CELEBRATING 50

Public Sector Economics

1/2026

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* The views expressed are those of the authors and not necessarily those of the OECD or the Croatian National Bank.

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PUBLIC SECTOR ECONOMICS
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This issue of *Public Sector Economics* brings together two winning entries from the 2025 *Hanžeković Foundation Competition* for papers in public sector economics, and four papers selected from submissions to a call for papers on exchange rate issues.

The winning entries in last year's Hanžeković Foundation Competition both analyse inflation in Croatia. Frane Banić and Guzmán González-Torres received the regular award for their paper *Different strokes for different folks: untangling supply and demand shocks using survey-data to assess sectoral inflationary pressures in Croatia*, while Mihael Brusan and Jakov Čorak received the student award for their paper *Inflation in Croatia: a new era of forecasting with machine learning*.

The four papers and a book review in the thematic part analyse the international monetary system at different levels, including the global dominance of the US dollar, its consequences for sovereign debt, inflation and growth, and the role of foreign currency reserves and policy credibility during crises and military conflicts. The contributions move from structural foundations, including why the dollar matters, to the transmission mechanisms operating through exchange rates to debt, inflation and growth, and then to policy buffers such as reserves and communication that shape outcomes under both normal and extraordinary conditions.

The paper *Public debt and the dollar* by Aaron Mehrotra examines one of the key transmission channels of dollar dominance, namely sovereign debt dynamics. Using a large cross-country panel, the paper shows that periods of US dollar appreciation are associated with higher public debt ratios over the medium term. This effect is concentrated in emerging market and developing economies, and is unsurprisingly strongest where foreign currency debt shares are high and market perceptions of debt sustainability are weak. The results highlight how the dollar acts not only as a trade and financial currency but also as a global financial condition factor that amplifies fiscal vulnerabilities. Advanced economies appear largely insulated from the negative impact of dollar appreciation on their public debt, underscoring asymmetric exposures within the international monetary system.

The second contribution, *When the guns roar: how the war, reserves and exports shape Ukraine's cost of external borrowing* by Sergii Sheludko shows, using the example of Ukraine, that military conflict sharply increases sovereign borrowing costs, while international reserves play a crucial stabilising role by narrowing spreads even in such circumstances. Export revenues provide some support but are highly volatile due to logistical disruptions. The findings demonstrate that, in the most adverse conditions, central bank foreign currency reserves remain a key policy buffer shaping market perceptions of debt sustainability and the country's access to external finance. This finding resonates with the broader conclusions of other papers in this special issue, on the vulnerability created by external exposure, the importance of credible buffers in maintaining economic stability, and the centrality of the dollar.

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Complementing the analysis of macroeconomic exposures to foreign currency fluctuations, the third paper, *Effects of reputation and monetary policy communication on exchange rate uncertainty: evidence from an emerging economy*, by Juan Camilo Anzuátegui Zapata, Danilo Rodríguez Arango and Sergio David Sánchez Varela shows how in Colombia an enhanced central bank reputation, clearer policy communication, and unanimous decision making significantly reduce exchange rate uncertainty, which is measured through disagreements in exchange rate expectations and exchange rate forecast errors. These findings suggest that even in emerging market economies exposed to large external real and financial sector shocks, a credible central bank and transparent communication can mitigate volatility and uncertainty, thereby dampening some of the adverse spillovers associated with global oil prices and dollar movements.

The fourth contribution, *Currency depreciation and inflationary pressure vis-à-vis monetary intervention: perspectives on growth and policy imperatives*, by Samson Edo and Eseosa Joy Sowemimo shifts attention to how exchange rate movements, often driven by global dollar cycles, affect economic growth in Sub-Saharan African countries. The study finds that currency depreciation and inflation exert a strong negative impact on growth, contradicting the simplistic view that depreciation boosts growth by raising export competitiveness. Importantly, foreign exchange interventions by central banks are found to be largely ineffective in offsetting these adverse pressures, reflecting constraints imposed by low reserve buffers and conflicting goals of monetary and fiscal policies. The paper reinforces the idea that exchange rate movements can entail persistent growth costs when domestic financial and institutional conditions are weak.

The review of Kenneth Rogoff's book *Our Dollar, Your Problem* rounds off this thematic issue by explaining why the US dollar remains at the centre of the international monetary system despite rising geopolitical fragmentation. The book emphasises the historical roots of dollar dominance, the unmatched depth and liquidity of US financial markets and the central role of US Treasury securities as global safe assets. While challengers such as the euro and the renminbi have gained ground at the margin, structural weaknesses, including fragmented financial markets in Europe and capital controls in China, limit their global expansion. The review situates current debates on de-dollarisation in a historical perspective, and stresses that the erosion of dollar dominance, if it occurs, is likely to be gradual rather than abrupt.

As the editors of this thematic issue, we would like to thank the authors for their efforts in preparing this set of stimulating and analytically rich papers; the reviewers for their insightful comments and patient reading of multiple versions of manuscripts; the copyeditor Marina Nekić from the Institute of Public Finance for her guidance in preparing the manuscripts; and the editor-in-chief Mihaela Bronić and co-editor Katarina Ott of *Public Sector Economics* for giving us the opportunity to arrange this special issue.

Different strokes for different folks: untangling supply and demand shocks using survey-data to assess sectoral inflationary pressures in Croatia

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Article**
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Abstract

While inflation has moderated across most of the euro area since its post-pandemic peak, some countries still face above-average price pressures. In Croatia, inflation has slowed but remains persistent, raising questions about its underlying origins. This paper analyses recent inflationary pressures in Croatia, using firm-level survey data on production constraints and capacity utilization to untangle supply and demand factors in services and manufacturing, considering sectoral inflation divergence. Unlike traditional approaches, our sectoral output gap captures both supply and demand side drivers of inflationary pressures. Findings show that post-pandemic inflation was mainly driven by supply factors, labour and intermediate input shortages, while ongoing demand pressures, especially in services, continue to fuel inflation. By examining structural and cyclical factors we offer new insights into how inflation behaves in smaller euro area economies, which could help policymakers refine their tools for managing inflation since one-size-fits-all solutions may fall short.

Keywords: sector-specific output gap, survey-data, inflation divergence, structural Phillips curve, Croatia

1 INTRODUCTION

The COVID-19 pandemic and the global energy crisis triggered a sharp spike in inflation worldwide. In the euro area, economists have identified several factors that drove this surge. Some believed inflation would ease as supply chains recovered and energy prices stabilized, especially after the disruptions caused by the pandemic and the war in Ukraine (ECB, 2022; IMF, 2022). Others argued that deeper demand-driven causes, such as strong post-pandemic consumer spending and a tight labour market could create longer-lasting price pressures (Ferreira, Abreu and Louçã, 2025).

By 2024, inflation in the euro area had largely cooled, with the average annual growth rate of the Harmonised Index of Consumer Prices (HICP) falling from 8.4% in 2022 to 2.4% – close to the European Central Bank's target. This decline was supported by a combination of tight monetary policy and targeted, temporary fiscal support. However, not all countries followed this trend. In Croatia, inflation remained stubbornly high, dropping from 10.7% in 2022 to 4% in 2024.

This paper seeks to shed light on why inflation in Croatia remains elevated and what this means for policymakers trying to bring it back to target. We explore whether the root causes are linked more to lingering supply issues, such as labour shortages and demographic challenges, or to ongoing demand pressures. To do this, we use sector-level survey data that track the extent to which businesses are using their capacity and what factors are limiting their output at a quarterly frequency. We use these data to build, to the best of our knowledge, an original output gap estimates by linking sector-level inflation to the incidence of each of the limiting factors across firms in a given sector.

We then break down inflationary pressures into supply-side and demand-side components and explore how Croatia's unique economic landscape, including an aging workforce and recent fiscal policies, helps explain these findings. Our analysis focuses on three key questions. First, can traditional ways of estimating economic slack, such as output gaps obtained by filtering aggregate output, accurately reflect inflationary trends in Croatia? Second, can a more advanced method, using a Bayesian VAR (BVAR) model with structured shocks, provide better insights, especially in the context of a small, open economy? And third, how do different shocks, whether temporary or long-lasting, influence inflation and output gaps?

Finally, we look at how these pressures play out across different sectors. We find that inflation in services remained high throughout 2022-2024, driven by both strong demand and persistent labour shortages. In contrast, inflation in manufacturing has eased more recently, although the sector still shows signs of inflationary pressures due to continued demand and limited labour availability. Survey-based results refute the output gap estimates for Croatia when using univariate filters (HP, one-sided HP, Hamilton). These methods capture demand-side pressures, thus omitting supply shocks by labelling them as permanent, which is misleading according to our novel approach. As we show, the fact that supply shocks were not negligible across sectors explains why traditional approaches to output gap estimates did not properly signal inflationary pressures in 2022-24. Also, we show that the Phillips curve in Croatia is not necessarily flat, contrary to previous domestic research. These insights are of added value for central bankers since the output gap is an important tool for monetary policy decisions, thus reflecting the need to take into account any potential temporary supply shock in the economy when formulating a monetary or macroprudential stance, where the latter could be a more effective tool in reducing inflation indirectly through increased demand because lending decisions are made independently at the national level.

The rest of the paper is structured as follows: section 2 examines the usefulness of traditional output gap measures and the BVAR approach in detecting inflationary pressures. Section 3 introduces a new, survey-based measure using firm-level data. Section 4 connects our findings to broader structural and cyclical forces at play in Croatia. Section 5 concludes.

2 DIFFERENT METRICS FOR ESTIMATING THE OUTPUT GAP AND WHY THE LATTER MATTERS FOR INFLATION

Price developments are primarily linked to economic slack, i.e., the intensity with which firms use resources such as equipment, technology, or the workforce in the production process, compared to their installed capacity (ECB, 2018).[1] When firms underutilize their productive capacity due to insufficient demand, they tend

[1] Inflation expectations also play a major role in price formation: if businesses expect high inflation, they will adjust their own prices accordingly in order to make up for the increased cost of their inputs and relative devaluation of their nominal profits. That is why central bank credibility and action is crucial in preventing inflationary spirals.

to limit their production and decrease their prices to attract customers and minimize losses. Conversely, when demand is strong, the increase in the intensity with which they produce their goods and services can lead to increases in production costs due to higher capital depreciation and higher wage bills, pressing firms to increase their own prices.

In macroeconomics, the level of output firms would usually achieve in the absence of shocks and policy changes, given the installed production capacity of the economy, is known as potential GDP. Economic slack, i.e., the distance between actual observed GDP and potential GDP as a percentage of the latter, is called the output gap. The output gap is a measure of the state of the economy: a positive output gap means the economy is producing above its usual level, while the opposite occurs when it is negative. When the business cycle is mainly driven by demand shocks, a positive output gap leads to an increase in inflationary pressures, whereas a negative output gap decreases inflationary pressures and, if negative enough, can eventually lead to deflation. For central banks, the output gap is thus a crucial input for monetary policy decisions, as conceptualized by the Taylor rule (Mazelis, Motto and Ristiniemi, 2023). In an economy dominated by demand shocks, a positive output gap signals the need for a restrictive monetary policy stance and vice versa.

Following this view, policy institutions have traditionally measured the output gap using a combination of statistical filters on aggregate output and the production function approach (Havik et al., 2014; De Masi, 1997). One crucial assumption behind most traditional output gap estimates is that supply shocks are permanent and thus only affect potential output (see e.g. Blanchard and Quah, 1989). When the economy is hit by temporary negative supply shocks, as was the case during and after the pandemic across all European economies, an output gap measured with traditional methods would result in a negative estimate, as the temporary fall in output would not register as a shift in potential. The relationship between the estimated output gap and inflation would turn upside down: for example, a large increase in input prices, such as the price of imported energy, can oblige firms to increase their prices, while simultaneously reducing the amounts of goods and services they produce (González-Torres, Gumiel and Szörfi, 2023). The output gap would therefore not be signalling the presence of inflationary pressures, possibly depriving monetary policy makers of an important input in their decision process.[2] Furthermore, given that the output gap is traditionally estimated using

[2] On the flipside, the output gap measure we propose is one to measure inflationary pressures, but not necessarily to reflect the state of the business cycle: the state of the business cycle, i.e., the distance between the actual output of an economy and its potential, is well measured by traditional output gap estimates, if we believe that supply shocks affect potential output directly. We therefore don't advocate using our output gap estimate as a way to estimate potential output. The question of how temporary supply shocks are, and possibly more importantly, how large temporary supply shocks are compared to permanent ones, is still an important issue in terms of estimating potential output. As shown below, our data are agnostic concerning what level of supply factors affecting firms in our sample is temporary rather than permanent; however, what they do suggest, is that the magnitude of the temporary supply shocks that hit the EA during and after the pandemic was significantly larger than ever before. In that sense, it would suggest that potential output, at least during the pandemic, fell significantly more strongly than suggested by traditional estimates.

aggregate data, which are only available in their final version with considerable delay, its real-time estimate is highly uncertain and prone to large revisions.

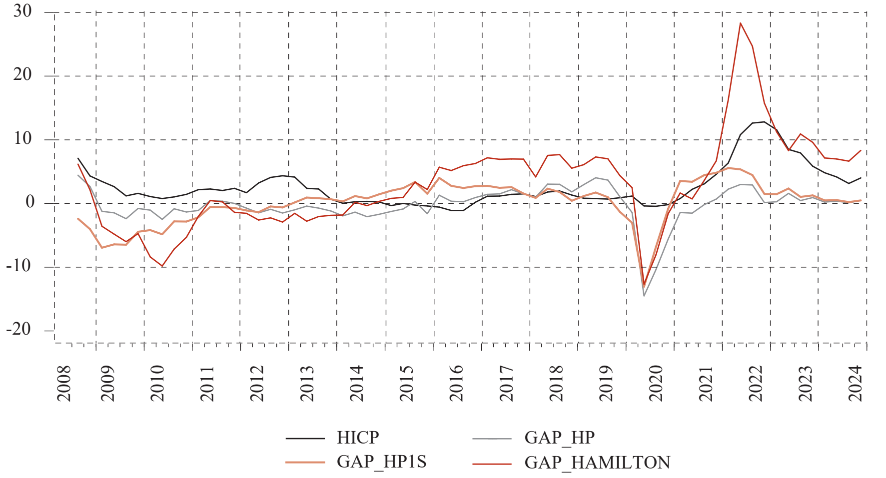
Recent international literature has increasingly questioned the effectiveness of traditional output gap measures in explaining inflation dynamics during the post-pandemic period. In the euro area, the ECB's analysis highlights how conventional models, such as those based on univariate filters (e.g., HP, Hamilton), often failed to capture the complex interplay of supply and demand shocks that drove inflation after 2020. These models tended to underestimate the role of supply-side factors, such as energy price spikes and supply chain disruptions, which were critical in shaping inflationary pressures, particularly in small open economies (Giannone and Primiceri, 2024). Similarly, in the United States, studies using macroeconomic models (e.g., DSGE and BVAR) have shown that while demand-side factors (e.g., expansionary fiscal and monetary policies) contributed to inflation, supply shocks, such as labour market tightness, bottlenecks, and energy price volatility, played a dominant role in the initial surge. Traditional output gap measures, which primarily focus on demand-driven slack, were often misaligned with actual inflation trends, as they struggled to account for the persistent effects of supply disruptions (Faria-e-Castro, 2025; Brooks, Orszag and Murdock, 2024). The Federal Reserve's analysis further underscores the importance of global and regional supply frictions, which were not adequately captured by traditional models (Federal Reserve, 2025).

We follow the international literature by using various slack measures to illustrate the previous points: univariate filters (HP, one-sided HP, Hamilton), which have previously been applied in the domestic literature (Jovičić, 2017; Grgurić, Nadoveza Jelić and Pavić, 2021; Arčabić and Banić, 2021), as well as and the BVAR approach, which has not yet been applied in the domestic literature.

Figure 1 presents estimates for the Croatian output gap using the Hodrick-Prescott (1997), the one-sided Hodrick-Prescott (Wolf, Mokinski and Schüler, 2020) and the Hamilton (2018) filters alongside total inflation, measured with HICP, in Croatia (details regarding the methodology of univariate filters are in the appendix). Although all three output gaps seem to become positive as inflation starts to rise after the pandemic, only the Hamilton filter seems to fully capture the inflationary pressures in that period: the HP and the one-sided HP filter indicate a neutral output gap aside from the beginning of 2022, most likely reflecting the effects of the energy crisis, which pushed inflation up while keeping output low. Furthermore, Croatia has been experiencing persistently high core inflation, mostly due to services, whose slowdown has been significantly less pronounced than that of headline inflation. This is not reflected in either HP filter.

Figure 1

Output gaps (in % of potential GDP), total HICP inflation (YoY, %) in Croatia



Source: Eurostat, authors' calculations.

Going a step further, one could argue that the Hamilton filter does not correctly signal those pressures either: even though it does estimate a highly positive output gap in the latter period, the estimates are not very different from other periods like the mid-2000s or late 2010s, when inflation was relatively low. Overall, this would lead us to think the Hamilton filter is highly volatile over the entire sample, regardless of inflation. Also, none of these methods directly take into account price developments and rely only on real GDP.

Blanchard (2018) emphasizes that in times of strong shocks (demand and/or supply), the HP or any univariate filter cannot properly distinguish between the different natures of shocks, thus estimating potential GDP and an output gap that do not follow price developments. Also, univariate filters like HP have other statistical disadvantages, e.g., end-of-sample problem, making the estimates sensitive to each new data point (Jovičić, 2017). Additionally, univariate filters do not have economic meaning, as distinct from some other advanced approaches like the production function or structural models. However, Banić, Pripužić and Rebić (2024) show that the output gap estimated with a production function does not deviate much from that estimated with an HP filter.

Finally, we can conclude that traditional output gap measures mostly failed to signal inflationary pressures for the period 2021-2024 in Croatia. To find the relationship between inflation and the output gap in Croatia, we also use a more advanced econometric approach. We estimate the output gap for Croatia with accumulated domestic and external demand shocks (usually characterized as temporary) using a BVAR, which is also a novel approach in the domestic literature, following the approach by Coibion, Gorodnichenko and Ulate (2017). However, our identification of structural shocks also takes into account the block exogeneity assumption for a small open economy (Deskar-Škrbić, Kotarac and Kunovac, 2020; Jovićić and Kunovac, 2017; Barišić and Kovač, 2022; Arias, Rubio-RamÌrez and Waggoner, 2014).

In this case, we use quarterly data from 2006Q1 to 2024Q4 on real gross domestic product (GDP) and the Harmonised Index of Consumer Prices (HICP) from Eurostat. Firstly, we adjust the variables for the seasonal component with Census-X12 and then use the annual rate of change in real GDP and HICP.

The structural shocks within the Bayesian Vector Autoregressive model are obtained through sign and zero restriction identification (see the appendix for more methodological and technical details), which is a common empirical strategy in the domestic literature (Deskar-Škrbić, Kotarac and Kunovac, 2020; Jovičić and Kunovac, 2017; Nadoveza, 2025). Regarding the imposed shocks (appendix, table A2), a domestic (Croatian) aggregate demand shock increases both GDP and HICP in Croatia, with no effect on euro area variables, while a domestic aggregate supply shock increases GDP and decreases HICP in Croatia, with no effect on euro area variables either. Regarding external (euro area) shocks, aggregate demand increases economic activity and inflation in the euro area with indeterminate effects on domestic (Croatian) GDP and HICP, while a supply shock increases GDP and HICP in the euro area with unrestricted effects on domestic (Croatian) GDP and HICP.

During 2020-24, Croatia experienced various combinations of domestic and external shocks, which are depicted on historical decomposition of the annual inflation and real GDP growth rate (see appendix, figures A4-A7). A historical decomposition is usually used to decompose the contribution of a specific shock *k* to an observed variable *j* in a model in period *t*:

$$y_{jt}^{k} = \sum_{h=0}^{t-1} \psi_{jk,h} \, x \, \varepsilon_{k,t-h} \tag{1}$$

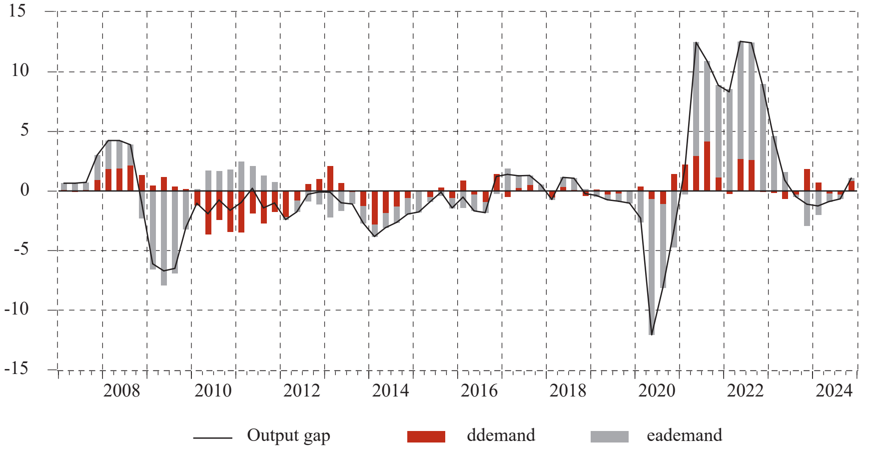
In the next step, we construct the output gap with accumulated domestic (Croatian) and external (euro area) demand shocks to real GDP:

$$y_{gdpt}^{demand} = \sum_{h=0}^{t-1} \psi_{gdp,h} x \, \varepsilon_{k,t-h} \tag{2}$$

Figure 2 shows that the output gap calculated as accumulated domestic and external demand shocks to GDP (like Coibion, Gorodnichenko and Ulate, 2017) explains demand-side inflationary pressures more accurately than univariate filters (figure 1), which only consider real GDP, while this model also captures external, euro area demand shocks (*eademand*), important for a small and open economy like Croatia.

Figure 2

Output gap in Croatia according to accumulated domestic and external demand shocks to real GDP (%, percentage points)



Note: ddemand corresponds to domestic (Croatian) demand shock, while eademand corresponds to euro area demand shock.

Source: Authors' calculations.

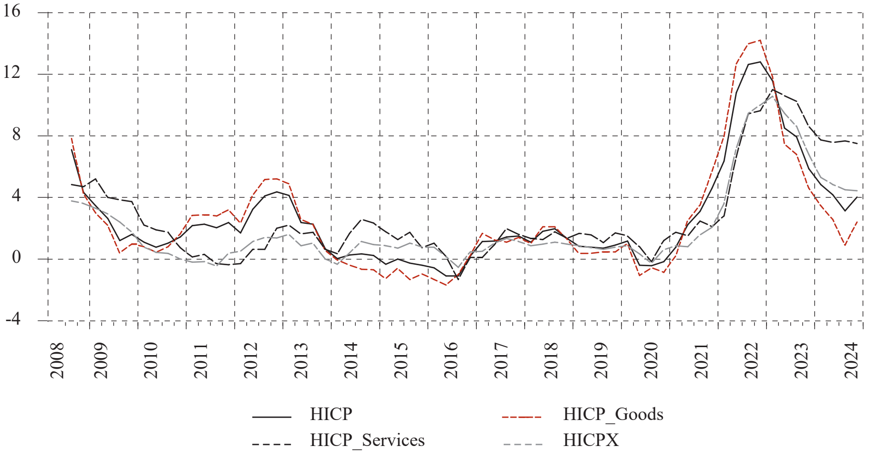
However, the approach by Coibion, Gorodnichenko and Ulate (2017) adheres to the premise that transitory supply shocks affect not the output gap but potential output. González-Torres, Gumiel and Szörfi (2023) show that including the effects of transitory supply shocks, such as supply bottlenecks during the pandemic and the energy market disturbances thereafter, in the output gap instead of potential output, helped the output gap comove significantly with inflation during those episodes. Regarding the pandemic supply shock, Granados and Parra-Amado (2024) highlight the importance of time adjustments to counteract the high degree of uncertainty and instability when using traditional approaches (univariate filters) for estimating the output gap. In Croatia, there were no scarring effects during the pandemic, mostly due to job retention schemes (Barišić and Kovač, 2022), which enabled a post-pandemic V-shaped economic recovery to some extent. The Next Generation EU programme also played a crucial part, both on the demand- and the supply side, through the fiscal and structural reform channels: demand-driven stimuli were channelled through higher government revenues and the supply side improved following the positive effects of structural reforms and investments (ECB, 2024).

Identifying supply shocks separately from demand shocks is crucial, as is estimating their duration. However, the literature, following Blanchard and Quah (1989), has usually used the duration of shocks to identify whether they came from demand (assumed to be temporary) or supply (assumed to be permanent). We instead propose the use of a sectoral-level survey to directly estimate the output gap. Our estimate lets us:

1) Construct sector-specific output gap estimates that take the price divergence in goods and services in Croatia into account (figure 3).
2) Derive a detailed decomposition of supply (labour, equipment and other) and demand factors, based on survey data.

Figure 3

Total HICP, Core HICP(X), HICP services, HICP goods for Croatia (YoY, %)



Source: Eurostat.

Namely, although inflation in Croatia is on a declining path in 2024, it is still above target and among the highest in the euro area, mostly due to the contribution of inflation in services. Thus, it is necessary to analyse which factors (demand and/or supply) are affecting the dynamics in services and manufacturing regarding inflationary pressures.

3 AN ALTERNATIVE OUTPUT GAP TO EXAMINE SURVEY-BASED SECTORAL INFLATIONARY PRESSURES IN CROATIA

Given that an aggregate output gap cannot signal neither (dis)inflationary pressures coming from a rich mix of shocks, nor divergent sectoral developments, especially when traditional measures of the output gap capture mostly demand shocks, we use a novel approach to estimate inflationary pressures. We construct a survey-based output gap in services and manufacturing using data from the European Commission's Business Surveys.[3] In particular, we take the responses on capacity utilization and the factors limiting production by sector. In any given quarter, firms indicate whether demand, supply or other factors are relevant in limiting production, as well as the percentage of their capacity they are using in

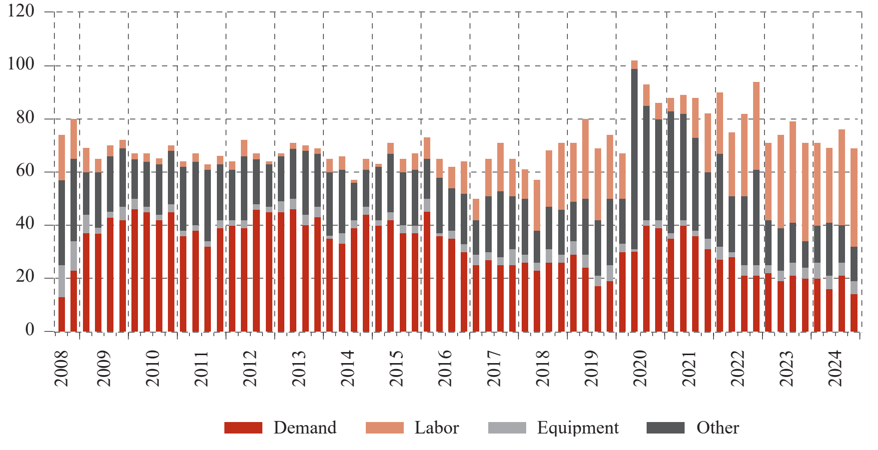
[3] The European Commission's business surveys gather information from firms across Europe regarding their rate of capacity utilization, i.e., a direct measure of economic slack, as well as the various factors that limit their production in a certain quarter, including insufficient demand, labour shortages, lack of equipment, materials, or space, and "other factors". Survey data for services includes three hundred companies and for manufacturing two hundred and forty companies in Croatia. The survey is available at: https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys_en.

production at that time. Using the information regarding limiting production factors, we can properly assess whether inflationary pressures stem from supply or demand factors by correlating sector-level inflation to the percentage of firms limited by each of the factors shown below. Due to data availability, we cover the period between 2008Q3 and 2024Q4.

Figure 4 indicates the survey-based factors limiting production in services for Croatia, reflecting an impulse from demand once the pandemic restrictions were lifted in the aftermath of the COVID-19 crisis. However, the sharp increase in labour shortages (mismatch of demand and supply on the labour market) which had partly already started growing right before the pandemic stands out beyond the increased demand. Figure 4 also shows a temporary increase in the number of firms affected by other factors during the pandemic, which can be related to some of the pandemic-related health measures imposed on the services sector in Croatia. Service sector firms in Croatia instead did not seem to be significantly affected by equipment bottlenecks.

Figure 4

Factors limiting production in services for Croatia (% of firms claiming specific factors limiting production)

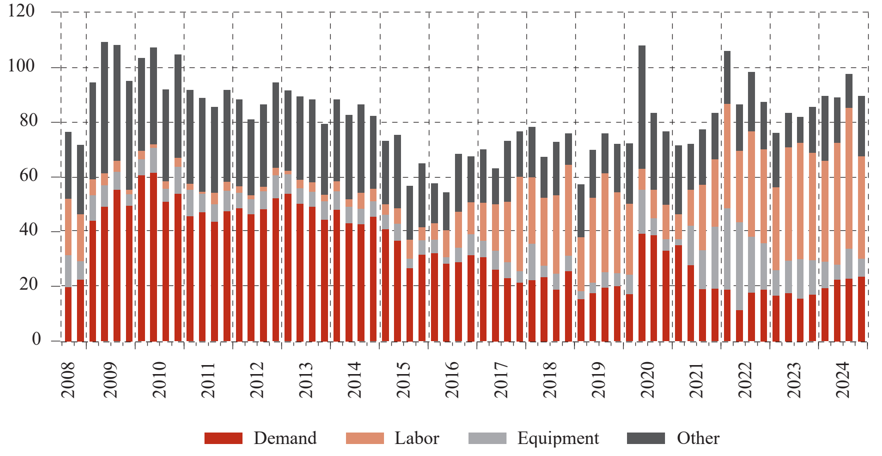


Note: The figure shows the percentage of firms claiming each factor limited their production in a given quarter. The sum of all firms claiming they were limited by some factor may add up to more than 100 percent, reflecting the fact that firms might identify more than one factor limiting their production.

Source: European Commission.

Turning to manufacturing, figure 5 shows an increase in demand post-pandemic analogous to that in services. Furthermore, the prevalence of firms facing labour shortages that started before the pandemic is also evident in manufacturing. However, contrary to what happened in the services sector, Croatian firms in the manufacturing sector reported a significant increased effect of equipment bottlenecks on their production after the pandemic. Other factors instead did not seem to limit manufacturing firms more significantly than before the pandemic.

Figure 5
Factors limiting production in manufacturing for Croatia (% of firms claiming specific factors limiting production)



Note: The figure shows the percentage of firms claiming each factor limited their production in a given quarter. The sum of all firms claiming they were limited by some factor may add up to more than 100 percent, reflecting the fact that firms might identify more than one factor limiting their production.
Source: European Commission.

We construct our alternative output gap measure in various steps. First, we use demeaned values of sectoral inflation and the factors limiting production to capture (dis)inflationary signals. On the one hand, we do so in recognition of the important role inflation expectations play in setting inflation, as illustrated, e.g., by Beaudry, Hou and Portier (2025). By using demeaned values, we abstract from inflation expectations in our estimates.[4] On the other hand, by using demeaned limiting factors, we try to approximate temporary shocks, thus recognizing that permanent shocks should by accounted variations of potential output as opposed to the output gap. Next, we extract the demand fluctuations from other and supply factors (labour and equipment) to address the potential issue of endogeneity: firms chose their inputs partly based on the demand they face. Demand levels might therefore directly affect whether firms claim to be limited by supply or other factors at any given time. We regress equipment (E), labour (L) and the other factors (O) on demand (D):

$$F_t = \gamma^F + \gamma_1^F D_t + \eta_t^F \tag{3}$$

where $F \in \{E, L, O\}$ and we construct the factors limiting production netted of demand using the residuals from equation (3) ($N_t^F = \eta_t^F$). Finally, we estimate the following equation (4), separately for services (with a linear trend) and manufacturing, where π represents demeaned inflation in services and manufacturing, respectively:

$$\pi_t = \alpha + \beta_1 D_t + \beta_2 N_t^E + \beta_3 N_t^L + \beta_4 N_t^O + \varepsilon_t \tag{4}$$

[4] We are implicitly assuming that inflation expectations are anchored throughout the sample. Introducing varying inflation expectations is the subject of forthcoming research.

Table 1
Survey-based sectoral factors limiting production regressions

	Manufacturing	Services
Demand	-0.102***	-0.220***
	(0.022)	(0.053)
Other factors	0.014	0.026
	(0.061)	(0.042)
Labour	0.086*	0.312***
	(0.042)	(0.072)
Equipment	0.208***	0.117
	(0.053)	(0.234)
Constant	1.402***	245.250
	(0.363)	(252.372)
Observations	64	64
Joint significance (chi2)	52.094	75.490
p	0.000	0.000

*Note: * p<0.10, ** p<0.05, *** p<0.010.*
Source: Authors' calculations.

Table 1 shows the results of estimating equation (4). Demand as a factor limiting production enters the regression with a negative coefficient, as a higher value signifies that firms have a harder time finding clients and thus suffer fewer inflationary pressures from demand. Supply factors enter the regression with a positive coefficient, as higher values reflect firms' finding it harder to employ the corresponding factors, thus raising their input prices, which they ultimately pass on to their final prices.

Finally, we construct our output gap by drawing an analogy between equation (4) and a Philips curve. Each of the factors limiting the production of firms simultaneously affect their pricing decisions, leading to various degrees of inflationary pressures. In traditional output gap estimates, which correctly reflect inflationary pressures created by demand shocks, an increase in demand should be positively correlated with price changes, thus leading to a positive output gap. However, when supply shocks (e.g. supply bottlenecks) hit firms, the shocks limit the production of firms, while still creating inflationary pressures, which can lead to dampening the slope coefficient of a traditional Philips curve. We therefore define our output gap measure as the fitted values of the regression (4) normalized to have the same volatility as capacity utilization in the data[5]:

$$\widehat{OG}_t = \left(\pi_t - \widehat{\varepsilon}_t\right) \frac{\sigma_{CU}}{\sigma_{\left(\pi_t - \widehat{\varepsilon}_t\right)}} \tag{5}$$

[5] We introduce the normalization for the purpose of making its magnitude comparable to a traditional output gap, to be able to overlay the two graphically. The normalization is innocuous as long as we limit our analysis to interpreting the time variation of the output gap compared to itself. We are careful, however, not to interpret its magnitude directly as the deviation of output from a level that would zero out inflationary pressures, as that would implicitly assume certain values for the elasticity of production with respect to the various shocks, which we don't estimate here. This latter point is the subject of ongoing research.

Table 2 emulates the Philips curve for our survey-based output gap, according to which we obtain the same regression coefficients as for equation (4). We find that a Philips curve estimated with the survey-based output gap does predict a significant slope, thus capturing all inflationary pressures present in Croatia.

