. The potential advantage of the digital euro would, therefore, lie in the ability to combine a high degree of privacy, the resilience of the public payment infrastructure and institutionally ensured accessibility. Whether this advantage will be realised will, nevertheless, depend on the final legal framework and the technical implementation of the protective mechanisms.

9 Conclusion

The paper has presented the digital euro as an effort to adapt directly accessible central bank money and its payment infrastructure to an increasingly digitalised environment. Its purpose is not to replace cash or private bank money, but to supplement them with a digital form of public money that would be universally accepted across the entire euro area. In this sense, the project has monetary, infrastructural and market dimensions – and likely a geopolitical one as well, given the increasingly vocal emphasis on sovereignty.

The phases of the digital euro project carried out so far have shown that it is possible to shape an operational model based on dual-layer distribution: the Eurosystem would issue the monetary value and provide the core infrastructure, while banks and other private intermediaries would retain the relationship with users. The online and offline modes, common standards, service portability and mechanisms for linking to bank accounts should ensure usability, but the final word on design still rests with the ECB Governing Council.

The most sensitive issue of market design will remain the allocation of costs and incentives. Free basic services for natural persons and the fee cap are intended to encourage use and protect merchants, but intermediaries must, at the same time, have a sustainable model for distribution and the development of additional services. A common infrastructure could lower barriers to cross-border expansion of European solutions and reduce dependence on non-European networks, but high fixed costs and concentration of technical providers may favour large players.

Risks to banking intermediation and financial stability cannot be ruled out, but the project design incorporates mechanisms to mitigate them. The absence of interest on holdings, individual limits and automatic transfer mechanisms should prevent the digital euro from becoming a significant store of value or a channel for large deposit outflows. The analyses carried out so far indicate that the aggregate effects under the scenarios examined could be managed, but the final calibration must depend on conditions closer to a possible issuance date and on the position of individual banks.

The acceptability of the digital euro will also depend on whether the envisaged level of privacy, security and accessibility is achieved in practice. The distinction between the online model, in which intermediaries must know the identity of users, and the offline model with local data processing is of fundamental importance. At the same time, a high level of protection must not make the service complex nor exclude persons who do not have a smartphone, a bank account or developed digital skills.

For Serbia, the digital euro is important as a change in the European payment environment, but the specific local consequences cannot yet be reliably determined. Access by Serbian residents would depend on the future legal framework and special arrangements with third countries. Domestic payment service providers and the National Bank of Serbia should, nevertheless, monitor the development of technical standards, the possible impact on cross-border payments and the risk that simpler use of the euro in digital form may affect the currency structure of the financial system. Hence, a gradual approach – without prejudging future access to the system or the need for a domestic central bank digital currency – seems justified.

The final assessment of the digital euro will depend less on whether it is technically feasible, and more on whether the legal and economic model succeeds in reconciling useability, privacy, intermediary sustainability, competition and financial stability. Only after the adoption of the Regulation, piloting and observation of actual user behaviour will it be possible to assess whether the digital euro truly becomes a functional public pillar of European payments, or remains a project with limited use capacity.

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WORKING PAPER

DEBT ASSUMPTION IN FINANCIAL ACCOUNTING AND GOVERNMENT FINANCE STATISTICS FRAMEWORKS AND STRENGTHENING INTEROPERABILITY BETWEEN FINANCIAL REPORTING AND STATISTICAL SYSTEMS

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Available at www.nbs.rs

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Debt assumption in financial accounting and Government Finance Statistics frameworks and strengthening interoperability between financial reporting and statistical systems

Tomo Vujović

Abstract: This paper analyses the treatment of debt assumption in Government Finance Statistics (GFS) and national accounts, with particular emphasis on its differences from financial accounting. Debt assumption occurs when general government assumes responsibility for debt originally incurred by, in particular, public non-financial corporations, resulting in the reallocation of the liability between institutional sectors.

The paper compares the statistical treatment under GFS and ESA 2010 with financial reporting practices in Serbia, highlighting differences in recognition, timing, classification, and cash to accrual adjustments. Practical examples illustrate the reconciliation of accounting records with statistical requirements.

A key contribution is the proposal to strengthen interoperability between financial reporting and macroeconomic statistics through bridging tables linking financial accounting classifications with GFS, ESA 2010, and related statistical classifications. The paper also proposes improvements in the structure and disaggregation of national financial reports, particularly in the context of IFRS 18 implementation.

The paper argues that financial accounting and macroeconomic statistics should retain their distinct objectives while being more closely connected through consistent classifications, reconciliation procedures, and sufficiently detailed source data. Such interoperability can improve the quality, consistency, and efficiency of national accounts, GFS, and balance of payments statistics and strengthen their use for economic analysis, forecasting, research, and macroeconomic policymaking.

Keywords: Financial accounting, national accounts – NA, government finance statistics – GFS, debt assumption, cash to accrual adjustment, government guarantees, journal entries, capital transfer expenditure, net lending/borrowing.
[JEL Code]: M41, E01, G30.

Non-technical summary

The paper examines how debt assumption is recorded in Government Finance Statistics (GFS) when the government effectively takes responsibility for debt originally incurred by a public non-financial corporation, particularly when a government guarantee is called because the corporation cannot meet its obligations.

A central issue is the different perspectives of financial accounting and macroeconomic statistics. Financial accounting focuses on individual reporting entities and legal and contractual arrangements, whereas national accounts and GFS focus on the economic substance of transactions and the sector that ultimately bears the economic risk. As a result, a liability may remain on a corporation's financial statements while being reallocated to the government for statistical purposes once the government has effectively assumed the economic burden.

The paper shows that debt assumption can affect government debt and fiscal indicators even before a formal legal transfer occurs. Practical examples illustrate differences between accounting and statistical recording, including cases involving partial or no repayment.

The analysis then addresses the broader interoperability between financial reporting and macroeconomic statistics. IFRS and IPSAS-based financial statements are important sources for national accounts and GFS; their quality, consistency, and level of detail therefore directly affect statistical compilation. Financial information that is sufficiently detailed and structured for systematic mapping to statistical classifications can reduce reliance on additional data collection, estimation, and reconciliation adjustments.

The paper also illustrates the practical link between financial accounting information and statistical measurement through cash to accrual adjustments. This is particularly important when governments use modified cash accounting and undertake substantial capital expenditure, as the timing of cash payments may differ significantly from the timing of the underlying economic activity. Such differences can materially affect the measurement of government expenditure, net lending/net borrowing, and gross fixed capital formation (GFCF). Accounts payable and advances help identify whether expenditure relates to economic activity already incurred or to payments made in advance, allowing cash-based information to be converted into an accrual measure consistent with national accounts. This improves the measurement of government consumption and investment and, consequently, their contribution to GDP and related aggregates such as GNI and GNDI.

Overall, the paper argues that financial accounting and macroeconomic statistics should retain their distinct purposes while becoming more interoperable. Stronger links between the two systems can improve the measurement of economic activity and government exposure, reduce unnecessary statistical adjustments, and provide a more reliable basis for macroeconomic analysis, forecasting, research, and policymaking.

Contents

1 Introduction

Debt assumption is an important transaction in National Accounts (NA) and Government Finance Statistics (GFS) because it can significantly affect government debt, fiscal balances, and the distribution of financial risk across institutional sectors. Under paragraph 20.222 of ESA 2010, debt assumption occurs when one unit assumes responsibility for another unit's outstanding liability, including cases where a government guarantee is called or activated.

The statistical treatment is based on the economic substance of the transaction. According to the 2022 Eurostat Manual on Government Deficit and Debt (MGDD), in certain circumstances, a liability may be reallocated to the government when economic responsibility has been effectively transferred, even before a formal legal transfer. The assessment considers factors such as the likelihood of recovery and the debtor's capacity to service the debt.

This economic substance approach highlights an important distinction between macroeconomic statistics and financial accounting. IFRS and IPSAS-based reporting apply recognition and measurement principles to individual entities within defined reporting boundaries, whereas NA and GFS classify transactions according to institutional sectors and their economic impact. Consequently, the same event may have different timing or classification in accounting and statistical reporting.

These differences are important because financial statements are major sources for NA, GFS, and balance of payments statistics. Their quality, consistency, and level of detail directly affect statistical compilation. Where accounting information is insufficient for statistical classification, additional data, estimates, and reconciliation procedures may be required.

The issue is particularly relevant in Serbia, where differences between modified cash government reporting and accrual based statistical recording require cash to accrual adjustments. Accounts payable and advances provide important information for determining when expenditure is economically incurred rather than paid, which is essential for accurately measuring government consumption, investment, GDP, and related macroeconomic aggregates.

Against this background, the paper analyses debt assumption in Serbia and compares its treatment under GFS, ESA 2010, IFRS, IPSAS, and relevant national accounting practices. Practical examples illustrate the related accounting entries and cash to accrual adjustments.

A key contribution is the proposal to strengthen interoperability between financial reporting and macroeconomic statistics through systematic bridging tables linking accounting classifications with GFS, ESA 2010, and related statistical classifications. The paper also proposes greater disaggregation of financial reports where existing aggregates are insufficient for statistical compilation. These measures could reduce *ad hoc* adjustments and additional data collection while improving the consistency, efficiency, and reliability of macroeconomic statistics.

The following chapter examines the financial accounting treatment of debt assumption and provides the basis for the subsequent comparison with its statistical treatment under NA and GFS.

2 Treatment of debt assumption under the financial accounting framework

The accounting treatment of debt assumption differs significantly from its treatment under statistical frameworks such as the System of National Accounts (SNA 2008/2025), ESA 2010/2030, and GFSM 2014. The principal difference arises because financial accounting considers the recognition and measurement of transactions from the perspective of individual reporting entities, whereas statistical frameworks assess their economic substance and sectoral implications.

2.1 Government perspective

In financial accounting, recognition of a government's assumption of a corporate liability depends primarily on the legal form of the transaction. Where no formal legal assumption of the debt occurs, the liability typically remains on the balance sheet of the original debtor, even if the government makes payments to the creditor. In such cases, the government may recognize a financial asset or receivable reflecting its claim against the corporation for amounts paid on its behalf.

Conversely, where a legally binding debt assumption or novation agreement exists, the liability is derecognized from the corporation's balance sheet and recognized by the government, potentially together with a corresponding financial asset when recovery is expected.

In government financial reporting systems in Serbia, such transactions are generally recorded using a modified approach combining accrual-based accounting and budgetary classifications. Payments made by the government on behalf of a corporation are recorded as expenditures, while corresponding claims are recognized as financial assets or receivables, subject to their recoverability.

Table 1 presents an illustrative scenario in which the government makes a payment of EUR 100,000 to a creditor on behalf of a corporation with an underlying guaranteed debt of EUR 1,000,000.

Within modified government accounting systems, the treatment of this transaction depends on whether a legally enforceable claim against the corporation exists. In the hypothetical and fictitious example presented in this study, it is assumed that the government takes over the entire debt and, in return for the payment made on the corporation's behalf, acquires a corresponding claim against the corporation. The corporation is further assumed to partially repay EUR 10,000 of this obligation to government.[11]

This framework is designed to illustrate three distinct levels of amounts applied to each journal entry, in order to demonstrate how the accounting treatment of debt assumption and guarantee activation varies under different magnitude scenarios. It is intended to present the full accounting mechanics of these transactions in a structured way, rather than reflect the empirical outcome, where repayment is partial or absent[12].

In practice, corporations whose obligations are settled by government intervention frequently do not fully repay the amounts due to financial constraints or insolvency. The accounting entries presented in Table 1 illustrate the treatment under the Serbian modified government accounting framework and reflect the accounting treatment applied in the illustrative case; they should not be interpreted as a generic IPSAS treatment. For this reason, the analysis presents two alternative scenarios: (a) partial repayment and (b) no repayment.

Table 1 **Recording of transactions under the government financial accounting framework, Modified system of financial accounting** (amounts in EUR)

GOVERNMENT - FINANCIAL ACCOUNTING FRAMEWORK - JOURNAL ENTRIES			
TYPE OF ITEM	**DESCRIPTION**	**DEBIT**	**CREDIT**
Asset	Recognized but unpaid obligation for guaranteed debt	1,000,000	
Liability-loan payable	Obligation for the new debt		1,000,000
Contra-liability account for loan payable	Obligation for the guaranteed debt	100,000	
Cash account	Payment from the government cash account to the creditor		100,000
Expense	Repayment of principal for guaranteed debt	100,000	
Contra-asset account	Recognized but unpaid obligation for guaranteed debt		100,000
Financial transaction	Repayment of principal for guaranteed debt	100,000	
Contra-item for the financial transaction	Repayment of principal for guaranteed debt-closing item		100,000
Asset	Recourse right for paid guarantees - Investment receivable	100,000	
Liability	Deferred other income and receipts		100.000
Cash account	Received money from the corporation for a claim	**10,000**	
Contra-asset account	Recourse right for paid guarantees		**10,000**
Contra-liability account	Deferred other income and receipts	**10,000**	
Revenue	Revenue from received payment		**10,000**

[11] The journal entries in Table 1 are based exclusively on the example provided in the text and reflect all assumptions stated therein. They may therefore differ from official accounting procedures in certain respects. Overall, the accounting procedure presented in Table 1 reflects the modified cash accounting method in nature.

One segment of the journal entries in Table 1 records the expense associated with the repayment of the principal of guaranteed debt (blue background). The author took into account that the Ministry of Finance presents this payment as an expense in the official dataset published on its website. Furthermore, the Treasury's P&L financial report also treats this amount as an expense when calculating the final financial result.

[12]In Serbian practice, the accounting procedure begins when the government initiates payment to the creditor. Table 1 illustrates this process through journal entries recorded for an amount of EUR 100,000. To simplify the presentation and focus on the core accounting and statistical treatment of the transaction, the author provides an example that includes only the principal amount and excludes interest payments and accruals.

At the end of the whole accounting operations presented in Table 1 the following aggregate financial positions and flows are obtained:

1. The government initially recognises the assumed liability of **EUR 1,000,000**. Following payment of **EUR 100,000** to the creditor, the outstanding liability is reduced to **EUR 900,000**;
2. A financial claim on the corporation is recognized in the amount of **EUR 90,000**, reflecting the initial claim of **EUR 100,000** reduced by the repayment of **EUR 10,000**;
3. A cash outflow of **EUR 100,000** is recorded corresponding to the payment made by the government to the creditor and
4. The impact on financial result of the transaction is **EUR -90,000**, reflecting an expense of **EUR 100,000** and a repayment inflow (revenue) by corporation of **EUR 10,000**.

In a case where there is no payment from corporation to the government, which is the more realistic scenario, we would have next positions:

1. The government records a liability of **EUR 900,000** corresponding to the remaining obligation after partial settlement;
2. A financial claim on the corporation of **EUR 100,000** is recognized, subject to impairment assessment depending on recoverability and
3. A cash outflow of **EUR 100,000** is recorded for the payment made to the creditor.
4. The impact on financial result of the transaction is **EUR -100,000**.

Even where collection of claims from corporations is considered unlikely in practice, under the government accounting framework the recognition of a claim against the corporation arising from paid guarantees, recorded as a debit entry together with the corresponding credit entry to Other deferred income and receipts, is necessary to complete the accounting procedure.

From a public sector accounting perspective, recognition of a receivable reflects the expectation of future recovery of amounts paid on behalf of the corporation. Where recovery is uncertain, the receivable may be subject to impairment or non-recognition depending on the applicable accounting and prudential requirements

2.2 Corporation perspective

Table 2 illustrates the accounting treatment under an accrual-based financial reporting framework where a government makes a payment to a creditor on behalf of a corporation without a formal legal debt assumption agreement. Unlike in Table 1, the full amount of the debt assumption is not recorded in the first journal entry. As such, an entry would not be consistent with the IFRS approach, while the statistical example for the corporation includes a corresponding entry.

Under IFRS/IAS principles, the accounting treatment depends on the substance of the transaction. In the absence of a legal debt assumption or other form of contractual novation, the corporation's obligation to the original creditor is not automatically extinguished. An assessment is therefore required to determine whether the government's payment represents a settlement of a part of the liability and whether a corresponding reimbursement obligation arises.

Accordingly, the government's payment may result in partial settlement of the existing liability to the creditor and recognition of a separate liability to the government, where the corporation is required to reimburse the amount paid on its behalf.

Table 2 **Recording of transactions under the corporation financial accounting framework, accrual method of financial accounting** (amounts in EUR)

CORPORATION - FINANCIAL ACCOUNTING FRAMEWORK JOURNAL ENTRIES			
TYPE OF ITEM	DESCRIPTION	DEBIT	CREDIT
Contra-liability account for loan payable	Removing the part loan from the liabilities side	100,000	
Revenue	Removing the loan liability without payment		100,000
Expense	Expense for the new obligation to government	100,000	
Other obligation	Obligation to the government for paid debt		100,000
Contra-liability account	Other obligations	**10,000**	
Cash account	Payment of obligation to the government		**10,000**

At the end of the accounting process presented in Table 2, the following positions are observed:

1. The corporation's liability to the original creditor is reduced to **EUR 900,000**, reflecting the portion of the obligation settled through the government's intervention, while the remaining liability continues to represent the unpaid balance of the original debt;
2. A separate liability to the government is recognized in the amount of **EUR 100,000**, representing the corporation's obligation to reimburse the government for payments made on its behalf. Where partial repayments are made (e.g. **EUR 10,000**), this liability is subsequently reduced, resulting in a remaining obligation of **EUR 90,000** and
3. The impact on financial results of the transactions is **EUR 0** (**100,000-100,000**) and cash outflow is **EUR 10,000**.

Where the corporation does not repay any amount to the government:

1. The liability to the creditor remains **EUR 900,000**;
2. A liability to the government of **EUR 100,000** is recognised and
3. The impact on financial results of the transactions is **EUR 0 (100,000-100,000)**.

This accounting treatment applies where there is no legal debt assumption. The corporation does not automatically remove its original liability. Whether the liability is derecognised and a new liability to the government is recognised depends on whether the government's payment settles the debt and whether the corporation has an obligation to reimburse the government under IFRS recognition criteria.

The accounting analysis therefore establishes an important distinction: legal form and enforceability are central to entity level recognition, while statistical treatment may subsequently require a different assessment based on economic substance and sectoral allocation. The following chapter applies these principles to the same illustrative transaction under NA and GFS.

3 Treatment of debt assumption under the statistical framework (national accounts/gfs)

3.1 Government perspective

Governments may intervene in the financing of public non-financial corporations by assuming or servicing their debt obligations. In such cases, the statistical recording depends on whether a financial claim is recognized and whether a legal debt assumption exists.

In this example, the government assumes responsibility for a corporation's debt in the amount of EUR 1,000,000 without acquiring a corresponding financial asset due to uncertainty regarding repayment. The transaction is therefore recorded as a capital transfer payable (D.9) from the government to the corporation.

The government subsequently repays EUR 100,000 of principal to the original creditor, while the corporation repays EUR 10,000 to the government. As no financial asset is recognized at inception, these flows are recorded as capital transfers (D.9). The EUR 10,000 repayment is included in the illustrative scenario to demonstrate the statistical treatment of a subsequent payment where no financial asset was recognized at the time of debt assumption. Accordingly, the payment is recorded as a capital transfer from the corporation to the government rather than as repayment of a recognized financial claim. Table 3 presents the statistical recording framework from the aspect of government.[13]

Table 3 **Recording of transactions under the government statistical framework** (amounts in EUR)

GOVERNMENT - STATISTICAL FRAMEWORK NA/GFS RECORDINGS			
TYPE OF ITEM	**DESCRIPTION**	**DEBIT**	**CREDIT**
Expense	Capital transfer expenditure	1,000,000	
Liability	New loan imputed on liability side by debt assumption		1,000,000
Loans payable (Contra-liability account)	Decreasing the assumed debt by payment from government cash account	100,000	
Cash account	Payment from government cash account to creditor		100,000
Asset	Other receivables from corporations	100,000	
Revenue	Capital transfer revenue		100,000
Expense	Capital transfer expenditure (claim not likely to be repaid)	100,000	

[13] The statistical recordings presented in Tables 3 and 4 are based on the example of a debt assumption given in the text, considering the financial accounting treatment in government accounts while adapting it to the relevant statistical standards.

GOVERNMENT - STATISTICAL FRAMEWORK NA/GFS RECORDINGS			
TYPE OF ITEM	DESCRIPTION	DEBIT	CREDIT
Liability	Other receivables from corporations		100,000
Asset	Cash account - collection of the payment from the corporation	**10,000**	
Revenue	Capital transfers revenue from collecting the cash from the original debtor		**10,000**

The statistical outcomes are as follows:

1. The government records a capital transfer expenditure (D.9)[14] of **EUR 1,000,000.** At the time of debt assumption, the government recognizes a liability of **EUR 1,000,000** to the original creditor, reflecting the transfer of responsibility for the outstanding debt.
2. Following the debt assumption, the government reduces its liability to the foreign creditor from **EUR 1,000,000** to **EUR 900,000** through a payment of **EUR 100,000** from its cash account**.**
3. The repayment of **EUR 10,000** by the corporation to the government is recorded as capital transfer revenue **(D.9)**, as no financial claim against the corporation was recognized and the payment is therefore treated as a capital transfer.
4. No financial claim against the public non-financial corporation is recorded because the claim is considered not likely to be repaid and is therefore not recognized as a financial asset (*in the given example it is shown like two consecutive recording operations which cancel each other out, in rows 4 and 5, blue backgrounds*).
5. The government Net lending/borrowing[15] (B.9) is **EUR −990,000 (-**1,000,000 + 10,000)

If no repayment is made by the corporation:

1. The government outstanding loan liability remains **EUR 900,000** (1,000,000-100,000).
2. The impact on Net lending/ borrowing (B.9) is **EUR −1,000,000** for the government.

3.2 Corporation perspective

In the absence of a legal debt assumption, the corporation's original liability remains unchanged in legal terms. For statistical purposes, however, where the government effectively assumes responsibility for the debt and no recoverable financial claim against the corporation is recognized, the corresponding debt is reallocated to the government, and the corporation records a capital transfer (D.9). Any subsequent payment by the corporation to the government is likewise recorded as a capital transfer rather than as repayment of a recognized financial

[14] According to the ESA 2010 national account framework, transaction D.9 (Capital transfers) may be recorded either as revenue or as expenditure, depending on the nature and direction of the transaction.

[15] Net lending/borrowing, according to the World Bank metadata glossary, equals government revenue minus expense, minus net investment in nonofficial assets. It is also equal to the net result of transactions in financial assets and liabilities. Net lending/borrowing is a summary measure indicating the extent to which the government is either putting financial resources at the disposal of other sectors in the economy or abroad, or utilizing the financial resources generated by other sectors in the economy or from abroad. This indicator is expressed as a percentage of Gross Domestic Product (GDP) which is the total income earned through the production of goods and services in an economic territory during an accounting period.

claim. Table 4 presents the statistical recording framework from the perspective of the corporation.

Table 4 **Recording of transactions under the corporation statistical framework** (amounts in EUR)

CORPORATION - STATISTICAL FRAMEWORK NA/GFS RECORDINGS			
TYPE OF ITEM	**DESCRIPTION**	**DEBIT**	**CREDIT**
Contra-liability account	Removing the loan from the liabilities section	1,000,000	
Revenue	Capital transfer revenue (decrease of liab.without payment)		1,000,000
Expense	Expense for the new debt to the government	100,000	
Other obligations	Obligation to the government for assumed debt		100,000
Contra-liability account	Obligation to the government for assumed debt	100,000	
Revenue	Removing the debt (claim not likely to be repaid)		100,000
Expenditure	Capital transfer expenditure	**10,000**	
Cash account	Payement for the obligation to the government		**10,000**

At the end of the whole statistical recording process presented in Table 4 as the result we have:

1. For statistical purposes, the corporation's outstanding loan liability is reduced to **EUR 0** because responsibility for the debt has been transferred to the government.
2. The debt assumption is recorded as a capital transfer revenue (D.9) in the amount of **EUR 1,000,000** by the corporation.
3. No financial liability to the government is recorded because no enforceable or repayable claim is recognized under the statistical treatment.
4. The corporation records B.9 of **EUR 990,000**, calculated as the capital transfer of **EUR 1,000,000** less the **EUR 10,000** payment made by itself to the government.

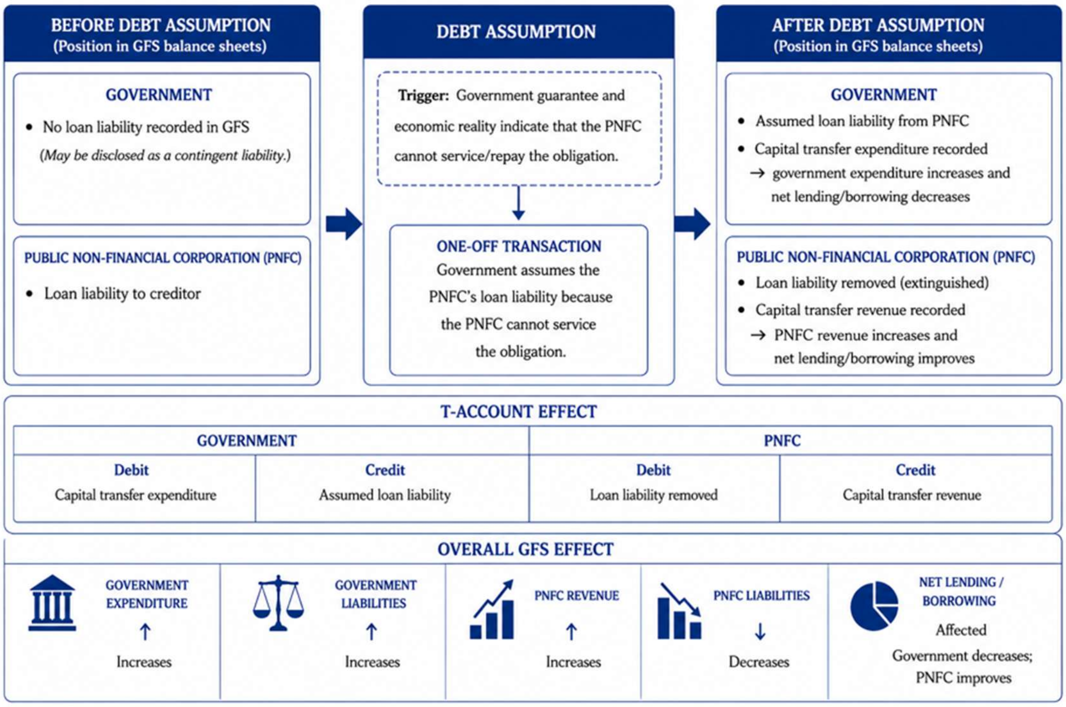
In the case where there is no payment from the corporation to the government in a realistic scenario, the resulting statistical position would be:

1. Outstanding loan liability: **EUR 0 (**1,000,000 − 1,000,000**)**.
2. No liability to government (no financial claim from the government towards the corporation is recognized).
3. B.9 equals **EUR 1,000,000,** because no **EUR 10,000** payment is deducted.