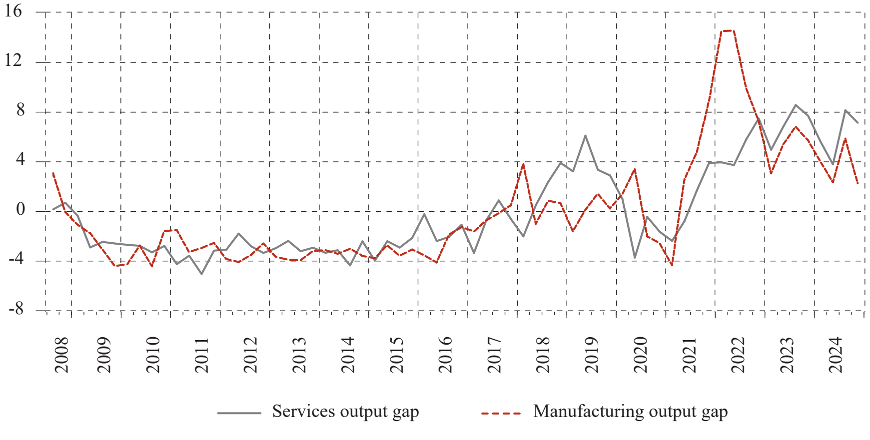
Table 2
Survey-based sectoral output gap regressions

	Manufacturing	Services
Survey-based output gap	0.492***	0.788***
	(0.071)	(0.133)
Constant	1.402***	245.250
	(0.343)	(214.620)
Observations	64	64
Joint significance (chi2)	52.094	75.491
p	0	0

*Note: * p<0.10, ** p<0.05, *** p<0.010.*
Source: Authors' calculations.

Our sectoral output gap points to divergent inflationary pressures recently by indicating ongoing pressures in services and a downward path in manufacturing in 2024 (figure 6).

Figure 6
Output gap for services and manufacturing in Croatia (%)



Source: Authors' calculation.

We decompose the survey-based sectoral output gap based on equation (5) (figures 7 and 8) into the contributions of each factor:

$$\widehat{OG}_t^{(F)} = \frac{\sigma_{\mathrm{CU}}}{\sigma_{(\pi_t - \widehat{\varepsilon}_t)}} \widehat{\beta}_F N_t^F \tag{6}$$

whereby $F \in \{D, E, L, O\}$, $N_t^F = \begin{cases} D_t,\ F = D \\ \eta_t^F,\ F \in \{E, L, O\} \end{cases}$.

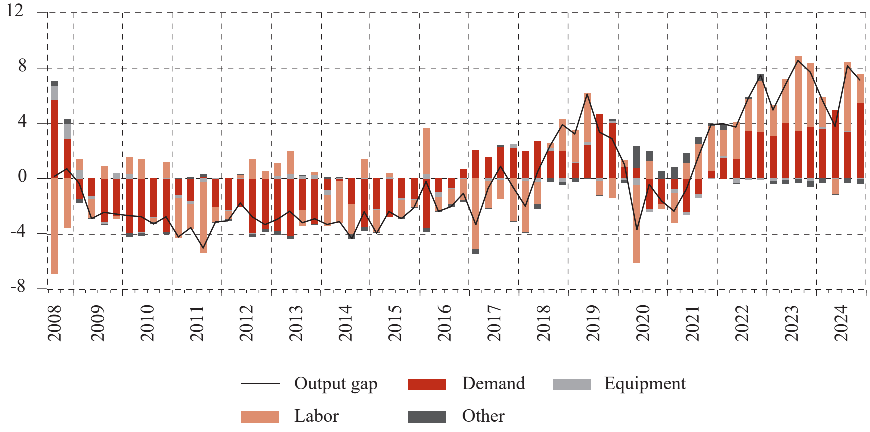
Our output gap shows that the bulk of ongoing inflationary pressures, both in services and manufacturing, come from demand. Labour shortages still play a minor role in pushing inflation up, but the post-pandemic related equipment shortages have been phased out by now. Compared to the aggregate output gap constructed with aggregate demand shocks in figure 1, we see that our measure once again converges to a similar inflationary signal, once the weight of supply shocks has fallen. This result points to the importance of both sector and supply-specific factors when estimating inflationary pressures with the output gap, as well as suggesting that the Phillips curve in Croatia is indeed positively sloped.

Our results are somewhat complementary to previous domestic research. Krznar (2011) concludes there is no relationship between economic slack and inflationary developments in Croatia, i.e. the traditional Phillips curve would appear to be flat. He arrives at this conclusion by estimating potential GDP and the output gap using an HP filter on GDP. As we argue, this is likely misleading in the post-pandemic period, since the HP output gap arguably only captures demand shocks. Krznar (2011) however argues in favour of the existence of a New Keynesian Phillips curve, by considering other variables such as foreign inflation, marginal production costs and inflation expectations. Marginal costs, in particular, reflect shocks to the supply factors present in our framework. Furthermore, our factors limiting production also pick up foreign prices, since a considerable share of inputs are imported. All in all, we can confirm the existence of a structural Phillips curve in Croatia. McLeay and Tenreyo (2020) emphasize that most research follows the approach proposed by Gordon (1981), using only demand shocks to correctly shape the Phillips curve, resulting in a flat slope. As they show on a structural Phillips curve, that is wrong. Yilmazkuday (2025) also highlights the importance of a shock-dependent approach to estimating the Phillips curve slope, which is flat if affected only by demand shocks and positive if affected by supply shocks, such as cost-push shocks and structural labour market disturbances.

Figure 7 shows our survey-based output gap in services in Croatia. From 2022 onwards, the output gap signals inflationary pressures, which can be explained both by increased demand and labour shortages. The output gap suggests firms are faced with severe labour shortages, which translate into higher costs and to some extent, spill over to final prices. However, this channel is highly seasonal and seems to have partly levelled off since a large portion of foreign workers work in services related to hospitality (Banić, Pripužić and Rebić, 2024). However, strong demand continues to contribute positively to the output gap in services, putting pressure on final prices. More specifically, demand in services related to hospitality is most likely based on foreign and domestic demand, which is also reflected in high inflation in services. Figure 7 also highlights a positive output gap in mid-2024, after a mild decrease in 2023Q1-Q2, which is a result of labour shortages during the summer tourist season, a time in which both foreign and domestic demand are substantial. However, the latest data show that Croatia could face a negative effect of price competitiveness in tourism,[6] which is expected to be reflected in the price formation in the upcoming years.

[6] See Box 5 in CNB (2016).

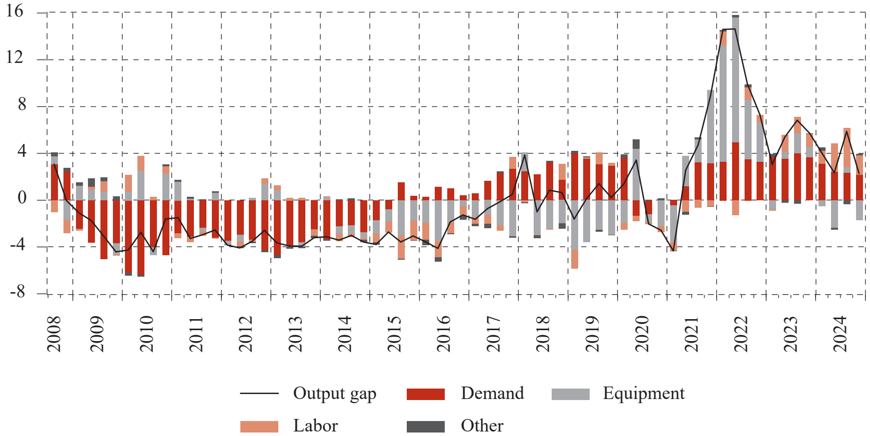
Figure 7
Survey-based output gap in services for Croatia (%, percentage points)



Source: Authors' calculation.

Turning to inflationary pressures in manufacturing, although strong demand explains a substantial part of the inflationary pressures since 2016, excluding 2020, figure 8 points to increased pressure on final prices in late 2021 and throughout 2022, mostly due to shortages in equipment and materials. Supply chain bottlenecks during the various lockdowns affected equipment and intermediate input prices globally, which, accompanied by strong demand, resulted in relatively high inflationary pressures in 2022. However, the inflationary effects of the bottlenecks phased out in 2023, while high demand persisted. Labour shortages, in contrast, did not seem to play a relevant role in manufacturing until 2024. At that point, demand contributed less to overall pressures than previously, while labour shortages recorded a higher annual contribution. Overall, in manufacturing, the inflationary pressures eased after 2022 and are currently below the post-energy crisis average.

Figure 8
Survey-based output gap in manufacturing for Croatia (%, percentage points)



Source: Authors' calculation.

As shown in figures 7 and 8, our survey-based sectoral output gap indicates precisely inflationary pressures in services and manufacturing in Croatia, contrary to traditional output gap estimates. This reflects the importance of accounting for supply factors, which are usually omitted when using univariate filters (HP, one-sided HP, Hamilton). In other words, our survey-based approach to estimating sectoral output gaps signals inflationary pressures more accurately than the aforementioned approaches.

4 DISCUSSION: STYLIZED FACTS ON RECENT STRUCTURAL AND CYCLICAL FACTORS IN CROATIA

After highlighting the pros of survey-based output gap as compared to traditional and more advanced econometric approaches, in this section we will point out some important structural and cyclical drivers of inflationary pressures in Croatia. Aside from other factors and equipment, which are mostly related to global cost-push situations during the Covid and energy crises, structural are mostly related to the tight labour market in Croatia, while cyclical drivers are related to economic policies.

Retrospectively, in the aftermath of the Global Financial Crisis, Croatia was faced with a negative output gap for almost a decade (figures 7 and 8). In manufacturing and services, these developments are mostly driven by demand side, followed by supply side, i.e. labour shortages (only in services). However, after the Croatian accession to EU in 2013, strict EU fiscal rules (Stability and Growth Pact), i.e. Corrective Arm of SDP, pushed fiscal policy makers towards restrictive procyclical stance (Banić and Žilić, 2024), which had negative and self-defeating economic effects (Deskar-Škrbić and Milutinović, 2021). However, when the relatively long recessionary episode in Croatia ended, demand in services (external to some extent) started to contribute positively to the output gap, while labour shortages operated in the opposite way due to structural factors after the EU accession in 2013, when a not negligible cohort of the working-age population emigrated to western EU economies. A similar pattern is observable in manufacturing, however, to a lesser extent. During the pandemic, the general escape clause of the SGP was activated, and countries were allowed to conduct expansionary countercyclical polices, which alongside the Next Generation EU programme helped countries (among which Croatia is considered as frontrunner, see appendix, figure A10) to economically recover from the pandemic on both the demand and the supply side (ECB, 2024).

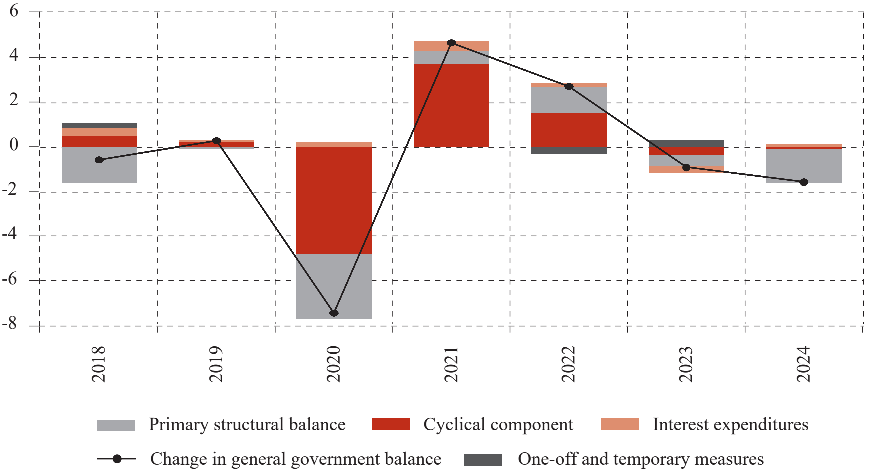
Regarding cyclical drivers of inflationary pressures, we will analyse decomposition of change in the general government balance in % of GDP (Δggb_t) expressed as:

$$\Delta ggb_t = \Delta i_t + \Delta spb_t + \Delta cyc_t + \Delta of_t \tag{7}$$

which reflects changes in interest expenditures (Δi_t), cyclical component (the effect of business cycle, Δcyc_t), structural primary balance (Δspb_t, i.e. fiscal stance) and in one-off and temporary measures (Δof_t). A negative change in the structural primary balance points to the expansionary fiscal stance in 2024 (figure 9), which is, in periods of positive aggregate output gap (2.2% of potential GDP in 2024, AMECO, 2025 – in line with our results), characterized as procyclical. Expansionary procyclical fiscal stance in 2024 is mostly due to the comprehensive wage-setting reform in Croatia (Nadoveza, 2025) (figures 10 and 11), as well as due to energy-compensatory measures and some other discretionary factors. Noteworthily, fiscal policy makers in Croatia due to a previously accumulated fiscal space did not breach deficit and debt reference values in 2024.

Figure 9

Decomposition of change in general government balance (% of GDP) in Croatia (percentage points)



Source: AMECO, authors' calculations.

Ivanac, Kunovac and Nadoveza (2024) concluded that wage spill-over on inflationary developments is possible in an environment characterized by demand shocks, which can be associated with positive output gap in Croatia. Hence, the contribution of domestic demand, especially in services can be associated to some extent with expansionary fiscal stance (light grey bars in figure 9). To mitigate inflationary pressures stemming from domestic demand, fiscal stance is expected to be restrictive, if the output gap is positive. Checherita-Westphal, Leiner-Killinger and Schildmann (2025) showed that fiscal policy can contribute to inflationary developments through the demand side, i.e. the output gap. Also, fiscal policy, in the light of the wage-setting reform in public sector (figures 10 and 11), apart from demand pressures, could have had negative effects on the private sector, i.e. on labour shortages (figures 7 and 8), thus generating inflationary pressures further, if workers shift to the public sector. Wage-setting reform in 2024 in the public sector (O, P, Q entities) resulted in substantial wage increase of more than 20% on average, while at the same time, the increase in other sectors like manufacturing and hospitality was much smaller, reflecting to some extent an increase in the minimum wage.

Figure 10
Average gross wages, annual %

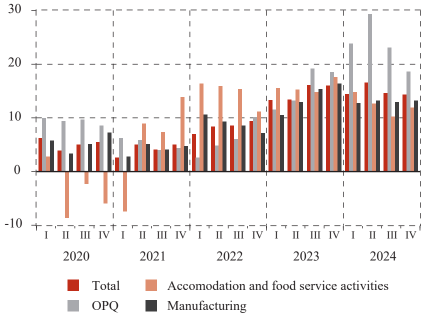
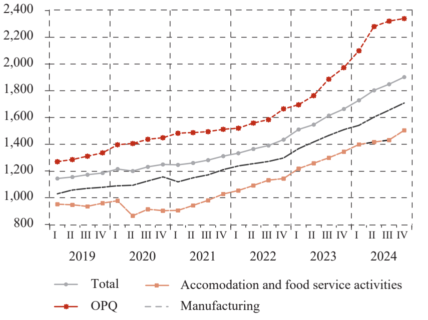


Figure 11
Average gross wages, levels (in euro)



Note: Data are seasonally-adjusted using X-12.
Source: CBS, authors' calculations.

When it comes to local Central Bank policy, the Croatian National Bank introduced on July 1st macroprudential measures to restrain consumption by limiting consumer lending, and consequently mitigate risks to financial stability.[7] Also, that part of the restriction related to new non-purpose cash loans could indirectly alleviate demand driven inflationary pressures (whereas tightening a year earlier would probably have been even more effective). In the upcoming years, both fiscal and macroprudential stances should be restrictive to absorb accumulated positive domestic demand contributions to inflationary pressures in the economy, which might not be enough considering structural factors on labour market, i.e. supply side of economics and external demand, especially in hospitality.

Regarding recent structural factors, the labour market is in the principal focus. In the aftermath of the pandemic, one can say that the demand in the labour market is largely satisfied by employing workers from third countries, but also pensioners according to the decomposition of employment changes (see appendix, figure A11). In 2023, a third of the increase in employment is related to foreign workers, part of the residual reflecting the contribution of foreign workers since the entrepreneurs do not record them correctly (Banić, Pripužić and Rebić, 2024).

In addition to the outflow of part of the working-age population to western EU countries, the continuation of a tight labour market is expected, which could additionally have an inflationary effect through the labour shortage (salmon bars on figures 7 and 8). Also, if demand on the labour market had not been met with foreign workers[8] and pensioners, the labour shortage would have made a stronger contribution to inflationary pressures.

[7] Macroprudential measures apply to all new housing and non-housing loans to consumers, and includes restrictions on the maximum monthly repayment ratio of the consumer's total debt to income (DSTI ratio), the maximum ratio of the amount of the housing loan to the value of the property pledged (LTV ratio), and the maximum loan maturity. For more details see Box 3.1. in CNB's publication "Macroprudential diagnostics" at: https://www.hnb.hr/en/analyses-and-publications/regular-publications/macroprudential-diagnostics.
[8] According to the Croatian Ministry of Internal Affairs (2025), from 1 January 2024 to 31 December 2024, 36% of the total residence and work permits issued to foreign workers were in construction, 27% in hospitality and 14% in industry.

Some specific labour market measures like increasing the participation rate (which is lower than the EU average) or a more generous package for returnees should be implemented, to avoid the scenario in which wage growth exceeds productivity growth (lower productivity is expected with strong participation of pensioners and low-skilled foreign workers on the labour market), thus generating further inflationary pressures. Figure 12 points to potential inflationary risks in Croatia, especially since 2024, when real compensation per employee (deflated with households' final consumption) growth rate reached almost double digits (mostly due to comprehensive wage-setting reform in the public sector), while the real productivity growth rate is in negative territory (although before the pandemic these two were broadly aligned, i.e. there was no signal for inflation). Bobeica, Ciccarelli and Vansteenkiste (2019) found a strong relationship between labour cost and inflation in big euro area economies, also highlighting the importance of relationship if demand shocks dominate, which currently contribute to inflationary pressures in both services and manufacturing (figures 7 and 8).

Figure 12

Real compensation per employee and real productivity growth rate (YoY, %)

Source: Eurostat, authors' calculations.

Taking into account the high increase in real compensation per employee and drop in productivity, unit labour cost increased in 2024 substantially on an annual level, which should be corrected either in numerator (compensation per employee) or denominator (productivity) to mitigate further inflationary pressures in Croatia. One way to tackle the productivity and innovation issues is to further increase expenditures for education, which amount to around 5.3% of GDP in 2023, and are 0.7 p.p. higher than average EU-27 (4.7% of GDP).

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5 CONCLUSION

Demand shocks, according to our results, have historically had a larger effect on the Croatian economy than supply shocks. The same applies to most western economies, where the last large recession caused by supply shocks before the pandemic came after the oil crises in the late 1970s. This historical fact has led economists, both in academia and in economic policy institutions, to rely on the traditional output gap, which correctly reflects inflationary pressures when demand shocks dominate, as a crucial input to the monetary policy decisions process. We have shown though that care needs to be applied in times like the current, in which large supply shocks affect our economy. Specifically, our analysis indicated that the survey-based sectoral output gap augmented with factors limiting production accurately signals inflationary pressures, especially when traditional approaches struggle to indicate the latter (on aggregate HICP average annual rate) in the aftermath of two recent crises (the pandemic and disturbances on energy markets after Russian invasion on Ukraine). These traditional approaches in terms of output gap usually capture only the demand side of the economy, while we have also shown the important role of supply shocks, which can also be temporary and not only permanent. Also, the proposed novel survey-based approach could be of added value in the forthcoming period regarding the intensified geopolitical tensions by tracking the effects of tariffs imposed by the US administration on specific supply factors like equipment and materials and consequently on a sector-specific output gap. Our method also suggests that relationship between economic slack and inflation is not broken, i.e. the Phillips curve in Croatia is alive when taking into account structural factors.

Looking at inflation targeting set by monetary authorities (e.g., ECB), one should bear in mind that monetary policy is a demand side instrument: it affects the economy by modifying interest rates, thus affecting firms' and households' incentives to consume and invest. By separately identifying the strengths of different shocks affecting firms' demand, labour shortages, and shortages in equipment, intermediates, and productive space, policy makers can design better economic policies to address the issues affecting the economy. Our measure suggests that the issues hitting manufacturing and services are currently different in Croatia: while demand might be strong in both sectors, the key difference seems to stem from larger (possibly foreign) demand in services and the consequent labour shortages. This means that restrictive monetary or macroprudential policy alone might not be enough to fight inflation, as long as supply shocks are prominent. On the positive side though, the persistently strong demand and the inflationary pressures could be a positive sign going forward: they might incentivize Croatian firms to invest in increasing their productive capacity, leading to further economic growth down the road. Also, from the perspective of the one-size-fits-all target of the ECB, inflation divergence, as recorded in services and manufacturing in Croatia might signal a further need to pursue restrictive fiscal and macroprudential stance, considering to large extent the currently strong demand domestic pressures.

With respect to untangled supply and demand contributions to sector-specific inflationary pressures, we have also highlighted the role of cyclical factors, which have generated inflationary pressures to some extent regarding domestic demand, while structural factors pointed to a low labour supply compared to the strong demand, which resulted in high inflow of foreign workers and high participation of pensioners. However, in the medium term, if strong demand is balanced with a labour supply consisting of low-productivity workers (pensioners and foreigners from third countries), high unit labour costs (expressed as the ratio of compensation per employee and productivity) will continue to generate inflationary pressures in the economy. Therefore, it will also be important to further increase spending on education and to include foreign workers in high-value-added activities.

Disclosure statement
The authors have no conflicts of interest to declare.

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APPENDIX

DATA AND SOURCES

Table A1

Data and sources

Variable	Data	Source
Total HICP	Harmonized Index of Consumer Prices, seasonally adjusted using X-12, average annual change	Eurostat
HICP Services	Harmonized Index of Consumer Prices in Services, seasonally adjusted using X-12, average annual change	Eurostat
De-meaned HICP Services	Difference between annual growth rate and average growth rate in HICP Services	Authors' calculations
HICP Goods	Harmonized Index of Consumer Prices in Goods, seasonally adjusted using X-12, average annual change	Eurostat
De-meaned HICP Services	Difference between annual growth rate and average growth rate in HICP Industrial Goods	Authors' calculations
Gross domestic product	GDP, constant prices, seasonally adjusted using X-12, average annual change	Eurostat
De-meaned values of factors limiting productions	Difference between current and average factor (demand, labour, equipment, other)	European Commission, authors' calculations
General Government Balance	Annual change in General Government Balance (in % of GDP)	AMECO
Interest Expenditures	Annual change in Interest Expenditures of General Government (in % of GDP)	AMECO
One-off and temporary measures	Annual change in one-off and temporary measures of General Government (in % of GDP)	AMECO
Cyclical component	Annual change in cyclical component (multiple of output gap and budget-to-gap semielasticity) (in % of GDP)	AMECO

Source: Authors.

OUTPUT GAP ESTIMATES WITH UNIVARIATE FILTERS

Optimization procedure for Hodrick-Prescott (1998) filter:

$$\hat{\tau}_{t|t,\lambda} = \min_{\tau}\left(\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \tau_t\right)^2 + \lambda\frac{1}{T}\sum_{t=2}^{T-1}\left[\left(\tau_{t+1} - \tau_t\right) - \left(\tau_t - \tau_{t-1}\right)\right]^2\right) \quad \text{(A1)}$$

with λ as a smoothing parameter for business cycle that we set to 1600, usually for quarterly data (Arčabić and Banić, 2021), y_t is real GDP and T refers to observations. HP optimization procedure selects the τ_t series and then estimates trend by minimizing sum of squares, known as potential GDP.

Optimization procedure for one-sided Hodrick-Prescott (Wolf et al., 2020) filter:

$$\hat{\tau}_{t|t,\lambda} = argmin_{\tau_t}\left(\min_{\tau_1,\ldots,\tau_{t-1},}\left(\sum_{t=1}^{T}\left(y_t-\tau_t\right)^2+\lambda\sum_{t=2}^{T-1}\left(\tau_{t+1}-2\tau_t+\tau_{t-1}\right)^2\right)\right) \quad \text{(A2)}$$

which is similar to standard HP filter, which considers not only current but also earlier observations, thus is called a real-time potential GDP.

Potential GDP estimate with Hamilton (2018) filter:

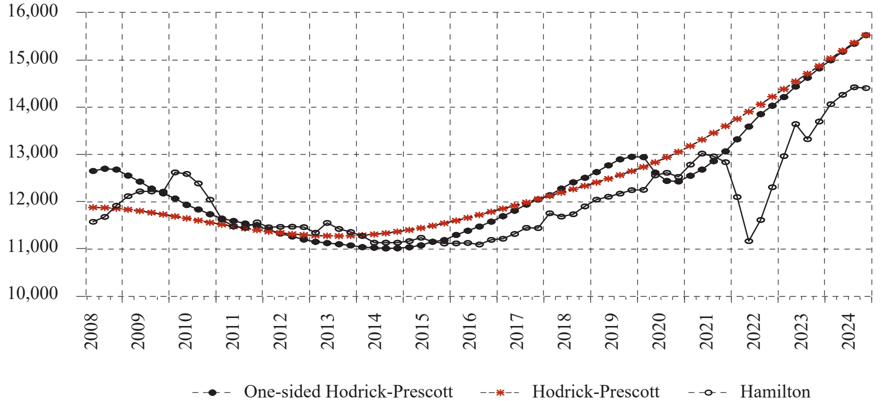
$$y_t = \Upsilon + \alpha_1 y_{t-8} + \alpha_2 y_{t-9} + \alpha_3 y_{t-10} + \alpha_4 y_{t-11} + c_t \quad \text{(A3)}$$

according to which Hamilton (2018) estimate the cycle (c_t) by regressing real GDP on constant (Υ) and four lags (k) of 2 years, addressing the end-of-sample problem in HP optimization procedure.

Output gap is then calculated as the difference between real GDP and potential GDP (HP, one-sided HP and Hamilton filters) in percentage of latter.

Figure A1

Potential GDP in Croatia with different filters (mil. euro)



Source: Authors' calculations.

OUTPUT GAP ESTIMATE USING BAYESIAN VECTOR AUTOREGRESSIVE MODEL WITH SIGN AND ZERO IDENTIFICATION OF STRUCTURAL SHOCKS

Following the procedure in Deskar-Škrbić et al. (2020), we estimate a BVAR model with k lags as follows:

$$A_0 y_t = \Omega + A_1 y_{t-1} + \ldots + A_k y_{t-k} + \varepsilon_t, \qquad t = 1,.., \mathrm{T}. \quad \text{(A4)}$$

where y_t is a vector of observable variables, Aj are n x n coefficients with invertible A_0, Ω is a vector of constants and ε_t, is a vector of structural shocks. The number of lags is set to four (k=4), which is common procedure when using quarterly data (Blake and Moomtaz, 2017) and in line with recent research (Barišić, Kovač and

Arčabić, 2023). Furthermore, we estimate a reduced-form model by multiplying the equation by A_0:

$$y_t = c + B_1 y_{t-1} + \ldots + B_k y_{t-k} + e_t, \qquad t = 1,.., \mathrm{T}, \tag{A5}$$

where $B_j = A_0^{-1} A_j$, $c = A_0^{-1}\Omega$ and $e_t = A_0^{-1}\,\varepsilon_t$.

To impose the block exogeneity assumption through zero restrictions, vector y_t^1 represents external variables (real GDP and HICP for euro area), while vector y_t^2 represents domestic variables (real GDP and HICP) so $y_t' = \left[y_t^{1'}, y_t^{2'} \right]$.

Matrix A_j from (A4) have block lower triangular form:

$$A_j = \begin{bmatrix} A_{11}^j & 0 \\ A_{21}^j & A_{22}^j \end{bmatrix}, \mathrm{j} = 0, \ldots, \mathrm{k} \tag{A6}$$

where block exogeneity is derived form coefficients of matrices B_j

$$B_j = \begin{bmatrix} B_{11}^j & 0 \\ B_{21}^j & B_{22}^j \end{bmatrix}, \mathrm{j} = 0, \ldots, \mathrm{k} \tag{A7}$$

The block exogeneity assumes that (3) implies (4) but vice versa does not hold (Deskar-Škrbić, Kotarac and Kunovac, 2020). In order to derive (3) from (4) we need to add more assumptions on A_0 or $(A_0)^{-1}$, which represents short-term (on impact) impulse response function. For more details regarding the methodology, see Deskar-Škrbić, Kotarac and Kunovac (2020). Following the approach of Deskar-Škrbić, Kotarac and Kunovac (2020) and Nadoveza (2025), we conduct Gibbs sampler using Independent Normal Inverse Wishart prior, and also standard Minnesota priors, setting $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 2$, and $\lambda_4 = 10000$, which is in line with Nadoveza (2025), who used tight priors.

Regarding imposed structural shocks, domestic (Croatian) aggregate demand shock increases both GDP and HICP in Croatia, with no effect on euro area variables, while domestic aggregate supply shock increases GDP and decreases HICP in Croatia, with no effect on euro area variables as well. Regarding external (euro area) shocks, aggregate demand increases economic activity and inflation in euro area with unknown effect on domestic (Croatian) GDP and HICP, while supply shock increases GDP and HICP in euro area with unrestricted effect on domestic (Croatian) GDP and HICP.

Table A2

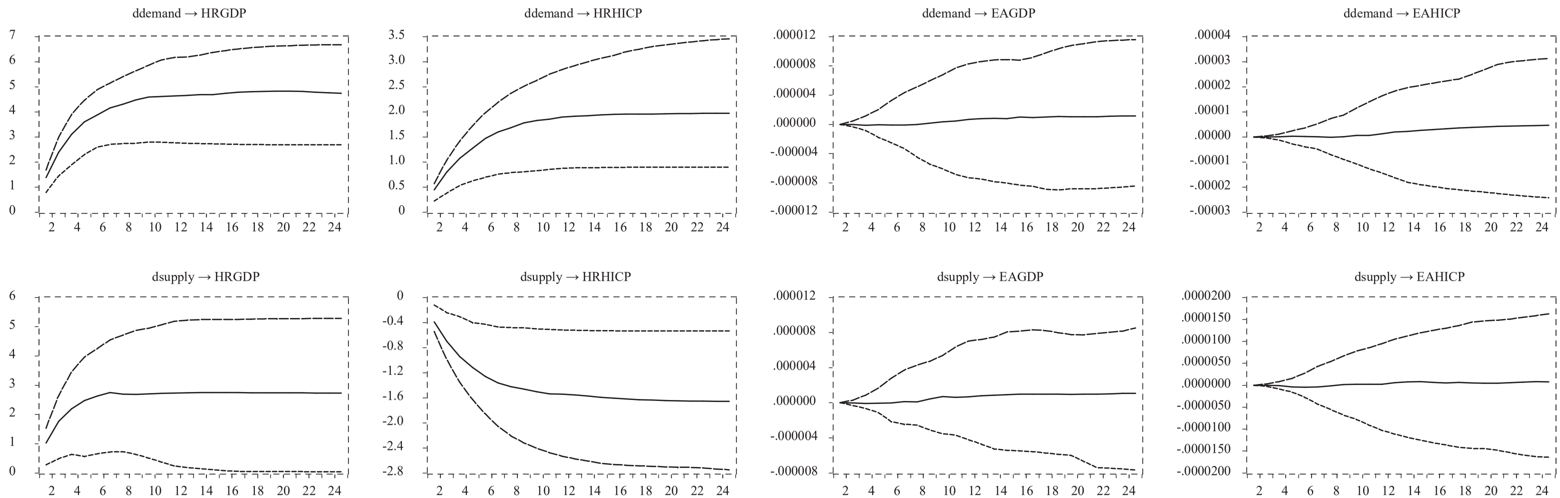
Restrictions for identification of structural shocks

Shock/variable	GDPHR	HICPHR	GDPHEA	HICPEA
Domestic demand	+	+	0	0
Domestic supply	+	-	0	0
External demand	?	?	+	+
External supply	?	?	+	-

Note: Positive reaction (+), negative reaction (-), unrestricted reaction (?), no reaction (0).

Figure A2

Cumulative impulse responses of annual change in real GDP and annual inflation rate (HICP) to domestic (Croatian) demand and supply shocks for Croatia and Euro area

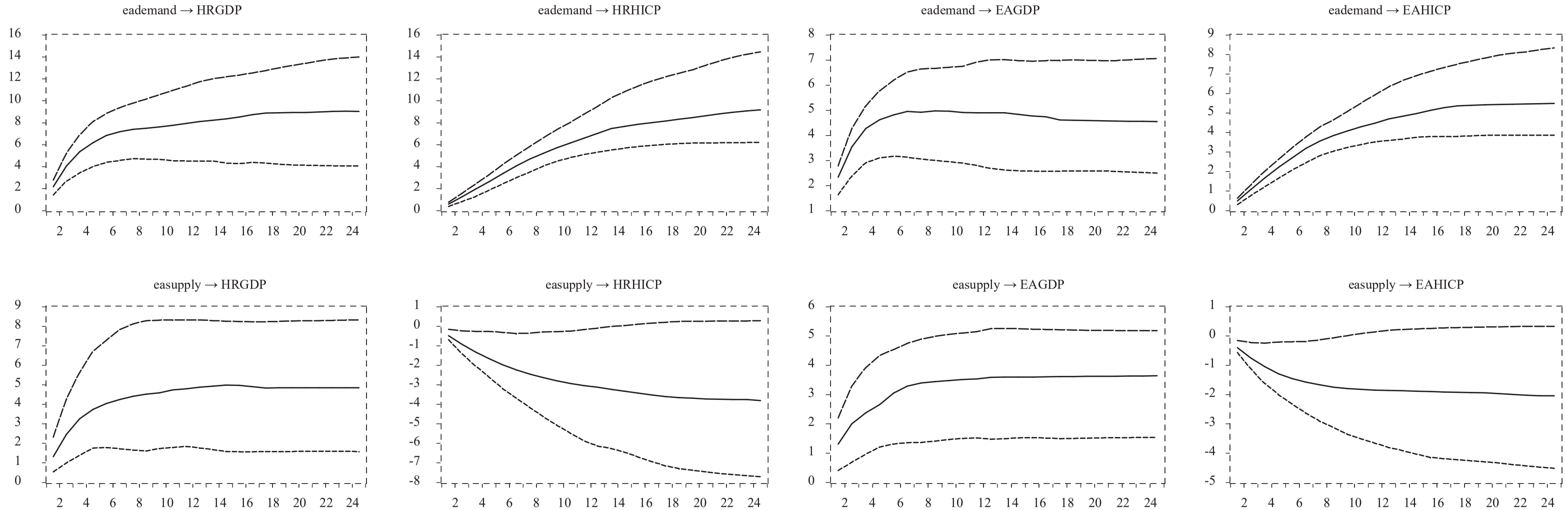


Note: Solid line represents the point-wise median and dashed lines represent lower and upper bounds to the 68% credible intervals. Abbreviation HR stands for Croatia, while EA for euro area. Ddemand corresponds to domestic demand shock, while dsupply to domestic supply shock. According to zero restrictions, there is no effect of domestic (Croatian), small open economy shocks to big (euro area) economy.