The comparison between Tables 1–4 demonstrates that the same economic event can produce materially different accounting and statistical results. The difference arises primarily from the recognition of financial claims, the assessment of recoverability, the legal status of the debt, and the statistical allocation of economic risk.

The statistical treatment must, however, also consider the institutional sector classification of the corporation. If a public non-financial corporation is itself classified within general government, the treatment of the transaction and its effect on consolidated government indicators can be substantially different.

Illustration 1 **Debt assumption under the GFS/NA framework**



4 Treatment of debt assumption when a public non-financial corporation is classified within the government sector for statistical purposes

Public non-financial corporations that receive substantial and persistent government support, including guarantees, subsidies, capital injections, or other financial assistance, may be classified within the general government sector under ESA 2010, particularly where they are non-market institutional units whose sales revenues do not cover a substantial share of production costs on a sustained basis. Railway and road infrastructure corporations are common examples. Such corporations may depend on government support to maintain operations and service their financial obligations. Creditors may therefore provide financing based partly on explicit or implicit government support rather than on the corporation's standalone financial capacity.

When a public corporation is classified within the general government, transactions with other government units are intra-sector transactions and are eliminated in consolidation. Consequently, liabilities already included within the general government perimeter should not be counted again in consolidated government debt. This is particularly important for government-guaranteed borrowing, requiring reconciliation of Public Debt Administration data with corporate financial statements to avoid double counting.

For public debt and GFS purposes, consolidated government finance statistics and Public Debt Administration records should therefore be considered together with corporate financial statements rather than mechanically aggregating individual corporate liabilities. A liability formally recorded by a corporation should not be counted again if it is already included in consolidated general government debt.

When the government services debt on behalf of such corporations, the corporation may record capital transfer or subsidy revenue, with corresponding government expenditure. These intra-sector flows are eliminated on consolidation and therefore do not affect consolidated net lending/borrowing, as they represent a reallocation of resources within the same institutional sector rather than the creation of a new external government liability.

Taken together with the preceding analysis, this example demonstrates that the statistical treatment of debt assumption depends on recognition rules, the existence and recoverability of financial claims, institutional-sector classification, and consolidation boundaries. Financial statements therefore cannot always be converted into macroeconomic statistics through mechanical aggregation, highlighting the need for stronger interoperability between financial reporting and statistical systems.

5 Closing remarks and general recommendations for improving the coherence and interoperability of accounting and statistical systems

The analysis of debt assumptions illustrates the broader difference between entity level financial reporting and macroeconomic statistics. Financial accounting applies recognition and measurement principles to individual reporting entities within defined legal and reporting boundaries, whereas statistical systems classify transactions according to institutional sectors and their economic substance. The objective should therefore not be to make the two systems identical, but to ensure sufficient interoperability to support reliable statistical compilation.

5.1 Financial reporting as a source for macroeconomic statistics

Strengthening IFRS/IAS and IPSAS-based financial reporting at the national level is essential for generating reliable source data for national accounts, balance of payments statistics, and GFS. This is consistent with ESA 2010 and the modernization priorities associated with ESA 2030, including improved data quality, greater use of administrative and accounting information, and more efficient statistical production.

National financial reporting systems should therefore enable accounting information, wherever practical, to be converted into statistical aggregates through transparent and systematic mapping. Financial instruments, transactions, and other economically relevant items should be identifiable at sufficient detail to permit appropriate statistical classification. Where accounting aggregates are too broad, additional disaggregation should be provided in the financial statements or in a supplementary Statistical Annex.

5.2 Disaggregation and statistical classification

The IFRS category "Cash and cash equivalents" illustrates the importance of disaggregation. It may include currency, deposits, and short-term debt securities, which are distinct financial instruments with potentially different counterpart sectors. Currency (F.21), deposits (F.22–F.29), and short-term debt securities (F.31) should therefore be identifiable separately rather than mapping the entire accounting category directly to deposits (F.2).

Similar information should be provided for "Other long-term investments and receivables," classified by instrument or investment type, "Deferred income and received donations," identified by counterpart sector, and crypto-assets, where information is necessary for their appropriate statistical classification. Such information may be included in the financial statements or supplementary tables forming part of a Statistical Annex, which should be a part of the external auditing process.

5.3 Consistency across financial statements

Interoperability also requires consistency across the financial statements. Changes in accounting positions should be traceable across the balance sheet, statement of profit or loss, cash flow statement, and statement of changes in equity, enabling statistical compilers to distinguish stocks from flows and reconcile changes between them.

For example, where crypto-assets are recognized, the balance sheet should identify the relevant stock, the statement of profit or loss, the applicable fair value gains or losses, and the cash flow statement of the related acquisition and disposal transactions. The same principle should apply to residency and counterpart sector information, allowing financial positions, income, expenses, and financial flows to be consistently allocated between residents and non-residents and, where relevant, among institutional sectors.

5.4 Mapping and bridging arrangements

Systematic mapping between accounting and statistical classifications should form an integral part of financial reporting and statistical compilation. Bridging tables can establish transparent relationships between financial statement items and the classifications used in ESA, GFS, and related statistical frameworks.

Such arrangements would make differences arising from recognition, valuation, timing, sector classification, consolidation, and other methodological requirements more transparent. They would also reduce reliance on ad hoc adjustments and facilitate reconciliation between accounting information and statistical aggregates.

5.5 Broader value of interoperability

The benefits of interoperability extend beyond statistical compilation. When accounting data are sufficiently detailed and consistently classified, they can be aggregated into measures of sectoral income, expenditure, investment, financial assets and liabilities, debt, and economic exposure. These measures provide an empirical basis for analyzing fiscal developments, financial stability, external vulnerabilities, investment, indebtedness, and the transmission of economic shocks, supporting research, forecasting, and policymaking.

Financial accounting and macroeconomic statistics should nevertheless retain their distinct purposes. Financial accounting focuses on entity-level recognition, measurement, performance, and accountability, whereas macroeconomic statistics reorganize information across entities and sectors to describe the economy as a whole. The objective should therefore be interoperability, not methodological convergence.

5.6 Institutional cooperation and continuous development

National charts of accounts and financial reporting systems should be treated as structures capable of continuous development rather than systems determined exclusively by legislation. Their design should involve sustained cooperation among legislators, accounting professionals, reporting entities, regulators, and statistical authorities.

Such cooperation can ensure that financial reporting fulfils its primary regulatory and accountability objectives while also generating information suitable for efficient statistical compilation. Supplementary statistical reporting can provide additional information, but it cannot fully compensate for deficiencies in the underlying accounting system. Where financial reporting does not provide the information required for statistical classification, statistical authorities must rely on additional data collection, estimates, assumptions, and adjustments.

5.7 Overall conclusion

The ultimate objective should be a coherent information chain from entity-level financial reporting to sectoral statistics and, ultimately, to macroeconomic analysis and policy. Financial reporting should retain its primary accounting purpose while providing, where practical, sufficiently structured and disaggregated information to support reliable macroeconomic statistics.

Greater interoperability would reduce duplication in data collection and the need for statistical adjustments while improving the consistency, timeliness, and analytical value of macroeconomic indicators.

Its implementation requires the involvement of statistical authorities in the design and continuous development of national charts of accounts and financial reporting requirements, ensuring that accounting information contains the classifications and details needed for national accounts and GFS. The Appendix provides a practical overview of cash, accrual, and modified-cash accounting and shows how accounts payable and advances support cash to accrual adjustments required for statistical compilation.

6 Appendix: financial accounting methods, practical examples and accounting considerations

Based on how revenues and expenses are recognized, how accounts receivable and payable are tracked, and whether the matching principle is applied, accounting systems may generally be classified into cash-based, accrual-based, and modified accounting frameworks. Here is a breakdown of these methods, including two modified variations:

6.1 Cash accounting

This is the simplest method. Transactions are recorded only when cash is received or paid.

Recognition: Revenues are recorded when cash is received; expenses are recorded when cash is paid.

Tracking: There is no formal recognition of accounts receivable, accrued revenue, accounts payable, or accrued expense.

Matching principle: The matching principle does not apply.

6.2 Accrual accounting

Accrual accounting provides a more comprehensive and accurate picture of a company's financial performance over a specific period.

- Recognition: Revenues are recorded when earned and expenses when incurred, regardless of when cash is received or paid.
- Tracking: Accounts receivable, accrued revenue, accounts payable, and accrued expenses are fully recognised and tracked.
- Matching principle: Expenses incurred to generate specific revenue are recognised in the same accounting period as the related revenue. For example, the COGS is recognised when the related product is sold rather than when the raw materials are purchased.

6. 3 Modified cash accounting - variation 1

This method combines cash and accrual principles according to the duration or nature of transactions.

Short-term assets and liabilities are managed using cash principles, while long-term assets and liabilities, such as major equipment and long-term loans, are managed using accrual principles.

6.4 Modified cash accounting -variation 2

This specific and complex method is sometimes used by government entities like non-market producers.

- Recognition: Revenues and expenses are recognized when cash is exchanged.
- Tracking: Unlike pure cash accounting, full tracking of accounts receivable and accrued revenue and Accounts Payable and Accrued expense is present.
- Matching principle: The matching principle is generally not applied.

Unique features

- Cash to accrual adjustment: Because all necessary data is tracked, it is possible to perform "cash to accrual adjustment" to calculate what the figures would be under accrual accounting.
- Fixed assets: Fixed assets are generally not capitalized in the same way as in accrual accounting. They are recorded as fixed assets but are also expensed through numerous entries across different debit and credit accounts to ensure a consistent balance.
- Recording system: The transaction-recording system is comprehensive. For example, a vendor transaction may include entries recording both the obligation and the subsequent cash payment.

The following two examples illustrate the operation of a modified cash accounting system and the use of accounts payable and advances in cash to accrual reconciliation.

6.5 Example 1 – Vendor transactions

The first example assumes:

1. Opening debit balance on the cash account amounting to EUR 10,000 (assumption);
2. Services received in period T+1 in the amount of EUR 500 on account;
3. Partial payment for services received in T+1 executed in month T+2 in the amount of EUR 300 and
4. Accrual of a new expense in the amount of EUR 2,000 in month T+3, invoice has been received.

Example 1 (amounts in EUR)

CASH ACCOUNTING

Debit	CASH		Credit
1)	10.000	300	3)
	9.700		

Debit	A/PAYABLE		Credit
		0	Beginning 1)
		0	2)
		0	4)
		0	

Debit	EXPENSES		Credit
1) Beginning	0		
2)	0		
3)	300		
4)	0		
	300		

ACCRUAL ACCOUNTING

Debit	CASH		Credit
1)	10.000	300	3)
	9.700		

Debit	A/PAYABLE		Credit
3)	300	0	Beginning 1)
		500	2)
		2000	4)
		2200	

Debit	EXPENSES		Credit
1) Beginning	0		
2)	500		
4)	2000		
	2500		

MODIFIED CASH ACCOUNTING

Debit	CASH		Credit
1)	10.000	300	3)
	9.700		

Debit	EXPENSES		Credit
1) Beginning	0		
3)	300		
	300		

Debit	A/PAYABLE		Credit
3)	300	0	Beginning 1)
		500	2)
		2000	4)
		2200	

Debit	CALCULAT. NOT PAID EXPENSES		Credit
1) Beginning	0	300	3)
2)	500		
4)	2000		
	2200		

CASH TO ACCRUAL ADJUSTMENT FOR

Debit	A/PAYABLE		Credit
Cash	300	**0**	Beginning
		2500	
		2200	

Adjustment 2500 = (22000 Credit Ending Stock) + (300 Debit Cash) - (0 Beginning Stock)

6.6 Example 2 – Advance payment

The second example assumes:

1. Opening debit balance on the cash account amounting to EUR 10,000 (assumption);
2. Services received in period T+1 in the amount of EUR 500 on account;
3. Partial payment for services received in T+1 executed in month T+2 in the amount of EUR 300 and
4. Advanced payment was made of EUR 1500 in the period T+3 for the service worth 2000, the invoice has not been received yet.

Example 2 (amounts in EUR)

MODIFIED CASH ACCOUNTING

Debit	CASH		Credit
1) Beginning	10000	300	3)
		1500	4)
	8200		

Debit	ADVANCES RECEIVABLES		Credit
1) Beginning	0		
4)	1500		
	1500		

Debit	EXPENSES - CASH METHOD		Credit
Beginning	0		
3)	300		
4)	1500		
	1800		

Debit	CALC. NOT PAID EXPENSES		Credit
1) Beginning	0	300	3)
2)	500		
	200		

Debit	ADVANCES PAID		Credit
		0	Beginning 1)
		1500	4)
		1500	

Debit	A/PAYABLE		Credit
3)	300	0	Beginning 1)
		500	2)
		200	

Debit	CASH TO ACCRUAL ADJUSTMENT FOR ADVANCES PAYABLE		Credit
Beginning	0	**0**	
Cash	1500		
	1500		

Debit	CASH TO ACCRUAL ADJUSTMENT FOR A/PAYABLE		Credit
Cash	300	0	Beginning
		500	
		200	

6.7 Cash to accrual adjustment

The formula for cash to accrual adjustment for all expenses and expenditures that are related to Accounts payable (Vendors) and Advances receivable (Prepayments) is:

= Cash + (Ending A/Payable - Beginning A/Payable) + (Beginning Advances Receivable - Ending Advances Receivable). Using the example:

EUR 1800 + (EUR 200 -EUR 0) + (EUR 0 – EUR 1500) = EUR 500.

The vendor account can be reconciled separately using a formula:

Ending Stock A/Payable + Cash Payments – X = Beginning Stock A/Payable, where X = Accrual expenses/expenditures. Therefore, X = Ending Stock A/P + Cash Payments – Beginning Stock A/P. Using the example:

EUR 200 + EUR 300 – EUR 0 = EUR 500.

Advance receivable (prepayments) can be recalled by the following formula:

Ending Stock A/Receivable – Cash Payments + X = Beginning Stock A/Receivable, where X = Accrual expenses/expenditures. Therefore, X = Beginning Stock A/R - Ending stock A/R + Cash payments. Using the example:

EUR 0 – EUR 1500 + EUR 1500 = EUR 0.

The EUR 500 represents the total amount of accrual expenses and expenditures related to advances and vendor accounts. In practice, allocating this amount to specific expenses and expenditures requires an appropriate allocation methodology. This may range from proportional allocation based on cash expenses and expenditures to more sophisticated methods.

Under a modified cash accounting system, reconciliation of vendor accounts[16] identifies liabilities for goods and services received but not yet paid. These liabilities may relate either to current expenditure or to the acquisition of non-financial assets. Accounts payable and advances should therefore be treated as separate but complementary control accounts: accounts payable represent obligations arising from economic events that have already occurred, while advances represent payments made before the related goods or services are received.

Where the opening and closing balances of accounts payable and advances receivable, together with related cash payments, are known, corresponding accrual expenditure can be derived from movements in these accounts. Expenditure incurred but not paid increases accounts payable, while cash payments reduce outstanding liabilities; conversely, prepayments create advances that should not be recognized as expenditure until the related economic event occurs.

[16] Vendors' accounts on the balance sheets of budgetary units operating under the modified cash accounting system should be divided into two main subcategories: vendors related to current expenditures (intermediate consumption) and vendors related to capital expenditures. This classification is necessary to ensure an accurate balancing procedure. These categories should then be further divided into domestic and foreign vendors, with additional classifications introduced where necessary. The same principle should be applied to advance receivables, i.e. prepayments.

Cash to accrual adjustment[17] is essential for national accounts because expenditure must be attributed to the period in which the underlying economic activity occurs rather than the period in which payment is made. Accurate adjustment is therefore necessary for measuring government final consumption expenditure and gross fixed capital formation (GFCF), and consequently GDP and related aggregates GNI and GNDI.

The adjustment is particularly important for governments using cash or modified-cash accounting, especially during periods of substantial capital expenditure. Significant balances in advances or assets under construction may indicate that cash payments differ materially from the timing of the underlying economic activity. Cash-to-accrual adjustments based on sufficiently detailed financial reporting information are therefore essential for the accurate calculation of statistical aggregates.

[17] Different financial accounting platforms and portals use several approaches to calculate cash to accrual adjustments for a given T-account, each based on different underlying logic. In the author's opinion, the approach presented in this paper in the overview section is the simplest, most transparent, and easiest to understand and remember. This approach is available on the financial accounting channel TLC Tutoring, along with many other useful financial accounting clarifications and explanations.

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WORKING PAPER

ANALYSIS OF FACTORS AFFECTING EURIBOR MOVEMENTS

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Available at www.nbs.rs

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Analysis of factors affecting Euribor movements

Aleksandar Melović

Abstract: The Euribor reference interest rate is one of the most important benchmarks in the euro money market. It is used to determine the interest rates on a wide range of financial products and, in the Republic of Serbia, also in setting the interest rates on the majority of housing loans. Therefore, understanding the factors that influence the level of the Euribor rate is of considerable importance to all stakeholders whose decisions are affected by this reference rate. In economic theory and practice, the monetary policy of the European Central Bank is considered to have the greatest influence on its movements, more specifically, changes in the three key interest rates set by this financial institution. Application of the Autoregressive Distributed Lag model established a statistically significant effect of the European Central Bank's reference rates on the movements of three-, six- and twelve-month Euribor rates. In the short term, a 1 pp increase in the reference rate leads to an increase of 0.83, 0.47 and as much as 1.2 pp in the three-, six- and twelve-month Euribor rates, respectively. A statistically significant effect of inflation was also identified, although its magnitude was smaller, with a regression coefficient of 0.0469 in the current period. Among other factors, market expectations regarding the European Central Bank's future policy stance should also be highlighted, as well as the adverse impact of geopolitical tensions on the economy and, consequently, on financial markets and Euribor movements.

Key words: Euribor, European Central Bank, benchmark interest rates, monetary policy, interest rate determinants
[JEL Code]: C22, E31, E43, E52

Non-technical summary

Few phenomena in economics have as broad and pervasive an impact across numerous economic activities and on a wide range of stakeholders in the economic sphere as the benchmark interest rate for the euro money market – Euribor. Designed to provide a representative measure of developments in the euro money market and to serve as a benchmark for determining interest rates on a wide range of financial products, such as housing loans, interest rate swaps, interest rate futures, and savings accounts, the Euribor rate has been in existence for nearly three decades.

Euribor is the average interest rate at which panel banks with a significant role in the euro money market lend to one another on an unsecured basis. It is calculated for maturities of one week and one, three, six, and twelve months.

Throughout its relatively long history, the Euribor rate has served as a market indicator of changes in the ECB's monetary policy, as well as of the changes brought about by the 2008 global financial crisis and the crises that have emerged in recent years, primarily as a result of the armed conflicts in Ukraine and the Middle East.

With the aim of improving the forecasting of Euribor movements, this paper examines the factors that have influenced the level of this benchmark rate. Among the numerous factors identified in the literature, the ECB's monetary policy is of particular importance. Through its three key interest rates, the ECB seeks to maintain price stability and keep inflation at 2% over the medium term. By setting its key interest rates, the ECB establishes the upper and lower bounds for market interest rates, thereby defining a corridor within which market rates, including Euribor, can fluctuate. Therefore, monitoring the ECB's monetary policy is crucial for understanding the dynamics of Euribor rates. Using the ARDL model, the analysis finds a statistically significant effect of the ECB's key interest rates on Euribor movements. Specifically, a 1 pp increase in the key interest rate in the short run leads to increases in the three-month, six-month, and twelve-month Euribor rates of 0.83, 0.47, and as much as 1.2 pp, respectively. In a hypothetical example, this means that if the ECB were to raise the deposit facility rate from 2% to 3%, the three-month Euribor would increase in the short run from, for example, 1% to 1.83%.

In addition to monetary policy, Euribor rates are influenced by inflation, geopolitical tensions, and market expectations regarding the future course of the ECB monetary policy. Consequently, market participants may sometimes adjust Euribor rates in line with their expectations even before the ECB changes its key interest rates.

Contents

1 Introduction

This paper examines the determinants of movements in the Euribor interest rate. As Euribor serves as a key benchmark for euro-denominated borrowing and, consequently, influences the pricing of financial products, identifying the factors that drive its movements and quantifying their respective effects is important for economic agents in making informed decisions. The paper analyses these factors, drawing on the European Central Bank (ECB) data on Euribor rates, the ECB's key interest rates – the deposit facility rate (DFR), main refinancing operations rate (MRO), and marginal lending facility rate (MLF) – as well as inflation data, with the aim of assessing the effects of monetary policy and inflation on Euribor dynamics. Furthermore, to facilitate a better understanding of the subject under consideration, the first part of the paper reviews the fundamental concepts related to the Euribor interest rate, with a particular focus on its key characteristics, types, and significance for the banking sector and the broader financial market. A part of the paper provides an overview of the methodology used to calculate the rate. Based on historical data, a brief review of the movements in different Euribor rates from their inception in January 1999 through July 2026 is presented, providing an initial insight into the dynamics of these rates over the entire period of their existence. The second part of the paper provides an overview of the factors affecting Euribor identified in economic theory and practice, together with the expected impact of each factor on the Euribor rate. In analysing how these factors affect the Euribor level, an Autoregressive Distributed Lag (ARDL) model is applied, using data on the six-month Euribor rate. The results indicate a joint effect of the ECB's key interest rates and inflation on the Euribor level, accounting for the rate dynamics over the entire period under review. The analysis finds that the monetary policy of the ECB is the most significant determinant of Euribor movements. Specifically, a 1 pp increase in the ECB's key interest rate is associated with a 0.303 pp increase in Euribor, while a 1 pp increase in inflation is associated with a 0.047 pp increase in Euribor. The concluding section discusses the factors that determined the level of Euribor rates over the historical period and that continue to shape their movements today, with the aim of contributing to a better understanding of the expected path of Euribor rates in the future.

2 Euribor – Key characteristics and significance

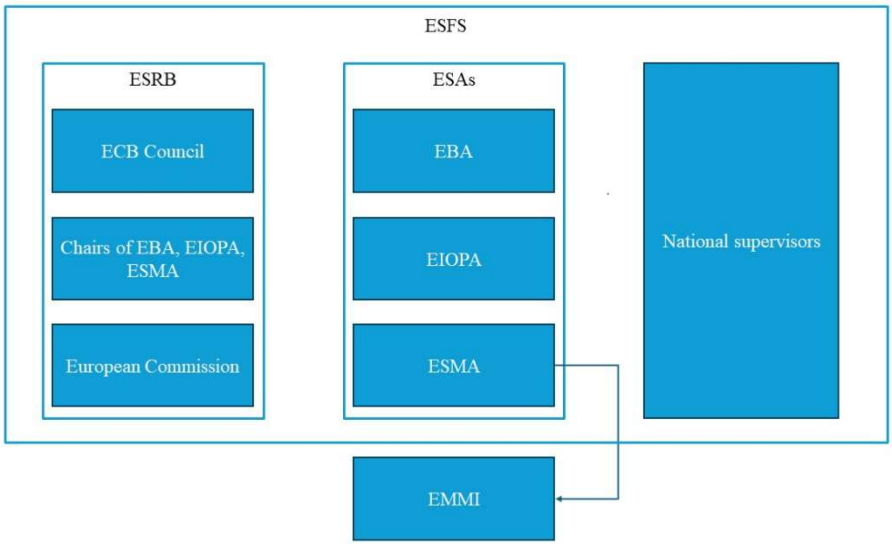
2.1 Key characteristics

Euribor is a benchmark interest rate for a wide range of financial products. The name Euribor is an abbreviation of the original English term Euro Interbank Offered Rate, referring to the rate at which a predefined group of banks lend funds to one another in euros. Euribor represents the average interest rate on such transactions, which involve short maturities and are conducted on an unsecured basis, i.e. without collateral. Unlike other benchmark rates in the market, such as €STR (Euro Short-Term Rate), which reflects overnight borrowing and is generally considered a risk-free rate, Euribor incorporates a risk component.

To gain a better understanding of the key characteristics of Euribor, it is useful to first examine the institutional framework within which it is calculated. In the euro money market, the European Money Markets Institute (EMMI) was established in 1999, coinciding with the introduction of the euro. EMMI is a non-profit organisation responsible for the development and administration of benchmark rates, the best known of which is Euribor. In addition to Euribor, the Institute develops Efterm, a forward-looking measure of the cost of money, and previously developed and calculated the overnight interbank interest rate Eonia. The calculation and publication of Eonia were discontinued at the beginning of 2022, following its replacement by €STR, which is calculated and published by the ECB. The Institute operates in accordance with the European Union's Benchmark Regulation (BMR), while its activities are supervised by the European Securities and Markets Authority (ESMA).