Source: Authors' calculations.

FIGURE A3

Cumulative impulse responses of annual change in real GDP and annual inflation rate (HICP) to external (euro area) demand and supply shocks for Croatia and Euro area

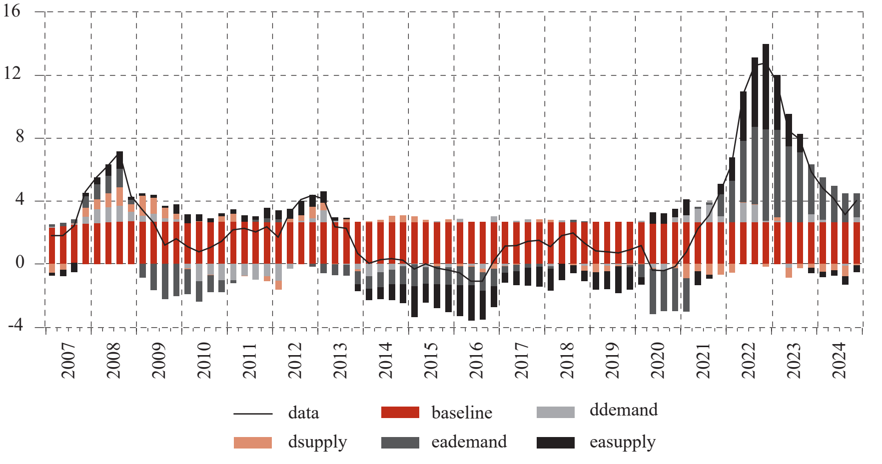


Note: Solid line represents the point-wise median and dashed lines represent lower and upper bounds to the 68% credible intervals. Abbreviation HR stands for Croatia, while EA for euro area. Eademand corresponds to external demand shock, while easupply to external (euro area) supply shock.

Source: Authors' calculations.

Figure A4

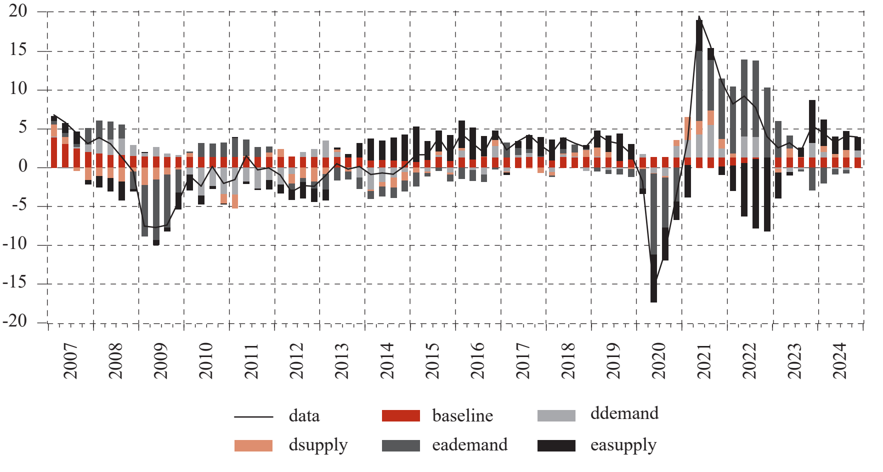
Historical decomposition of annual change in HICP for Croatia (%, percentage points)



Source: Authors' calculations.

Figure A5

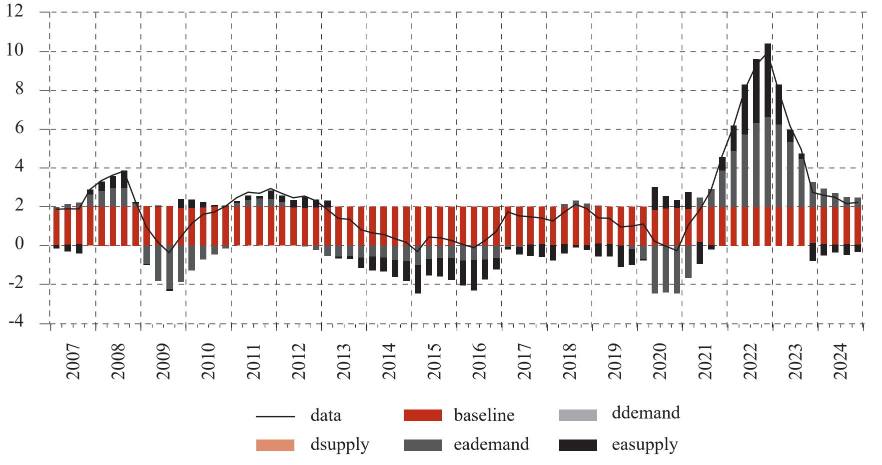
Historical decomposition of annual change in real GDP for Croatia (%, percentage points)



Source: Authors' calculations.

FIGURE A6

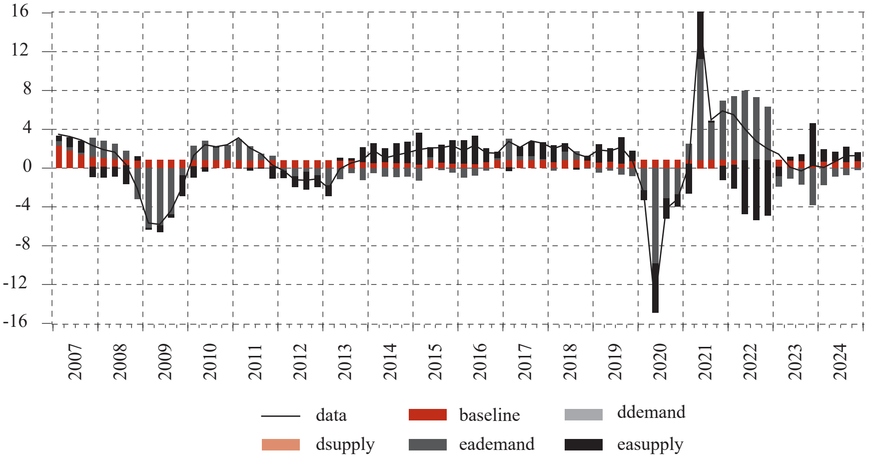
Historical decomposition of annual change in HICP for Euro area (%, percentage points)



Source: Authors' calculations.

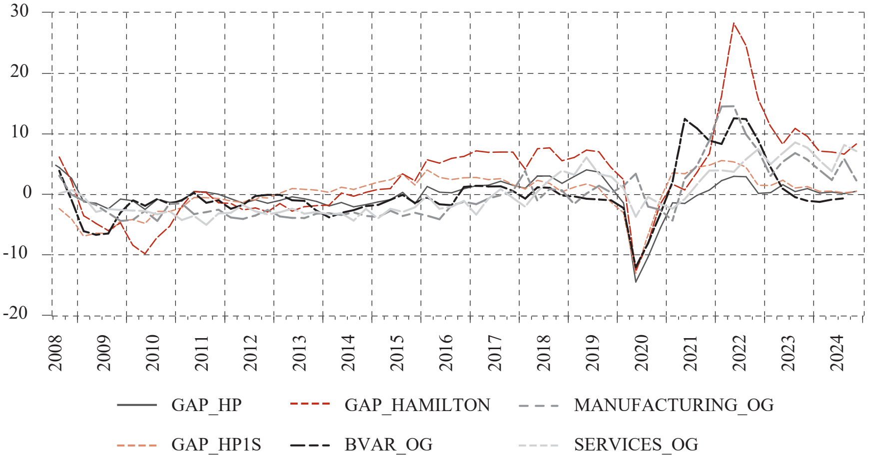
FIGURE A7

Historical decomposition of annual change in real GDP for Euro area (%, percentage points)



Source: Authors' calculations.

Figure A8
Aggregate and sectoral output gap in Croatia (% of potential GDP)

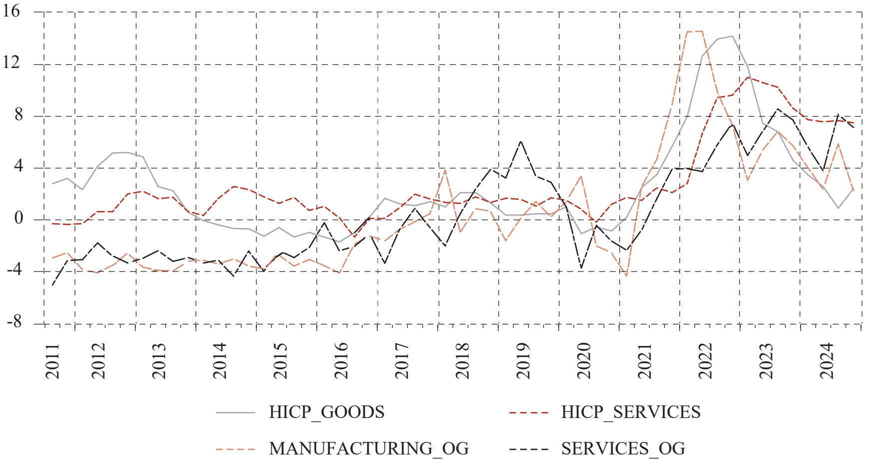


Source: Authors' calculations.

SECTORAL INFLATION RATE AND OUTPUT GAP IN CROATIA

Aside of period between 2011 and 2013 for manufacturing, sectoral output gap indicates inflationary pressures relatively accurate, especially in the aftermath of C-19 crisis and energy crisis. In more detail, strong mixture of different supply (C-19 and energy) and demand (Next Generation EU instrument, tourism, expansionary procyclical fiscal stance) reflected in positive output gap, in line with dynamics of sectoral price developments. Also, probably the increased quality of survey data to some extent contributed to more precise assessment of sectoral output gap, thus inflationary pressures in Croatia.

Figure A9
Sectoral inflation rate and output gap in Croatia (%)



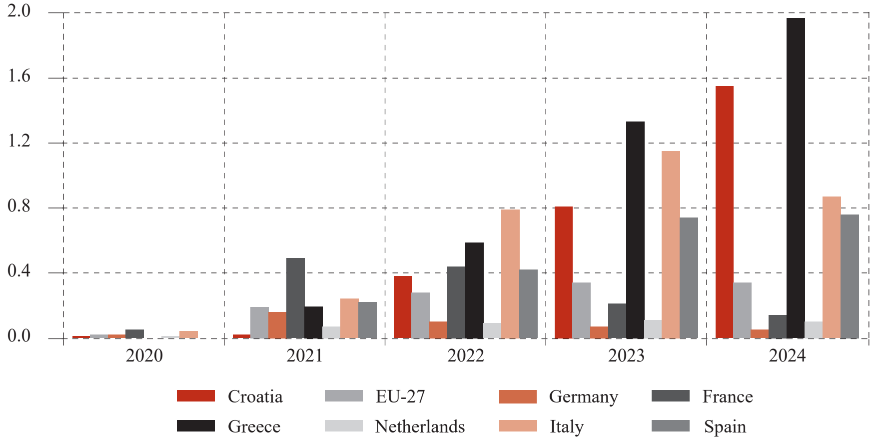
Source: Eurostat, authors' calculations.

USES OF RECOVERY AND RESILIENCE FACILITY (RRF) IN THE EU

According to Eurostat data, Croatia is one of frontrunners when it comes to RRF uses, reaching more than 1.5% of GDP in 2024, while EU average was below 0.5% of GDP. Consequently, as ECB (2024) analysis suggests, demand, i.e. fiscal and supply side, i.e. structural reforms both affected real GDP and potential GDP. However, in short-run, these demand side effects could affect output gap, if override supply side effects, which come at place with significant time lag, especially when it comes to structural reforms.

Figure A10

Uses of RRF in the EU (% of GDP)

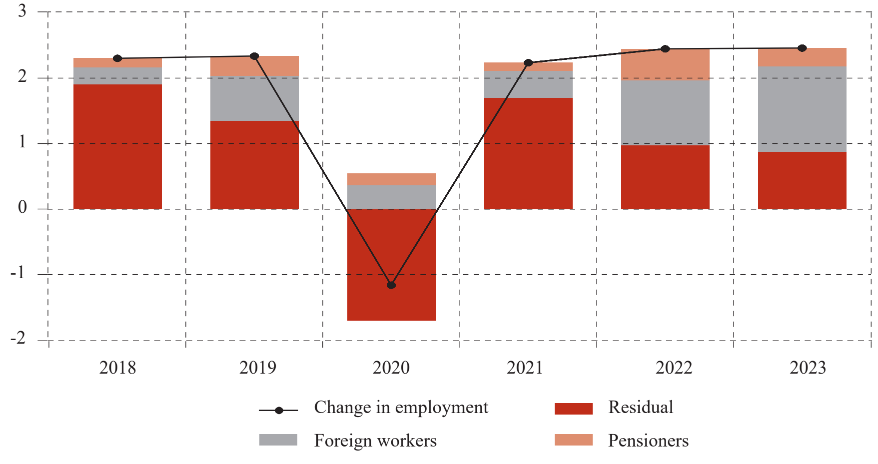


Source: Eurostat.

CHANGE IN EMPLOYMENT IN CROATIA

Figure A11

Decomposition of change in employment in Croatia (percentage points)



Note: Residual includes inactive persons, unemployed persons and other foreign workers which were not recorded properly.

Sources: CPII, Banić et al. (2024), authors' calculations.

Inflation in Croatia: a new era of forecasting with machine learning

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Abstract

This paper examines the use of machine learning methods for forecasting inflation in Croatia. Out-of-sample forecasts are generated for multiple horizons using ten models and four alternative sets of input features comprising lags of the target variable, conventional macroeconomic indicators, unconventional variables including Google Trends data, and a combined feature set. Forecast accuracy is assessed across models and relative to a benchmark for the full sample as well as for the periods before and after March 2020 (COVID-19). The results indicate that no single model consistently outperforms others across all settings; however, machine learning methods, particularly tree-based models, deliver superior performance under specific conditions. The forecasts produced by the two best-performing models, SARIMA and LightGBM, exceed the accuracy of the European Commission's projections. As the first paper to apply machine learning to inflation forecasting in Croatia, this study introduces modern analytical techniques into the Croatian forecasting literature.

Keywords: inflation, machine learning, forecasting, macroeconomics, Croatia

1 INTRODUCTION

After decades of low and stable inflation in developed economies, galloping inflation seemed almost unimaginable. In extreme cases, some economists considered it a phenomenon of the past. However, due to recent shocks, inflation has once again emerged as one of the key macroeconomic issues, spurring intense interest from both the academic and professional communities. In this context, successful inflation forecasting becomes crucial for economic policymakers, especially for central banks implementing monetary policy. Timely and reliable inflation forecasts are essential for making adequate monetary policy decisions, such as those related to changing key interest rates, primarily because of the medium-term nature of the monetary transmission mechanism. For this reason, central banks must act in an anticipatory manner and rely primarily on projections of future inflation developments.

Inflation forecasting is a challenging task, as confirmed by the large forecast errors produced by models used by many central banks and international institutions (Medeiros et al., 2021: 100). In recent years, machine learning (ML) models have gained importance due to their numerous advantages over traditional econometric models used in macroeconomic modelling. The big data environment naturally complements ML methods because it allows for the exploitation of their ability to process a large number of features and uncover complex relationships within the data.

The main goal of this paper is to determine which ML model is the most successful in out-of-sample inflation forecasting in Croatia. Particular emphasis is placed on comparing the predictive capabilities of ML models against traditional econometric time series approaches, such as SARIMA. The paper further examines the forecasting performance of the models under different conditions, before and after the COVID crisis. The pandemic, a strong exogenous shock, caused high levels of volatility and uncertainty, producing an environment that the models, trained during more stable macroeconomic periods (with the exception of the 2008 crisis), had not previously encountered. Separating less volatile from more volatile periods, therefore, shows whether the models can maintain accuracy in a changed macroeconomic environment and how informative conventional versus unconventional features are in stable as compared to stressful times. Finally, the best model is selected and its forecasts are compared with the forecasts of the European Commission.

This paper contributes to the literature in at least two ways. First, the paper investigates the application of modern ML methods to inflation forecasting in Croatia and constitutes, to the best of the authors' knowledge, the first contribution of its kind in the Croatian literature. Second, the comparison of inflation forecasts across different economic regimes, using various models and features, provides a wealth of information regarding the predictive capabilities of the models, as well as the informativeness and importance of the features employed.

The remainder of the paper is organized as follows. The second chapter presents an extensive review of the international and domestic literature on inflation forecasting using various models, with a particular focus on ML models. The third chapter includes a description of all variables used, including an explanation of their categorization, and sets out the methodological framework, focusing on model selection, data preparation and transformation, the forecasting procedure, and measures of forecast accuracy (the prediction error indicators used). Chapter four presents the results, namely the forecast errors of all utilized models, and selects the best models, whose predictions are then compared with those of the European Commission. Fifth chapter discusses the results. The conclusion is provided at the end of the paper.

2 LITERATURE REVIEW

The modelling of inflation is one of the fundamental issues in macroeconomic analysis and has been the subject of various theoretical and empirical approaches over decades. The typical framework for understanding inflation dynamics long relied on the concept of the Phillips curve. Although Blinder (1997: 241) emphasizes that the Phillips curve served as a reliable tool in inflation forecasting for decades, later works question its predictive power. For instance, Atkeson and Ohanian (2001) demonstrate that the Phillips curve in the US does not even outperform simple naive models in forecasting inflation and conclude that "the search for yet another Phillips curve-based inflation forecasting model should be abandoned". Similar findings are confirmed by Ang, Bekaert and Wei (2005), who show that ARMA models and, in particular, forecasts based on surveys, achieve lower forecast errors than Phillips curve models.

The poor empirical forecasting performance of traditional theoretical models has prompted researchers to experiment with different sets and types of variables, as well as various model approaches, in order to improve the accuracy of inflation forecasts. In this context, the literature shows a growing interest in including additional information in models to enhance the accuracy of inflation forecasts. For example, Chen, Turnovsky and Zivot (2014) include aggregates of world commodity prices in models, Forni et al. (2003), Stock and Watson (2003), and Monteforte and Moretti (2013) use financial variables, while Groen, Paap and Ravazzolo (2013) and Ang, Bekaert and Wei (2005) use expectation variables. As the set of relevant predictors expanded, researchers often resorted to factor models, which compress information from a multitude of variables into a few latent components – factors (e.g. Eickmeier and Ziegler, 2008). However, their efficiency largely depends on the quality of the variables used in constructing the factors. Some research indicates that expanding the database does not necessarily result in better forecasting outcomes (e.g. Barhoumi, Darné and Ferrara, 2009).

In the last decade, ML models have received special attention in the literature. Unlike factor models, which reduce dimensionality by summarizing information into a few components, ML models allow for the direct inclusion of a large number of features. Although the application of ML to inflation forecasting is still relatively new, numerous empirical studies in the international literature already confirm its advantages over traditional econometric models. Nakamura (2004) shows that neural networks outperform a simple univariate AR model in forecasting US inflation at short horizons. Subsequent studies confirm the superior performance of ML and regularized models to that of traditional linear benchmarks. In particular, Medeiros and Mendes (2016) and Garcia, Medeiros and Vasconcelos (2017) find that LASSO-type models dominate standard AR and factor models in forecasting inflation in the US and Brazil, respectively. Using a broader set of ML techniques, Medeiros et al. (2021) report that Random forest (RF) delivers the lowest forecast errors for US inflation and performs robustly across different economic conditions, a result also supported by Ülke, Sahin and Subasi (2018) for more volatile time series. However, evidence suggests that this superiority is not uniform across time. Naghi, O'Neill and Zaharieva (2024) show that while RF outperforms benchmark models prior to COVID-19, its performance deteriorates during the pandemic and high-inflation period, when SVM and GBM yield more accurate forecasts. Overall, the literature indicates that ML methods tend to outperform ARMA-type benchmarks (Araujo and Gaglianone, 2023), particularly at longer horizons where tree-based models such as RF and XGBoost perform especially well, although simpler autoregressive models may remain competitive in smaller samples and data-constrained economies (Ivașcu, 2023).

Inflation has received limited attention in the Croatian economic literature, as most studies have concentrated on explaining inflation dynamics and their links with other macroeconomic variables (e.g. Payne, 2002), with little emphasis placed on inflation forecasting. This gap in the literature constitutes the main motivation for this paper. To the authors' best knowledge, only two studies explicitly examine inflation forecasting in Croatia. Pufnik and Kunovac (2006) use a SARIMA model to forecast short-term inflation and show that, over longer horizons, aggregating forecasts of individual CPI sub-components improves accuracy relative to directly forecasting the aggregate CPI. Kunovac (2007) applies principal component analysis and finds that information extracted from a large set of macroeconomic variables enhances forecasting performance, with even a single factor outperforming benchmark models.

3 METHODOLOGY AND DATA

Although numerous definitions of machine learning exist in the literature, this paper relies on the definition provided by Masini, Medeiros and Mendes (2021: 77), according to which: "machine learning is the combination of automated computer algorithms with powerful statistical methods to learn (discover) hidden patterns in rich datasets". This definition highlights the key characteristic of ML: the model's ability to autonomously learn complex patterns from a large amount of data, including nonlinearities and interactions among variables.

To forecast inflation in Croatia, a total of ten linear and non-linear models were employed, utilizing the traditional SARIMA model as a primary benchmark. The forecasting success of each model is also compared with a naive model's forecast using the slightly adjusted MASE forecast error, which is introduced later.

3.1 DATA

The target variable is the month-on-month inflation rate, measured as the monthly change in the Harmonised Index of Consumer Prices (HICP). The model specification includes lagged inflation and ten additional variables which, after applying the transformations described in section 3.2, give rise to several hundred input features. This approach aims to maximise forecasting accuracy while remaining feasible given the available computational resources.

Table 1

Input features

Variable	Feature label	Source
Lagged target variable	*laghicp*	Eurostat
Unemployment rate	*unemp*	CBS
Industrial production volume index	*ind*	CBS
Real retail trade turnover, annual change rates (seasonally and calendar-adjusted)	*retail*	CBS
US 10-year and 2-year treasury yield spread	*spread*	FRED
Average Brent and WTI crude oil prices	*bwti*	EIA
Baltic exchange dry index	*badi*	Bloomberg
Consumer confidence index	*conf*	CNB
Economic policy uncertainty index	*epu*	EPU (Sorić and Lolić 2017)
Search popularity of "Urlaub in Kroatien" (Vacation in Croatia) in Germany	*gturlaub*	Google Trends
Search popularity of the term "Inflation" in Germany	*gtinfl*	Google Trends

Source: Authors' own elaboration.

PUBLIC SECTOR
ECONOMICS
50 (1) 39-65 (2026)

Table 1 provides an overview of the input features. The first variable (*laghicp*) captures lagged inflation. The remaining variables are grouped into *conventional* and *unconventional* features. The former correspond to the variables listed in rows two to seven and represent macroeconomic indicators commonly used in inflation modelling (hard data). The latter correspond to the last four rows and include high-frequency indicators and sentiment measures (soft data) that provide timely information on current economic conditions and expectations and are widely used in contemporary modelling.

3.2 FEATURE TRANSFORMATION

The time series used in the analysis begin on 31 January 2006 and were retrieved on 31 March 2025. To replicate authentic forecasting conditions and prevent data leakage, missing values caused by publication delays (e.g., unemployment data) were filled by shifting the corresponding variables forward by one month. Following this alignment, an extensive feature engineering process was applied to the 11 base variables using five distinct transformation methods:

1) Rolling mean: the average of the previous six months is computed, which reduces short-term volatility and emphasises medium-term trends.
2) Exponential moving average (EMA): unlike the rolling mean, the EMA assigns greater weight to more recent observations, meaning that newer features are of greater importance in the model than older ones.
3) First differences: obtained by subtracting consecutive observations ($y_t - y_{t-1}$), which removes the trend component and transforms the series into stationary processes.
4) Lags: for each variable, lags from one to nine months were generated, as some of the utilized variables have a proven forecasting property several months ahead.
5) Standardization: every feature was converted to a form with a mean of zero and a standard deviation of one.

These transformations expanded the initial input space to a maximum of 440 features. Consequently, due to the initialization period required for lags and moving averages, the final usable dataset consists of 215 observations.

3.3 MODELS

The forecast is given by the equation:

$$\pi_{t+h} = G_h(x_t) + u_{t+h}, \quad h = 1, ..., H; \qquad t = 1, ..., T \tag{1}$$

where π_{t+h} is the inflation in month $t + h$, $x_t = (x_t, ..., x_{nt})^T$ is the vector of input data (features). $G_h(\cdot)$ is the function that connects the input data with inflation, and u_{t+h} is a random error with a mean value of zero (Medeiros et al., 2021). The goal of the model is to estimate the function G_h that minimizes the forecast error.

Ridge regression (RR) was proposed by Hoerl and Kennard (1970). In essence, it is a linear regression model that differs from the usual OLS only in the estimation of the coefficient parameter. The sum of the least squares of deviations is minimized, as is standard, with an added penalty term applied to the error function. The penalty function is defined as:

$$\sum_{i=1}^{n} p\left(\beta_{h,i};\lambda\right) := \lambda \sum_{i=1}^{n} \beta_{h,i}^{2} \tag{2}$$

where $\beta_{h,i}$ is the i-th parameter for horizon h, λ is the regularization factor which, as a hyperparameter, determines the strength of the penalization, and the penalty function $p\left(\beta_{h,i};\lambda\right)$ assigns λ for the square of each coefficient β (Medeiros et al., 2021).

Lasso was proposed by Tibshirani (1996). Similar to the RR model, it is a linear regression model. Unlike the former (L2), it uses L1 penalization, which can be defined as follows:

$$\sum_{i=1}^{n} p\left(\beta_{h,i};\lambda\right) := \lambda \sum_{i=1}^{n} \left|\beta_{h,i}\right| \tag{3}$$

where the notation is read similarly to that for ridge regression. Lasso performs simultaneous regularization and variable selection. Less informative features receive a coefficient equal to zero, meaning the model discards features that do not contribute to inflation forecasting.

The Elastic net (ENet) model, developed by Zou and Hastie (2005), combines the RR and Lasso approaches. In other words, the ENet model uses L1 and L2 penalization for balanced regularization in the following way:

$$\sum_{i=1}^{n} p\left(\beta_{h,i};\lambda,\alpha\right) := \alpha\lambda \sum_{i=1}^{n} \beta_{h,i}^{2} + (1-\alpha)\lambda \sum_{i=1}^{n} \left|\beta_{h,i}\right| \tag{4}$$

where $\alpha \in [0, 1]$ (Medeiros et al., 2021).

Support vector regression (SVR), introduced in the paper by Drucker et al. (1997) is a regularised regression approach that can capture nonlinear relationships through a feature mapping $\phi(\cdot)$ (or, equivalently, a kernel). In SVR, the model is chosen to be as flat as possible while allowing errors within an ε-insensitive tube, which leads to the optimisation problem:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\left(\xi_i + \xi_i^*\right) s.t. \begin{cases} y_i - \left(w^T \phi\left(x_i\right) + b\right) \le \varepsilon + \xi_i \\ (w^T \phi\left(x_i\right) + b) - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{5}$$

Here, ε sets the width of the tube, while C controls how strongly violations outside the tube are penalised via the slack variables ξ_i, ξ_i^*. In practice, the problem is solved by moving to the dual formulation and solving a quadratic programming problem, as described in the paper. The resulting predictor depends only on a subset of training observations (the "support vectors"), which makes the method particularly attractive in high-dimensional settings. In forecasting applications, SVR is then applied by tuning ε, C, and kernel parameters (e.g., via cross-validation) and evaluating the fitted function on new inputs to generate predictions.

The Random Forest (RF) is an ensemble of multiple simple decision trees designed to reduce the variance of individual regression trees. It is created by combining a large number of randomly constructed trees (Breiman, 2001). A regression tree is in itself a nonparametric model that approximates an unknown nonlinear function using local predictions and the recursive partitioning of the covariate space (Breiman, 1996). The RF for a regression problem is defined as an ensemble of M randomly generated trees. For the j-th tree in the ensemble, the predicted value at query point x is denoted by $m_n\left(x;\Theta_j, D_n\right)$, where Θ_j represents independent random variables controlling the construction process of individual trees, and $D_n = \{\left(X_1, Y_1\right), \ldots, \left(X_n, Y_n\right)\}$ represents the training sample. The goal is to use the dataset D_n to construct an estimate $m_n : [0,1]^p \rightarrow \mathbb{R}$ of the function m. The estimate of the RF with a finite number of trees is then given by the expression:

$$m_{M,n}\left(x;\Theta_1, \ldots, \Theta_M, D_n\right) = \frac{1}{M}\sum_{j=1}^{M} m_n\left(x;\Theta_j, D_n\right) \tag{6}$$

(Scornet, Biau and Vert, 2015). Since the number of trees can be made very large in practice, it's natural to consider the case $M \rightarrow \infty$. Then, the RF estimate converges to the expectation of the individual tree predictions (Scornet, Biau and Vert, 2015):

$$m_n\left(x;D_n\right) = E_{\Theta}\left[m_n\left(x;\Theta, D_n\right)\right] \tag{7}$$

The Gradient Boosting Model (GBM) constructs a complex predictor by summing shallow regression trees, where each new tree f_m is trained to minimize the residual errors of the previous ensemble (Friedman, 2001). The final model is represented as:

$$F_M\left(x_t\right) = F_0\left(x_t\right) + \sum_{m=1}^{M} v f_m\left(x_t\right) \tag{8}$$

where v acts as a shrinkage parameter to control overfitting. While the standard GBM effectively captures non-linearities, advanced implementations have been developed to improve efficiency. XGBoost (Extreme Gradient Boosting) optimizes the standard GBM framework by adding explicit regularization terms $\Omega(f)$ and utilizing parallel processing, resulting in more robust generalization (Friedman, 2001; Chen and Guestrin, 2016). For further scalability in high-dimensional environments, LightGBM introduces Gradient-based One-side sampling (GOSS) and Exclusive feature bundling (EFB). These techniques drastically reduce data scanning requirements by focusing on instances with large gradients and bundling sparse features, achieving up to 20-fold faster training speeds with comparable accuracy (Ke et al., 2017).

Neural networks (NNs) are multi-layer systems of interconnected neurons inspired by biological processes, whose purpose is to map input features into forecasts through a sequence of nonlinear transformations. Although NNs are highly effective at modelling complex nonlinear relationships, they are often described as "black-box" models due to the limited interpretability of their parameters. Consider a multilayer perceptron (MLP) with a total of L layers, where the first $L - 1$ layers are hidden and the L-th layer is the output layer. Let x_t denote the input vector at time t. We define the layer outputs (activations) recursively using the notation z as:

$$z_0 = x_t,$$
$$z_\ell = \sigma_\ell\left(W_\ell z_{\ell-1} + b_\ell\right), \ell = 1, \ldots, L-1 \tag{9}$$

where W_ℓ and b_ℓ denote the weight matrix and bias vector of layer ℓ, and $\sigma_\ell(\cdot)$ is the nonlinear activation function of that layer (e.g., ReLU). The h-step-ahead forecast is then obtained via an affine projection from the last hidden layer:

$$\hat{\pi}_{t+h} = g\left(W_L z_{\mathrm{L}-1} + b_L\right) \tag{10}$$

where $g(\cdot)$ is the output-layer function. The set of parameters $\left\{W_\ell, b_\ell\right\}_{\ell=1}^{L}$ is estimated by minimizing a loss function $\mathcal{L}(\pi_{t+h}, \hat{\pi}_{t+h})$. The gradients of the loss with respect to the parameters are computed using the backpropagation algorithm, and the parameters are updated using a chosen optimization procedure (Rumelhart, Hinton and Williams, 1986).

Although traditionally considered a statistical time series model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) is increasingly integrated into modern ML frameworks, often serving as a robust benchmark for automated predictive systems. SARIMA extends the standard ARIMA architecture by explicitly incorporating seasonal components, enabling the effective recognition of periodic patterns. The model is formally defined by the expression:

$$\Phi_P\left(B^s\right)\phi_p\left(B\right)\left(1-B^s\right)^D\left(1-B\right)^d \pi_t = \Theta_Q\left(B^s\right)\theta_q\left(B\right)\varepsilon_t \tag{11}$$

where B denotes the lag operator, $(1 - B)$ and $(1 - B^S)$ represent the non-seasonal and seasonal differencing required for stationarity, while the polynomials ϕ and θ (along with their seasonal counterparts) capture the autoregressive and moving average dynamics. Parameter selection is performed by automated algorithms (auto-SARIMA) that optimize the model structure based on information criteria such as the Akaike information criterion (AIC), ensuring both transparency and diagnostic robustness (Hyndman and Athanasopoulos, 2021).

Developed by Facebook's research division, the Prophet model specializes in forecasting time series characterized by pronounced seasonal patterns and occasional anomalies. Unlike traditional autoregressive models, Prophet relies on an additive decomposition methodology that treats the forecasting problem as a curve-fitting exercise, separating the signal into three distinct components:

$$y\left(t\right) = g\left(t\right) + s\left(t\right) + h\left(t\right) + \varepsilon_t \tag{12}$$

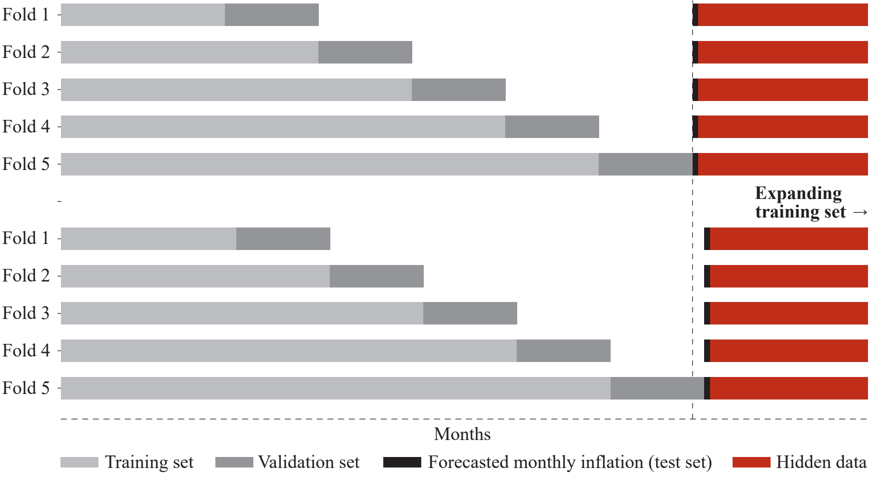
where $g(t)$ represents trend component, $s(t)$ is the seasonal component, $h(t)$ represents the influence of holidays or specific events (Taylor and Letham, 2018; Hyndman and Athanasopoulos, 2021).

3.4 FORECASTING PROCEDURE

To ensure generalization and prevent overfitting, this study employs an expanding window cross-validation technique, specifically adapted for time series data. As illustrated in figure 1, the model is initially trained on a fixed set, which progressively expands by the addition of one new month of data in each iteration. Following each expansion, the model is fully retrained and validated on the subsequent month, a process that meticulously simulates real-world forecasting and eliminates data leakage.