ESMA is part of the European System of Financial Supervision (ESFS), where, together with other key financial and regulatory institutions, it works to ensure the effective implementation of rules governing the financial sector, with the aim of safeguarding financial stability, strengthening confidence in the financial system as a whole, and ensuring an appropriate level of protection for users of financial services. The ESFS also includes the Governing Council of the ECB, which is of particular relevance to the subsequent analysis of the Euribor rate.

Figure II.1 **Structure of the European System of Financial Supervision (ESFS)**



Source: Author's own elaboration based on ESMA (n.d.).

Euribor is calculated for five different maturities, resulting in the following Euribor rates.

- EURIBOR 1W (one-week maturity),
- EURIBOR 1M (one-month maturity),
- EURIBOR 3M (three-month maturity),
- EURIBOR 6M (six-month maturity),
- EURIBOR 12M (twelve-month maturity).

In previous years, as many as fifteen Euribor rates with different maturities were published. However, following November 2013, this number was reduced to five rates in order to address concerns regarding the reliability of the calculated rates and to focus on those rates most widely used in practice.

2.2 Significance of Euribor

The significance of Euribor stems from the fact that it is regarded as "the most important benchmark interest rate for all types of financial products, such as interest rate swaps, interest rate futures, savings accounts, and mortgage loans" (Lleshaj & Kripa, 2021, p. 1332). This is also the case in the banking sector of the Republic of Serbia, where, for euro-indexed housing loans, Euribor is incorporated, either directly or indirectly, into the calculation of the interest rate charged to the borrower. It is therefore important for stakeholders to monitor movements in Euribor rates in order to make informed decisions. It is equally important that all requirements governing the calculation of Euribor are duly complied with, so as to ensure that the rate is as accurate as possible and provides a representative reflection of actual movements in the euro money market. The methodology used to calculate Euribor is discussed in greater detail in the following chapter.

In general, interbank interest rates serve as indicators of the cost of financing and provide a concise and clear picture of the overall condition of the financial system, as they reflect the level of confidence and degree of liquidity among participants in the financial market (Gómez Yubero, Ollero García-Agulló, & Palomero Aguilar, 2026).

It is also worth highlighting the significance of Euribor in the context of the ECB's monetary policy. As will be discussed in greater detail later in the paper, the ECB conducts monetary policy by setting three key interest rates. Through these rates, the ECB seeks to steer money market conditions and achieve its primary objective of maintaining price stability. These rates establish upper and lower bounds for other market interest rates, within which, as will be demonstrated, Euribor also fluctuates. Consequently, Euribor and other interbank interest rates play an important role in the monetary policy transmission mechanism, as they move within the framework established by the ECB and contribute to the achievement of its monetary policy objectives. Their significance also stems from the fact that they reflect market expectations regarding the future course of the ECB's monetary policy (Gómez Yubero et al., 2026).

3 Methodology for calculating Euribor rates and overview of their movements over the entire historical period

EMMI calculates and publishes Euribor based on data submitted by panel banks. The panel of banks comprises financial institutions selected to ensure that the Euribor reflects developments in the euro money market in a representative manner and serves as a representative indicator of conditions in that market. Although euro-denominated transactions are collected and analysed for the purpose of calculating Euribor, a bank does not necessarily have to be based in a euro area country to be included in the panel. Rather, it is important that the bank is able to provide a representative indication of developments in the euro money market on account of its significant level of activity in that market. The UK bank Barclays Bank PLC was previously a member of the panel; however, as of 27 February 2026, it ceased submitting data on transactions and interest rates. The current panel comprises 21 banks from 11 countries, all of which are euro area member states.

In recent years, a number of reforms have been implemented with regard to the methodology used to calculate the Euribor rate, with the aim of ensuring a more accurate calculation. Prior to these reforms, panel banks submitted estimated data, whereas, following the implementation of the reforms, banks submitted data on actual transactions during the period from 2014 to 2019. "In its early stages, Euribor was calculated on the basis of declarative submissions from contributing institutions, reflecting their expert judgement as to the rate at which they could obtain unsecured funding in the interbank market." (Gómez Yubero et al., 2026, p. 54). This method of calculation left scope for subjective judgement, given that the data were not necessarily required to be based on actual transactions. In the early years of its application, when markets were relatively stable, this approach to calculation incurred no problems. However, during the crisis period, which began as early as 2007, it became apparent that the application of this methodology for calculating the Euribor rate created scope for opportunistic behaviour of participants in the panel of banks. Following the reform, the transition to a hybrid approach to calculating Euribor improved its economic representativeness. The data underlying the calculation thus became more responsive to changes in liquidity and in the rates at which banks borrow from one another, compared with the earlier dynamics of Euribor, which had been more stable due to the lower sensitivity of subjective assessments to such changes (Gómez Yubero et al., 2026). The methodological changes therefore represented significant progress in mitigating the impact of human judgement on the level of the Euribor rate and enabled a more objective and representative reflection of prevailing conditions in the euro money market.

What data are submitted to EMMI?

The basic concept underlying the calculation of Euribor is that each panel bank submits data on unsecured borrowing transactions and the interest rate at which it borrowed, for transactions with maturities of one week and one, three, six and twelve months. In addition, for a transaction to be eligible for inclusion in the Euribor calculation, its value must exceed EUR 10 mn. The transaction must also be denominated in euros and must constitute an unsecured borrowing transaction. However, it is not always the case that every bank executes transactions meeting these criteria on a daily basis. Therefore, the Euribor rate is currently calculated using two levels of information classified according to their quality.

Level 1

This category comprises transaction data that meet the criteria outlined above. These data represent the highest-quality information and, under ideal conditions, only such data would be used to calculate the Euribor rate. Where there is an insufficient number of transactions eligible for inclusion in the calculation, the methodology proceeds to the second level, Level 2, which involves performing certain calculations, as described in more detail below.

Level 2

When a bank does not have a sufficient number of eligible transactions, three techniques are used to calculate its contribution. These techniques are always applied sequentially, provided that eligible data are not available for the respective technique.

Level 2.1 – An adjusted linear interpolation from adjacent Defined Tenors is performed. For example, if a bank does not have eligible transactions for the six-month tenor, data on eligible transactions submitted by the bank for the adjacent three- and twelve-month tenors are used. Linear interpolation is then performed to derive the bank's calculated contribution for the six-month tenor.

Level 2.2 – A mathematical adjustment is applied to data on transactions at non-Defined Tenors. For example, if a bank has a transaction with a seven-month tenor, a mathematical adjustment is applied to derive the equivalent interest rate for a six-month tenor.

Level 2.3 – Where there are no appropriate data available for applying Levels 2.1 and 2.2, eligible data from previous days are used, with the application of a Market Adjustment Factor. For example, data on eligible transactions previously submitted by the bank are used, adjusted to reflect market developments that have occurred in the meantime.

Once the contributions of each individual panel bank have been calculated for each tenor, the contributions are sorted, and the highest 15% and lowest 15% of values are discarded in order to eliminate the impact of extreme values. A simple arithmetic mean is then calculated from the remaining 70% of the data, and this value is taken as the Euribor rate.

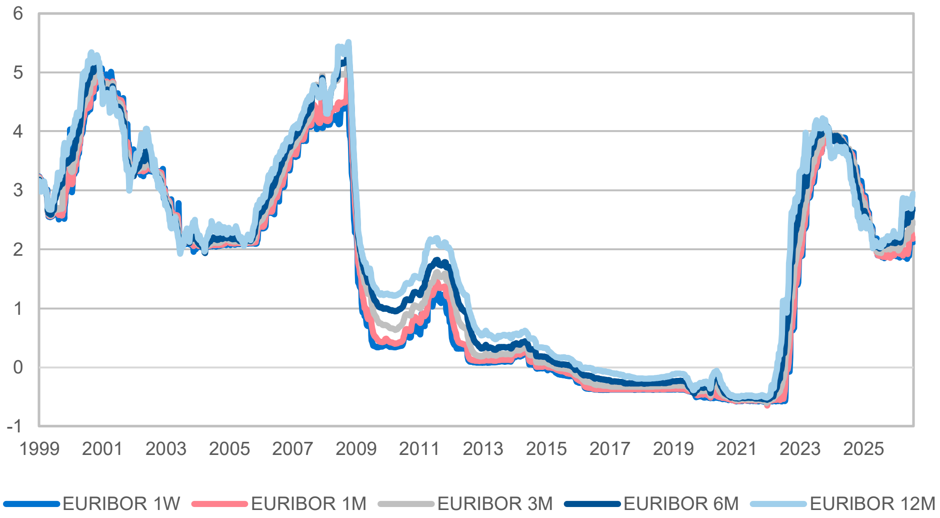
Data on the Euribor rate are published every working day at 11:00 a.m. The latest data are available exclusively to interested parties subscribed to receive real-time data. On the following day, the data become available to the wider public through various online platforms.

How have Euribor interest rates evolved?

In order to adequately assess the factors influencing the dynamics of the Euribor interest rate, this chapter also examines the evolution of Euribor interest rates from the beginning of the publication of daily data through to the latest available observations. Accordingly, the analysis covers the period from 1 January 1999 to 31 July 2026.

In the initial days, Euribor rates fluctuated at around 3%, followed by an upward trend in all tenors in the subsequent months, with the 12-month rate reaching as high as 5.3%. In the early 2000s, interest rates declined. In the period preceding the 2008 global financial crisis, Euribor rates recorded their strongest increase up to that point, reaching their highest historical levels, with the 12-month rate peaking at 5.5%. In the months that followed, rates declined sharply, reflecting the collapse of the financial system and the consequent loss of confidence in the banking system. Following a period of rising rates, which brought them to around 2%, negative rates were recorded from the mid-2010s onward, with Euribor rates reaching their historical lows. At one point, the one-month Euribor rate fell to as low as -0.65%. The trend of negative interest rates continued over the following several years, despite an increase recorded during the onset of the Covid-19 crisis. At the beginning of 2022, following the outbreak of the war in Ukraine, interest rates moved out of negative territory and increased sharply through autumn 2023, when they reached around 4%. In the subsequent months, all rates resumed a downward trend, which came to a halt during the summer of 2025, when rates stood at around 2%. This trend continued until spring of the current year, when a modest increase in interest rates was observed again. By the end of the period under review, the rate reflecting the longest maturity, i.e. the 12-month rate, had reached a level close to 3%.

Chart 1 **Movement of Euribor benchmark interest rates**
(weekly data, p.a., in %)



Source: Euribor Rates (n.d.).

4 Theoretical overview of the factors influencing Euribor dynamics

To conduct a comprehensive analysis of the factors influencing the dynamics of the Euribor rate, it is necessary to consider the theoretical foundations underlying this phenomenon and review the findings from empirical research to date. Accordingly, this chapter examines, from a theoretical perspective, the factors affecting Euribor rates and reviews the existing literature presenting empirical evidence in this regard.

Since the interest rate represents the price of capital in the money market, its level and dynamics are determined by the supply of and demand for money (Vilmunen, 2024). According to Juotasniemi (2026), interest rate dynamics are influenced by the supply of and demand for credit, inflation, and central bank policy. In the case of the Euribor rate, this refers to the interest rate policy conducted by the ECB. In addition, the level of interest rates is affected by the degree of liquidity in the banking system (Gómez Yubero et al., 2026), as well as by market expectations regarding the ECB’s future policy stance. This is attributable to the forward-looking nature of the Euribor rate, particularly in the case of longer tenors (three, six and twelve months). In line with their expectations regarding the ECB’s policy over the forthcoming period, market participants may adjust these rates in advance (Juotasniemi, 2026). In addition to the factors outlined above, geopolitical tensions are also considered among the significant determinants, as they increase uncertainty and investors’ risk aversion, slow economic activity through disruptions to supply chains, and generate other adverse effects on the economy (ECB, 2024). It has been observed that the ECB considers geopolitical risks to be among the key threats to financial stability (Juotasniemi, 2026). During periods of heightened geopolitical tensions, the ECB seeks to preserve stability through its interest rate policy, which is also reflected in the level of the Euribor rate (Juotasniemi, 2026).

Interest rates tend to increase in response to higher demand for money and credit and rising inflation, whereas weaker demand for money and declining prices exert downward pressure on interest rates. Geopolitical tensions have an adverse effect on interest rates, contributing to higher rate levels.

The role of the ECB will be analysed in greater detail below. The ECB conducts monetary policy in the European Monetary Union with the primary objective of maintaining price stability by keeping inflation at 2% over the medium term. Low inflation would put downward pressure on interest rates and slow economic activity, whereas high inflation would lead to higher interest rates, which would also adversely affect lending activity and reduce demand for credit. For this reason, the ECB sets three key interest rates through which it seeks to influence the money market and maintain price stability. These are the interest rate on the deposit facility, the interest rate on the main refinancing operations, and the interest rate on the marginal lending facility.

The following is a description of the aforementioned rates according to the ECB (n.d.):

- Deposit Facility Rate – DFR

The interest rate at which banks can place overnight deposits with the ECB at a predetermined rate. In theoretical terms, this rate represents the lower bound for the Euribor rate, given that no bank would be willing to lend at a rate below that at which it can place a deposit with the ECB, particularly since placing deposits with the ECB is considered virtually risk-free.

- Main Refinancing Operations – MRO

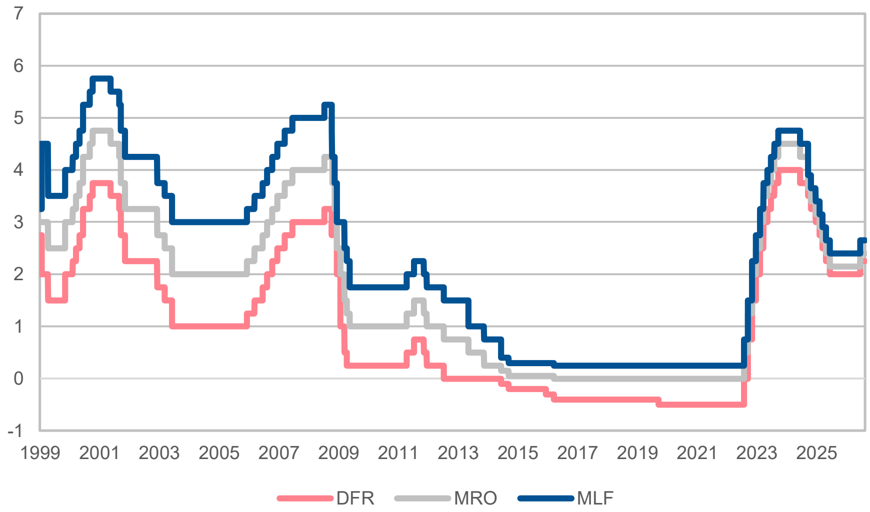
Commercial banks can borrow funds from the ECB at this rate for a period of one week, subject to the provision of eligible collateral. In this way, the ECB manages liquidity over a seven-day horizon. This rate is higher than the DFR.

- Marginal Lending Facility – MLF

Like the DFR, the MLF is an interest rate applicable to overnight transactions; however, in this case, banks borrow from the central bank at this rate against eligible collateral. This rate is higher than the MRO rate and represents the upper bound for interest rates, as no bank would borrow at a higher rate than the rate at which it can obtain funding from the central bank.

Since the introduction of the euro, the ECB initially raised interest rates, before lowering them and maintaining them at a stable level in the mid-2000s. In the period preceding the 2008 Global Financial Crisis, a policy of raising key interest rates was pursued; following the outbreak of the crisis, these rates were reduced sharply with the aim of stimulating lending and economic activity. Over the previous decade, the ECB maintained the interest rate on the deposit facility below zero. Subsequently, in response to the increase in inflation driven by the energy crisis and the war in Ukraine, it pursued a policy of raising interest rates in order to mitigate these adverse effects. Monetary policy easing was observed from mid-2024, while, as of March 2024, the ECB's Governing Council decided to steer monetary policy primarily through the DFR. In recent months, monetary policy has been tightened slightly amid renewed uncertainty stemming from the energy crisis, this time due to tensions in the Strait of Hormuz and the conflict between Iran and the United States. A graphical presentation of the ECB's three key interest rates is provided in the following chart.

Chart 2 **Movement of the ECB's key interest rates**
(six-week data, p.a., in %)



Source: ECB (n.d.).

Given that the ECB's interest rates establish the corridor within which Euribor rates fluctuate, it may be assumed that the principal determinant of the dynamics and level of the Euribor rate is the ECB's monetary policy. Market expectations regarding the ECB's future policy stance also play an important role. The actual level of the Euribor rate is expected to be determined by other market factors, while the influence of non-market factors should not be overlooked, particularly that of geopolitical tensions, which are becoming increasingly important in view of their growing frequency and their impact on economic activity.

5 Analysis of the factors influencing the dynamics of the Euribor interest rate

This section of the paper focuses on analysing the impact of various factors on the dynamics of the Euribor rate. Given that theory indicates that the monetary policy of the ECB has the greatest influence on the level of Euribor rates, the analysis will focus primarily on the impact of the DFR and the MRO. In addition, the analysis will examine the impact of inflation on Euribor dynamics. In order to obtain a more comprehensive assessment of the factors influencing Euribor, the joint impact of inflation, the DFR and the MRO will also be examined.

5. 1 Review of the existing literature

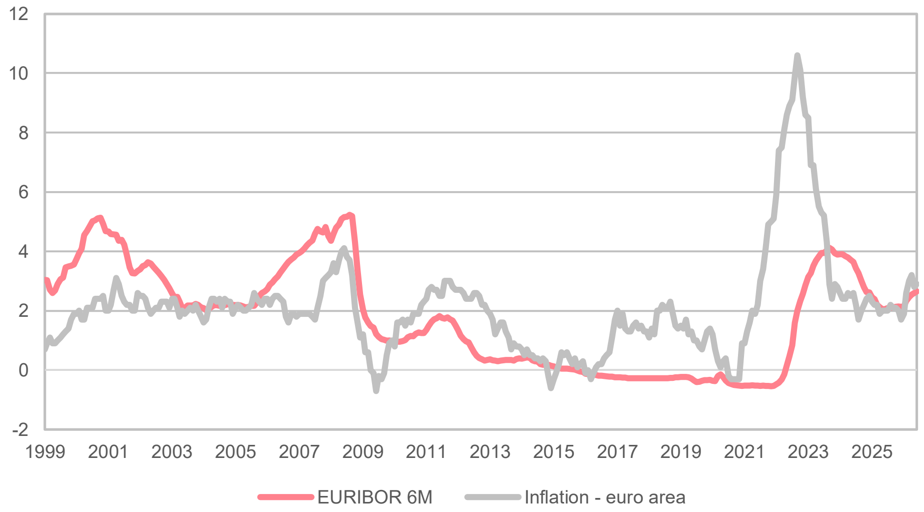
In their study, Abbassi and Linzert (2011) examine the impact of monetary policy on the dynamics of the Euribor rate, focusing on developments before and after the onset of the 2008 global financial crisis. According to their findings, an expected 25-bp change in the key interest rate led to an increase of 17 bp in the three-month Euribor, while the six-month and twelve-month Euribor rates increased by 19 and 23 bp, respectively. These findings confirm the strong influence of monetary policy on interest rate dynamics. The low degree of persistence observed over the period under review indicates that the ECB maintained stable control over longer-term interest rates. In the period following the outbreak of the crisis, different results were observed in respect of the aforementioned case. In addition to an increase in the persistence of Euribor rates across all three tenors, the influence of the ECB's monetary policy diminished, as an expected 25 bp change in the key interest rate resulted in an increase of only around 3 bp in each of the three Euribor rates under consideration. However, given that monetary policy measures were effective in lowering interest rates, the authors concluded that the reduced influence of the ECB through the policy rate channel was offset by effective liquidity management in the money market.

In their study, Iommetti (2025) analyses the impact of inflationary pressures on the ECB's monetary policy. Given that monetary policy affects the level of Euribor, understanding the factors that influence the ECB's monetary policy stance is of particular importance. The study uses data for 2022 and 2023, a period characterised by substantial inflationary pressures following the Covid-19 crisis, as well as supply chain disruptions caused by the war in Ukraine, against the backdrop of the ECB's previously accommodative monetary policy stance. The high coefficient of determination, $R^2 = 0.996$, indicates a strong relationship between inflation dynamics and the main refinancing rate. Conversely, during periods of declining inflation, when the real interest rate becomes positive, the model's predictive power decreases. The study develops a model that can be used to forecast ECB interest rates under specific conditions characterised by elevated inflation. These findings indicate that inflation is one of the factors influencing Euribor, with an expected indirect impact through the ECB's monetary policy.

5. 2 Impact of inflation on Euribor dynamics

The impact of inflation on the dynamics of Euribor will first be examined. Economic theory suggests that an increase in the general price level in the economy leads to higher money market interest rates and, consequently, to an increase in the Euribor rate. For the purposes of the analysis, monthly inflation data for the euro area published by the ECB will be used, covering the period from January 1999 to July 2026. For the same period, the analysis will use the ECB's monthly data on the Euribor rate with a six-month tenor (EURIBOR 6M).

Chart 3 **Dynamics of Euribor 6M and y-o-y inflation in the euro area**
(monthly data, p.a., in %)



Source: ECB (n.d.).

An examination of the trajectories of inflation and the six-month Euribor rate reveals broadly similar trends. During periods of rising inflation, the Euribor rate also tends to increase, while periods of declining inflation are generally accompanied by a decrease in Euribor. Of particular importance is the observation that, as inflation began to rise sharply in mid-2021, the Euribor rate also started to increase, albeit with a certain lag. However, the chart also indicates some deviations from the co-movement of the two variables, particularly during the period from 2015 to 2020. During this period, inflation underwent phases of increase, relative stagnation, and decline, whereas the six-month Euribor rate remained relatively stable throughout the period under review. This phenomenon can be explained by the broadly unchanged ECB monetary policy stance over the same period. Despite inflationary pressures, interest rates were maintained at broadly the same level, which in turn contributed to the relative stability of the Euribor rate. The ECB's monetary policy stance in 2021 and 2022 indicates that the ECB did not immediately respond to mounting inflationary pressures by raising policy rates, resulting in a subsequent increase in Euribor relative to the rise in inflation.

Model methodology and specification

The analysis uses monthly data for the euro area covering the period from January 1999 to July 2026. Following data cleaning and the introduction of time lags, the final sample comprises N = 328 observations.

Model: An ARDL model was estimated, with the six-month Euribor rate as the dependent variable and inflation with a time lag and the lagged six-month Euribor rate as independent variables:

$$EURIBOR_t = \beta_0 + \beta_1 EURIBOR_{t-1} + \beta_2 INFLATION_{t-1} + \beta_3 INFLATION_{t-2} + \beta_4\, INFLATION_{t-3} + \varepsilon_t$$

In the formula:

- $EURIBOR_t$ – the dependent variable, Euribor 6M,

- β_0 – the constant term in the model,
- $\beta_1 EURIBOR_{t-1}$ – the impact of the lagged Euribor rate on the current Euribor rate,
- β2 – the estimated coefficient on inflation in the previous month,
- $INFLATION_{t-1}$ – the inflation rate one month earlier,
- β_3 – the estimated coefficient on inflation two months earlier,
- $INFLATION_{t-2}$ – the inflation rate two months earlier,
- β_4 – the estimated coefficient on inflation three months earlier,
- $INFLATION_{t-3}$ – the inflation rate three months earlier,
- ε_t – the stochastic error.

The results of the analysis:

Table 1 **Results of the analysis of the impact of inflation on Euribor 6M**

	coeff.	stand. error	*t* - statistics	*p* - value
constant	-0.0516	0.013	-4.020	0.000
$EURIBOR_{t-1}$	0.990	0.005	215.065	0.000
$INFLATION_{t-1}$	0.078	0.023	3.320	0.001
$INFLATION_{t-2}$	0.017	0.037	0.456	0.649
$INFLATION_{t-3}$	-0.0631	0.024	-2.664	0.008

Source: Author's calculations using the Python programming language.

The model exhibits an exceptionally high coefficient of determination ($R^2 = 0.994$; adjusted $R^2 = 0.994$), which is common for time series with a strong autoregressive structure. The first lag of Euribor has a coefficient of 0.9900 (t = 215.065). Inflation with a one-month lag has a statistically significant positive effect, with an estimated coefficient of 0.0780, while the non-robust and robust p-values are 0.001 and 0.019, respectively. The second lag of inflation does not have a statistically significant positive effect (coefficient = 0.0170; p = 0.649; robust p = 0.676). The third lag of inflation exhibits a negative effect, with a coefficient of -0.0631 and p-values of 0.008 and 0.029 for the non-robust and robust estimates, respectively.

However, the overall effect of inflation is statistically significant.

F – test:

F = 26.45

$p = 2.52 \times 10^{-15}$

The following hypothesis is tested:

$$H_0 : \beta_{INF1} = \beta_{INF2} = \beta_{INF3} = 0$$

H1: At least one of the coefficients is not equal to zero.

Given the results of the F-test, with $p < 0.001$, the null hypothesis is rejected, confirming that overall inflation has a significant impact on the dynamics of the six-month Euribor rate.

Model diagnostics and robustness

Model diagnostics revealed a high degree of multicollinearity, as indicated by elevated VIF values for the inflation lags (ranging from 30 to 77). This is a common occurrence in successive lags of macroeconomic time series; nevertheless, the model was retained to capture the overall dynamics of the distributed lags.

Autocorrelation and heteroskedasticity:

The Breusch–Godfrey test indicates the presence of autocorrelation in the residuals ($p < 0.001$), while the Breusch–Pagan test indicates the presence of heteroskedasticity, with $p < 0.001$.