Figure 1

Illustrative display of the expanding window approach



Source: Authors' own elaboration.

Model selection within each cross-validation fold is determined by minimizing the Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(\pi_t - \widehat{\pi}_t\right)^2 \tag{13}$$

Final predictive performance is evaluated using two metrics. The first is the RMSE defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\pi_t - \widehat{\pi}_t\right)^2} \tag{14}$$

The second metric used is the out-of-sample MASE (OMASE), which is nearly identical to the measure proposed by Hyndman and Koehler (2006), with the exception that the denominator here is the out-of-sample MAE of the naive model, whereas Hyndman and Koehler employ the in-sample MAE of the naive model. OMASE can be written as:

$$OMASE = \frac{\frac{1}{n}\sum_{t=1}^{n}\left|\pi_t - \widehat{\pi_t}\right|}{\frac{1}{n-m}\sum_{t=m+1}^{n}\left|\pi_t - \pi_{t-m}\right|}, m = 12 \tag{15}$$

where m is the length of the seasonal cycle (for monthly data 12). An OMASE value below 1 indicates that the model under evaluation outperforms the naive seasonal benchmark.

To rigorously evaluate forecasting performance and feature importance under varying economic conditions, 12 experimental configurations were developed by crossing three evaluation periods with four distinct input feature sets:

- Evaluation periods:
  - The entire available period.
  - The period up to February 2020.
  - The period from March 2020 onward (the start of the lockdown).
- Input feature combinations:
  - Target variable lags only.
  - Lags + *conventional* features.
  - Lags + *unconventional* features.
  - All available variables combined.

To benchmark performance against that of the European Commission (EC), generated monthly forecasts are aggregated into annual inflation rates (see appendix). The study strictly replicates the data availability constraints of the EC's three key reporting cycles to ensure a fair comparison:

1) Spring Forecast (current year): Published in May with an April cut-off. Only information available by the end of April is used, with delayed-release variables imputed using lagged values. Given the availability of a HICP flash estimate for April, eight monthly inflation rates must be forecast, corresponding to horizons h = 1, ..., 8.
2) Autumn Forecast (current year): Published in November with an October cut-off. Data availability is aligned analogously, including a flash estimate for October. As ten monthly observations are known, forecasts are generated for the remaining two months (h = 1, 2).
3) Autumn Forecast (following year): Based on the same October cut-off and information set as the autumn forecast for the current year. Constructing the annual inflation rate for the following year requires forecasting the final two months of the current year and all twelve months of the next year, resulting in fourteen monthly projections (h = 1, ..., 14).

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4 RESULTS

This chapter reports the results of all models used to forecast monthly inflation in Croatia. The forecasting setup and evaluation procedure follow the framework outlined in chapter 3, with specific reference to section 3.4. Owing to computational constraints, forecasts are first generated for horizons of 3, 6, and 9 months, after which the best-performing model is employed to produce forecasts for the full set of 14 horizons. Table 2 presents RMSE forecast errors for the period up to March 2020, corresponding to the pre-COVID-19 sample.

Table 2

RMSE in the pre-COVID-19 period for the 3-, 6- and 9-month forecasting horizons

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	3	0.2941	/	/	/
RIDGE		0.3233	0.3188	0.3270	0.3133
LASSO		0.3349	**0.3470**	**0.3353**	0.3286
ENET		0.3361	**0.3448**	**0.3351**	0.3291
PROPHET		0.3509	0.6340	1.6688	0.8964
NN		0.3239	**0.3856**	0.3267	0.3435
SVR		0.3420	0.3535	0.3580	0.3622
RF		0.3609	**0.3741**	**0.3872**	**0.3622**
XGBOOST		0.3420	0.3166	**0.3679**	0.3037
LGBM		0.3180	**0.3468**	0.3286	0.3211
SARIMA	6	0.2874	/	/	/
RIDGE		0.3236	0.3144	0.3253	0.3123
LASSO		0.3404	0.3726	0.3594	0.3637
ENET		0.3499	0.3729	0.3638	0.3596
PROPHET		0.3778	0.6283	2.3085	1.0580
NN		0.3239	0.3543	**0.3992**	**0.3624**
SVR		0.3382	0.3530	0.3487	0.4065
RF		0.3409	0.3787	0.4631	0.4065
XGBOOST		0.2993	0.3112	0.3211	0.3270
LGBM		0.2728	0.3428	**0.3867**	0.3130
SARIMA	9	0.2905	/	/	/
RIDGE		0.3167	0.3096	0.3144	0.3007
LASSO		0.3314	0.3359	0.3356	0.3369
ENET		0.3349	0.3430	0.3365	0.3372
PROPHET		0.3554	0.7249	1.5218	0.7932
NN		0.3071	0.3248	0.3225	0.3337
SVR		0.3405	0.3226	0.3237	**0.3585**
RF		0.3067	0.3199	**0.4429**	**0.3585**
XGBOOST		0.2641	0.2983	0.2892	0.2946
LGBM		0.2962	0.3068	0.2632	0.2804

Note: Darker shading corresponds to lower RMSE values. Bolded entries denote combinations of models and feature sets that achieved OMASE > 1. Non-bolded entries achieved OMASE < 1. In appendix in tables A1-A3 results are presented as indices relative to the SARIMA model.

Source: Authors' calculations.

The results presented in table 2 indicate that tree-based models (LightGBM and XGBoost) achieve above-average accuracy in a period of subdued volatility (the period preceding the outbreak of the COVID-19 pandemic). At longer forecasting horizons (6 and 9 months), they consistently outperform the traditional SARIMA model, with their performance in some cases further enhanced by the inclusion of external features. Among the linear models, only the Ridge model maintains OMASE values below one across all horizons. Given that ENet and Lasso perform substantially worse than Ridge, it can be concluded that the feature exclusion induced by the L1 penalty does not, in this case, contribute to improved forecast accuracy. Prophet is the only model in the pre-COVID-19 period that fails to outperform the simple (naïve) forecasting model under any combination of input features. Moreover, for no other model does the inclusion of external features deteriorate forecasting performance to the same extent as it does for Prophet. Table 2 does not reveal any clear or systematic pattern whereby unconventional variables consistently improve forecasting accuracy relative to conventional variables, or vice versa. Table 3 reports the forecasting errors for the period following the onset of the COVID crisis.

Table 3

RMSE in the post-COVID-19 period for the 3-, 6- and 9-month forecasting horizons

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	3	0.5653	/	/	/
RIDGE		0.6081	**0.6710**	0.6581	0.6362
LASSO		0.5952	0.6332	0.6063	0.6208
ENET		0.5869	0.6342	0.6207	0.6272
PROPHET		0.5774	**0.8437**	**0.9092**	**3.2657**
NN		0.6186	**0.7196**	0.6576	0.6210
SVR		0.6364	0.6434	0.6059	0.6697
RF		0.6335	0.6281	0.6768	0.6697
XGBOOST		0.6637	0.6773	0.5894	0.5786
LGBM		0.6294	0.5923	0.5716	0.5746
SARIMA	6	0.5836	/	/	/
RIDGE		0.5862	**0.8057**	0.6623	**0.7214**
LASSO		0.6002	0.6542	0.6123	0.6112
ENET		0.5895	0.6507	0.6205	0.6354
PROPHET		0.6112	**0.9299**	**1.2737**	**3.5227**
NN		0.5979	**0.9232**	**0.6839**	**0.7940**
SVR		0.6343	0.6690	0.6401	0.6962
RF		0.6559	0.6527	**0.7164**	0.6962
XGBOOST		0.6622	**0.7050**	0.6103	0.6797
LGBM		0.6603	0.6029	0.6321	0.6086
SARIMA	9	0.5792	/	/	/
RIDGE		0.5745	**0.8741**	0.6380	**0.7602**
LASSO		0.5882	0.5936	0.6274	0.6055
ENET		0.5862	0.6032	0.6272	0.6087
PROPHET		0.5946	**1.1732**	**1.0935**	**7.5208**
NN		0.5963	**1.0482**	0.6661	**0.8043**
SVR		0.6323	0.6498	0.6482	0.6812
RF		0.6223	0.6556	0.6945	0.6812
XGBOOST		0.6438	0.6536	0.6372	0.6368
LGBM		0.6349	0.5886	0.5953	0.6082

Source: Authors' calculations.

Table 3 shows that the SARIMA model consistently achieves the lowest RMSE across all forecasting horizons. Among the ML models, the closest competitor to SARIMA is LightGBM. At shorter horizons, LGBM particularly benefits from the inclusion of conventional variables, whereas at longer horizons it attains higher predictive accuracy when unconventional features are included. Among the linear models, the Ridge model without external variables proves to be the most stable across horizons, although Lasso and ENet fall within a comparable accuracy range. Prophet records OMASE values below 1 only when it relies exclusively on lags of the target variable, which suggests that the expanded feature set offers insufficient informational value for this model. Neural networks also perform best when only temporal lags of the target variable are used, indicating that they have limited ability to extract useful information from additional external predictors. Furthermore, tables 2 and 3 reveal that OMASE values fall below 1 more frequently in the post-COVID than in the pre-pandemic period. This implies that, after the onset of the pandemic, models more often outperformed the naïve benchmark in terms of forecast accuracy. At the same time, table 3 shows that RMSE values for all models are considerably higher than those reported in table 2, pointing to increased unpredictability of inflation in the post-pandemic environment. Heightened volatility, structural changes in the economy, and global shocks such as supply chain disruptions and the sharp rise in energy prices all contributed to this increased uncertainty, ultimately reducing the predictive accuracy of all models under consideration. Finally, table 4 reports forecasting errors for the full sample period.

The results in table 4 for the full observation period reveal several important patterns regarding model performance. First, SARIMA attains the lowest forecasting errors across the selected horizons. Second, among the linear models, the lowest forecast errors are most frequently obtained when only temporal lags of the target variable are used as input features. Third, among the nonlinear models, LightGBM with external variables exhibits consistent predictive superiority over the other models. Across multiple feature combinations and all horizons, it records low RMSE and OMASE values, often the lowest among all models except SARIMA. Alongside LightGBM, XGBoost also stands out among nonlinear models, although its predictive performance is somewhat less consistent across different sets of external variables.

To enable a comparison between the best-performing model and the European Commission's forecasts in the final stage of the analysis, we proceed to select a model that will serve as the representative model for the final forecast and comparison. Since it is difficult to establish a single criterion to unambiguously identify the most successful model, the most appropriate approach appears to be focusing on the consistency of each model's results across different macroeconomic regimes.

Given that SARIMA achieves the lowest forecasting errors in most cases, across all horizons and all periods examined, it can be regarded as the best-performing model for forecasting inflation in Croatia. If SARIMA is excluded as a traditional time-series benchmark, LightGBM emerges as the most consistent performer among the ML models. LightGBM regularly attains low forecasting errors in all periods considered and across nearly all combinations of input variables (see appendix table A4).

Table 4
RMSE over the full observation period for the 3-, 6- and 9-month forecasting horizons

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	3	0.4772	/	/	/
RIDGE	3	0.5161	0.5606	0.5531	0.5341
LASSO	3	0.5124	0.5390	0.5194	0.5283
ENET	3	0.5042	0.5406	0.5304	0.5337
PROPHET	3	0.5014	**0.7687**	**1.1886**	**2.6113**
NN	3	0.5238	**0.6114**	0.5526	0.5303
SVR	3	0.5410	0.5489	0.5234	0.5699
RF	3	0.5437	0.5433	0.5813	0.5699
XGBOOST	3	0.5607	0.5647	0.5145	0.4901
LGBM	3	0.5302	0.5108	0.4914	0.4915
SARIMA	6	0.4888	/	/	/
RIDGE	6	0.5004	**0.6592**	0.5557	**0.5962**
LASSO	6	0.5188	0.5664	0.5319	0.5329
ENET	6	0.5097	0.5642	0.5392	0.5489
PROPHET	6	0.5325	**0.8255**	**1.7516**	**2.8295**
NN	6	0.5089	**0.7542**	**0.5894**	0.6601
SVR	6	0.5385	0.5671	0.5453	**0.6001**
RF	6	0.5547	0.5620	**0.6299**	**0.6001**
XGBOOST	6	0.5500	**0.5839**	0.5171	0.5688
LGBM	6	0.5431	0.5173	0.5496	0.5139
SARIMA	9	0.4864	/	/	/
RIDGE	9	0.4904	**0.7095**	0.5373	**0.6251**
LASSO	9	0.5039	0.5089	0.5346	0.5191
ENET	9	0.5033	0.5176	0.5346	0.5214
PROPHET	9	0.5147	**1.0221**	**1.2750**	**5.9239**
NN	9	0.5036	**0.8434**	0.5597	0.6644
SVR	9	0.5377	0.5460	0.5469	0.5790
RF	9	0.5224	0.5496	**0.6103**	0.5790
XGBOOST	9	0.5292	0.5434	0.5313	0.5322
LGBM	9	0.5292	0.4981	0.4949	0.5080

Source: Authors' calculations.

Accordingly, two models are selected for the final inflation forecasting exercise: SARIMA, as the traditional time-series model that consistently delivers the strongest results, and LightGBM, which has proven to be the most successful among ML approaches. Using these models, monthly inflation rates (month-over-month) are forecast for each of the 14 horizons. The resulting monthly forecasts are then transformed, as described in section 3.4, into annual inflation rates (year-over-year) by incorporating the contributions of realised monthly inflation rates. This enables comparison with the European Commission's forecasts across the three forecasting cycles. Figure 2 presents the comparison of actual average annual inflation with the European Commission's projections and the forecasts generated by the SARIMA and LightGBM models for all three forecasting scenarios: (1) the autumn forecast for the current year (h = 2); (2) the spring forecast for the current year (h = 8); and (3) the autumn forecast for the following year (h = 14).

Figure 2

Forecasted average annual inflation rate by the European Commission compared with forecasts from the SARIMA and LightGBM models (in %)

Note: Owing to the longer forecasting horizon of 14 months, the first year for which a complete annual inflation forecast can be computed in the last panel is 2018, whereas for shorter horizons (2 and 8 months) forecasts begin in 2017. Since the most recent publication of the European Commission available at the time of writing was released in autumn 2024, the final estimate for the current-year forecast refers to 2024. In the case of the next-year forecast (the 14-month horizon), the most recent projection refers to 2025.

Source: Authors' calculations; European Commission.

Figure 2 shows that the SARIMA and LightGBM models outperform the European Commission's forecasts in all forecasting scenarios. For the shortest horizon (h = 2, autumn forecast for the current year), the differences between the models and the European Commission are small, as most observations for that year are already known; nevertheless, our models provide slightly more accurate estimates. At the medium horizon (h = 8, spring forecast for the current year), the deviations between forecasted and realised values become larger, which is expected given the greater uncertainty and the longer time span until the end of the year. Even so, SARIMA and LightGBM continue to exhibit smaller errors relative to actual outcomes than the European Commission. The largest deviations occur at the longest horizon (h = 14, autumn forecast for the following year), clearly illustrating the difficulty of predicting inflation more than a year in advance. Even in this case, the forecasts generated by the two models remain closer to the realised values than those of the European Commission, thereby confirming their superiority under conditions of pronounced uncertainty. Finally, the figure reveals a clear distinction between SARIMA and LightGBM. SARIMA forecasts inflation more accurately during the stable pre-COVID period, whereas LightGBM delivers more precise predictions in the volatile post-pandemic environment.

5 DISCUSSION

The central question addressed in this study is whether ML models outperform benchmark models in forecasting inflation in Croatia and, if so, which ML approach performs best. The results suggest that ML methods achieve forecasting accuracy comparable to, and in some cases exceeding, that of standard univariate econometric models. This finding is consistent with recent evidence showing that ML techniques can improve inflation forecasts relative to traditional approaches (Medeiros et al., 2021; Araujo and Gaglianone, 2023). Among the ML methods considered, tree-based models perform particularly well, in line with results reported in related empirical studies.

Beyond model choice, forecasting performance is strongly influenced by the quantity and informational content of the predictors. Recent studies emphasize the benefits of data-rich environments, where models exploit large sets of potential predictors (e.g. Medeiros et al., 2021; Araujo and Gaglianone, 2023). In contrast, this paper adopts a parsimonious, *ad hoc* selection of key variables. While this simplifies the modelling framework, it may limit the gains typically associated with ML in data-rich settings. Nevertheless, given the available sample size, the selected predictors appear adequate: LightGBM performs competitively relative to SARIMA, suggesting that the essential information for forecasting inflation is captured by this reduced feature set. This approach is also motivated by structural constraints of the Croatian data environment, characterized by relatively short time series and a limited number of high-frequency macroeconomic indicators, a limitation also noted for other small economies (e.g. Ivașcu, 2023). As longer time series become available, the relative performance of ML models, particularly tree-based methods, may improve.

Differences between our results and those reported for larger economies can also be explained by specific features of the Croatian macroeconomic environment. For much of the sample period, monetary policy relied on the exchange rate as the nominal anchor, while external shocks played a dominant role in shaping inflation dynamics (Globan, Arčabić and Sorić, 2015). Under such conditions, inflation exhibits strong persistence and pronounced trend and seasonal components, making it particularly amenable to models such as SARIMA. Previous studies document the strong performance of ARIMA-type models in forecasting Croatian inflation (Pufnik and Kunovac, 2006) and in explaining its dynamics (Živko and Bošnjak, 2017), while our results confirm that SARIMA remains a reliable benchmark in this setting. The pronounced autoregressive nature of inflation implies that models explicitly exploiting its temporal structure can be highly effective, helping to explain the strong performance of SARIMA relative to more complex alternatives.

Finally, the results indicate that, over the sample period, our models consistently produced forecasts closer to realised inflation outcomes than those published by the European Commission, even in periods of heightened uncertainty. These results should, however, be interpreted with caution. Forecasts produced by institutions such as the European Commission may incorporate elements of forward guidance aimed at shaping public expectations, which can generate systematic deviations from realised outcomes, particularly during episodes of large shocks. While such practices may support short-term expectation anchoring, persistent forecast errors may ultimately weaken institutional credibility, raising the question of whether expectation management through official forecasts enhances macroeconomic stability or undermines trust over time. This trade-off remains an open empirical question with important implications for the design of official forecasting frameworks.

6 CAVEATS

This section outlines several important limitations related to data availability and methodological choices underlying the empirical analysis.

A first limitation concerns the use of single-extraction Google Trends series. Recent studies have shown that Google Trends data are subject to sampling variation, implying that repeated extractions of the same query may yield different values and thereby raising concerns regarding reproducibility (e.g. Cebrián and Domenech, 2024). To address this issue, some contributions propose averaging multiple extractions of the same query. However, implementing such procedures would substantially increase the data-collection burden and delay model estimation. Consequently, the analysis relies on a single extraction per query, a practice that has also been adopted in earlier studies (e.g. Choi and Varian, 2012). Nevertheless, this choice represents a limitation that should be considered when interpreting the results.

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A second limitation relates to hyperparameter optimisation. Due to computational constraints, the range of hyperparameters considered in the grid search was necessarily restricted, although it was not excessively narrow. Future work could address this limitation by expanding the grid search to cover a wider set of hyperparameter values, provided sufficient computational resources are available. Alternatively, the use of alternative hyperparameter tuning strategies beyond grid search, such as random search or Bayesian optimisation, could be considered in future research.

A third limitation concerns differences in model selection and evaluation procedures across model classes. The SARIMA models were specified using the Akaike information criterion (AIC), in line with standard practice in the econometric time-series literature, where information criteria are commonly employed for model selection. In contrast, machine learning models were trained and evaluated using an expanding-window cross-validation approach, which is more typical in the contemporary forecasting literature. This design choice was motivated by the intention to place each modelling approach in its natural methodological setting. Nevertheless, the use of different training and evaluation frameworks may limit the strict comparability of results across model classes. Future research could address this issue by applying a unified evaluation strategy (such as CV) to all models.

7 CONCLUSION

After several years of stability and low inflation in advanced economies, inflation has once again moved to the forefront of attention in both academic and policy circles. The sudden shocks associated with the COVID-19 pandemic, disruptions in global supply chains and increased geopolitical tensions triggered a sharp rise in prices, posing a significant challenge for policymakers, particularly central banks, which rely on accurate inflation forecasts to design effective monetary measures. In this context, timely and precise inflation projections are essential. This paper therefore examines the potential of modern machine learning methods for forecasting inflation in Croatia, a country where the literature on inflation forecasting, and especially on the application of machine learning, remains notably limited.

The findings show that no single model performs best across all time periods and feature sets. However, SARIMA, a traditional time-series model, stands out as the most reliable and consistently accurate model overall. Tree-based models, especially LightGBM, also exhibit strong predictive capabilities and outperform other machine learning methods across a variety of feature combinations. As data availability expands and new macroeconomic conditions are incorporated over time, it is reasonable to expect that models such as LightGBM will increasingly assume a leading role in inflation forecasting.

In the final comparison with the European Commission's projections, both SARIMA and LightGBM produce more accurate forecasts of average annual inflation across all forecasting scenarios, even at longer horizons. This further confirms their predictive superiority. The results also reveal an important pattern: before the COVID-19 crisis, during a period of greater macroeconomic stability, SARIMA generated more accurate forecasts than LightGBM, whereas in the post-COVID period LightGBM delivered more precise predictions than SARIMA.

Overall, the results point to a considerable potential for machine learning methods in inflation forecasting. By incorporating diverse input variables and evaluating models across different economic regimes, this study contributes to the empirical literature and highlights several avenues for further research. Given that inflation is a multidimensional and complex phenomenon, sophisticated tools are required, and machine learning models, when applied with due care, appear to offer a promising solution.

Disclosure statement

The authors have no conflicts of interest to declare.

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APPENDIX

CONVERSION TO YEAR-OVER-YEAR INFLATION RATES

Table A1 illustrates the procedure for converting monthly inflation rates into year-over-year inflation rates, which facilitates understanding of equations (A1) to (A4). The year-over-year inflation rate in month t is defined as:

$$1+\pi_t^{yoy}=\frac{P_t}{P_{t-12}}=\frac{P_t}{P_{t-h}}\cdot\frac{P_{t-h}}{P_{t-12}} \tag{A1}$$

where P_t denotes the consumer price index in month t. The contribution of monthly inflation rates to the year-over-year rate for the most recent h months is given by:

$$\frac{P_t}{P_{t-h}}=\prod_{s=t-h+1}^{t}\left(1+\hat{\pi}_s^{mom}\right) \tag{A2}$$

In equation (A2), we use the forecasted monthly inflation rates $\hat{\pi}_s^{mom}$, while in equation (A3) we retain the realised monthly rates π_s^{mom}. The contribution of realised monthly changes in the HICP index over the months that remain in the base after the most recent h months drop out is expressed as:

$$\frac{P_{t-h}}{P_{t-12}}=\prod_{s=t-11}^{t-h}\left(1+\pi_s^{mom}\right) \tag{A3}$$

Combining equations (A2) and (A3) yields:

$$\hat{\pi}_t^{yoy}=\left[\prod_{s=t-h+1}^{t}\left(1+\hat{\pi}_s^{mom}\right)\right]\left[\prod_{s=t-11}^{t-h}\left(1+\pi_s^{mom}\right)\right]-1 \tag{A4}$$

Table A1

RMSE expressed as indices relative to the SARIMA model for the pre-COVID-19 period

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	3	100.0	/	/	/
RIDGE		109.9	108.4	111.2	106.5
LASSO		113.9	**118.0**	**114.0**	111.7
ENET		114.3	**117.2**	**113.9**	111.9
PROPHET		119.3	215.6	567.4	304.8
NN		110.1	**131.1**	111.1	116.8
SVR		116.3	120.2	**121.7**	**123.2**
RF		122.7	**127.2**	**131.7**	**123.2**
XGBOOST		116.3	107.7	**125.1**	103.3
LGBM		108.1	**117.9**	111.7	109.2
SARIMA	6	100.0	/	/	/
RIDGE		112.6	109.4	113.2	108.7
LASSO		118.4	129.6	125.1	126.5
ENET		121.7	129.7	126.6	125.1
PROPHET		131.5	218.6	803.2	368.1
NN		112.7	123.3	**138.9**	**126.1**
SVR		117.7	122.8	**121.3**	**141.4**
RF		118.6	131.8	161.1	141.4
XGBOOST		104.1	108.3	111.7	113.8
LGBM		94.9	119.3	**134.6**	108.9

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	9	100.0	/	/	/
RIDGE		109.0	106.6	108.2	103.5
LASSO		114.1	115.6	115.5	116.0
ENET		115.3	118.1	115.8	116.1
PROPHET		122.3	249.5	523.9	273.0
NN		105.7	111.8	111.0	114.9
SVR		117.2	111.0	111.4	**123.4**
RF		105.6	110.1	**152.5**	**123.4**
XGBOOST		90.9	102.7	99.6	101.4
LGBM		102.0	105.6	90.6	96.5

Source: Authors' calculations.

Table A2

RMSE expressed as indices relative to the SARIMA model for the post-COVID-19 period

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	3	100.0	/	/	/
RIDGE		107.6	**118.7**	116.4	112.5
LASSO		105.3	112.0	107.3	109.8
ENET		103.8	112.2	109.8	110.9
PROPHET		102.1	**149.2**	**160.8**	**577.7**
NN		109.4	**127.3**	116.3	109.9
SVR		112.6	113.8	107.2	118.5
RF		112.1	111.1	119.7	118.5
XGBOOST		117.4	119.8	104.3	102.4
LGBM		111.3	104.8	101.1	101.6
SARIMA	6	100.0	/	/	/
RIDGE		100.4	**138.1**	113.5	123.6
LASSO		102.8	112.1	104.9	104.7
ENET		101.0	111.5	106.3	108.9
PROPHET		104.7	**159.3**	**218.2**	**603.6**
NN		102.5	**158.2**	**117.2**	**136.1**
SVR		108.7	114.6	109.7	119.3
RF		112.4	111.8	**122.8**	119.3
XGBOOST		113.5	**120.8**	104.6	116.5
LGBM		113.1	103.3	108.3	104.3
SARIMA	9	100.0	/	/	/
RIDGE		99.2	**150.9**	110.2	131.3
LASSO		101.6	102.5	108.3	104.5
ENET		101.2	104.1	108.3	105.1
PROPHET		102.7	**202.6**	**188.8**	**1298.5**
NN		103.0	**181.0**	115.0	**138.9**
SVR		109.2	112.2	111.9	117.6
RF		107.4	113.2	119.9	117.6
XGBOOST		111.2	112.8	110.0	109.9
LGBM		109.6	101.6	102.8	105.0

Source: Authors' calculations.

Table A3
RMSE expressed as indices relative to the SARIMA model for the full observation period

Model	Horizon	*lag*	*unconv*	*conv*	*all*
SARIMA	3	100.0	/	/	/
RIDGE		108.2	117.5	115.9	111.9
LASSO		107.4	113.0	108.8	110.7
ENET		105.7	113.3	111.1	111.8
PROPHET		105.1	**161.1**	**249.1**	**547.2**
NN		109.8	**128.1**	115.8	111.1
SVR		113.4	115.0	109.7	119.4
RF		113.9	113.9	121.8	119.4
XGBOOST		117.5	118.3	107.8	102.7
LGBM		111.1	107.0	103.0	103.0
SARIMA	6	100.0	/	/	/
RIDGE		102.4	**134.9**	113.7	**122.0**
LASSO		106.1	115.9	108.8	109.0
ENET		104.3	115.4	110.3	112.3
PROPHET		108.9	**168.9**	**358.3**	**578.9**
NN		104.1	**154.3**	**120.6**	**135.0**
SVR		110.2	116.0	111.6	**122.8**
RF		113.5	115.0	**128.9**	**122.8**
XGBOOST		112.5	**119.5**	105.8	116.4
LGBM		111.1	105.8	112.4	105.1
SARIMA	9	100.0	/	/	/
RIDGE		100.8	**145.9**	110.5	**128.5**
LASSO		103.6	104.6	109.9	106.7
ENET		103.5	106.4	109.9	107.2
PROPHET		105.8	**210.1**	**262.1**	**1217.9**
NN		103.5	**173.4**	115.1	**136.6**
SVR		110.5	112.3	112.4	119.0
RF		107.4	113.0	**125.5**	119.0
XGBOOST		108.8	111.7	109.2	109.4
LGBM		108.8	102.4	101.7	104.4

Source: Authors' calculations.

Table A4

Average RMSE by feature set used

Period	Variables	SARIMA	RIDGE	LASSO	ENET	PROPHET	NN	SVR	RF	XGB	LGBM
Before the pandemic	*lag*	0.291	0.321	0.336	0.340	0.361	0.318	0.340	0.336	0.302	0.296
	unconv	/	0.314	0.352	0.354	0.662	0.355	0.343	0.358	0.309	0.332
	conv	/	0.322	0.343	0.345	1.833	0.349	0.343	0.431	0.326	0.326
	all	/	0.309	0.343	0.342	0.916	0.347	0.376	0.376	0.308	0.305
Average RMSE		**0.291**	0.317	0.343	0.345	0.943	0.342	0.351	0.375	**0.311**	0.315
After the pandemic	*lag*	0.576	0.59	0.595	0.588	0.594	0.604	0.634	0.637	0.657	0.642
	unconv	/	0.784	0.627	0.629	0.982	0.897	0.654	0.645	0.679	0.595
	conv	/	0.653	0.615	0.623	1.092	0.669	0.631	0.696	0.612	0.600
	all	/	0.706	0.613	0.624	4.770	0.740	0.682	0.682	0.632	0.597
Average RMSE		**0.576**	0.683	0.612	0.616	1.860	0.728	0.651	0.665	0.645	**0.608**
Full observation period	*lag*	0.484	0.502	0.512	0.506	0.516	0.512	0.539	0.540	0.547	0.534
	unconv	/	0.643	0.538	0.541	0.872	0.736	0.554	0.552	0.564	0.509
	conv	/	0.549	0.529	0.535	1.405	0.567	0.539	0.607	0.521	0.512
	all	/	0.585	0.527	0.535	3.788	0.618	0.583	0.583	0.530	0.504
Average RMSE		**0.484**	0.570	0.526	0.529	1.645	0.608	0.554	0.571	0.540	**0.515**

Source: Authors' calculations.

Public debt and the dollar

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Abstract

We examine the relationship between the broad dollar exchange rate and public debt, using a global panel of over 140 countries. We show that a broad dollar appreciation is associated with higher public debt in the medium run. This pattern is mostly driven by emerging market and developing economies. We further show that it occurs especially in countries that have higher shares of FX debt and for which the market perceptions of debt sustainability are more adverse.

Keywords: public debt, fiscal policy, broad dollar exchange rate

1 INTRODUCTION

The major shocks that have hit the global economy over the past two decades – the Global Financial Crisis (GFC) and the COVID-19 pandemic – have lifted public debt to post WWII-highs (BIS, 2023). This increase has coincided with concerns about a secular decline in GDP growth rates (Rachel and Summers, 2019), as well as with a more recent rise in government borrowing costs as central banks hiked interest rates in the face of the post-pandemic inflation surge (OECD, 2025). These developments raise concerns about fiscal sustainability and underscore the need to understand the drivers of public debt accumulation.

One factor affecting the evolution of public debt is the exchange rate. The effects are most direct in the case of foreign currency-denominated debt, where a currency depreciation increases the debt-to-GDP ratio measured in the domestic currency and therefore, *ceteris paribus*, the debt servicing burden. The US dollar is particularly important, given its dominant role in global finance (Obstfeld and Zhou, 2022). The events of the 1980s are a case in point: the dollar appreciation that accompanied the tightening of US monetary policy contributed to the debt crises in emerging market and developing economies (EMDEs) that had large dollar liabilities.

But even for sovereigns that mostly borrow in local currency, developments in the dollar could indirectly affect public debt. Indeed, an appreciation of the broad US dollar exchange rate, which measures the value of the dollar against all major trading partners of the United States, is generally associated with tighter global financial conditions (Shin, 2019). These effects tend to outweigh those of the bilateral dollar exchange rates (Avdjiev et al., 2019). The broad dollar exchange rate has also been documented to be a risk factor for economic growth, especially in emerging market economies. Hofmann and Park (2020) show that a broad dollar appreciation dampens growth-at-risk (the lowest 5% of growth outcomes), affecting investment and exports, working through the financial channel. In addition, commodity-exporting EMEs tend to be negatively affected through the commodity price channel, as their terms-of-trade deteriorate when the dollar appreciates; see e.g. Allen et al. (2025). Such effects could also have implications for public debt ratios. Yet, although debt sustainability analyses frequently examine the effects of exchange rates (see e.g. IMF, 2021), academic literature has provided less evidence on the implications of the broad US dollar exchange rate, which is closely related to global financial conditions. We aim to bridge this gap in the literature.

In this paper, we examine the effects of the broad US dollar exchange rate on public debt in a global panel of over 140 countries, spanning both advanced economies (AEs) and EMDEs. Our baseline estimates focus on the relationship between the dollar and future public debt over a medium-term horizon of three years. We also investigate the importance of a potentially relevant channel driving the effects, the share of sovereign borrowing denominated in foreign currency.

We report two key findings. First, while a current broad dollar appreciation is associated with higher public debt ratios over the medium run in the global panel of countries, the effect is mostly driven by EMDEs – there is no statistically significant relationship in advanced economies. Second, the effect occurs in those EMDEs where a larger share of debt is denominated in foreign currency. Moreover, it takes place in countries where market perceptions of debt sustainability, captured by sovereign credit ratings, are more adverse.

In addition to papers analysing the global role and implications of the US dollar mentioned above, our paper is related to three other strands of literature.

First, it relates to studies analysing the drivers of public debt and deficits. An earlier theoretical literature modelled public debt as a means of redistributing income over time (Barro, 1979; Lucas and Stokey, 1983). Public debt has also been shown to result from political economy considerations, influencing the choices of successor governments (Alesina and Tabellini, 1990). There are a number of papers analysing systematic fiscal behaviour through fiscal reaction functions where debt stabilisation is an important consideration (e.g. Bohn, 1998; Ghosh et al., 2013; Mauro et al., 2015; Mendoza and Ostry, 2008). Blanchard (2019) discusses the costs of public debt in an environment of low interest rates. Di Serio (2024) and Patel and Peralta-Alva (2025) analyse the drivers of public debt using VAR models, but do not focus on the effects of the exchange rate. Another recent paper has examined the determinants of public debt in an "at risk" framework, evaluating how various economic and financial factors affect the future public debt distribution (Furceri et al., 2025). We contribute to this literature by focusing in particular on the effects of the broad dollar exchange rate on debt dynamics.

The second related strand in the literature examines the implications of the exchange rate for public debt. Related to debt sustainability analyses mentioned above, Calvo, Izquierdo and Talvi (2003) and Carrera and Vergara (2012) highlight how currency depreciations can change the path of primary balances that would be consistent with sustainable fiscal policy in Latin America. Acosta-Ormaechea (2020) shows that intra-year exchange rate fluctuations affect public debt projections in economies with large foreign currency denominated liabilities, as flows (e.g. interest payments) are converted into local currency using average annual

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exchange rates, but stocks (e.g. the public debt ratio) are converted with year-end exchange rates. Fisera, Workie Tiruneh and Hojdan (2021) study the impact of exchange rate depreciations on external debt ratios in a panel of emerging economies, focusing on the bilateral US dollar rate, while Coulibaly et al. (2024) examine the impact of large exchange rate depreciations on public debt in Africa. We add to this literature in two ways. First, we examine the public debt implications of the broad dollar, which, as discussed above, has been highlighted to be closely linked to global financial conditions. Second, we analyse the implications in a global sample, including advanced as well as emerging and developing economies.

Third, the paper adds to research that studies the implications of the currency denomination of debt. Earlier literature highlighted the inability of EMDE sovereigns to borrow in local currency, a phenomenon referred to as "original sin" (Eichengreen and Hausmann, 1999). These countries had fragile financial positions and were highly sensitive to foreign shocks, resulting in greater macroeconomic volatility. Yet, as emerging economies developed their domestic government bond markets (Mehrotra, Miyajima and Villar, 2012), the risks associated with EME sovereign borrowing evolved as well. Carstens and Shin (2019) discuss the "original sin redux", where the currency risks have shifted from the emerging market sovereign borrowers to the advanced economy lenders, but emerging market currency depreciations still tighten EMEs' financial conditions. At the same time, Eichengreen, Hausmann and Panizza (2023) point out that lower income EMDEs have generally not graduated from "original sin" and continue to borrow predominantly in foreign currency. We contribute to this literature by comparing the medium-term effects of fluctuations in the broad US dollar exchange rate on public debt between countries at different levels of foreign currency borrowing.

This paper is structured as follows. The next section describes the methodology and data. This is followed by empirical evidence in section 3. Finally, section 4 concludes.

2 METHODOLOGY AND DATA

We analyse the drivers of public debt by means of panel fixed effects ordinary least squares regressions of the type:

$$debt_{i,t+h} = \alpha_i + X_{it}\beta + \epsilon_{it} \tag{1}$$

In (1), the dependent variable is the level of public debt h years ahead, expressed in percent of GDP. The data are based on ex-post realised figures. The vector X_{it} contains the explanatory variables at time t; α_i denotes country fixed effects, included to account for time-invariant factors that could affect country-specific debt developments; and ϵ_{it} is the error term.[1]

[1] We note that our exercise is a forecasting-type exercise that does not establish causality. Thus, similarly to work on growth-at-risk (Adrian, Boyarchenko and Giannone, 2019), we include the current value of the dependent variable as part of the regressors but do not apply instrumental variable techniques to establish causal relationships.

The explanatory variables in (1) can be defined into three broad groups.

First, we include global factors that could affect public debt. Our key variable of interest is the change in the broad nominal US dollar exchange rate, defined so that an increase denotes a USD appreciation. This variable measures the value of the US dollar against the currencies of United States' main trading partners (26 economies). Its tendency to signal fluctuations in global financial conditions has been well established (see Shin (2019) and the references therein). The global block also includes the changes in global food prices and global oil prices, respectively. These global variables vary across time but not across countries.[2] Their inclusion is consistent with studies employing panel data econometrics to analyse, for example, the impact of the broad US dollar exchange rate on economic activity (Hofmann and Park, 2020), as well as on cross-border bank flows and investment (Avdjiev et al., 2019).

A second block consists of variables related to current fiscal policy and fiscal space. Here, we include the current level of public debt, real GDP growth, primary fiscal balance, interest expenditures and government revenues.

A third block consists of crisis related variables. We include a dummy for the Global Financial Crisis (GFC) which obtains a value of one in 2008 and 2009, and zero otherwise. We also include a similarly defined dummy variable for systemic banking crises to capture the potentially large fiscal costs of financial distress (Borio, Farag and Zampolli, 2023).[3]

When evaluating the channels through which changes in the US dollar could affect future debt ratios, we estimate an otherwise identical model to (1), but additionally interact the US dollar exchange rate with variables capturing various country-specific debt characteristics for which sufficient cross-country data are available. In particular, we consider the share of public debt denominated in foreign currency; the share of external debt (private and public) denominated in foreign currency; and the sovereign credit rating of the country, as indicated by the average of foreign currency long-term sovereign debt rating given by Moody's, Standard and Poor's, and Fitch ratings. The objective of this exercise is to understand the debt characteristics that could render the public debt ratios in some economies particularly sensitive to fluctuations in the US dollar.

As to data sources, all fiscal variables are from the IMF's Public Finances in Modern History database (an updated and expanded version of Mauro et al., 2015).[4]

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[2] As our dependent variable, the *h*-years-ahead public debt ratio, is country-specific, but the broad dollar measures the value of the dollar against all major trading partners, there is less of a concern about reverse causality from debt to the dollar.

[3] All of the variables in the global block, i.e. the broad dollar exchange rate, global food and global oil prices, display only weak correlation (with correlation coefficients below 0.1) with the dummy variables for the GFC and systemic banking crises, respectively.

[4] https://www.imf.org/external/datamapper/datasets/FPP.

The data for gross public debt refer to the general government sector whenever available (central government otherwise). At the start of our sample period in 2000, the public debt data refer to the general government in 80 economies and to the central government in 68 economies. The broad nominal US dollar exchange rate is from the US Federal Reserve. The data on banking crises are from Nguyen, Castro and Wood (2022) which extends the database of Laeven and Valencia (2020); the data on currency crises are from the same source. The data on the share of public debt denominated in foreign currency are from the updated dataset of Arslanalp and Tsuda (2014); data on the share of external debt in foreign currency and sovereign credit ratings are from Kose et al. (2022). Finally, the data on global commodity prices are from the World Bank.[5] Appendix table A1 lists the data sources and data transformations.

We estimate the model over 2000-19, thus excluding the fiscal consequences of the COVID-19 pandemic. All data are annual. The global panel covers 148 economies, 30 of which are classified as advanced and 118 as emerging and developing, based on the country classification in the IMF's Public Finances in Modern History database. Appendix table A2 lists the countries in the two groups. For some of the estimated models, the country coverage is narrower due to data availability.

The fiscal variables are expressed in percent of GDP, and the GDP growth rate is in percentage. A logarithmic transformation is applied to the broad US dollar index, global food and global oil prices; these three series are subsequently multiplied by 100 and first differences are taken (see also table A1). Appendix table A3 lists summary statistics of the variables included in the baseline model (excluding any dummy variables).

3 EMPIRICAL EVIDENCE

This section presents the empirical evidence. First, we discuss the estimates from the baseline model regarding the relationship between the dollar and future public debt. Second, we analyse the channels that could underpin the key findings. Third, we evaluate the implications of alternative exchange rate measures for future public debt.

3.1 BASELINE RESULTS

The results from the baseline model for the global sample of 148 economies are shown in table 1. The dependent variable is the three-year-ahead public debt ratio, expressed as percentage of GDP. Column (1) includes as explanatory variables only the current debt ratio and the current percent change in the broad USD exchange rate.

The estimates in column (1) show that a broad USD appreciation is systematically related to higher public debt over the medium term in the global sample. In particular, a one percent dollar appreciation in year *t* is associated with around a 0.6

[5] https://www.worldbank.org/en/research/commodity-markets.

percentage point higher public debt ratio after three years. The relationship is highly statistically significant. Column (1) also indicates an important persistence in public debt – a one percentage point increase in public debt-to-GDP today carries over to a 0.6 percentage point rise in government debt three years down the road.

Table 1

Baseline model, all economies

	(1)	(2)	(3)	(4)	(5)
	All econ.				
Variables	Debt_{t+3}				
Debt	0.636***	0.636***	0.621***	0.626***	0.611***
	(0.040)	(0.040)	(0.045)	(0.042)	(0.046)
ΔDollar	0.584***	0.570***	0.390***	0.602***	0.539***
	(0.079)	(0.094)	(0.080)	(0.083)	(0.098)
GDP growth			-0.450***		-0.489***
			(0.123)		(0.132)
Primary balance			-0.891***		-0.899***
			(0.152)		(0.154)
Interest expenditures			-0.225		-0.322
			(0.962)		(0.985)
Government revenues			0.290		0.310*
			(0.180)		(0.176)
Food price inflation		0.003			0.172***
		(0.043)			(0.052)
Oil price inflation		-0.008			-0.080**
		(0.033)			(0.040)
GFC				-3.273***	-4.900***
				(1.143)	(1.053)
Banking crises				7.047***	4.123**
				(2.407)	(2.033)
Constant	20.178***	20.205***	15.177***	20.735***	15.429***
	(2.103)	(2.104)	(5.637)	(2.224)	(5.522)
Observations	2,960	2,960	2,960	2,960	2,960
R-squared	0.426	0.426	0.465	0.431	0.471
# of economies	148	148	148	148	148

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, $Debt_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

These results remain robust to the inclusion of a battery of control variables, as shown in the other columns of table 1. Column (2) adds other global variables, i.e. growth in food and oil prices; column (3) includes variables related to fiscal policy and fiscal space; column (4) considers dummy variables related to crises; and column (5) all of the above. Most importantly, the coefficient on *ΔDollar* is only slightly lower in column (5) than in column (1) and remains highly statistically significant. Higher real GDP growth and higher primary balances lead to lower public debt ratios in the medium run. And while banking crises lead to persistently

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higher public debt, consistent with the large fiscal costs of financial crises, the opposite is true for the GFC in the global sample.

Table 2

Baseline model, advanced economies

	(1)	(2)	(3)	(4)	(5)
	AEs				
Variables	$Debt_{t+3}$				
Debt	0.779***	0.794***	0.716***	0.787***	0.762***
	(0.059)	(0.059)	(0.065)	(0.070)	(0.065)
ΔDollar	-0.318***	0.109	-0.386***	-0.354***	0.064
	(0.084)	(0.080)	(0.077)	(0.091)	(0.102)
GDP growth			-0.388*		0.166
			(0.221)		(0.237)
Primary balance			-1.274***		-1.204***
			(0.266)		(0.225)
Interest expenditures			-3.180***		-3.788***
			(0.833)		(0.798)
Government revenues			1.603***		1.645***
			(0.476)		(0.459)
Food price inflation		0.276***			0.236***
		(0.053)			(0.046)
Oil price inflation		-0.039			-0.001
		(0.032)			(0.034)
GFC				8.001***	6.566**
				(2.666)	(2.559)
Banking crises				6.874**	4.880**
				(2.642)	(2.201)
Constant	18.899***	17.031***	-34.698*	16.642***	-41.509**
	(3.862)	(3.917)	(17.339)	(4.597)	(16.569)
Observations	600	600	600	600	600
R-squared	0.558	0.567	0.644	0.610	0.682
# of economies	30	30	30	30	30

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, $Debt_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

We also note that employing the Hausman test on the model in column (5) of table 1 provides support for the fixed effects specification. In particular, we clearly reject the null hypothesis that the individual effects are uncorrelated with the regressors (p-value below 0.01). While the Pesaran-Yamagata test for slope homogeneity vs. heterogeneity on the same specification rejects slope homogeneity (p-value below 0.01), we prefer to apply the standard fixed effects model. Allowing for slope heterogeneity would arguably lead to imprecise estimates, given the relatively short time dimension of our panel.

Tables 2 and 3 show that the debt-increasing effect of dollar appreciation in the global sample stems from the impact obtained for EMDEs. In particular, for AEs, table 2 shows that the coefficient on *ΔDollar* is not statistically significant when all the control variables are included (column (5) in table 2). In some of the estimated models, the coefficient on the broad USD exchange rate is actually negative, suggesting that a dollar appreciation would be associated with *lower* public debt ratios in the medium run. By contrast, for EMDEs, table 3 shows that a dollar appreciation leads to higher public debt. In these economies, the coefficient on *ΔDollar* is highly statistically significant in all models and close in economic significance to that observed in the global sample (table 1). In particular, column (5) in table 3 suggests that a one percent appreciation in the broad USD dollar exchange rate is associated with a 0.7 percentage point increase in public debt ratios three years down the road in EMDEs.

There are also other interesting differences between the variables affecting future public debt in AEs and EMDEs. For one, the public debt ratios in EMDEs benefit from higher growth even over the medium term, while there is no statistically significant relationship in AEs. Meanwhile, the coefficient on interest expenditures is positive and significant in AEs but statistically insignificant in EMDEs. This suggests that higher interest expenses trigger future government deleveraging in AEs, perhaps due to the perceived need to improve fiscal health. Indeed, if we replace three-years-ahead public debt by future primary balances (either one, two or three-years-ahead) as the left-hand side variable, we obtain a positive and statistically significant coefficient on interest expenditures for AEs.[6] This implies that higher interest expenditures today lead to higher future primary balances and reduce public debt ratios.[7] Finally, banking crises and the GFC are associated with higher public debt in AEs, while the GFC prompted deleveraging by the public sector in EMDEs. These findings may partly reflect the sample period (2000-19) which generally featured more frequent financial stress in advanced economies than in their emerging market counterparts.

[6] These results are available upon request.

[7] This result is consistent with Tkacevs and Vilerts (2019) who document a positive impact of government borrowing costs on cyclically adjusted primary balances for a sample of OECD countries.

Table 3
Baseline model, emerging market and developing economies

	(1)	(2)	(3)	(4)	(5)
			EMDEs		
Variables			$Debt_{t+3}$		
Debt	0.621***	0.620***	0.592***	0.609***	0.577***
	(0.046)	(0.046)	(0.055)	(0.047)	(0.055)
ΔDollar	0.778***	0.666***	0.571***	0.813***	0.662***
	(0.088)	(0.113)	(0.089)	(0.090)	(0.117)
GDP growth			-0.418***		-0.480***
			(0.124)		(0.137)
Primary balance			-0.803***		-0.810***
			(0.168)		(0.166)
Interest expenditures			0.392		0.394
			(1.209)		(1.223)
Government revenues			0.162		0.182
			(0.187)		(0.181)
Food price inflation		-0.046			0.163***
		(0.051)			(0.061)
Oil price inflation		-0.008			-0.101**
		(0.041)			(0.048)
GFC				-5.805***	-6.878***
				(1.205)	(1.119)
Banking crises				-2.652	-3.156
				(2.663)	(2.599)
Constant	18.894***	19.140***	17.440***	20.108***	18.465***
	(2.269)	(2.251)	(5.421)	(2.341)	(5.233)
Observations	2,360	2,360	2,360	2,360	2,360
R-squared	0.414	0.415	0.449	0.421	0.458
# of economies	118	118	118	118	118

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, $Debt_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

To what extent do these results hold for other estimation horizons? The baseline results discussed above relate to the medium term, given that the dependent variable is the three-year-ahead public debt ratio. Appendix table A3 shows the estimates for models where the dependent variable is either the one-, three- or five-year-ahead debt ratio. All the models include the full set of control variables (not shown). The results confirm the key result that the relationship between the US dollar and future debt is stronger for EMDEs than it is for AEs, across the different horizons. When the one-year-ahead debt ratio is used (first column), the change in the US dollar exchange rate also obtains a positive and statistically significant coefficient in the group of AEs. However, its economic magnitude is only around one half of the coefficient estimate in EMDEs. For the five-year-ahead debt ratio (third column), the coefficient on the change in the exchange rate is not statistically significant for AEs, but it remains significant for EMDEs.

3.2 CHANNELS

Why would the change in the US dollar exchange rate be systematically related to the future level of public debt in one group of countries while remaining insignificant in others? An important factor is likely to be the structure of public debt, in particular its currency denomination.

To examine this issue, we first use data on the share of public debt denominated in foreign currency, obtained from the updated dataset of Arslanalp and Tsuda (2014). For data consistency reasons, we only use data for EMDEs, 115 of which have available data for at least part of our sample period.[8] Small island nations aside, some EMDEs have *all* of their outstanding public debt denominated in foreign currency during part of the sample, including Cambodia, El Salvador and Nicaragua. The opposite – all outstanding public debt denominated in *local* currency – is also true for some EMDEs during part of the sample period, including China, Iran and Saudi Arabia. While we do not have information on the exact currency composition of FX denominated debt for our sample, a large part of FX debt is generally assumed to be denominated in the US dollar. Important exceptions are European emerging markets where FX debt tends to be predominantly denominated in euros (and, in some cases, Swiss francs).

We interact the change in the US dollar exchange rate with a dummy variable equal to one if FX denominated debt in the economy in a particular year is higher than the sample median (53%) and zero otherwise. The results are shown in the first two columns of table 4, where the dummy variable is denoted as "FX share of debt".

The results show that an appreciation of the US dollar is systematically related to higher future public debt in EMDEs where FX denominated debt accounts for a larger share of total public debt. Column (1) in table 4 includes only the current level of public debt, the change in the dollar exchange rate, a dummy denoting a high FX share of public debt and the associated interaction variable between the exchange rate and the dummy for high FX share. While the interaction variable obtains a positive coefficient in column (1), it is not statistically significant. However, when the battery of control variables is included (column (2)), the interaction variable obtains a statistically significant positive coefficient. The coefficient estimates imply that in EMDEs with a high share of FX debt, a one percent appreciation of the US dollar is associated with a 0.8 percentage point higher public debt ratio over the medium term (0.464 + (0.338 * 1) = 0.802, with a p-value below 0.01). For EMDEs with lower FX-denominated debt, the impact is lower (0.464), and the difference between the two groups of countries is statistically significant at the 95% level. We also note that EMDEs with higher FX debt shares on average have almost three percentage points lower public debt ratios than their other EMDE peers – the coefficient on the dummy variable "FX share of debt" on its own is -2.939 and it is weakly statistically significant. This result might stem from the lower debt limits that EMDEs with high FX debt shares could face given their

[8] The corresponding data for AEs refer to debt securities only (updated dataset of Arslanalp and Tsuda, 2012).

greater vulnerabilities. Alternatively, FX debt might be cheaper to issue (with a lower interest rate than domestic currency debt), resulting in lower accumulated debt ratios over time.

Table 4

Evidence on the underlying channels

	(1)	(2)	(3)	(4)	(5)
Variables			**Debt$_{t+3}$**		
Debt	0.618***	0.572***	0.453***	0.490***	0.574***
	(0.051)	(0.056)	(0.088)	(0.104)	(0.055)
ΔDollar	0.644***	0.464***	-0.168	-0.138	0.362**
	(0.145)	(0.162)	(0.137)	(0.149)	(0.140)
ΔDollar * FX share of debt	0.243	0.338**			
	(0.181)	(0.170)			
FX share of debt	-4.046*	-2.939*			
	(2.208)	(1.713)			
ΔDollar * Ext FX debt			0.609**	0.419**	
			(0.231)	(0.160)	
Ext FX debt			-5.696***	-4.674**	
			(2.004)	(2.011)	
Food price inflation		0.154**		0.287***	0.044
		(0.063)		(0.073)	(0.063)
Oil price inflation		-0.101**		-0.158**	-0.118**
		(0.051)		(0.061)	(0.048)
GDP growth		-0.602***		-0.672**	-0.484***
		(0.181)		(0.290)	(0.137)
Primary balance		-0.781***		-1.139**	-0.820***
		(0.165)		(0.497)	(0.167)
Interest expenditures		0.186		-0.243	0.403
		(1.223)		(1.577)	(1.219)
Government revenues		0.174		0.670	0.174
		(0.175)		(0.485)	(0.180)
GFC		-7.508***		-6.370***	-8.959***
		(1.122)		(2.023)	(1.180)
Banking crises		-2.544		-3.926	-2.970
		(2.632)		(4.909)	(2.646)
ΔVIX					0.078***
					(0.015)
Constant	21.225***	21.357***	31.699***	12.452	19.697***
	(1.987)	(5.148)	(4.607)	(16.130)	(5.193)
Observations	2,202	2,202	487	487	2,360
R-squared	0.413	0.455	0.266	0.385	0.463
# of economies	115	115	38	38	118

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, Debt$_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

We also investigate the relevance of *external* debt denominated in foreign currency for the exchange rate-public debt relationship. In addition to external FX debt incurred by the public sector, private sector FX liabilities could also add to future public debt. Unsustainable credit booms to finance consumption and investment by foreign capital can eventually lead to financial strains, a drop in output, exchange rate depreciation and a deterioration of public finances, coupled with fiscal stimulus to reignite economic growth (see also Borio, Farag and Zampolli, 2023). Governments may also resort to bailouts of private borrowers, including through the rescue of failing banks. We use the variable "external debt in foreign currency in percent of total external debt" from Kose et al. (2022). Data availability is much sparser in this case than in the results discussed earlier – only 38 economies can be included in the estimation.

Using these data, we again create a dummy variable (denoted by "Ext FX debt") that obtains the value of one for those country-year observations that exceed the sample median and a value of zero otherwise. We observe that no advanced economy falls into the country group with higher external FX debt share (corresponding to above 90% of total external debt). Notably, some EMDEs have *all* of their external debt (public + private) denominated in foreign currency. The country featuring most annual observations with fully FX denominated external debt in our sample is Namibia, followed by Moldova. By contrast, the lowest share of FX denominated external debt in our sample occurred in Cyprus (5.1% in 2011).

Despite the much smaller sample in these estimations, the share of external debt denominated in FX also appears to matter for the dollar-public debt relationship. In column (3) where the estimation only includes a narrow set of control variables, the interaction variable between *ΔDollar* and the dummy variable "Ext FX debt" is positive and statistically significant. The same holds when all the control variables are included (column (4)). The coefficient estimates in column (4) imply that in economies with a higher FX denominated share of external debt, a one percent appreciation of the US dollar is associated with a 0.3 percentage point higher public debt ratio over the medium term (-0.138 + (0.419 * 1) = 0.281, with a *p*-value of 0.055). In economies with a lower FX share of external debt, there is no statistically significant relationship. However, as mentioned earlier, the estimates should be interpreted with some caution due to the much smaller available estimation sample. Moreover, we acknowledge that, for the common available sample period, the share of public debt denominated in foreign currency and the share of external debt in foreign currency are positively and closely correlated (correlation coefficient of 0.57). This means that for estimations employing the FX share of total external debt, the FX share of public debt might be an important driving factor.

Another, complementary, channel for the baseline results could be a global risk-off shock, leading to increased demand for safe assets, capital outflows from EMDEs and dollar appreciation. The currency depreciation in EMDEs can then mechanically raise their debt ratios. In this case, the correlation between USD appreciation and higher debt ratios in EMDEs can reflect capital flow reversals. To incorporate this channel, we include the change in the log VIX index in the estimation in column (5), capturing an increase in global risk aversion. The coefficient estimate on this variable is statistically significant and suggests that a 10% increase in the VIX index is associated with a 0.8 percentage point increase in the public debt ratio in EMDEs three years ahead.

The previous results suggest that the currency denomination of debt plays an important role in the dollar-public debt relationship. We next show that it is the economies deemed most vulnerable by the rating agencies that experience an increase in public debt over the medium term when the broad dollar appreciates.

To see this, we consider interaction variables similar to those used above, interacting the change in the dollar exchange rate with a dummy variable capturing the sovereign credit rating. The data that we use to construct the dummy refers to the average rating of foreign currency long-term sovereign debt given by Moody's, Standard and Poor's, and Fitch, and is obtained from Kose et al. (2022). The latter authors transform the credit ratings into a numerical variable that ranges from 1 (worst rating) to 21 (highest rating). Over our sample period, the rating for AEs ranges from 3 to 21, with an average of 18. For EMDEs, the range is from 1 to 19, with a mean of 10. Thus, the average rating is much lower for EMDEs.

As with the variables related to the currency denomination of debt, we create a dummy variable that obtains a value of one for the country-year observations when a country's credit rating is above the sample median and zero otherwise, and also interact the dummy variable with the change in the log broad dollar exchange rate. The credit rating variable is available for almost the entire baseline sample of AEs and EMDEs, unlike the indicators for the currency denomination of debt.

Table 5 shows that a broad dollar appreciation has little effect on future public debt in countries with stronger credit ratings. Consider column (2), where the sample includes both AEs and EMDEs, and the estimation uses a full set of control variables. In economies with below-median credit ratings, a one percent broad dollar appreciation is associated with 0.636 percentage point higher public debt three years down the road. This effect is highly statistically significant. By contrast, in countries with above-median credit ratings, the relationship between the dollar and public debt is close to zero and not statistically significant (0.636 – (0.596 * 1) = 0.040, with a *p*-value of 0.658.)

Column (4) provides corresponding evidence for advanced economies only, with a full set of control variables. In this group, the dollar appreciation has little effect on future public debt, and the sovereign credit rating does not seem to matter for the relationship between the exchange rate and future public debt. At the same time, there are only a handful of country-year observations among advanced economies where sovereign credit ratings fall below the global sample median – these correspond to less than 5% of all observations in the advanced economy sample.

Table 5

Interaction between credit ratings, exchange rate and public debt

	(1)	(2)	(3)	(4)	(5)	(6)
	All econ.		AEs		EMDEs	
Variables	$Debt_{t+3}$					
Debt	0.723***	0.693***	0.785***	0.783***	0.699***	0.639***
	(0.077)	(0.077)	(0.069)	(0.074)	(0.108)	(0.116)
ΔDollar	0.667***	0.636***	-0.342	-0.020	0.695***	0.556***
	(0.133)	(0.142)	(0.369)	(0.313)	(0.135)	(0.150)
ΔDollar * Credit rating	-0.587***	-0.596***	0.025	0.092	-0.214	-0.427**
	(0.171)	(0.147)	(0.417)	(0.354)	(0.195)	(0.165)
Credit rating	3.115	1.808	1.163	5.108	2.751	1.379
	(2.461)	(1.798)	(3.373)	(3.686)	(2.772)	(2.000)
GDP growth		-0.701***		0.115		-0.808***
		(0.199)		(0.229)		(0.228)
Primary balance		-1.253***		-1.145***		-1.232***
		(0.184)		(0.236)		(0.235)
Interest expenditures		-0.897		-3.895***		0.048
		(1.203)		(0.804)		(1.735)
Government revenues		0.628**		1.696***		0.487
		(0.277)		(0.442)		(0.304)
Food price inflation		0.286***		0.240***		0.287***
		(0.056)		(0.047)		(0.068)
Oil price inflation		-0.129***		-0.003		-0.171***
		(0.035)		(0.038)		(0.046)
GFC		-3.374**		6.049**		-5.915***
		(1.342)		(2.588)		(1.539)
Banking crises		1.715		5.536**		-4.465
		(2.044)		(2.227)		(3.242)
Constant	16.087***	4.304	17.429**	-49.681***	15.964***	10.900
	(4.774)	(8.743)	(7.044)	(15.924)	(5.503)	(8.905)
Observations	2,149	2,149	600	600	1,549	1,549
R-squared	0.423	0.497	0.558	0.684	0.384	0.460
# of economies	125	125	30	30	95	95

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, $Debt_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

By contrast, the debt consequences of broad dollar appreciations vary strongly within the group of EMDEs. Column (6) shows that in EMDEs with lower credit ratings, a 1% broad dollar appreciation is associated with a 0.556 percentage point increase in the level of public debt three years on. This effect is highly statistically significant. In EMDEs with a higher credit rating, the effect is only 0.101 percentage points and it is not statistically significant (0.556 – (0.427 * 1) = 0.129, with a *p*-value of 0.317). Thus, broad dollar appreciations are associated with higher future public debt in economies that are also considered more vulnerable by rating agencies and thus have lower foreign currency sovereign ratings.

3.3 FURTHER EVIDENCE ON THE EXCHANGE RATE

The previous estimations used the first difference of the log broad dollar exchange rate in the estimations, i.e. the appreciation or depreciation of the dollar exchange rate. In this section, we consider three other exchange rate measures.

First, we use the *level* of the exchange rate in the estimation instead of the first difference. The rationale is that perhaps the level of the broad dollar – say, a historically strong level – could matter for future debt developments. The results are shown in table 6. Columns (1) and (2) show the results for the global sample; columns (3) and (4) for AEs; and columns (5) and (6) for EMDEs.

In the global sample, the level of the broad dollar is not associated in a statistically significant way with future public debt. This is the case when only current public debt and the dollar exchange rate are included as control variables (column (1) in table 6) and when all the control variables are included (column (2)).

The same message arises in the AE and EMDE samples considered separately. To be sure, when only current public debt and the dollar exchange rate are included as control variables, there is some evidence of a statistically significant relationship between the level of broad dollar and future public debt. And, interestingly, the relationship is actually negative for AEs, implying that a higher level of the broad dollar is associated with lower future public debt (column (3) in table 6). For EMDEs, by contrast, the relationship is positive, like the baseline estimation (column (5)). However, when all control variables are included (columns (4) and (6)), in neither AEs or EMDEs do we find a statistically significant relationship between the level of the broad dollar and future public debt. These findings suggest that it is indeed the change in the dollar exchange rate (i.e., appreciation or depreciation) that has persistent effects on the debt trajectory.

As a second alternative exchange rate measure, we replace the change in the broad dollar by a dummy variable capturing currency crises. We use data from Nguyen et al. (2022), where currency crises are defined according to the depreciation of the domestic currency against the US dollar. Specifically, the authors define the occurrence of a currency crisis when the nominal depreciation of the currency is at least 30% a year and it is at least 10% higher than the previous year's change. Using this definition, our estimation sample features 73 crises, two of which occurred in AEs and 71 in EMDEs.

Table 6

Results with the level of the broad dollar exchange rate

	(1)	(2)	(3)	(4)	(5)	(6)
	All econ.		AEs		EMDEs	
Variables	$Debt_{t+3}$					
Debt	0.636***	0.609***	0.748***	0.762***	0.592***	0.568***
	(0.044)	(0.048)	(0.065)	(0.065)	(0.054)	(0.058)
Dollar (level)	0.086	0.054	-0.315***	-0.013	0.225***	0.092
	(0.057)	(0.045)	(0.078)	(0.044)	(0.067)	(0.059)
Food price inflation		0.052		0.218***		0.022
		(0.057)		(0.045)		(0.067)
Oil price inflation		-0.105***		-0.005		-0.130***
		(0.038)		(0.033)		(0.045)
GDP growth		-0.506***		0.170		-0.507***
		(0.138)		(0.235)		(0.145)
Primary balance		-0.923***		-1.182***		-0.855***
		(0.156)		(0.219)		(0.169)
Interest expenditures		-0.358		-3.784***		0.349
		(0.984)		(0.798)		(1.224)
Government revenues		0.343*		1.638***		0.232
		(0.178)		(0.460)		(0.183)
GFC		-3.543***		6.633**		-4.999***
		(1.013)		(2.410)		(1.073)
Banking crises		4.453**		4.875**		-2.816
		(2.087)		(2.232)		(2.764)
Constant	-19.143	-9.856	166.439***	-35.171	-83.496***	-24.090
	(25.263)	(21.728)	(37.202)	(23.650)	(29.608)	(27.552)
Observations	2,960	2,960	600	600	2,360	2,360
R-squared	0.410	0.466	0.577	0.682	0.393	0.451
# of economies	148	148	30	30	118	118

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, $Debt_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

Table 7 shows that the implications of currency crises for public debt appear to differ from those resulting from changes in the broad dollar exchange rate, but the statistical significance of the results is weak. Considering those specifications where all control variables are included (columns (2), (4), (6)), we obtain a weakly statistically significant and negative relationship between currency crises and future public debt in the sample of EMDEs. In particular, a currency crisis today is associated with four percentage points lower public debt three years down the road, perhaps because it hinders countries' access to debt markets. Another reason could be that currency crises tend to be associated with higher future inflation (see graph 5 in Banerjee et al., 2024), which would then lower future debt ratios through an increase in the denominator (nominal GDP). For AEs, there is no statistically significant relationship, which is not surprising given the absence of frequent currency crises in this country group.

Table 7
Implications of currency crises

	(1)	(2)	(3)	(4)	(5)	(6)
	All econ.		AEs		EMDEs	
Variables	Debt$_{t+3}$					
Debt	0.644***	0.616***	0.759***	0.768***	0.623***	0.581***
	(0.040)	(0.050)	(0.062)	(0.067)	(0.045)	(0.059)
Currency crises	-1.130	-4.124	23.039**	7.068	-1.587	-4.213*
	(2.669)	(2.522)	(8.432)	(8.106)	(2.669)	(2.418)
GDP growth		-0.524***		0.225		-0.525***
		(0.154)		(0.212)		(0.162)
Primary balance		-0.914***		-1.126***		-0.851***
		(0.158)		(0.240)		(0.173)
Interest expenditures		-0.271		-3.670***		0.427
		(1.019)		(0.739)		(1.261)
Government revenues		0.330*		1.588***		0.220
		(0.186)		(0.465)		(0.193)
Food price inflation		0.044		0.198***		0.011
		(0.057)		(0.043)		(0.067)
Oil price inflation		-0.109***		0.006		-0.139***
		(0.039)		(0.031)		(0.047)
GFC		-3.968***		6.875**		-5.714***
		(1.083)		(2.627)		(1.153)
Banking crises		4.232**		4.808*		-2.253
		(2.052)		(2.460)		(2.658)
Constant	20.093***	15.431***	19.774***	-40.358**	19.270***	18.445***
	(2.088)	(5.849)	(4.052)	(16.156)	(2.221)	(5.575)
Observations	2,912	2,912	588	588	2,324	2,324
R-squared	0.402	0.459	0.564	0.685	0.376	0.443
# of economies	147	147	30	30	117	117

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, Debt$_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

As a third alternative, instead of using the nominal broad dollar, we use the real broad dollar exchange rate, thus taking into consideration the relative price levels between countries. The results are shown in appendix table A5. We find that the coefficients on the change in the broad real dollar exchange rate are similar in magnitude and statistical significance to those for the nominal broad exchange rate. This result is likely to stem from price stickiness in the short run and the tendency of nominal exchange rates to fluctuate more than the relative price levels.

4 CONCLUSION

In this paper, we have shown that an appreciation of the broad dollar is associated with an increase in public debt ratios over the medium term. However, the strength of the relationship varies greatly among economies. It is generally stronger in EMDEs and especially in those countries that have larger shares of foreign currency-denominated public debt. By contrast, the effect is small or non-existent in advanced economies and in those countries that predominantly borrow in their domestic currency. We have also shown that the positive relationship between the broad dollar appreciation and future public debt arises especially in countries that are deemed more vulnerable by rating agencies and thus have lower foreign currency sovereign ratings.

While we have explored the relationship between the broad dollar and the level of public debt, future research could provide useful insights into the bond market implications of exchange rate changes. This includes the effects of exchange rate changes for market liquidity, depth and market access for sovereign borrowers, for example.

Disclosure statement
The author has no conflicts of interest to declare.