To eliminate the effect of heteroskedasticity on statistical inference, HC3 robust standard errors were employed. In the model with robust standard errors, the conclusions remain unchanged, as the coefficients on $INFLATION_{t-1}$ ($p = 0.019$) and $INFLATION_{t-2}$ ($p = 0.029$) remain statistically significant.

The short-term contribution of inflation to the Euribor rate at time t ($DINF_t$) is defined below by the following general formula:

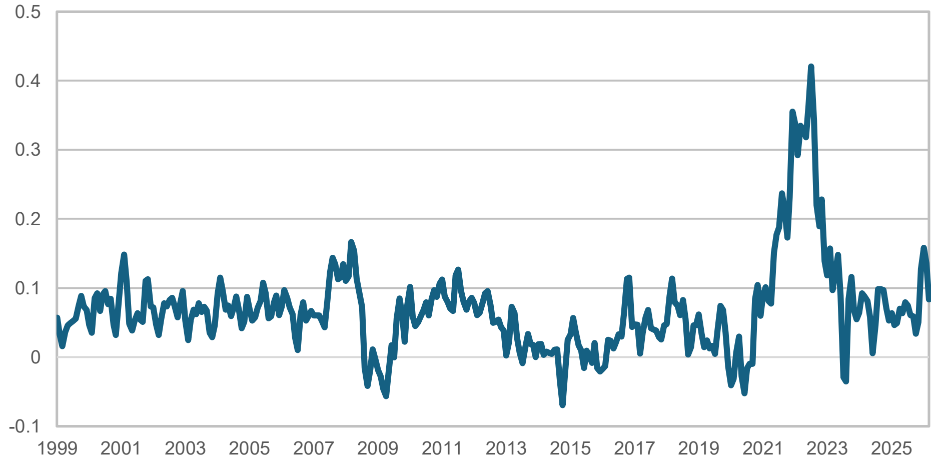
$$DINF_t = \beta_2 INFLATION_{t-1} + \beta_3 INFLATION_{t-2} + \beta_4 INFLATION_{t-3}$$

By substituting the estimated coefficients for the three inflation lags from Table 1, we obtain the following explicit form of the equation:

$$DINF_t = 0{,}078*INFLATION_{t-1} + 0{,}017*INFLATION_{t-2} - 0{,}0631*INFLATION_{t-3}$$

The following chart presents the estimated short-term contribution of inflation to the Euribor rate, expressed in pp. It can be observed that the contribution was positive throughout most of the period under review, ranging from approximately 0.03 to 0.12. The largest effect, at around 0.42 pp, was recorded in late November 2022, shortly after inflation had reached its peak and begun to decline. Based on the foregoing, it may be concluded that inflation has a statistically significant effect on the dynamics of Euribor, assuming that this effect is transmitted indirectly, given the role of the ECB's monetary policy. As noted above, the ECB's monetary policy defines the corridor within which interest rates move and is, to a considerable extent, influenced by inflation developments.

Chart 4 **Estimated contribution of inflation to Euribor 6M**
(monthly data, in pp)

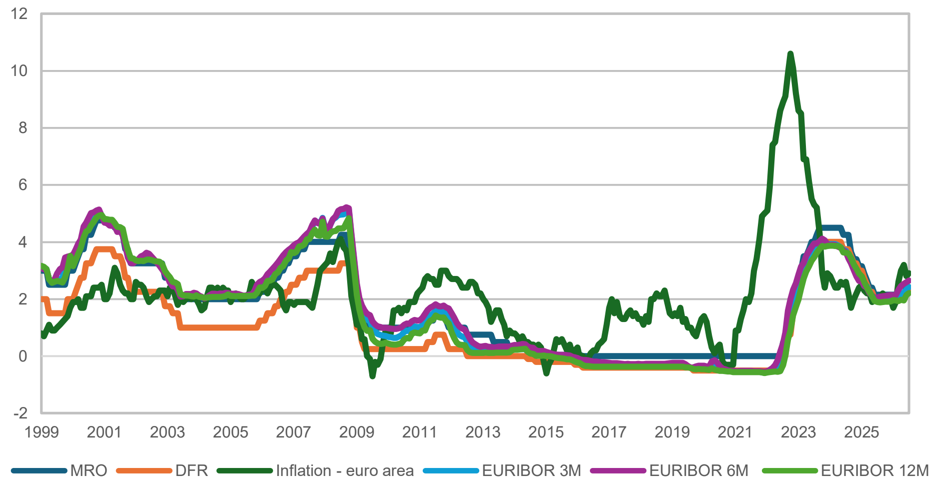


Source: Author's calculations using the Python programming language.

5. 3 Impact of the DFR, MRO, and inflation on Euribor dynamics

The impact of the ECB's interest rates on the dynamics of the three-month, six-month, and twelve-month Euribor rates, together with the impact of inflation, will be analysed below. However, the following chart shows similar trends across all variables under consideration, particularly the close alignment between the movements in Euribor rates and the ECB's interest rates.

Chart 5 **Movements of Euribor 3M, Euribor 6M, Euribor 12M, euro area inflation, DFR and MRO**
(monthly data, p.a., in %)



Source: ECB (n.d.).

In a period of limited liquidity, the MRO rate was the main reference rate, whereas following 2015, amid a period of abundant liquidity, the DFR gradually gained importance. Following the decision of the ECB's Governing Council in March 2024, monetary policy has been steered primarily through the DFR (ECB, 2024). Against this background, the independent variable is denoted as the ECB interest rate in this paper, with data on the MRO reference interest rate used for the period from January 1999 to December 2014, and data on the DFR reference interest rate used for the period from January 2015 to July 2026.

The analysis uses monthly data for the euro area covering the period from January 1999 to July 2026. Following adjustments made for the purposes of model estimation, the final sample comprises N = 331 observations. An ARDL model is employed.

Impact on Euribor 3M

Based on automatic selection (AIC = -670.109) and the information criteria (BIC = -620.799), together with the low standard deviation of the innovations of 0.084, an ARDL (3, 3, 3) model was estimated. The dependent variable is the three-month Euribor, while the independent variables are lagged Euribor, euro area inflation, and the ECB reference interest rate, which combines the MRO and DFR rates. The VIF values for inflation and the ECB interest rate are 1.698, well below the reference threshold of 5, confirming that the model does not suffer from multicollinearity.

$$EURIBOR_t = \alpha_0 + \sum_{(i=1)}^{3} \phi_i \, EURIBOR_{(t-i)} + \sum_{(j=0)}^{3} \beta_j \, ECB_{(t-j)} + \sum_{(k=0)}^{3} \gamma_k \, INF_{(t-k)} + \varepsilon_t$$

In the formula:

- $EURIBOR_t$ – the dependent variable Euribor 3M in period t,
- α_0 – constant in the model,
- $\sum_{(i=1)}^{3} \phi_i \, EURIBOR_{(t-i)}$ – the autoregressive component of the model captures the effects of Euribor from the previous period, two periods earlier, and three periods earlier on the current Euribor, while ϕ_i represents the coefficients measuring the effects of these values,
- $\sum_{(j=0)}^{3} \beta_j \, ECB_{(t-j)}$ – the component of the model captures the effects of the ECB interest rate from the previous period, two periods earlier, and three periods earlier on the current Euribor, while β_j represents the coefficients measuring the effects of these lagged values,
- $\sum_{(k=0)}^{3} \gamma_k \, INF_{(t-k)}$ – the component of the model captures the effects of inflation in the previous period, two periods earlier, and three periods earlier on the current Euribor, while γ_k represents the coefficients measuring the effects of these values,
- ε_t – stochastic error.

Table 2 **Results of the analysis of the impact of inflation and ECB interest rates on Euribor 3M**

	coeff.	stand. error	*z* - statistics	p - value
α_0	0.0009	0.009	0.104	0.917
$EURIBOR_{t-1}$	1.2252	0.059	20.763	0.000
$EURIBOR_{t-2}$	-0.4472	0.088	-5.093	0.000

	coeff.	stand. error	*z* - statistics	p - value
$EURIBOR_{t-3}$	0.1519	0.054	2.827	0.005
ECB_{t}	0.3613	0.039	9.324	0.000
ECB_{t-1}	-0.0282	0.054	-0.519	0.604
ECB_{t-2}	-0.0533	0.054	-0.995	0.321
ECB_{t-3}	-0.2087	0.044	-4.789	0.000
INF_{t}	0.0335	0.015	2.212	0.028
INF_{t-1}	-0.0145	0.024	-0.609	0.543
INF_{t-2}	-0.0002	0.024	-0.009	0.993
INF_{t-3}	-0.0168	0.015	-1.093	0.275

Source: Author's calculations using the Python programming language.

The results presented in Table 2 indicate that the coefficient of 0.0009, with p = 0.917, has no statistically significant effect on Euribor 3M. Despite the three low p-values, the endogenous variable has a statistically significant effect on its own current value, with the effect being positive at the first and third lags (1.2252 and 0.1519, respectively), while a negative effect of -0.4472 is estimated at the second lag. The current ECB interest rate has a strong and statistically significant effect, with a coefficient of 0.3613 and p = 0.000, as does its value at the third lag (coefficient = -0.2087; p = 0.000). The first and second lags do not have a statistically significant effect on Euribor 3M. The current inflation rate has a small but statistically significant effect on Euribor, whereas its lagged values do not have a statistically significant effect.

When conducting the bounds test for cointegration, the calculated F-statistic was 3.819, which is above the upper critical value at the conventional significance levels. The lower-bound p-value was 0.021, while the upper-bound p-value was 0.092. These results provide limited evidence of a cointegrating relationship between three-month Euribor, ECB monetary policy, and inflation in the euro area.

The results of the ECM (Error Correction Model) estimation show that the error-correction coefficient (associated with EURIBOR $3M_{t-1}$ in the ECM model) is -0.0702 (p = 0.001). This indicates a negative, stable, and statistically significant, but relatively slow adjustment mechanism toward the long-run equilibrium, with 7% corrected each month.

Short-run effect of the ECB interest rate in the ECM model: 0.3613 + 0.2620 + 0.2087 = 0.8320

A 1 pp increase in the ECB interest rate over the short run, spanning several months, increases EURIBOR 3M by approximately 0.83 pp, while only the effect of current inflation is statistically significant.

The cointegration equation is as follows:

$$EURIBOR\ 3M_t = 0.013 + 1.014 * ECB_t + 0.029 * INF_t$$

A 1 pp increase in the ECB interest rate in the long run increases EURIBOR $3M_t$ by approximately 1.01 pp, while the effect of inflation is negligible.

Impact on Euribor 6M

Based on the information criterion (BIC = -644.353) and automatic selection (AIC = -689.906), the true ARDL (2, 1, 5) model was estimated, where the dependent variable is the six-month Euribor, while the independent variables are lagged Euribor, euro area inflation, and the ECB reference interest rate (ECB, which combines the MRO and DFR rates).

$$EURIBOR_t = \alpha_0 + \sum_{(i=1)}^{3} \phi_i \, EURIBOR_{(t-i)} + \sum_{(j=0)}^{3} \beta_j \, ECB_{(t-j)} + \sum_{(k=0)}^{3} \gamma_k \, INF_{(t-k)} + \varepsilon_t$$

In the formula:

- $EURIBOR_t$ – Dependent variable: Euribor 6M in period t,
- α_0 – constant in the model,
- $\sum_{(i=1)}^{3} \phi_i \, EURIBOR_{(t-i)}$ – the autoregressive component of the model captures the effects of Euribor in the previous period and two periods earlier on the current Euribor, while ϕ_i represents the coefficients measuring the effects of these lagged values,
- $\sum_{(j=0)}^{3} \beta_j \, ECB_{(t-j)}$ – the component of the model captures the effects of the ECB interest rate in the previous period, two, three, four, and five periods earlier on the current Euribor, while β_j represents the coefficients measuring the effects of these lagged values,
- $\sum_{(k=0)}^{3} \gamma_k \, INF_{(t-k)}$ – the component of the model captures the effects of inflation in the previous period and two periods earlier on the current Euribor, while γ_k represents the coefficient measuring the effects of these values,
- ε_t – stochastic error.

Table 3 **Results of the analysis of the impact of inflation and ECB interest rates on Euribor 6M**

	coeff.	stand. error	*z* - statistics	p - value
constant	-0.0516	0.009	0.032	0.975
$EURIBOR_{t-1}$	1.3554	0.054	25.200	0.000
$EURIBOR_{t-2}$	-0.4175	0.054	-7.731	0.000
ECB_t	0.3033	0.040	7.665	0.000
ECB_{t-1}	0.0018	0.053	0.034	0.973
ECB_{t-2}	-0.1091	0.052	-2.080	0.038
ECB_{t-3}	-0.232	0.052	-4.439	0.000
ECB_{t-4}	-0.0243	0.053	-0.458	0.647

	coeff.	stand. error	z - statistics	p - value
ECB_{t-5}	0.1206	0.036	3.353	0.001
INF_t	0.0469	0.014	3.247	0.001
INF_{t-1}	-0.0399	0.015	-2.727	0.007

Source: Author's calculations using the Python programming language.