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APPENDIX

Table A1
Data sources, units and transformations

Variable	Source	Unit & transformation
Government debt	IMF's Public Finances in Modern History (IMF PFMH)	% of GDP, level
Primary balance	IMF PFMH	
Interest expenditures	IMF PFMH	
Gov't revenues	IMF PFMH	
GDP growth	IMF PFMH	%
ΔDollar	US Federal Reserve	First difference of log level, multiplied by 100
Food price inflation	World Bank	
Oil price inflation	World Bank	
GFC		1 in 2008-09; 0 otherwise
Banking crises	Nguyen et al. (2022)	1 in crisis years; 0 otherwise
Currency crises	Nguyen et al. (2022)	
External FX debt	Kose et al. (2022)	% of total external debt
FX share of public debt	Update of Arslanalp and Tsuda (2014)	% of total public debt
Credit rating	Kose et al. (2022)	1 (worst) to 21 (best)
ΔVIX	FRED database	First difference of log level, multiplied by 100

Table A2

List of countries in the sample, by country group

AEs	EMDEs			
United States	South Africa	St. Lucia	Angola	Tunisia
United Kingdom	Argentina	St. Vincent & Gren.	Burundi	Uganda
Austria	Bolivia	Suriname	Cabo Verde	Burkina Faso
Belgium	Brazil	Trinidad & Tobago	Central African Rep.	Solomon Islands
Denmark	Chile	Bahrain	Chad	Fiji
France	Colombia	Iran	Comoros	Kiribati
Germany	Costa Rica	Jordan	Congo, Rep.	Vanuatu
Italy	Dominican Republic	Kuwait	Congo, Dem. Rep.	Papua New Guinea
Luxembourg	Ecuador	Lebanon	Benin	Marshall Islands
Netherlands	El Salvador	Oman	Equatorial Guinea	Micronesia
Norway	Guatemala	Qatar	Ethiopia	Azerbaijan
Sweden	Haiti	Saudi Arabia	Gabon	Albania
Switzerland	Honduras	UAE	Ghana	Georgia
Canada	Mexico	Yemen	Guinea-Bissau	Kyrgyz Republic
Japan	Nicaragua	Bangladesh	Guinea	Bulgaria
Finland	Panama	Bhutan	Kenya	Moldova
Greece	Paraguay	Myanmar	Lesotho	Russia
Iceland	Peru	Cambodia	Madagascar	Tajikistan
Ireland	Uruguay	Sri Lanka	Morocco	China
Portugal	Venezuela	India	Mozambique	Ukraine
Spain	Antigua & Barbuda	Indonesia	Niger	Uzbekistan
Australia	Bahamas, The	Korea	Nigeria	Hungary
New Zealand	Aruba	Malaysia	Rwanda	Mongolia
Cyprus	Barbados	Maldives	Seychelles	Croatia
Israel	Dominica	Pakistan	Senegal	North Macedonia
Czech Republic	Grenada	Philippines	Namibia	Bosnia & Herz.
Slovak Republic	Guyana	Thailand	Sudan	Poland
Estonia	Belize	Vietnam	Eswatini	Romania
Latvia	Jamaica	Djibouti	Tanzania	
Slovenia	St. Kitts and Nevis	Algeria	Togo	

Table A3
Summary statistics

Variable	Mean	Std. dev.	Min	Max
Debt	52.718	35.665	0.488	269.305
ΔDollar	0.434	4.598	-6.354	12.306
ΔDollar_real	0.142	4.333	-6.525	10.921
Dollar	462.867	9.071	448.661	475.117
GDP growth	3.710	4.715	-36.392	110.505
Prim. balance	0.420	5.516	-30.289	52.533
Interest exp.	2.058	1.942	0.000	17.314
Gov't revenues	28.918	13.981	0.637	136.204
Food price infl.	2.958	11.718	-18.583	28.905
Oil price infl.	2.678	15.773	-23.968	39.338
ΔVIX	-2.298	25.351	-35.586	62.259

Note: Debt, primary balance, interest expenditures and government revenues are expressed as percentage of GDP. The table excludes variables used in the estimation as dummy variables. The summary statistics for all variables are based on 2,960 observations.

Table A4

Relationship between the US dollar and debt over different horizons

	All econ.		
Variables	**Debt$_{t+1}$**	**Debt$_{t+3}$**	**Debt$_{t+5}$**
Debt	0.904***	0.611***	0.354***
	(0.029)	(0.046)	(0.057)
ΔDollar	0.479***	0.539***	0.982***
	(0.051)	(0.098)	(0.120)
Constant	3.631	15.429***	24.203***
	(2.622)	(5.522)	(6.776)
Observations	2,960	2,960	2,810
R-squared	0.820	0.471	0.248
# of economies	148	148	148
	AEs		
	Debt$_{t+1}$	**Debt$_{t+3}$**	**Debt$_{t+5}$**
Debt	0.960***	0.762***	0.505***
	(0.020)	(0.065)	(0.088)
ΔDollar	0.275***	0.064	0.243
	(0.043)	(0.102)	(0.164)
Constant	-11.822**	-41.509**	-46.109**
	(5.628)	(16.569)	(20.687)
Observations	600	600	570
R-squared	0.914	0.682	0.455
# of economies	30	30	30
	EMDEs		
	Debt$_{t+1}$	**Debt$_{t+3}$**	**Debt$_{t+5}$**
Debt	0.891***	0.577***	0.319***
	(0.036)	(0.055)	(0.070)
ΔDollar	0.540***	0.662***	1.154***
	(0.062)	(0.117)	(0.143)
Constant	4.776*	18.465***	25.731***
	(2.489)	(5.233)	(6.614)
Observations	2,360	2,360	2,240
R-squared	0.806	0.458	0.250
# of economies	118	118	118

*Note: All variables include the full set of control variables (not shown), as in column 5 of tables 1, 2 and 3. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is either the one-year, three-year or the five-year-ahead public debt ratio, as indicated in the column headings. All explanatory variables are at period t. All models include country fixed effects.*

Table A5

Model with real broad dollar exchange rate

	(1)	(2)	(3)	(4)	(5)	(6)
	All econ.		AEs		EMDEs	
Variables			$Debt_{t+3}$			
Debt	0.635***	0.611***	0.779***	0.762***	0.616***	0.575***
	(0.040)	(0.046)	(0.059)	(0.065)	(0.046)	(0.055)
ΔDollar_real	0.578***	0.506***	-0.391***	0.126	0.796***	0.615***
	(0.084)	(0.096)	(0.092)	(0.102)	(0.091)	(0.116)
Food price inflation		0.123**		0.243***		0.102
		(0.054)		(0.044)		(0.063)
Oil price inflation		-0.059		0.007		-0.075
		(0.041)		(0.036)		(0.049)
GDP growth		-0.497***		0.160		-0.491***
		(0.134)		(0.239)		(0.138)
Primary balance		-0.915***		-1.222***		-0.829***
		(0.155)		(0.226)		(0.167)
Interest expenditures		-0.359		-3.801***		0.366
		(0.987)		(0.805)		(1.226)
Government revenues		0.323*		1.646***		0.196
		(0.175)		(0.459)		(0.181)
GFC		-4.417***		6.524**		-6.269***
		(1.049)		(2.524)		(1.121)
Banking crises		4.214**		4.840**		-3.099
		(2.039)		(2.206)		(2.607)
Constant	20.412***	15.368***	18.850***	-41.544**	19.336***	18.524***
	(2.125)	(5.547)	(3.904)	(16.565)	(2.288)	(5.271)

	(1)	(2)	(3)	(4)	(5)	(6)
	All econ.		AEs		EMDEs	
Variables	$\mathbf{Debt_{t+3}}$					
Observations	2,960	2,960	600	600	2,360	2,360
R-squared	0.424	0.470	0.560	0.682	0.412	0.457
# of economies	148	148	30	30	118	118

*Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the three-year-ahead public debt ratio, $Debt_{t+3}$. All explanatory variables are at period t. All models include country fixed effects.*

When the guns roar: how the war, reserves and exports shape Ukraine's cost of external borrowing

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Abstract

This study examines factors shaping Ukraine's cost of external borrowing amid the 2022 Russian invasion. It focuses on the impact of the intensity of military activities, the size of central bank reserve assets, and the volume of grain and oilseed exports on sovereign bond spreads. Estimates from an ARDL model with data from September 2021 to July 2024 suggest a stable long-term relationship between the spreads, military activities and reserve assets, with escalating military actions widening the spreads and larger reserves narrowing them. The effects of exports on the spreads are not statistically significant, probably reflecting the difficulty to transport large quantities of grain and oilseeds in wartime conditions. The findings underscore the role of monetary policy in managing the cost of external borrowing, and the importance of foreign exchange reserves in mitigating sovereign debt and foreign exchange market risks in wartime conditions.

Keywords: external borrowing, sovereign spreads, war, international reserves, commodity exports

1 INTRODUCTION

Maintaining sufficient international liquidity is one of the core responsibilities of the central bank, especially under conditions of global financial fragmentation. By securing foreign exchange for vital imports and external debt obligations, monetary authorities of small open economies ensure sovereign creditworthiness and sustain confidence in domestic price and financial stability. These tasks become critical during crises of non-economic origin such as the Covid pandemic and Russia's full-scale invasion of Ukraine. Such shocks, combined with unpredictable market reactions, create serious challenges for monetary policy and may undermine the confidence of foreign creditors if not effectively addressed. Improving the effectiveness of monetary response requires, in turn, a deeper analysis of its potential influence on external borrowing costs during extraordinary events.

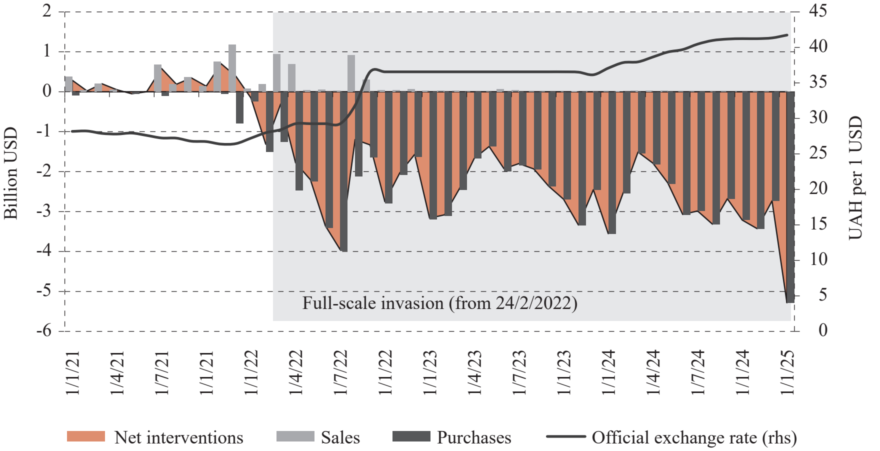
The motivation for this study stems from the need to address a key question that Russia's unprovoked military aggression against Ukraine has raised for the National Bank of Ukraine (NBU): does the central bank of a country subjected to regular attacks and partial occupation retain some degree of control over its cost of external borrowing? A clear challenge in pursuing this inquiry lies in the limited availability of empirical data and the frequency of certain variables relative to the duration of the military conflict. By utilising the maximum feasible sample, the paper nevertheless derives sufficiently reliable conclusions.

Before the full-scale invasion, Ukraine operated under an inflation-targeting framework, which was adopted in 2016. Price stability was the declared primary goal, with the policy rate as the main instrument. The hryvnia was managed under a flexible exchange rate regime. The NBU intervened occasionally to smooth volatility rather than to defend a certain level of the exchange rate. Reserves were accumulated through market purchases, external borrowing, multilateral loans, and strong export revenues from agricultural products and metals.

As can be seen in graph 1, with the war starting in February 2022, the framework was swiftly adjusted. The hryvnia was pegged to the US dollar at UAH 29.25/USD in late February to prevent capital flight and stabilise expectations. FX interventions became large and regular, but reserves increased markedly, primarily due to large-scale official external financing from international partners. At the same time, strict capital controls and cash market restrictions significantly curtailed private demand for foreign currency. As a result, foreign currency inflows systematically exceeded the amounts required to support the peg, allowing the NBU to accumulate reserves despite depreciation pressures.

Graph 1

Foreign exchange interventions and official exchange rate, 2021-24



Source: National Bank of Ukraine (2025).

Already by the summer of 2022, four months after the beginning of the Russian invasion, the NBU emphasised its strategic commitment to a gradual return to prewar flexible exchange rate and inflation targeting policies. However, the continuation of hostilities and absence of progress on peace initiatives demonstrated that the wartime shocks were more persistent than initially expected. As a result, the NBU was forced to partially revert to ultra-tight monetary policy: the policy rate was raised to 25% in June 2022 and a wide set of capital and currency restrictions was prolonged. In these conditions, the cost of domestic government borrowing converged closely to Ukraine's sovereign eurobond yields. Thus, while the formal inflation-targeting regime was preserved, the war environment changed its operation fundamentally, with foreign exchange reserves turning into the principal buffer for exchange rate stability and investor confidence.

Against this backdrop, the paper investigates the short- and long-term effects of military actions, developments in NBU reserve assets, and the exports of Ukraine's primary products – grains and oilseeds – on the cost of external borrowing, as measured by the spread on Ukraine's long-term sovereign eurobonds. It finds a positive long-run cointegration relationship between the spreads and intensified military actions, and a negative one between the spreads and reserve assets. However, no significant long-term cointegration relationship between the spreads and the volume of Ukraine's agricultural commodity exports could be established. The paper contributes to the literature on monetary and exchange rate policy in emerging market economies by analysing the adjustment of Ukraine's policy framework following the full-scale invasion. It relates to studies on the cost of external borrowing and FX interventions in emerging markets, as well as to the growing literature on macroeconomic policy under extreme shocks. The main contribution lies in the documentation and interpretation of the interaction between the intensity of military events, commodity exports, and reserve dynamics in a wartime setting characterised by severe capital controls and large official external inflows. Using a detailed dataset on FX operations and policy instruments compiled from official sources, the paper shows how the National Bank of Ukraine was able to stabilise expectations on external markets for its sovereign debt. By focusing on the mechanics of policy implementation rather than model-based counterfactuals, the analysis provides policy-relevant insights into the functioning of monetary and exchange rate policy under conditions that fall outside standard crisis episodes studied in the existing literature.

Existing studies have largely overlooked the influence of international reserves on sovereign bond spreads in a country experiencing active wartime conflict. This paper addresses that gap and offers novel insights into the FX market and sovereign debt dynamics of a major food commodity exporter navigating an unprecedented war environment. It examines the combined influence of the intensity of military actions, the volume of international reserves, and the dynamics of food commodity exports on external markets' perception of Ukraine's sovereign risk. A quantitative analysis of the relationship among these variables in the short- and long-term also sheds light on the effectiveness of the central bank's efforts to maintain the cost of external borrowing under control in conditions of escalating physical attacks and disruptions to commodity export logistics. Another contribution of the paper is the use of an ARDL model to test several hypotheses related to the main research question. One advantage of this approach is that it can yield reliable results despite limited sample size.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the dataset and the methodological framework. Section 4 presents key estimation and diagnostic test results. Section 5 interprets the findings and relates them to previous empirical findings. Section 6 concludes.

2 LITERATURE REVIEW

The literature that comes closest to the subject matter of this study is the one that investigates the role of central bank reserves on a country's financial stability during crises (e.g. Lowe, 2018). Since the 1990s, emerging markets have built sizable reserves to guard against capital flow reversals and debt rollover risks.

Higher reserves are shown to reduce sovereign spreads, thereby lowering default risk and borrowing costs, although this effect weakens beyond a threshold of around 15% of GDP and is less evident in smaller economies. Fatum, Hattori and Yamamoto (2023), for example, analyse China's reserve accumulation and its unintended effects on private sector risk-taking, using CDS spreads and stock indices as proxies. They find evidence that during upswings higher reserves act as implicit insurance and correlate with increased risk appetite, thus potentially leading to moral hazard. In crisis periods, on the other hand, high reserves may strengthen the precautionary saving motive and thereby weaken the effectiveness of expansionary monetary and fiscal policies. This finding parallels Lowe's (2018) concerns about diminishing returns to reserves accumulation.

The empirical link between larger foreign exchange reserves and the lower likelihood of sovereign debt crises was also established by Hernández (2018) and Yeyati and Gómez (2019). Yeyati and Gómez (2019) and Sosa-Padilla and Sturzenegger (2023) also argued that the impact of reserves on sovereign spreads depended on how the reserves were financed: reserves backed by domestic, income-linked debt reduced default risk, while those based on external borrowing had little or even negative effect on the spreads. Kartal et al. (2023) confirmed a number of intuitively appealing bidirectional relationships: higher reserves strengthened the exchange rate, this in turn helped narrow the sovereign CDS spreads, and lower spreads facilitated additional reserves accumulation. Similarly, Tüysüz and Gül (2024) confirmed that lower bond yields and a stronger domestic currency helped narrow the CDS spreads, and Aizenman and Jinjarak (2020) argued that reserve dynamics explained much of the variation in sovereign spreads and exchange rates.

The financial impact of Russia's full-scale invasion of Ukraine has also attracted some attention in the empirical literature. Nagy and Neszveda (2025) demonstrated that, in wartime, CDS markets were the earliest indicator of sovereign vulnerability, with spreads widening at least two weeks before the stock market began to drop. Shen, Feng and Sun (2024) documented how the war in Ukraine amplified global sovereign debt risks. Assaf, Gupta and Kumar (2023) further showed that active hostilities in Ukraine unevenly affected stock prices, with net exporters in the region suffering the heaviest losses.

In terms of empirical methodology, the studies that come closest to the research question in this paper are Zhou (2021), who applied linear and nonlinear ARDL to assess the effects of macroeconomic performance on South Africa's long-term bond yield, and Sunal and Yağcı (2024), who showed that the volatility of Turkey's CDS spreads depended on the exchange rate, oil prices, and stock prices in the long term, while short-term variation is driven by lagged U.S. Treasury yields and COVID-19 dynamics.

3 DATA AND METHODOLOGY

For the purposes of this study, the cost of Ukraine's external borrowing is defined as:

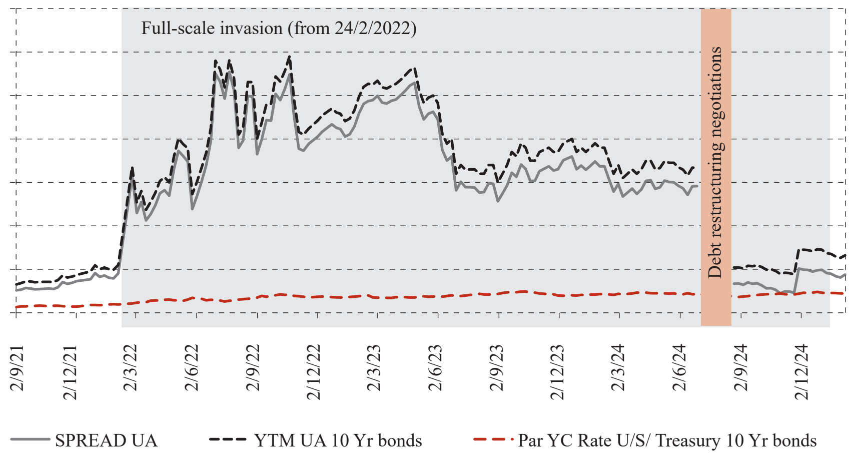
$$SPREAD_{UA}^{t} = Y_{UA\,10\,Yr\;bonds}^{t} - Y_{U.S.\,Treasury\,10\,Yr\;bonds}^{t} \tag{1}$$

where $SPREAD^{t}_{UA}$ is the spread on Ukraine's 10-year sovereign bonds at time t; $Y^{t}_{UA\,10\,Yr\,bonds}$ is the interest rate on Ukraine's 10-year sovereign bonds denominated in USD at time t; and $Y^{t}_{U.S.\,Treasury\,10\,Yr\,bonds}$ is the interest rate on 10-year US Treasury bonds at time t.

The 10-year bonds were chosen because they are the longest-maturity Ukrainian securities traded abroad. CDS spreads, often used in similar studies, were not used because the data after September 2022 are unreliable. US Treasury par yield-curve rates are assumed equivalent to yields to maturity.

Graph 2

Sovereign bond spread of Ukraine and its components, Sep 2021 – Feb 2025 (in %)



Sources: US Department of the Treasury (2025); Eavex Capital (2025); author's calculations.

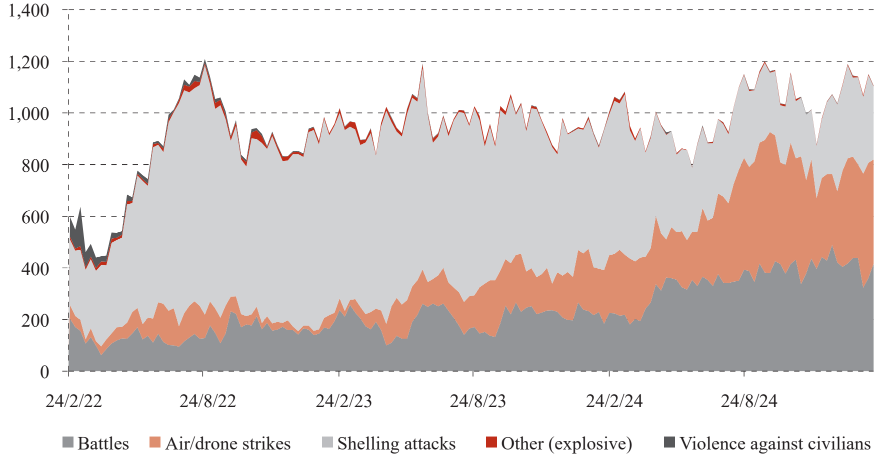
Graph 2 shows a sharp rise in Ukraine's 10-year sovereign bond yield to maturity (YTM) and spread since the full-scale invasion began, with notable volatility. A data gap in July – August 2024 reflects debt restructuring negotiations with international creditors, resulting in a new 10-year bond with a coupon rate reduced to 1.75% (from 7.38%), lowering the YTM proportionally. The data series interruption and YTM availability from September 2021 limit the sample to September 2021 – July 2024.

The explanatory variables were selected to represent the influence of military actions, measures taken by the central bank, and economic opportunities to replenishing foreign currency reserves. When accounting for the impact of military events, the objectivity of observations is critical. Given the sample's time frame and data frequency, the regularly updated Armed Conflict Location and Event Data (ACLED)

Ukraine Conflict Monitor was chosen as the indicator of the intensity of military actions. Military events in this database are shown on a weekly basis, from Saturday to the Friday of the preceding week, and classified into five categories: battles, air/drone strikes, shelling attacks, other (explosive) attacks, and violence against civilians (graph 3). Most prevalent in the first year were shelling attacks. Starting in the summer of 2023, air/drone strikes became increasingly prominent, reaching their highest relative share by the fall of 2024. Battles followed a nearly identical pattern from May 2024 through the end of the observation period. The two remaining categories were measured on a significantly smaller scale.

Graph 3

Dynamics of military events in Ukraine, Feb 2022 – Feb 2025 (number of events)



Source: ACLED (2025).

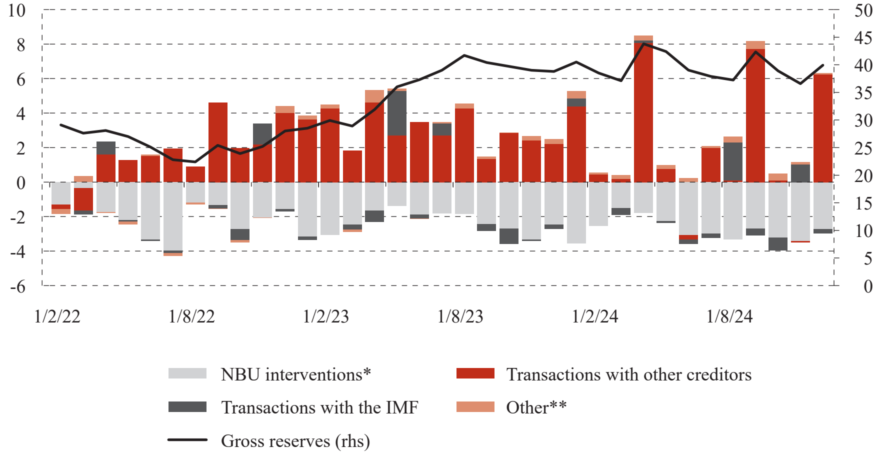
The paper uses the number of violent events rather than fatalities (or other metrics) as the core measure of war intensity because it is very difficult to estimate reliably the number of deaths amid ongoing hostilities. ACLED (2025) defines an "event" as a discrete instance of military violence occurring at a specific location on a given day as reported in military statements, media, and other monitoring sources. When aggregating for intensity analysis, ACLED (2025) recommends focusing on event volumes over time and space, as this provides a more consistent proxy for conflict dynamics and allows cross-event type comparisons (e.g. frontline escalations). A cumulative indicator of intensity of military conflict was calculated as a simple sum of reported military events:

$$W_t = \sum_{a \in A} a_t, A = \{B, D, S, X, V\} \tag{2}$$

where A is the set of indicators for the number of military events (battles, air/drone strikes shelling attacks, other (explosive) attacks and violence against civilians); W_t is the total number of military events at time t; and a_t is the number of specific military events at time t.

Graph 4

NBU gross reserve assets, Jan 2022 – Nov 2024 (billion USD)



** (+) refers to FX purchases to increase reserves; (-) refers to FX sales from reserves.*
*** Revaluation of financial instruments due to changes in their market value and exchange rate fluctuations, and other transactions.*

Source: National Bank of Ukraine (2025).

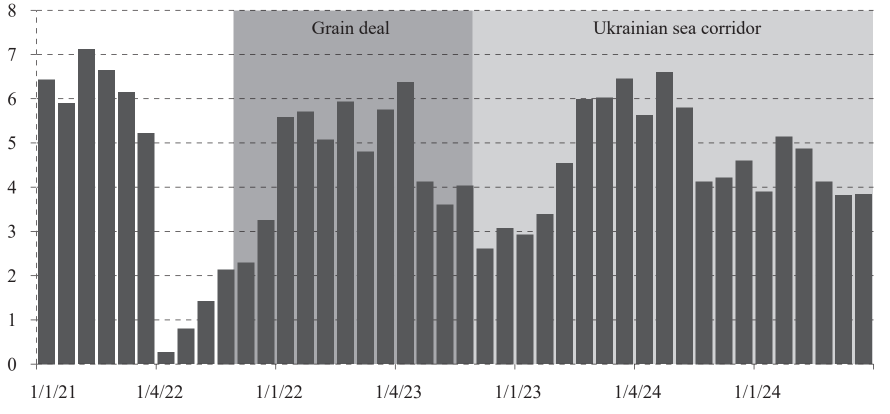
Central bank efforts to manage the cost of external borrowing are measured by the volume of its gross reserve assets (foreign exchange reserves). While net reserves could offer a more precise measure of international liquidity, the distinction between gross and net reserves is less clear under wartime conditions. A significant portion of Ukraine's external financing, formally recorded as loans, is concessional, subject to restructuring, or expected to be repaid from external sources (e.g., revenues from frozen Russian assets). These liabilities exert less market pressure on sovereign bond spreads than conventional foreign debt held by the central bank, so market participants primarily focus on gross reserves as the key liquidity buffer.

The NBU publishes data on reserves and their composition at the beginning of each month. Reserves were rising with minor interruptions from August 2022. The main contribution came from transactions with other creditors (excluding the IMF), essentially external financial assistance in the form of loans and grants, and net interventions by the NBU, which were negative throughout the period. Transactions with the IMF – both in terms of financing inflows and outflows – occasionally had a noticeable (but not decisive) influence on reserves.

Following Kovalenko et al. (2024), foreign currency inflows to Ukraine's domestic market are measured by the physical volume of grain and oilseed exports. Russia's military actions in the Black Sea disrupted export flows, redirecting logistics and intermittently halting maritime routes. Graph 5 shows a sharp decline in export volumes from March to July 2022 due to threats to civilian vessels, with sea routes previously handling 95-97% of exports. Partial restoration via the so-called Grain deal and, from August 2023, the Ukrainian sea corridor, stabilised export volumes.

Graph 5

Grain and oilseed exports, Sep 2021 – Feb 2025 (in million metric tons)



Sources: FAO (2022); Centre for Economic Strategy (2025).

As data on gross reserves and grain and oilseed exports are monthly, data on sovereign spreads and military events had to be transformed from weekly to monthly frequency. For spreads, the following transformation was used:

$$SPREAD_{UA}^{m} = \frac{1}{W}\sum_{t=1}^{W} SPREAD_{UA}^{t} \tag{3}$$

where $SPREAD^{m}_{UA}$ is the average monthly spread on Ukraine's 10-year sovereign bonds in month m; W is number of weeks in a month; t is the week within a month; and $SPREAD^{t}_{UA}$ is the spread on Ukraine's 10-year sovereign bonds for week t. Military events were also aggregated into monthly frequency using formula (2). Aggregating weekly observations on spreads and military actions into monthly frequency smooths out short-term fluctuations in these data, but so does transforming monthly data on reserves and export volumes into weekly frequency, so it is hard to argue that the latter would have been preferable.

Table 1

Descriptive statistics for variables, monthly averages, September 2021 – July 2024

	SPREAD[1]	WAREV[2]	GRES[3]	AGRXP[4]
Mean	3,132	3,271	32.915	4.573
Median	3,166	3,783	30.941	5.080
Maximum	4,965	5,000	43.767	7.120
Minimum	526	0	22.387	0.270
Std. dev.	1,361	1,590	6.400	1.798
Skewness	-0.616	-1.221	0.024	-0.701
Kurtosis	2.501	3.107	1.605	2.554
Jarque-Bera p-value	0.276	0.013	0.242	0.207
Observations	35	35	35	35

[1] Spread on Ukraine's 10-year sovereign bonds in USD, in basis points.
[2] Number of military events.
[3] Gross reserve assets of the NBU, in billions of USD.
[4] Volume of grain and oilseed exports, in millions of metric tons.

Source: Author's calculations.

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Descriptive statistics for the variables are presented in table 1. Reserve assets are closest to normal distribution, with skewness near zero, kurtosis below 3, and the Jarque-Bera statistic indicating approximate normality. Bond spreads and grain/oilseed exports display mild negative skewness and flatter-than-normal tails, yet still pass the normality test. The number of military events stands out for strong negative skewness with the Jarque-Bera statistic indicating a non-normal distribution, which is considered in diagnostics. The high mean and median values of sovereign spreads are consistent with market conditions in the aftermath of the invasion of Ukraine – market yields on 10-year Ukrainian sovereign bonds reached 40-60% (graph 2). For one-, three- and five-year bonds, yields exceeded 100% in some cases (Eavex Capital, 2025).

Table 2

Correlation matrix of variables

	SPREAD	WAREV	GRES	AGRXP
SPREAD	–	0.840	0.004	-0.206
WAREV	0.840	–	0.352	-0.258
GRES	0.004	0.352	–	0.170
AGRXP	-0.206	-0.258	0.170	–

Source: Author's calculations.

Table 2 assesses the degree of linear dependence among variables. There is a strong positive relationship between sovereign spreads and military events, suggesting a high sensitivity in external markets to the progression of hostilities. Correlation between the spreads and gross international reserves is close to zero, which is surprising in view of the empirical findings discussed above. Correlation between the spreads and grain/oilseed exports is weakly negative, consistent with expectations. Correlations among independent variables are moderate – the highest correlation coefficient of 0.35 is between reserves and military actions – suggesting that multicollinearity is unlikely to be a major modelling issue.

Table 3

Augmented Dickey-Fuller test statistics

	Test for unit root in:				Exogenous	
	Level		1st difference		Constant	Linear trend
	t-stat.	Prob.	t-stat.	Prob.		
SPREAD	-1.435	0.832	-6.355	0.000	+	+
WAREV	-1.764	0.700	-7.875	0.000	+	+
GRES	-1.606	0.769	-5.032	0.001	+	+
AGRXP	-2.303	0.177	-5.332	0.000	+	

Source: Author's calculations.

Table 3 presents stationarity test statistics. All variables have a unit root in levels but become stationary in first differences. This suggests that an autoregressive distributed lag (ARDL) model is appropriate to estimate the relationship between sovereign bond spreads and three explanatory variables, and that there is a potential cointegrating relationship among them.

Table 4 summarises the characteristics of model variables.

Table 4
Characteristics of model variables

	Indicator	Units	Order of integration	Expected coefficient sign	Data source
SPREAD	Spread on Ukrainian sovereign 10-year bonds in USD	Basis points	I(1)	NA	US Department of the Treasury (2025); Eavex Capital (2025)
WAREV	Number of military events	Thousand events	I(1)	+	Armed Conflict Location and Event Data (2025)
GRES	Gross reserve assets of NBU	Billion USD	I(1)	-	National Bank of Ukraine (2025)
AGRXP	Volume of Ukrainian grain and oilseed exports	Million metric tons	I(1)	-	FAO (2022); Centre for Economic Strategy (2025)

Source: Author's calculations.

The ARDL model for this study is specified as follows:

$$SPREAD_t = \alpha + \sum\nolimits_{i=1}^{p} \beta_i SPREAD_{t-i} + \sum\nolimits_{j=0}^{q_1} \gamma_{1,j} WAREV_{t-j} + \sum\nolimits_{j=0}^{q_2} \gamma_{2,j} GRES_{t-j} + \sum\nolimits_{j=0}^{q_3} \gamma_{3,j} AGRXP_{t-j} + \epsilon_t \quad (4)$$

where α is a constant; p is the number of lags $i=1,\dots p$ of the dependent variable; j is the number of lags for independent variables, $j=1,\dots,q_k$; and ϵ_t is the random error term.

One advantage of using ARDL is its ability to produce reliable estimates despite a limited sample size, which here includes only 35 observations. According to Nkoro and Uko (2016), the error correction representation of the model becomes relatively more efficient with small or finite sample sizes when there is a long-term relationship between variables. The critical values for the bounds test calculated by Narayan (2005) for sample sizes ranging from 30 to 80 observations are used, as traditional critical values are typically derived for larger samples. The model is estimated with the EViews 13 package, but cointegration test results are interpreted manually rather than relying on the software's built-in critical value statistics for the bounds test.

4 ESTIMATION RESULTS

Estimation of the linear ARDL model was conducted with an unrestricted constant and no trend. During the automatic selection based on the Akaike information criterion, this limited the maximum number of lags for the dependent variable and regressors to three. After a preliminary evaluation of 192 variants (table A2), an ARDL(1,0,0,1) model was selected. Based on equation (4), this model can be expressed as follows:

$$SPREAD_t = \alpha + \beta_1 SPREAD_{t-1} + \gamma_{1,0} WAREV_t + \gamma_{2,0} GRES_t + \gamma_{3,0} AGRXP_t + \gamma_{3,1} AGRXP_{t-1} \quad (5)$$

The model was estimated using data from October 2021 to July 2024 (34 observations). Most coefficient estimates are statistically significant at the 1% level and have the expected sign (table 5). The exception is the coefficient on the volume of exports, which is negative and insignificant (current value) or significant only at the 10% level (lagged value).

Table 5

Estimates of ARDL (1,0,0,1) model[1]

Coefficient	Estimated value	Standard error	t-statistic	Probability
α	1,762.5	419.7	4.200	0.000
β_1	0.6	0.1	6.038	0.000
$\gamma_{1,0}$	348.1	103.4	3.368	0.002
$\gamma_{2,0}$	-55.2	13.8	-4.005	0.000
$\gamma_{3,0}$	-85.6	62.7	-1.365	0.183
$\gamma_{3,1}$	121.5	63.4	1.917	0.065

[1] *Adj. R2 = 0.899, standard error of regression = 414.8, F-statistic = 59.452 (p = 0.000), Durbin-Watson statistic = 2.355.*

Source: Author's estimates.

Table 6 presents cointegration test results.

Table 6

Bounds test statistic values for ARDL (1,0,0,1) model

Test statistic	Value	Sample size	Narayan (2005) critical values (case 3, k=3)		Probability (%)
			I(0)	I(1)	
F-statistic	6.381	30	5.333	7.063	1
		35	5.198	6.845	
		30	3.710	5.018	5
		35	3.615	4.913	
		30	3.008	4.150	10
		35	2.958	4.100	

Source: Author's estimates.

The bounds test refers to a model with three cointegrating variables (k=3) and an unrestricted constant (so-called case 3). The F-statistic of 6.381 exceeds the I(1) critical value at the 5% significance level for a sample of 35 observations, as per Narayan (2005). The t-statistic calculated from the same test, at -3.796, also suggests rejecting the null hypothesis at the 5% level. This provides sufficient evidence to indicate the existence a long-term cointegrating relationship among the model's variables.

Diagnostics of residuals indicates no potential issues with autocorrelation, heteroscedasticity, or assumed normal distribution of regression residuals (table 7). Likewise, multicollinearity tests using variance inflation factors (VIF) indicate that multicollinearity does not significantly affect the estimates: the centred VIF values range from 1.519 (GRES) to 4.654 (WAREV), well below the critical threshold of 10.

Table 7
Diagnostics of residuals for ARDL (1,0,0,1) model

Test	Statistic value	p-value	Interpretation
Breusch-Godfrey (LM)	F = 0.810	0.456	No autocorrelation
White (cross terms incl.)	F = 1.667	0.174	No heteroscedasticity
Skewness	-0.112	NA	Weak negative
Kurtosis	2.752	NA	Slightly below normal
Jarque-Bera	0.158	0.924	Normal residuals

Source: Author's estimates.

The cumulative sum of standardised residuals remained within the critical bounds at the 5% significance level, indicating the absence of structural breaks in model parameters. The cumulative sum of squares test also indicated the stability of the residual variance. Finally, the validity of the linear model was checked with the Ramsey regression equation specification error test: the F-statistic value was 0.540 with a p-value of 0.469, ruling out the presence of omitted nonlinear effects. The model was next estimated in conditional error correction form to assess the short- and long-term dynamics of model variables. The error correction coefficient SPREAD(-1) is negative and statistically significant at the 1% level, indicating the very quick adjustment of spreads to deviations from the long-term equilibrium (table 8). The immediate effects of war events (WAREV) and the size of NBU's reserves (GRES) are also statistically significant and have the expected signs. The estimated effects of grain and oilseed exports (AGRXP) exhibit alternating signs and lack statistical significance. However, this does not affect the overall significance of the error correction model, as the F-statistic value is 6.076 (p = 0.001), and the R-squared is 0.52.

Table 8
Conditional error correction model for ARDL (1,0,0,1)

Variable	Coefficient	Standard error	t-statistic	Probability
SPREAD(-1)	-0.4	0.1	-3.796	0.001
WAREV	348.1	103.4	3.368	0.002
GRES	-55.2	13.8	-4.005	0.000
AGRXP(-1)	35.9	50.1	0.717	0.479
D(AGRXP)	-85.6	62.7	-1.365	0.183
C	1,762.5	419.7	4.200	0.000

Note: SPREAD(-1) reflects the speed of error correction.
Source: Author's estimates.

Table 9 shows the long-term coefficients of the cointegrating equation, normalised with respect to the dependent variable. The coefficients on war events and gross reserves are large and statistically significant at the 1% significance level, while the one on grain and oilseed exports is not statistically significant and has the wrong sign.

Table 9
Long-term cointegrating coefficients for ARDL (1,0,0,1) model

Variable	Coefficient	Standard error	t-statistic	Probability
WAREV	901.9	146.1	6.172	0.000
GRES	-143.1	41.9	-3.413	0.002
AGRXP	93.1	124.8	0.746	0.461

Note: Coefficients derived from the CEC regression.
Source: Author's estimates.

Given the unique context of a wartime economy, this analysis applied to a relatively short period following the significant structural break caused by the onset of the war. Extending the sample to a pre-war period was not feasible, so the analysis effectively tested a "war cointegration" rather than conventional long-run cointegration. Nevertheless, the estimates and test results seem to be sufficiently reliable to allow their economic interpretation.

5 DISCUSSION

Evidence of strong cointegration between Ukraine's sovereign spreads, war events and NBU foreign reserves suggests that, despite Russia's full-scale invasion, the NBU retained some control over the country's external borrowing costs even in the most precarious wartime conditions.

Military events intensity exerts a lasting impact on Ukraine's sovereign spreads: the estimated coefficient indicates that each thousand military events add nearly 902 bps (≈9%) to the spread. This strong effect reflects the impact that destruction of infrastructure and of trade routes, among other consequences of the invasion, have on investor confidence in Ukraine's USD-denominated debt.

The size of the central bank's foreign reserves helps significantly narrow the spreads in both short and long term: each additional $1 billion in reserves lowers borrowing costs by 143 basis points. Reserves thus act as a strong buffer for Ukraine's external debt in wartime conditions.

The effect of the volume of grain and oilseed exports on the spreads is less clear, as the estimated coefficients are unstable and are not statistically significant. This statistically weak link probably reflects wartime disruptions to maritime logistics of grain and oilseed exports via the Black Sea, and the relatively short time span of the study, as exporters may have eventually found alternative transportation routes to ship grain and oilseeds abroad.

6 ROBUSTNESS CHECK AND LIMITATIONS

To check robustness of estimates to an alternative measurement of the dependent variable, the model was re-estimated by using the logarithm of spreads as the dependent variable. This transformation allows for elasticity-based interpretation. Estimates obtained from an ARDL (3,1,0,1) model confirmed the baseline results that higher reserves narrowed the spreads, war intensity widened them, while exports had no statistically significant effect (table A4).

Despite the overall reliability of baseline estimates from the perspective of model diagnostics and test results, the above analysis remains limited in several respects. One is the small sample size constrained by data availability and debt restructuring in mid-2024. Although the ARDL method is suitable for small samples and the bounds test results were adapted to the number of observations, a longer time series could reveal additional dynamics, particularly given the evolving nature of military actions. Relatedly, data on military actions may not fully capture the qualitative impact of events such as attacks on energy infrastructure or the destruction of the Kakhovka Dam, potentially underestimating their economic consequences.

Another limitation is that aggregating data on spreads and war events from weekly to monthly frequency probably resulted in some loss of information about the short-term dynamics between these variables. Separately, it was not possible to account for potential endogeneity between reserves accumulation in response to rising spreads, or between military actions and exports of grain and oilseeds. The spreads may have also been partly influenced by other exports, e.g. metallurgy products, or global factors not modelled in the paper. More generally, a bootstrap analysis to assess the accuracy of standard errors could not be implemented given the nature of the dataset.

7 CONCLUSION

The existence of a long-run cointegration relationship linking Ukraine's sovereign spreads to both military attacks and foreign reserves highlights the critical role of the central bank in maintaining liquidity during an existential crisis. Previous work established this relationship during economic and financial crises (e.g. Afonso et al., 2021), but this is perhaps the first time that it has also been confirmed for a country in wartime conditions.

For central banks of countries in potential conflict zones this is a powerful message: the preservation and, to the extent possible, accumulation of foreign exchange reserves are the key priority when the guns start to roar on a country's soil. High reserves can help mitigate perceptions of riskiness of externally held sovereign debt, particularly during escalations of hostilities, and thereby help reduce external borrowing costs. As commodity exporting countries will likely find it hard to replenish foreign reserves by increasing exports in wartime conditions, central banks would be well advised to plan for such an FX war chest in good times, and thereby enhance economic resilience in crisis situations.

Disclosure statement

The author has no conflicts of interest to declare.

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Table A1

Values of model variables

Year/month	SPREAD Basis points	WAREV Number of events	GRES Billion USD	AGRXP Million metric tons
2021/09	525.5	0	28.706	6.44
2021/10	554.3	0	29.654	5.90
2021/11	590.6	0	30.598	7.12
2021/12	694.0	0	30.941	6.65
2022/01	842.5	0	29.087	6.15
2022/02	836.0	739	27.553	5.22
2022/03	2,666.0	2,098	28.107	0.27
2022/04	2,405.8	2,342	26.945	0.80
2022/05	3,230.6	2,637	25.102	1.42
2022/06	2,894.0	3,247	22.802	2.14
2022/07	4,544.0	5,000	22.387	2.29
2022/08	4,671.8	4,534	25.439	3.25
2022/09	4,401.5	4,185	23.932	5.58
2022/10	4,789.4	4,401	25.246	5.71
2022/11	4,374.5	3,581	27.955	5.08
2022/12	4,038.3	4,189	28.494	5.93
2023/01	4,219.8	3,581	29.928	4.81
2023/02	4,447.8	3,844	28.870	5.75
2023/03	4,899.3	3,698	31.887	6.38
2023/04	4,903.5	4,608	35.953	4.13
2023/05	4,965.4	3,807	37.321	3.61
2023/06	4,352.3	4,282	39.027	4.03
2023/07	3,165.8	4,666	41.738	2.61
2023/08	2,829.5	3,975	40.405	3.08
2023/09	2,816.5	4,671	39.723	2.93
2023/10	3,201.6	4,081	38.987	3.39
2023/11	3,109.3	3,934	38.796	4.54
2023/12	3,366.3	4,517	40.514	5.99
2024/01	3,396.0	3,783	38.534	6.02
2024/02	3,402.0	3,718	37.060	6.46
2024/03	2,877.3	4,985	43.767	5.63
2024/04	2,847.4	3,695	42.404	6.60
2024/05	2,958.3	3,642	39.037	5.80
2024/06	2,949.8	4,333	37.896	4.13
2024/07	2,847.0	3,701	37.235	4.22

Sources: US Department of the Treasury (2025); Eavex Capital (2025); ACLED (2025); National Bank of Ukraine (2025); FAO (2022); Centre for Economic Strategy (2025); author's estimates.

Table A2

Model selection criteria – summary for top 20 models

Model no.	LogL[1]	AIC[2]	BIC[3]	HQ[4]	Model specification
191	-236.038	15.127	15.402	15.218	ARDL(1,0,0,1)
175	-235.173	15.136	15.456	15.242	ARDL(1,1,0,1)
47	-233.554	15.160	15.572	15.296	ARDL(3,1,0,1)
127	-235.810	15.176	15.496	15.282	ARDL(2,0,0,1)
63	-234.948	15.184	15.551	15.306	ARDL(3,0,0,1)
187	-235.982	15.186	15.507	15.293	ARDL(1,0,1,1)
111	-234.996	15.187	15.554	15.309	ARDL(2,1,0,1)
192	-238.001	15.188	15.417	15.263	ARDL(1,0,0,0)
190	-236.030	15.189	15.510	15.296	ARDL(1,0,0,2)
159	-235.126	15.195	15.562	15.317	ARDL(1,2,0,1)
174	-235.158	15.197	15.564	15.319	ARDL(1,1,0,2)
171	-235.165	15.198	15.564	15.319	ARDL(1,1,1,1)
173	-234.181	15.199	15.611	15.335	ARDL(1,1,0,3)
143	-234.416	15.214	15.626	15.350	ARDL(1,3,0,1)
31	-233.528	15.220	15.679	15.372	ARDL(3,2,0,1)
43	-233.546	15.222	15.680	15.373	ARDL(3,1,1,1)
46	-233.554	15.222	15.680	15.374	ARDL(3,1,0,2)
189	-235.582	15.224	15.590	15.345	ARDL(1,0,0,3)
128	-237.584	15.224	15.499	15.315	ARDL(2,0,0,0)
183	-235.767	15.235	15.602	15.357	ARDL(1,0,2,1)

[1] Log likelihood. [2] Akaike information criterion. [3] Bayesian information criterion. [4] Hannan-Quinn criterion.

Source: Author's estimates.

Table A3

Multicollinearity tests – variance inflation factors (VIF)

Variable	Coefficient variance	Uncentred VIF	Centred VIF
SPREAD(-1)	0.010	23.923	3.778
WAREV	10,685.3	28.586	4.654
GRES	190.1	42.523	1.519
AGRXP	3,931.1	18.285	2.430
AGRXP(-1)	4,015.5	19.229	2.562
C	176,130.1	34.799	NA

Source: Author's estimates.

Table A4
Estimates of ARDL (3,1,0,1) model

Coefficient	Value	Standard error	t-statistic	Probability
α	-0.681	0.441	-1.543	0.136
β_1	0.465	0.168	2.767	0.011
β_2	0.270	0.163	1.661	0.110
β_3	-0.250	0.149	-1.678	0.107
$\gamma_{1,0}$	0.097	0.058	1.676	0.107
$\gamma_{1,1}$	0.106	0.061	1.751	0.093
$\gamma_{2,0}$	-0.019	0.006	-3.185	0.004
$\gamma_{3,0}$	-0.088	0.028	-3.195	0.004
$\gamma_{3,1}$	0.085	0.030	2.871	0.009

Source: Author's estimates.

Effects of reputation and monetary policy communication on exchange rate uncertainty: evidence from an emerging market economy

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Abstract

This paper examines whether central bank reputation and communication attenuated exchange rate uncertainty in Colombia over 2007-21. Uncertainty is measured by means of disagreements and forecast errors of the dollar exchange rate. We construct a central bank reputation index, an index of the clarity of its policy meeting minutes, and a measure of central bank board dissent. We control for the Colombia – US interest rate differential, inflation expectations disagreement, economic policy uncertainty, and special oil industry factors. We estimate equations via GMM and assess robustness with ARDL and VAR models. The findings indicate that a stronger central bank reputation and clearer communication reduce exchange rate uncertainty. Unanimous monetary policy decisions reduce disagreements concerning expectations, while external shocks such as new fracking activities exacerbate volatility. These results underscore the importance of enhancing transparency and cohesion in monetary policy decisions to mitigate uncertainty in foreign exchange markets.

Keywords: exchange rate uncertainty, monetary policy, communication, emerging economy, reputation

1 INTRODUCTION

Uncertainty about the future behaviour of the exchange rate can have major implications for inflation, public debt management, and the real sector. In emerging market economies (EMEs), these channels are typically stronger than in advanced economies: exchange rate pass-through tends to be higher and faster, public and private balance sheets are more exposed to exchange rate volatility, foreign exchange markets are thinner, and external risk premia and terms of trade shocks amplify transmission of exchange rate fluctuations to economic activity and inflation.

The case of Colombia is interesting in this context for institutional reasons. Fiscal policy follows balanced budget rules, and monetary policy has followed inflation targeting since 2000. The Central Bank of Colombia has maintained a floating exchange rate regime since 1999, occasionally intervening and maintaining an adequate level of international reserves. The bank's board sets the policy rate and communicates its stance through press releases and minutes: when vote tallies are disclosed, that extra information can signal consensus or dissent within the board, shaping expectations and the sensitivity of the exchange rate to news. In this setup, institutional reputation and granularity of information on monetary policy decisions and votes can be a key driver of heterogeneity in exchange rate expectations, in addition to central bank FX interventions.

Despite a growing literature on how central bank communication and FX intervention reduce exchange rate uncertainty, little is known about how central bank reputation, interest rate decisions, and communication channels such as minutes shape exchange rate expectations in EMEs. We contribute to this gap on three fronts. First, we document the link between central bank reputation and disagreements and forecast errors in exchange rate expectations. Second, we assess the marginal role of minutes and vote disclosure, including unanimity, as signals that help coordinate exchange rate expectations. Third, we explore whether communication effects are stronger when uncertainty is high.

Our findings suggest that the central bank's reputation helps reduce disagreements and forecast errors in exchange rate expectations. In addition, minutes of central bank policy meetings serve as a communication channel that can reduce exchange rate uncertainty, especially when board decisions on policy rates are unanimous.

The remainder of the paper is organised as follows. Section 2 describes the data and methodology. Section 3 presents the results. Section 4 concludes.

2 METHODOLOGY

We derive exchange rate expectations from monthly surveys of economic analysts' expectations conducted by the Central Bank of Colombia.[1] This survey collects the expectations of a diverse group of financial market participants, including banks, brokerage firms, pension funds, insurance companies, international organisations and economic research centres. The survey is conducted monthly, with an average of 40 entities participating, via an electronic form available on the central bank's website.

Data collection takes place during the first week of each month. Participants provide their expectations for different time horizons, from the current month, to three, six, nine, twelve, and twenty-four months ahead, as well as the end of the following year. The main variables consulted in the survey include the representative exchange rate, total inflation and core inflation (excluding food), the policy rate, and GDP growth.

A key feature of the survey is that it is conducted before key events such as monetary policy meetings. This allows the survey to capture market expectations before the decisions that could significantly affect the economy, such as changes in interest rates or exchange rate policy.

Graph 1 charts the monthly path of the exchange rate, inflation, and the policy interest rate in Colombia from June 2007 to December 2021. The exchange rate was relatively stable at around 2,000 COP/USD between 2009 and 2014. With the rise of US oil shale output (fracking), the peso weakened markedly, reaching about COP 3,400 per USD in 2016. Pandemic-related uncertainty then pushed it past COP 3,500 per USD in 2020, and to roughly 4,000 in 2021.

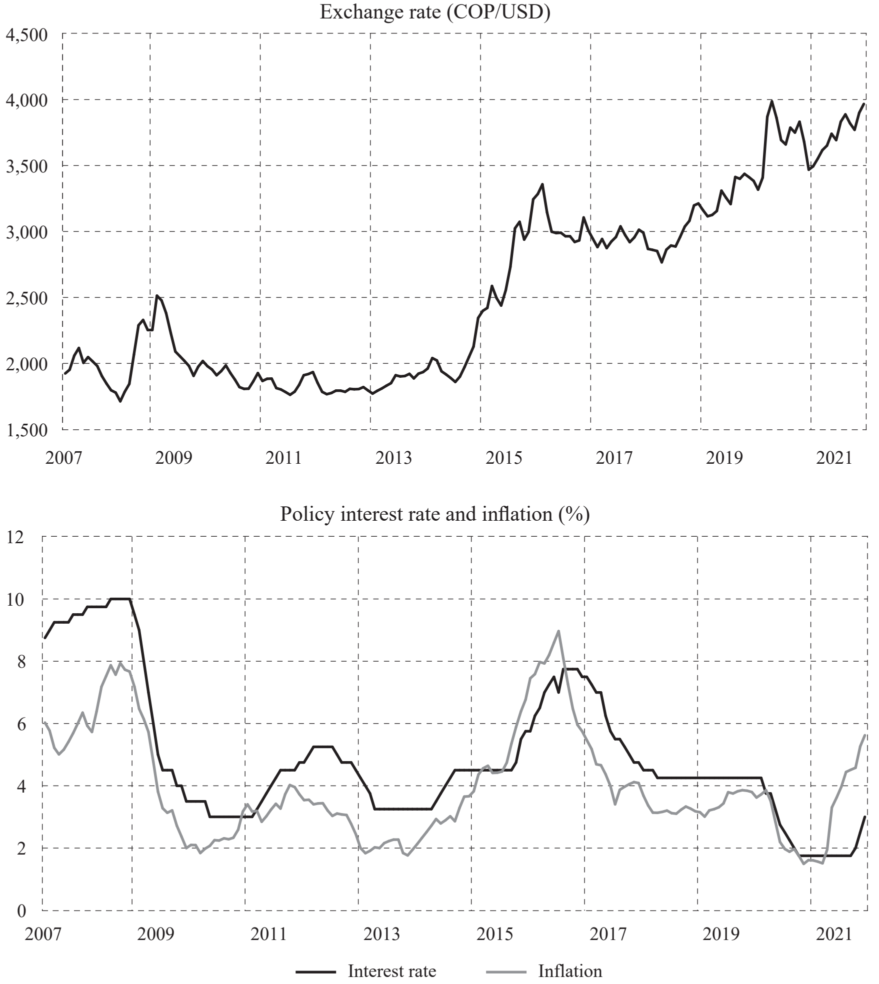
Inflation and the policy rate have moved together: whenever inflationary pressures emerged, the central bank would raise interest rates until the pressures eased. This co-movement reflects the inflation targeting framework that the central bank has operated since 2000. The inflation target narrowed over time and in 2010 settled on a point target of 3%, with a tolerance range of +2 and -4 percentage points around the target.

[1] Monthly Survey of Economic Analysts' Expectations (EME) are available at: https://suameca.banrep.gov.co/estadisticas-economicas/encuestas.

Throughout the period, inflation stayed below 10%. Three inflationary episodes stand out. The first, from 2007 to 2009, was driven by the commodity (mining and energy) boom and by strong aggregate demand, which pushed inflation above 7%. The second episode, in 2015, resulted from a combination of rapid peso depreciation and weather-related shocks, which boosted inflation to almost 9%. The expansionary fiscal and monetary policies after the onset of the Covid pandemic helped fuel a third bout of inflation in 2021.

Graph 1

Evolution of the exchange rate, inflation, and the policy rate in Colombia, 2007-2021



Source: Central Bank of Colombia.

Disagreements in expectations and forecast errors are often used in the literature as measures of dispersion in expectations of macroeconomic variables (Seelajaroen, Budsaratragoon and Jitmaneeroj, 2020; Galvis and Anzoátegui, 2019; Mankiw and Wolfers, 2003). We use disagreements and errors in exchange rate

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expectations of financial market participants as a measure of exchange rate uncertainty. Typically, disagreement is calculated using the interquartile range, which is less affected by abrupt changes in extreme sample values (Mankiw and Wolfers, 2003). However, the Central Bank of Colombia does not publish forecast information for each agent surveyed, making it impossible to calculate disagreement using this method. Instead, we calculate disagreements in exchange rate expectations as the difference between the highest (maximum) and lowest (minimum) values expected by survey participants, as proposed by Beckmann and Reitz (2020). Disagreements in exchange rates, Dis_Ex_t, are thus defined as:

$$Dis\_Ex_t = Ex\_rate_t^{Max} - Ex\_rate_t^{Min} \quad (1)$$

where $Ex\_rate_t^{Max}$ is the maximum and $Ex\_rate_t^{Min}$ is the minimum value of exchange rate expectations in the survey for a given month.

According with Beckmann and Czudaj (2017) and Bacchetta, Mertens and Van Wincoop (2009), forecast error can be calculated as a deviation of the expected from the observed exchange rate:

$$Error_t = Ex\_rate_t^{obs} - Ex\_rate_{t-n}^{\exp} \quad (2)$$

where $Ex\_rate_{t-n}^{\exp}$ refers to the average expectation of financial market participants.

A positive sign of the forecast error indicates that the exchange rate depreciated more than market participants had expected, i.e. they underestimated the exchange rate related risks in a given period. A negative sign of the forecast error indicates that the market participants overestimated the exchange rate-related risks in a given period.

Graph 2 depicts the evolution of disagreement in expectations and forecast errors for the COP/USD exchange rate between 2007 and 2021. Several phases can be identified, associated with salient economic events.

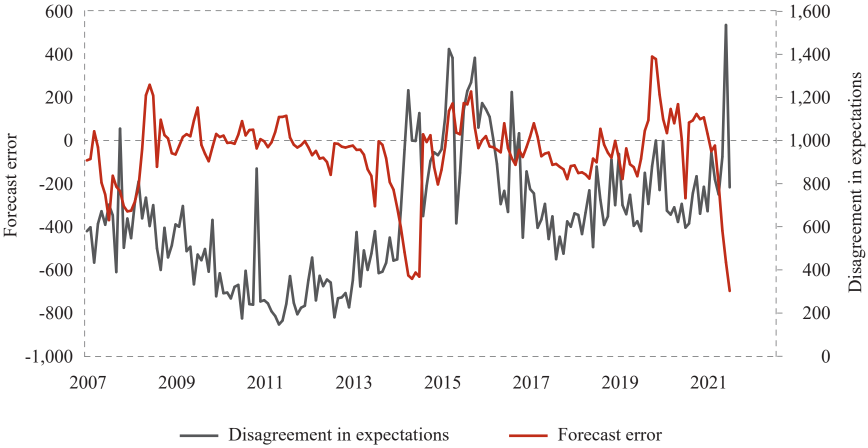
Between 2007 and 2013, disagreements in exchange rate expectations and forecast errors were relatively stable, except during the Global Financial Crisis of 2008-09. Between 2002 and 2014, the Colombian economy experienced a mining and energy boom. Foreign direct investment in the mining and energy sectors increased tenfold between 2002 and 2010, coal production increased by 80%, and oil production by 36%. Gold production increased by 340% between 2006 and 2010 (Sankey, 2020). This economic dynamic led to a significant improvement in Colombia's fiscal position, and in 2011 credit rating agencies assigned an investment grade rating to the country's sovereign debt.

From 2014 until 2017, a marked shift can be observed. Disagreement about exchange rate expectations increased significantly and forecast errors started to fluctuate widely.

This pattern reflected the decline in international oil prices following the boom in hydraulic fracturing (fracking) in the United States, which materially affected economies with trade balances driven by oil and other energy commodity exports. In 2020-2021, high uncertainty associated with the Covid pandemic again amplified disagreements in exchange rate expectations and widened the fluctuations of forecast errors.

Graph 2

Disagreement in expectations and forecast errors for the COP/USD exchange rate



Sources: Central Bank of Colombia; authors' calculations.

2.1 CENTRAL BANK REPUTATION

Reputation in monetary policy is usually defined as a backward-looking measure indicating the ability to anchor inflation to the target (Anzoátegui et al., 2024). Inflation anchoring serves as a performance metric for monetary authorities, and it influences the formation of macroeconomic expectations among financial market participants (Seelajaroen, Budsaratragoon and Jitmaneeroj, 2020). Central banks that fulfil their commitment to anchor inflation reduce macroeconomic volatility and uncertainty. Reputation can thus be considered a necessary condition that enhances trust in future policies.

Based on the criteria outlined in the inflation targeting framework defined by the Central Bank of Colombia, Galvis and de Mendonça (2017) constructed a central bank reputation index ($REPU_t$) that captures deviations of inflation outcomes from the targets and ranges announced each year:

$$REPU_t = \begin{cases} 1 & \text{if} \quad INF_t = INF_t^* \\ 1 - \dfrac{1}{INF_t^{Bound} - INF_t^*}\left[INF_t - INF_t^*\right] & \text{if} \quad INF_t^{LB} < INF_t < INF_t^{UB} \\ 0 & \text{if } INF_t \geq INF_t^{UB} \, o \, INF_t \leq INF_t^{LB} \end{cases} \qquad (3)$$

Deviations are normalised within a range of 0 to 1, so the reputation index is equal to 1 when the twelve-month accumulated inflation (INF_t) matches the target (INF_t^*). The index takes values between 0 and 1 when inflation lies within the target range but is above or below the inflation target. Reputation equals zero when inflation exceeds the upper bound (INF_t^{UB}), or falls below the lower bound (INF_t^{LB}).

The challenge the central bank faces in building its reputation consists of stabilising prices around the inflation target and its ranges. Longer lasting and larger deviations normally lead to interest rate adjustments, which may result in capital flows that in turn affect the exchange rate. Foreign exchange market participants take account of these relationships when forming their exchange rate expectations, so it is important to consider central bank reputation as a distinct determinant of exchange rate uncertainty.

2.2 COMMUNICATION AND DISAGREEMENTS AMONG POLICYMAKERS

The effectiveness of monetary policy depends not only on the use of instruments such as interest rates but also on the management of expectations. Central bank communication can shape inflation expectations and is therefore very important in an inflation-targeting framework. To guide these expectations, it uses various communication tools in its efforts to achieve transparency.

In the case of the Central Bank of Colombia, press releases, meeting minutes, monetary policy reports, and accountability reports to Congress have become the main monetary policy communication tools (Anzoátegui and Galvis, 2019). Empirical evidence suggests that market participants pay most attention to minutes of monetary policy meetings (Anzoátegui, Rodríguez and Galvis, 2024; Guío et al., 2020). This tool has been used since late 2007 to provide detailed information about decisions on policy interest rates, and to explain the direction of monetary policy and policymakers' perspectives on the economic situation. Since the minutes report inflation outcomes, deviations from the target, projections, and the rationale behind monetary policy decisions, their clarity can serve as a useful measure to assess the influence of monetary policy communication on exchange rate uncertainty.

Clarity in monetary policy statements can be measured using various indicators of readability. These indicators help analyse the quality of writing in terms of text length, logical sentence order, and text structures that facilitate proper comprehension (Ferrando-Belart, 2004). We use the Inflesz readability indicator, specifically designed to measure the legibility and understanding of Spanish language texts by Barrio-Cantalejo et al. (2008) to construct the following readability index for the Central Bank of Colombia policy meeting minutes:[2]

$$Inflesz_t = 206{,}835 - \frac{62.3S}{P} - \frac{P}{F} \tag{4}$$

[2] The minutes were analysed using: https://legible.es/.

where S is the total number of syllables in the minutes, P is the total number of words, and F is the total number of sentences. The intuition behind this indicator is that many syllables per word and many words per sentence reduce readability. If someone must process a text with long words or sentences, it will be harder to grasp the message, requiring a higher level of education. The readability of meeting minutes can thus improve if they are designed with shorter words and sentences.

According to the scale proposed by Barrio-Cantalejo et al. (2008), the index can be divided into five categories (table 1).

Table 1
Inflesz perspicuity scale

Numeric scale	Interpretation	Education required to interpret the text and type of publication
>80	Very easy	Primary education – comics, graphic novels
65-80	Quite easy	Primary education – press, bestselling novels
55-65	Normal	Primary education – general press, sports press
40-55	Little difficult	High school education – scientific dissemination, specialised press
0-40	Very difficult	University education – scientific text

Source: Barrio-Cantalejo et al. (2008).

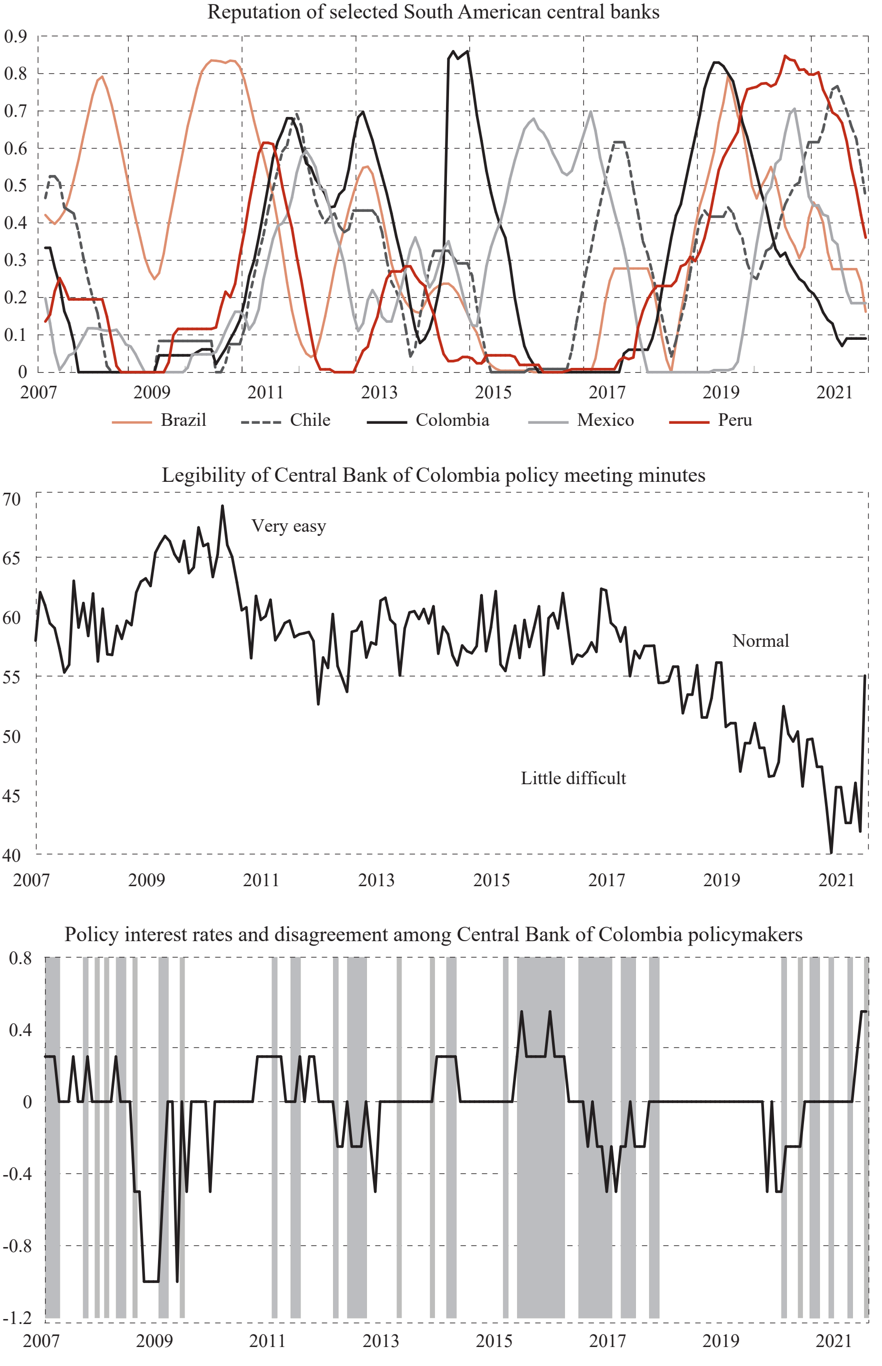
We use this scale to operationalise the clarity of the central bank's policy meeting minutes: higher scores reflect shorter words and sentences and thus greater accessibility, while very low scores reflect longer words and sentences and thus greater demands on reading comprehension.

Beyond assessing the readability of the minutes, it is important to identify the effects of disagreement among those responsible for monetary policy. According to Crump, Eusepi and Moench (2013), differences in policymakers' positions tend to intensify in an environment of higher inflation, unemployment, and greater output volatility. Anzoátegui and Galvis (2022) argue that these differences serve financial market participants as signals (or noise) in the formation of macroeconomic expectations. To capture the effects of disagreement among policymakers on exchange rate uncertainty, we use a dummy variable (Dis_Junta_t) that takes a value of 1 when monetary policy decisions are made by majority vote, and 0 when decisions are unanimous.

Graph 3 shows the index of reputation for several South American central banks, and indicators of clarity of communication and disagreement among monetary policymakers for the Central Bank of Colombia over the 2007-21 period. The top panel suggests that South American central banks find it difficult to maintain a high level of reputation. The index that describes the degree of inflation anchoring fluctuates widely between zero (inflation outside the target ranges) and at most 0.85 (inflation close to target), the latter over short periods only. In the case of Colombia, the reputation index increased only to fall sharply four times over this period.