When conducting the bounds test for cointegration, the calculated F-statistic was 4.978, which is above the upper critical value at the conventional significance levels. Both p-values are below the standard 5% significance threshold, with the lower-bound p-value equal to 0.00351 and the upper-bound p-value equal to 0.0214. Thus, the null hypothesis of no cointegration is rejected, confirming the existence of a stable long-run equilibrium relationship between the six-month Euribor, ECB monetary policy, and inflation in the euro area.

The results of the ECM estimation show that the error-correction coefficient (associated with $EURIBOR_{t-1}$ in the ECM model) is -0.0621 ($p = 0.001$), indicating a negative, stable, and statistically significant, but relatively slow adjustment mechanism toward the long-run equilibrium, with approximately 6.2% corrected each month.

Impact of the ECB interest rate: The central bank's reference interest rate has a dominant and highly statistically significant effect on the movement of market interest rates in both the short and long run, with the current value having a coefficient as high as 0.3033, with $p < 0.001$. A 1 pp increase in the ECB interest rate is associated with an increase in Euribor of approximately 0.3033 pp in the same period.

Short-run effect of the ECB interest rate in the ECM model: $0.3033 + 0.2448 + 0.1356 – 0.0963 – 0.1206 = 0.4668$

A 1 pp increase in the ECB interest rate over the short run, spanning several months, increases EURIBOR 6M by approximately 0.47 pp, while only the effect of current inflation is statistically significant.

Impact of inflation: The current inflation value, INF_t, has a statistically significant positive short-run effect, with a coefficient of 0.0469 and $p = 0.001$, while INF_{t-1} exhibits a small negative effect, with a coefficient of -0.0399 and $p = 0.007$. In practical terms, a 1 pp increase in inflation in the current period is associated with an increase in Euribor of approximately 0.047 pp in the same period.

The cointegration equation is as follows:

$$EURIBOR\ 6M_t = 0.0051 + 0.9726 * ECB_t + 0.1127 * INF_t$$

The long-run effect of the ECB interest rate is as high as 0.97, indicating that the exogenous variable also has a stronger effect in the long run than in the short run. The long-run effect of inflation is approximately 0.113, indicating that the effect of inflation is stronger in the long run than in the short run.

Using the selected ARDL (2, 1, 5) model and conducting the bounds test for cointegration, the existence of a long-run equilibrium relationship among the variables under consideration was successfully established. The ECM estimation reveals a stable adjustment mechanism toward long-run equilibrium, with the ECB reference interest rate playing a dominant role in determining the movement of market interest rates and, consequently, Euribor. It was also found that inflation has a statistically significant short-run effect on Euribor, albeit a smaller one. This is consistent with the actual functioning of the money market, where inflation exerts an indirect influence through monetary policy, which directly affects interest rates and, in turn, adjusts to inflation dynamics. Therefore, it can be concluded that there is a significant short- and long-run relationship between six-month Euribor, euro area inflation, and the ECB's reference interest rate.

Impact on Euribor 12M

Based on automatic selection (AIC = -662.39) and the information criteria (BIC = -613.08), the ARDL (3, 3, 3) model was estimated, where the dependent variable is the twelve-month Euribor, while the independent variables are lagged Euribor, euro area inflation, and the ECB reference interest rate, which combines the MRO and DFR rates. The VIF values for inflation and the ECB interest rate are 1.7, well below the reference threshold of 5, confirming that there is no multicollinearity problem in the model.

$$EURIBOR_t = \alpha_0 + \sum_{(i=1)}^{3} \phi_i \, EURIBOR_{(t-i)} + \sum_{(j=0)}^{3} \beta_j \, ECB_{(t-j)} + \sum_{(k=0)}^{3} \gamma_k \, INF_{(t-k)} + \varepsilon_t$$

In the formula:

- $EURIBOR_t$ – the dependent variable: Euribor 12M in period t,
- α_0 – constant in the model,
- $\sum_{(i=1)}^{3} \phi_i \, EURIBOR_{(t-i)}$ – the autoregressive component of the model captures the effects of Euribor in the previous period, two periods earlier, and three periods earlier on the current Euribor, while ϕ_i represents the coefficients measuring the effects of these lagged values,
- $\sum_{(j=0)}^{3} \beta_j \, ECB_{(t-j)}$ – the component of the model captures the effects of the ECB interest rate in the previous period, two periods earlier, and three periods earlier on the current Euribor, while β_j represents the coefficients measuring the effects of these lagged values,
- $\sum_{(k=0)}^{3} \gamma_k \, INF_{(t-k)}$ – the component of the model captures the effects of inflation in the previous period, two periods earlier, and three periods earlier on the current Euribor, while γ_k represents the coefficients measuring the effects of these lagged values,
- ε_t – stochastic error.

Table 4 **Results of the analysis of the impact of inflation and ECB interest rates on Euribor 12M**

	coeff.	standard error	z – statistics	p - value
α_0	0.0002	0.009	0.027	0.978
$EURIBOR_{t-1}$	0.8616	0.055	15.583	0.000
$EURIBOR_{t-2}$	-0.0115	0.073	-0.158	0.875
$EURIBOR_{t-3}$	0.0713	0.049	1.456	0.147
ECB_{t}	0.5588	0.037	15.194	0.000
ECB_{t-1}	-0.0884	0.058	-1.516	0.130
ECB_{t-2}	-0.1356	0.057	-2.366	0.019
ECB_{t-3}	-0.2532	0.050	-5.104	0.000
INF_{t}	0.0256	0.015	1.676	0.095
INF_{t-1}	-0.0107	0.024	-0.443	0.658
INF_{t-2}	-0.0086	0.024	-0.356	0.722
INF_{t-3}	-0.0096	0.016	-0.617	0.538

Source: Author's calculations using the Python programming language.

The results presented in Table 4 indicate that the coefficient, with a value of 0.0002 and p = 0.978, has no statistically significant effect on Euribor 12M. The effect of the endogenous variable at the first lag on its current value is statistically significant and positive (coefficient = 0.8616, p = 0.000), while the effects of the second and third lags are not statistically significant. The current ECB interest rate has a strong and statistically significant effect, with a coefficient of 0.5588 and p = 0.000, while the values of the second and third lags are statistically significant and negative.

When conducting the bounds test for cointegration, the calculated F-statistic was 4.189, which is above the upper critical value at the conventional significance levels. The lower-bound p-value is 0.0119, while the upper-bound p-value is 0.0589, providing limited evidence of a cointegrating relationship between the twelve-month Euribor, ECB monetary policy, and inflation in the euro area.

The results of the ECM estimation show that the error-correction coefficient (associated with EURIBOR $12M_{t-1}$ in the ECM model) is -0.0786 (p = 0.001), indicating a negative, stable, and statistically significant, but relatively slow adjustment mechanism toward the long-run equilibrium, with approximately 7.9% corrected each month.

Short-run effect of the ECB interest rate in the ECM model: 0.5588 + 0.3887 + 0.2532 = 1.2007

A 1 pp increase in the ECB interest rate over the short run, spanning several months, increases EURIBOR 12M by approximately 1.2 pp, indicating that monetary policy has a stronger effect on EURIBOR 12M than on EURIBOR 3M and, particularly, EURIBOR 6M.

The cointegration equation is as follows:

$$EURIBOR\ 12M_t = 0.0025 + 1.038 * ECB_t + 0.041 * INF_t$$

In the long run, a 1 pp increase in the ECB interest rate increases EURIBOR $12M_t$ by approximately 1.04 pp, while the effect of inflation is negligible.

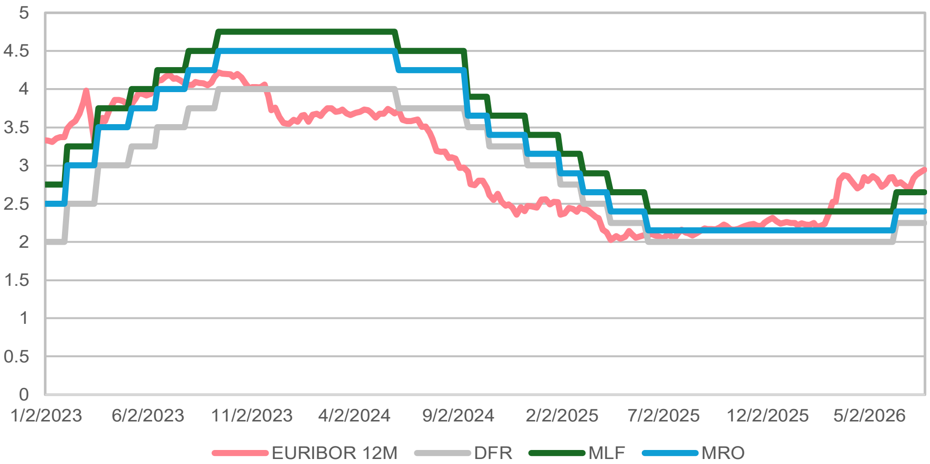
5.4 Other factors affecting Euribor

As mentioned earlier in the paper, ECB interest rates form a corridor within which market interest rates fluctuate. However, the data presented in the following charts point to a different situation in practice. The chart examines the movements of the twelve-month Euribor and all three ECB interest rates. A deviation from the theoretical assumption can be observed: at the end of 2023, Euribor fell below the prevailing DFR, while in the first half of the current year, it exceeded the MLF, which is considered the upper bound that Euribor would theoretically be expected to reach.

This raises the question of why such an outcome is observed in practice. The answer can be found by considering the type of interest rate and taking into account the other factors affecting Euribor. Namely, as mentioned earlier, in addition to the ECB's monetary policy, Euribor is also influenced by market expectations regarding the future course of monetary policy. As a result, market interest rates may change even before the ECB officially changes its policy rate. This can explain precisely the situation in which Euribor falls significantly below the lower bound of the corridor, as the market anticipated that the ECB would embark on monetary easing and lowered interest rates in advance. Given that the Euribor under consideration has a 12-month maturity, market expectations that the ECB will reduce its reference interest rates in the future become particularly pronounced.

Another interesting situation can be observed when examining the data for the current year. During a period of geopolitical tensions, which have had a particularly pronounced impact on energy prices, the market responded by raising one-year borrowing rates even before the ECB began tightening monetary policy.

Chart 6 **Movement of Euribor 12M, DFR, MRO and DLF**
(daily data, p.a., in %)



Source: Bank of Finland, (n.d.), ECB (n.d.).

5.5 Overall assessment of the analysis results

The results of the preceding analyses confirm the strong influence of the ECB's monetary policy on Euribor rates across all maturities. Although the analysis of the impact of inflation on Euribor confirmed a statistically significant effect of inflation, the model incorporating both inflation and monetary policy indicates that the ECB monetary policy is the primary determinant of Euribor. It is noteworthy, however, that over shorter observation horizons, Euribor movements occasionally deviate from the corridor defined by the ECB, indicating that other factors also influence Euribor level, such as market expectations and geopolitical tensions. Therefore, when assessing the future path of Euribor, it is essential to monitor the factors underlying the ECB's policy decisions and market expectations, while also bearing in mind that actual outcomes depend on other factors whose impact is often difficult to anticipate and whose evolution cannot be influenced.

6 Conclusion

Let us conclude by reviewing the key findings addressed in this paper. Despite all the challenges it has faced over its nearly three-decade-long history, the Euribor rate remains one of the key indicators in financial markets and determines the cost of many of the financial products discussed above, which, in the case of Serbia, most commonly include housing loans. The change in the calculation methodology has minimized the human factor, which, as noted earlier, had a negative impact on the objectivity of the data. The data calculated under the new methodology are more representative and better reflect actual conditions in the money market. Among the main factors influencing the level of Euribor rates is undoubtedly the monetary policy of the ECB, which, by setting three key interest rates, determines the corridor within which market interest rates, and consequently Euribor, fluctuate. Using the ARDL model, it was found that a 1 pp increase in ECB interest rates leads to a short-run increase in the three-month Euribor of 0.83 pp, the six-month Euribor of 0.47 pp, and the twelve-month Euribor of as much as 1.2 pp. This finding indicates that the ECB's monetary policy has a stronger impact on longer-term Euribor rates. In addition, the analysis shows that a 1 pp increase in inflation in the current period leads to an increase in the six-month Euribor of 0.047 pp, while the corresponding effect on the three-month Euribor amounts to only 0.03 pp. For the twelve-month Euribor, the estimated effect is not statistically significant. These findings suggest that inflation affects Euribor indirectly, primarily through its influence on the ECB's monetary policy. As noted above, among the factors influencing Euribor are market expectations regarding the future course of monetary policy, as well as the significant impact of geopolitical tensions on interest rate dynamics and the economy as a whole. Therefore, all stakeholders in the banking sector and the broader financial market seeking to project future Euribor rates should take ECB monetary policy into account, while also monitoring non-market factors that may have a potentially significant impact, most notably geopolitical tensions. This paper provides a basic overview of the factors influencing Euribor rates. Further research into this phenomenon could examine the effects of other macroeconomic indicators, as well as factors that may not have been considered to date in the analyses of the determinants of Euribor dynamics.

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