Graph 3

Indicators of central bank reputation, clarity of communication and disagreement among monetary policymakers



Note: Shaded areas in the bottom panel indicate periods when interest rate decisions were taken by majority vote; blank areas periods when they were taken unanimously.

Sources: Central Bank of Colombia; authors' calculations.

The panel in the middle shows that the policy meeting minutes issued by the Central Bank of Colombia were comprehensible to a broad audience until mid-2018, but afterwards the clarity of its communication worsened. The likely reason is that in July 2019 the section on macroeconomic context was removed from the minutes, while the remaining sections on policy discussion and options and the policy decision contained fewer words and paragraphs but with a more technical language.

The bottom panel traces changes in the policy interest rate and disagreement on the policy decision among the central bank policymakers. The latter was rescaled from a 0-1 scale to the scale of policy rate changes (with zero indicating no change) so that both series can share a single axis. The grey shading marks meetings with majority decisions; white areas indicate periods when policy decisions were taken with unanimity.

2.3 ESTIMATING FRAMEWORK AND CONTROL VARIABLES

We use two equations to evaluate the effects of central bank reputation and communication on exchange rate expectations and forecast errors in the financial market:

$$\begin{aligned} Dis\_Ex_t &= \beta_1 + \beta_2 Dis\_Ex_{t-1} + \beta_3 \Delta REPU_t + \beta_4 \Delta Inflesz_t \\ &+ \beta_5 Dis\_Junta_t + \sum\nolimits_{i=1}^{4} \beta_6 X_{it-1} + \varepsilon_t^1 \end{aligned} \tag{5}$$

$$\begin{aligned} Error_t &= \beta_7 + \beta_8 Error_{t-1} + \beta_9 \Delta REPU_t + \beta_{10} \Delta Inflesz_t \\ &+ \beta_{11} Dis\_Junta_t + \sum\nolimits_{i=1}^{4} \beta_{12} X_{it-1} + \varepsilon_t^2 \end{aligned} \tag{6}$$

The first dependent variable, Dis_Ex_t, represents disagreement in exchange rate expectations, while Dis_Ex_{t-1} is its lag that captures the inertia of expectations. The second dependent variable, $Error_t$, captures forecast errors, with $Error_{t-1}$ representing its lag, which captures the persistence of errors.

In addition to indicators of central bank reputation, the clarity of its policy meeting minutes, and disagreement among policymakers, we include a vector of four control variables that may also influence exchange rate expectations in financial markets: interest rate differentials (Dif_i_t), inflation uncertainty ($dis\_inf_t^e$), technology shocks ($Frack_t$), and economic policy uncertainty (EPU_t).

Expectations of increases in domestic policy rate (or an actual increase therein) relative to the foreign policy rate normally lead to exchange rate appreciation. There is thus a direct (though not necessarily causal) relationship between policy rate differentials and exchange rate expectations: a widening of the differential in principle reduces the dispersion of exchange rate expectations and forecast errors in FX markets. The interest rate differential is calculated as the difference between the policy interest rates of the Central Bank of Colombia and the Federal Reserve.

Inflation uncertainty is another macroeconomic variable that affects exchange rate expectations and their forecast errors. According to Beckmann and Czudaj (2017), disagreements in inflation expectations reflect uncertainty of financial market participants about the central bank's ability to anchor inflation expectations to target. Greater disagreements indicate that market participants are more uncertain about the future economic environment for domestic prices. To measure inflation uncertainty, we calculate the difference between maximum and minimum twelve-month inflation expectations in central bank monthly surveys of financial analysts.

The implementation of oil extraction technologies associated with hydraulic fracturing (fracking) led to a rapid and unexpected decline in oil prices between 2014 and 2016. According to Toro et al. (2015) and Melo-Becerra et al. (2016), the collapse of oil prices affected numerous macroeconomic variables, including terms of trade, national income, investment, the external and fiscal balance, and foreign capital inflows. These effects culminated in a sharp peso depreciation that influenced exchange rate uncertainty. Understanding the effects of fracking on exchange rate uncertainty is an important element of empirical analysis. We use a dummy variable for fracking that equals to 1 from July 2014 to February 2016 and zero for all other periods.

We also include an economic policy uncertainty based on Baker, Bloom and Davis (2016). Rúa and Marín-Rodríguez (2024), Abid (2020) and Arouri et al. (2016) found that economic policy uncertainty affected movements and volatility of the exchange rate in EMEs, and had direct effects on investor confidence and capital flows and hence on the exchange rate.

3 ESTIMATIONS AND RESULTS

To avoid spurious regressions, we first checked that the time series are stationary. The results of various unit root tests are shown in table A2. We examined unit root properties using the breakpoint unit root test (Perron, 1997), specifying a break at the intercept. For disagreements in exchange rate expectations (Dis_Ex_t), the estimated breakpoint date was November 2014 (test statistic -4.96, 5% critical value -5.64), leading to the rejection of the unit root null hypothesis. For exchange rate forecast errors ($Error_t$), the estimated breakpoint date was November 2014 (test statistic -4.62, 5% critical value -4.44). These findings suggest stationarity around a shifted mean, which is consistent with structural effects due to fracking, allowing us to use these variables in levels (table A3).

All explanatory variables were stationary in their original form. We further used Breusch-Godfrey and Breusch-Pagan-Godfrey tests to assess serial correlation and heteroskedasticity for the ARDL-HAC model in equations (5) and (6). The results suggested no serial correlation in either regression, and heteroskedasticity only in equation 6 (table A4).

We used the Generalised Method of Moments (GMM) to estimate the regressions, using a Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix to address heteroskedasticity detected in equation (6).

Applying a Newey-West robust covariance matrix (HAC) to address heteroskedasticity detected in equation (6).

We considered overidentification restrictions in selecting instrumental variables for an efficient GMM estimator using a standard Hansen J test. Following the methodological approach proposed by Johnston (1984), we selected instruments based on data from prior periods to ensure their exogeneity. In addition, we estimated the two-step GMM with corrections to address small-sample downward biases on standard errors.

The estimation results are reported in tables 2 and 3. The basic model evaluates the effect of monetary policy reputation and communication on exchange rate expectations and exchange rate forecast errors. The extended model includes a time variable. We used the standard deviation to normalise the measurement of variables.[3]

The estimated coefficient on the lag of disagreements in exchange rate expectations (Dis_Ex_{t-1}) is positive and significant at the 1% level in all models, suggesting the presence of rigidities in the formation of exchange rate expectations. According to Beckmann and Reitz (2020), agents update information slowly, prolonging uncertainty in the FX market. Coibion and Gorodnichenko (2015) and Mankiw and Reis (2002) argued that the persistence of lags was associated with differences in access to and processing of information, and noisy updating of information sets.

Parameter estimates associated with reputation ($REPU_t$) are negative and significant in all models, indicating that monetary policy reputation could reduce disagreements in exchange rate expectations and their forecast errors. Carrière-Swallow et al. (2021) similarly provided evidence that monetary policy frameworks that controlled inflation generally reduced exchange rate volatility and exchange rate pass-through to consumer prices.

Parameter estimates associated with monetary policy communication indicate that policy meeting minutes and voting records are an effective tool for guiding exchange rate expectations. The estimated coefficient on the clarity of minutes ($\Delta Inflesz_t$) is negative and significant across all models, suggesting that greater efforts to enhance the readability of minutes have the potential to reduce exchange rate uncertainty. This result is in line with findings of Bacchetta, Mertens and Van Wincoop (2009), who argued that heterogeneity in exchange rate expectations occurred as a consequence of information rigidities.

Coefficient estimates on disagreement among monetary policymakers (Dis_Junta_t) are positive and significant in most models. This suggests that interest rate decisions made by majority vote lead to more dispersed exchange rate expectations and greater exchange rate forecast errors, thereby heightening the uncertainty in FX markets. Anzoátegui and Galvis (2022), Tsang and Yang (2025), and Blot, Hubert and Labondance (2025) obtained similar results.

[3] The data were normalised using Z standardisation, which is defined as: $Z = \dfrac{X - \mu}{\sigma}$.

Table 2

Effects of monetary policy reputation and communication on disagreements of the exchange rate

Dep. variable Dis_Ex_t	**GMM-HAC estimates**						**GMM-Windmeijer estimates**					
Regressors	**(Eq 5.1)**	**(Eq 5.2)**	**(Eq 5.3)**	**(Eq 5.4)**	**(Eq 5.4)**	**(Eq 5.5)**	**(Eq 5.1)**	**(Eq 5.2)**	**(Eq 5.3)**	**(Eq 5.4)**	**(Eq 5.4)**	**(Eq 5.5)**
C	-0.02 (-0.57)	-0.11 (-1.58)	-0.19** (-2.09)	-0.19** (-1.97)	-0.17 (-2.35)	0.21** (-2.35)	-0.02 (-0.51)	-0.11* (-1.83)	-0.19** (-2.27)	-0.19* (-1.89)	-0.17 (-1.40)	-0.23** (-2.03)
Dis_Ex_{t-1}	0.76*** (12.96)	0.75*** (13.65)	0.71*** (9.97)	0.66*** (11.14)	0.58*** (6.64)	0.51*** (7.49)	0.76*** (9.65)	0.75*** (11.65)	0.71*** (8.46)	0.66*** (10.44)	0.58*** (5.78)	0.48*** (4.61)
$\Delta REPU_t$	-0.22** (-2.90)	-0.35*** (-3.67)	-0.39*** (-2.91)	-0.33*** (-2.63)	-0.47** (-2.09)	-0.419* (-1.81)	-0.22** (-2.20)	-0.35*** (-4.13)	-0.39*** (-2.62)	-0.33** (-2.28)	-0.47** (-2.45)	-0.46* (-1.85)
$\Delta Inflesz_t$	-0.08** (-2.07)	-0.072* (-1.68)	-0.09* (-1.89)	-0.12** (-2.04)	-0.15*** (-2.80)	-0.10** (-1.99)	-0.08** (-2.04)	-0.07* (-1.65)	0.083* (-1.74)	-0.11** (-1.98)	-0.15*** (-2.83)	-0.09* (-1.68)
Dis_Junta_t		0.27* (1.80)	0.41** (2.22)	0.42*** (2.18)	0.40* (1.67)	0.45** (2.60)		0.28** (1.99)	0.41** (2.29)	0.42** (2.14)	0.40* (1.65)	0.48** (2.36)
$Frack_t$			0.40*** (3.53)	-0.34*** (3.80)	0.28** (1.99)	-0.36*** (3.26)			0.40*** (2.89)	0.34*** (3.64)	0.27** (2.21)	0.38** (2.52)
$dis\_inf^e_t$				0.11** (2.03)	0.28*** (2.97)	0.25*** (3.38)				0.11** (2.07)	0.28*** (2.86)	0.25** (2.31)
Dif_i_t					-0.13** (-2.11)	-0.14* (-2.61)					-0.13** (-2.11)	-0.14** (-2.12)
EPU_t						0.17** (2.34)						0.18** (1.85)
R2adj	0.68	0.67	0.66	0.68	0.62	0.62	0.65	0.68	0.66	0.68	0.62	0.61
J-stat	2.52	1.63	1.76	0.58	1.77	8.37	2.50	1.60	1.90	0.55	1.73	7.93
P(J-stat)	0.92	0.99	0.94	0.99	0.77	0.81	0.92	0.99	0.92	0.99	0.70	0.84
No. of inst.	11	13	12	13	12	22	11	13	12	13	12	22

**** Denotes significance at 1%, ** at 5%, and * at 10% level. t-statistics in brackets. P(J-stat) is the p-value of the J-test for over-identification.*

Table 3

Effects of monetary policy reputation and communication on forecast errors of the exchange rate

Dep. variable $Error_t$	**GMM-HAC estimates**						**GMM-Windmeijer estimates**					
Regressors	**(Eq 5.1)**	**(Eq 5.2)**	**(Eq 5.3)**	**(Eq 5.4)**	**(Eq 5.4)**	**(Eq 5.5)**	**(Eq 5.1)**	**(Eq 5.2)**	**(Eq 5.3)**	**(Eq 5.4)**	**(Eq 5.4)**	**(Eq 5.5)**
C	0.01 (0.37)	0.008 (0.19)	0.01 (0.23)	0.01 (0.33)	0.03 (0.74)	-0.16* (-1.75)	0.01 (0.37)	0.008* (0.18)	0.01 (0.20)	0.01 (0.28)	0.03 (0.67)	-0.16 (-1.52)
Dis_Ex_{t-1}	0.76*** (9.33)	0.73*** (10.41)	0.79*** (9.38)	0.79*** (11.55)	0.72*** (11.05)	0.71*** (11.69)	0.76*** (8.71)	0.73*** (8.94)	0.79*** (7.47)	0.79*** (8.25)	0.72*** (8.71)	0.69*** (5.47)
$\Delta REPU_t$	-0.12*** (-3.50)	-0.14*** (-3.94)	-0.10*** (-3.28)	-0.12*** (-4.00)	-0.14*** (-4.37)	-0.11*** (-3.55)	-0.12*** (-3.37)	-0.14*** (-3.65)	-0.10*** (-2.74)	-0.12*** (-3.35)	-0.14*** (-4.05)	-0.13*** (-3.38)
$\Delta Inflesz_t$	-0.22* (-1.95)	-0.46** (-2.23)	-0.18** (-2.13)	-0.18** (-2.18)	-0.21** (-2.32)	-0.41*** (-3.18)	-0.22* (-1.81)	-0.46** (-2.10)	-0.18* (-1.73)	-0.18* (-1.70)	-0.21* (-1.91)	-0.32* (-1.66)
Dis_Junta_t		0.16** (2.05)	0.18*** (2.70)	0.16** (2.20)	0.21*** (2.63)	0.13** (1.98)		0.16** (2.02)	0.18** (2.27)	0.16* (1.87)	0.21** (2.42)	0.19* (1.91)
$Frack_t$			-0.16 (-1.02)	-0.11 (-0.94)	-0.18 (-1.53)	-0.17 (-1.62)			-0.16 (-0.73)	-0.11 (-0.71)	-0.18 (-1.32)	-0.30 (-1.50)
$dis\_inf^e_t$				0.07* (1.76)	0.13** (2.48)	0.13* (1.86)				0.07 (1.20)	0.13** (2.02)	0.16** (2.50)
Dif_i_t					-0.10* (-1.95)	-0.06 (-1.32)					-0.10* (-1.67)	-0.08 (-1.36)
EPU_t						0.001** (2.02)						0.001* (1.70)
R2adj	0.65	0.64	0.65	0.67	0.67	0.67	0.65	0.64	0.65	0.67	0.67	0.67
J-stat	1.69	1.12	5.60	5.06	3.54	7.87	1.69	1.12	5.60	5.06	3.54	9.86
P(J-stat)	0.42	0.88	0.23	0.65	0.61	0.85	0.42	0.88	0.23	0.65	0.61	0.70
No. of inst.	6	9	10	14	13	22	6	9	10	14	13	22

**** Denotes significance at 1%, ** at 5%, and * at 10% level. t-statistics in brackets. P(J-stat) is the p-value of the J-test for over-identification.*

The dummy variable for the period when the use of fracking technology in the United States surged is positive and statistically significant in all models. This result confirms that the sharp decline in crude oil prices driven by an oversupply led to significant exchange rate and movements and increased exchange rate uncertainty. Toro et al. (2015) and Melo-Becerra (2016) similarly found that the collapse in oil prices disrupted the dynamics of capital flows and terms of trade, leading to faster depreciation and greater instability in the Colombian foreign exchange market.

The estimated parameters on discrepancies in inflation expectations ($dis\_inf_t^e$) are positive and statistically significant in almost all regressions. This suggests that greater disagreement in inflation forecasts is associated with greater disagreement in exchange rate forecasts. Similar results were found by Beckmann and Reitz (2020).

Parameter estimates for the interest rate differential (Dif_i_t) are negative and statistically significant in most specifications, suggesting that an increase in the domestic relative to the foreign policy rate (i.e. a wider differential, given that policy rates in Colombia were most of the time higher than in the United States) reduces disagreements about future exchange rates and exchange rate forecast errors. This evidence is consistent with Dick, MacDonald and Menkhoff (2015).

The estimated parameter associated with the economic policy uncertainty index is positive and statistically significant in all models. This indicates that greater uncertainty about economic policies, derived from newspaper articles about Colombia's economy, also increases the dispersion of exchange rate expectations and exchange rates forecast errors among FX market participants.

4 ROBUSTNESS ANALYSIS

4.1 ARDL ESTIMATES

As the first robustness check we re-estimated the models using the autoregressive distributed-lag (ARDL) approach proposed by Pesaran and Shin (1999) and Pesaran, Shin and Smith (2001). Under the assumption of having a group of time series variables, some in I(0) and others in I(1), but none equal to or greater than I(2), this method is useful for small samples. Pesaran, Shin and Smith (2001) note that the ARDL model provides a simple univariate framework for testing the existence of a single-level relationship between y_t and x_t when it is not known with certainty whether the regressors are purely I(0), purely I(1), or mutually cointegrated.

We estimate the following error correction models:

$$\begin{aligned} Dis\_Ex_t = {} & \alpha_0 + \sum_{i=1}^{p} \varphi_i Dis\_Ex_{t-i} + \sum_{i=1}^{p} \theta_i \Delta REPU_{t-i} + \sum_{i=1}^{p} \eta_i \Delta Inflesz_{t-i} + \sum_{i=1}^{p} \gamma_i Dis_{Junta_{t-i}} \\ & + \sum_{i=1}^{p} \omega_i dis\_inf_{t-1}^{e} + \sum_{i=1}^{p} \psi_i Dif_{i_{t-i}} + \sum_{i=1}^{p} \Omega_i EPU_{t-i} + \delta_1 Dis\_Ex_{t-1} + \delta_2 REPU_{t-1} \qquad (7) \\ & + \delta_3 Inflesz_{t-1} + \delta_4 Dis_{Junta_{t-1}} + \delta_5 dis\_inf_{t-1}^{e} + \delta_6 Dif_{i_{t-1}} + \delta_7 EPU_{i_{t-1}} + \xi_t \end{aligned}$$

$$Error_t = \alpha_0 + \sum_{i=1}^{p} \varphi_i Error_{t-i} + \sum_{i=1}^{p} \theta_i \Delta REPU_{t-i} + \sum_{i=1}^{p} \eta_i \Delta Inflesz_{t-i} + \sum_{i=1}^{p} \gamma_i Dis_{Junta_{t-i}}$$
$$+ \sum_{i=1}^{p} \omega_i\, dis\_inf^{e}_{t-1} + \sum_{i=1}^{p} \psi_i Dif_{i\,t-i} + \sum_{i=1}^{p} \Omega_i EPU_{t-i} + \delta_1 Error_{t-1} + \delta_2 REPU_{t-1} \quad (8)$$
$$+ \delta_3 Inflesz_{t-1} + \delta_4 Dis_{Junta_{t-1}} + \delta_5\, dis\_inf^{e}_{t-1} + \delta_6 Dif_{i_{t-1}} + \delta_7 EPU_{i_{t-1}} + \xi_t$$

where p is the optimal lag length. The second part of the right-hand side of both equations with parameters δ_i represents the levels relationship. To determine the lag orders for the variables in each equation, we select a model that optimises the adjusted R-squared. We check the existence of relationships in levels through an F-test for each equation. When a level relationship exists, the F-test indicates which variable should be normalised. The null hypothesis for the nonexistence of the relationship in level among variables in both equations is that all δ_i coefficients are equal to zero, and the alternative is that they are all different from zero. According to Pesaran, Shin and Smith (2001), the F-test provides critical values for the lower bound for the cases where all regressors are I(0), and for the upper bound when all regressors are I(1). When the test statistic is below the lower bound, we cannot reject the null hypothesis and conclude that cointegration is not present. When the test statistic is above the upper bound, we can reject the null hypothesis and conclude that cointegration is possible. In that case, we proceed with a t-test of significance of the error correction parameter δ.

The F-test statistics reported in tables 4 and 5 exceed the respective upper critical values, so the null hypothesis can be rejected for both equations. The coefficient on the lagged error correction term is significant at the 1% level with the expected negative sign, confirming the result of the bounds test for cointegration.

Table 4
ARDL – Level relationships obtained from Equation (5) – Dis_Ex_t

***Dis_Ex_t* – ARDL(1, 0, 0, 0, 0)**

Bounds test			**Critical value bounds**
Test statistic	**Value**	**Significance**	I(1) bound
F-statistic	7.86	1%	4.99
K	7		
Long run coefficients			
Variables	**Coefficient**	**Std. error**	**t-statistic**
$REPU_t$	-0.20*	(0.12)	-1.68
$Inflesz_t$	-0.24*	(0.13)	-1.82
Dis_Junta_t	0.42*	(0.22)	1.86
$dis\_inf^e_t$	0.27*	(0.14)	1.92
Dif_i_t	-0.10	(0.12)	-0.79
EPU_t	0.31***	(0.11)	2.75

**** Denotes 0.01, ** 0.05, and * 0.10 level of significance.*

Table 5

ARDL – Level relationships obtained from Equation (6) – $Error_t$

***$Error_t$* – ARDL(1, 0, 0, 1, 0)**			
Bounds test			**Critical value bounds**
Test statistic	**Value**	**Significance**	I(1) bound
F-statistic	5.07	1%	3.99
K	7		
Long run coefficients			
Variables	**Coefficient**	**Std. error**	**t-statistic**
$REPU_t$	-0.49**	(0.20)	-2.43
$Inflesz_t$	-0.79*	(0.43)	-1.84
Dis_Junta_t	0.78**	(0.38)	2.02
$dis\_inf^e_t$	0.39*	(0.20)	1.89
Dif_i_t	-1.85	(0.98)	-1.88
EPU_t	0.37**	(0.18)	2.00

**** Denotes 0.01, ** 0.05, and * 0.10 level of significance.*

Relative to the results reported in tables 2 and 3, coefficient estimates reported in tables 4 and 5 show no change in coefficient signs. Solid central bank reputation, clear communication, and unanimous policy decisions reduce exchange rate uncertainty, while greater dispersion of inflation expectations and greater economic policy uncertainty increase it. Only the coefficient estimates on the interest rate differential are not statistically significant in these specifications.

4.2 VAR ESTIMATES AND IMPULSE-RESPONSE ANALYSIS

For the second robustness check we used a vector autoregressive (VAR) model and analysed impulse response functions.[4] We used a generalised impulse response function to eliminate the problem of variable ordering. This approach resolves potential issues with contemporaneous correlation among variables and is suitable for analysis without distinguishing between dependent and independent variables. We estimated the VAR and analysed impulse response for the two dependent and eight explanatory variables estimated with GMM. The lag order was set to one, based on the Hannan-Quinn (HQ) information criterion, which is suitable for small samples. The roots of the VAR satisfied the stability condition.

As in GMM estimations, estimated coefficients for the lag of dependent variables were positive and significant, indicating a strong persistence of uncertainty about the exchange rate. Estimated coefficients for the reputation variable were negative and statistically significant. Improved reputation and greater clarity of policy meeting minutes reduced disagreements about future exchange rates and forecast errors for up to one year. The estimated coefficients on disagreement among monetary policymakers was positive and significant: policy decisions made by majority vote increased the dispersion of exchange rate expectations for three months, and exchange rate forecast errors for twelve months.

[4] The results are available from the authors upon request.

Regarding control variables, the effects of the fracking dummy were positive and statistically significant in both VARs. The sharp decline in oil prices led to a persistent increase in exchange rate expectations and forecast errors over a one-year period. Likewise, the coefficients on differences in inflation forecasts were positive and statistically significant in both specifications, with a one-year impact on dependent variables after a shock. For interest rate differential, negative effects were estimated in both models but were not statistically significant in the regression on exchange rate expectations. Shocks in economic policy uncertainty had a positive and significant effect on both dependent variables over a period of at least one year.

5 CONCLUSIONS

This paper explored the impact of the reputation and communication skills of the Central Bank of Colombia on disagreement in exchange rate expectations and exchange rate forecast errors by FX market participants in Colombia.

The results suggest that reputation plays a crucial role in anchoring exchange rate expectations. Strong reputation, built on consistently meeting inflation targets, significantly reduces uncertainty in the foreign exchange market. Clear and consistent monetary policy communication is another important avenue for reducing disagreements in exchange rate expectations and forecast errors. Clear and accessible language is correlated with less dispersion in exchange rate expectations and greater forecasting accuracy. This underscores the importance of not just disseminating information but doing so in a manner that enables market participants and other economic agents to align their expectations with monetary policy goals. Separately, disagreement among monetary policymakers also influences exchange rate uncertainty: greater cohesion of their votes shapes exchange rate expectations in an important way.

Exogenous factors such as the impact of fracking also have a significant effect on the volatility of exchange rate expectations. Such events increase disagreements in expectations and exchange rate forecast errors, highlighting their sensitivity to external shocks. This finding highlights the need for the central bank to maintain proactive and effective communication in periods of high uncertainty in order to mitigate the destabilising effects of such events.

The findings in this study suggest that in emerging economies with developing financial markets, a central bank that is committed to anchoring inflation to its target, invests in clear, high-effort communication and acts cohesively in policy rate decisions can help foster stability in domestic foreign exchange markets. Any persistence and sluggish adjustment of disagreement in exchange rate expectations and forecast errors point to natural frictions in the processing of information.

Disclosure statement

The authors have no conflict of interest to declare.

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APPENDIX

Table A1

Descriptive statistics and correlations among variables

Variables	Mean	Min.	Max.	Std. dev.	Kur	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) $Error_t$	-58.71	-697.40	389.51	171.88	6.02	1								
(2) Dis_Ex_t	2,538.71	1,778.80	3,759.21	636.21	1.65	0.14*	1							
(3) $REPU_t$	0.28	0.00	0.87	0.27	2.05	-0.19**	-0.14*	1						
(4) $Inflesz_t$	57.03	40.03	69.33	5.67	3.68	-0.00	-0.70***	-0.21***	1					
(5) Dis_Junta_t	0.41	0.00	1.00	0.49	1.13	0.05	0.11	-0.23***	0.01	1				
(6) $Frack_t$	0.10	0.00	1.00	0.31	7.84	-0.30***	-0.05	0.29***	0.06	0.02	1			
(7) $dis\_inf^e_t$	4.47	1.80	9.09	1.71	3.39	-0.07	-0.41***	-0.38***	0.40***	0.23***	0.06	1		
(8) Dif_i_t	1.83	0.09	4.60	0.73	4.71	0.13*	-0.16**	-0.33***	0.38***	0.23***	0.21***	0.51***	1	
(9) EPU_t	118.67	47.31	376.84	49.67	9.07	0.33***	0.42***	-0.13*	-0.46***	0.10	-0.01	0.02	-0.02***	1

(***) Denotes significance at 1%, (**) at 5%, and (*) at 10% test level.

Source: Authors' calculations based on data from the Central Bank of Colombia.

Table A2

Unit root and stationarity tests

Variables	ADF				PP				KPSS			
	Lags	Esp.	Test	CV (5%)	Band	Esp.	Test	CV (5%)	Band	Esp.	Test	CV (5%)
$Error_t$	0	C	-3.48	-3.46	4	C	-3.63	-3.46	10	C	0.06	0.73
Dis_Ex_t	0	N	-2.12	-2.57	4	C	-4.03	-3.46	10	C	0.44	0.73
$REPU_t$	0	N	-3.35	-2.57	8	N	-2.42	-1.94	10	C	0.16	0.73
$Inflesz_t$	0	C	-3.74	-3.43	5	C	-2.90	-3.46	10	C,T	0.21	0.14
Dis_Junta_t	0	C	-8.53	-3.46	7	C	-8.97	-3.46	8	C	0.08	0.73
$dis\_inf_t^e$	0	C	-4.39	-3.46	7	C	-4.13	-2.87	10	C	0.48	0.73
Dif_i_t	0	N	-2.52	-1.94	8	C	-2.10	-1.94	9	C	0.07	0.14
EPU_t	0	C	-5.27	-2.87	3	C	-5.05	-2.87	8	C,T	0.10	0.14

CV = critical value. Trend (T), and/or constant (C), or neither trend nor constant (N) are included based on the Schwarz information criterion.

The KPSS test was performed using the Newey-West bandwidth.

Source: Authors' calculations.

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Table A3
Unit root with break test

Series	Specification	Estimated break	t-stat	5%
$Error_t$	Intercept break	Nov. 2014	-4.96	-4.64
Dis_Ex_t	Intercept break	Sep. 2014	-4.62	-4.44

Source: Authors' calculations.

Table A4
Serial correlation and heteroskedasticity tests

Test	Breush-Godfrey LM test		Breush-Pagan-Godfrey test	
	F-stat	P-value	F-stat	P-value
Eq. [5] ARDL-HAC	1.47	0.08	0.96	0.46
Eq. [6] ARDL-HAC	1.72	0.18	5.81	0.00

Source: Authors' calculations.

Currency depreciation and inflationary pressure vis-à-vis monetary intervention: perspectives on growth and policy implications

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Abstract

This study investigates the effects of currency depreciation, inflation, and efforts to offset depreciation through foreign exchange intervention in a sample of ten Sub-Saharan African countries considered to have had the worst performing currencies from 1990 to 2023. Using dynamic ordinary least squares and error correction estimation techniques we show that depreciation and inflation have significant negative effects on growth, which cannot be offset by central bank interventions. Gross fixed investment and trade openness help promote growth. Diagnostic tests indicate that the estimates are reliable. They are also robust to the exclusion of several explanatory variables. We find a bidirectional Granger causality between currency depreciation and growth, and strong predictive capacity of the estimated model. These findings provide support for the view that greater exchange rate flexibility does not help promote exports and growth in economies with pronounced structural weaknesses and inefficient macroeconomic policies.

Keywords: currency depreciation, inflation, foreign exchange intervention, economic growth, exchange rates, developing economies, Sub-Saharan African countries

1 INTRODUCTION

Following economic reforms that resulted in the adoption of more flexible exchange rates, most Sub-Saharan African countries have experienced persistent currency weakness over the past three decades. Central banks often intervened in the foreign exchange market in an effort to contain depreciation pressures. But with low foreign reserve buffers, interventions could at best provide only temporary relief. Sub-Saharan African countries have also experienced pronounced inflation over the past three decades, which interacted with depreciation to dampen economic growth. Failure to contain fiscal spending has likely played a key role in both currency weakness and inflation. By increasing aggregate demand, public spending has led to high imports of goods and services that generated demand for foreign currency and exerted a downward pressure on the domestic currency. High fiscal deficits required additional government borrowing and led to rising public debt, increasing sovereign risk and leading to further downward pressure on the domestic currency (Okot, Kaltenbrunner and Perez, 2022).

The effects of depreciation on growth in developing economies have been analysed extensively in academic and policy discussions. As early as the 1980s, Sub-Saharan countries had accumulated large external debts that they could not service, resulting in their exclusion from international capital markets. The IMF and the World Bank helped restructure that debt, but the crisis resurfaced in the 1990s when greater exchange rate flexibility led to currency crises with undesirable effects on trade and growth (Ojong and Bessong, 2017). One trigger for these crises was exchange rate mismanagement, notably inappropriate foreign currency interventions. This led the IMF and the World Bank to provide guidelines on intervention in foreign exchange markets (Park, 2019). The thinking behind these efforts was that the expected growth benefits of depreciation – stimulating exports, discouraging imports, increasing external competitiveness and thereby promoting growth – could only be realised when exchange rates were well managed. The possibility that depreciation could do little to encourage growth in an environment of structural and institutional rigidities and ineffective macroeconomic policies was not thoroughly considered, however.

To fill that gap, this paper aims to provide more insight on the growth effects of currency depreciation in Sub-Saharan Africa. The novelty of our study is that we consider the growth effects of depreciation together with those of inflation, and try to assess to what extent central bank interventions in the foreign exchange market help offset these effects. The study covers the period from 1990 to 2023 in a sample of ten Sub-Saharan countries listed by the World Bank (2023) as having the worst performing currencies in Africa: Angola, Burundi, Congo DR, Ghana, Kenya, Malawi, Nigeria, Rwanda, Sierra Leone and Zambia. Our main finding is that depreciation and inflation have significant negative growth effects that cannot be offset by central bank interventions, while fixed investment and trade openness help promote growth.

The remainder of the paper is structured in six sections. Section 2 reviews the literature; section 3 describes stylised facts on growth, exchange rates and inflation in Sub-Saharan Africa; section 4 provides background data analysis; section 5 outlines the empirical framework; section 6 presents the estimation results; and section 7 concludes the paper.

2 LITERATURE REVIEW

In neoclassical open economy macro models, domestic currency depreciation usually promotes trade and economic growth by helping switch domestic demand and output from imported to domestic goods (Dornbusch, 1987). The success of depreciation depends on the so-called Marshall-Lerner condition, i.e. the capacity of the domestic economy to produce and meet the additional demand for domestic goods: if the sum of absolute price elasticities of demand for exports and imports exceeds unity, currency depreciation may stimulate output through an initial increase in the price of foreign relative to home goods. This process helps divert spending from imported to domestic goods, thereby encouraging growth.

A related argument is that by increasing the price of traded relative to home goods, domestic currency depreciation helps shift resources into traded goods production. Depreciation thus acts as a subsidy to the traded goods sector (Benigno, Converse and Fornaro, 2015). Rodrik (2008) further argued that weak domestic currencies encourage growth in developing economies by compensating for their institutional weaknesses and market failures, which often lead to underinvestment in the traded goods sector. Depreciation could also facilitate growth by stimulating competition and increasing returns to scale in production, as well as investment and saving, by redistributing income from consumers to financially constrained firms (Di Nino, Eichengreen and Sbracia, 2011; Gluzmann, Levy-Yeyati and Sturzenegger, 2012).

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The structuralist view stressed, by contrast, the contractionary effects of currency depreciation on the economy. This view dates back to the early post-World War II period when Hirschman (1949) and Meade (1951) argued that the Marshall-Lerner condition may not hold in many cases: the price elasticity of exports is often low for structural reasons, so a weaker domestic currency may not stimulate exports much. Similarly, Diaz-Alejandro (1963) argued that even when depreciation does raise the profits of domestic tradable industries, their investment may not rise because they often have a high propensity to save. Bruno (1979) noted that in countries where manufacturing inputs are largely imported, the rise in the costs of production after depreciation may dominate any boost to output from improved export price competitiveness. This view was later reinforced by van Wijnbergen (1989), who advocated a guided exchange rate policy that would prevent depreciation from disrupting the economy.

Empirical studies have found support for both views. Among those that on balance found greater support for the neoclassical view, Rodrik (2008) analysed a small sample of developing countries over 1950-2004 and found evidence that depreciation supported growth in China, India, South Korea, Taiwan, Uganda and Tanzania, while in Mexico the effects were largely contractionary. Habib, Mileva and Stracca (2016) studied a panel of 150 countries over 1970-2010 and found that real depreciation raised GDP growth more significantly in developing countries than advanced economies. Huong (2019) confirmed strong expansionary effects of depreciation on growth through trade and capital investment in Vietnam using advanced econometric techniques. Han (2020) found similar effects via the foreign direct investment channel in a sample of 150 countries over 1997-2017.

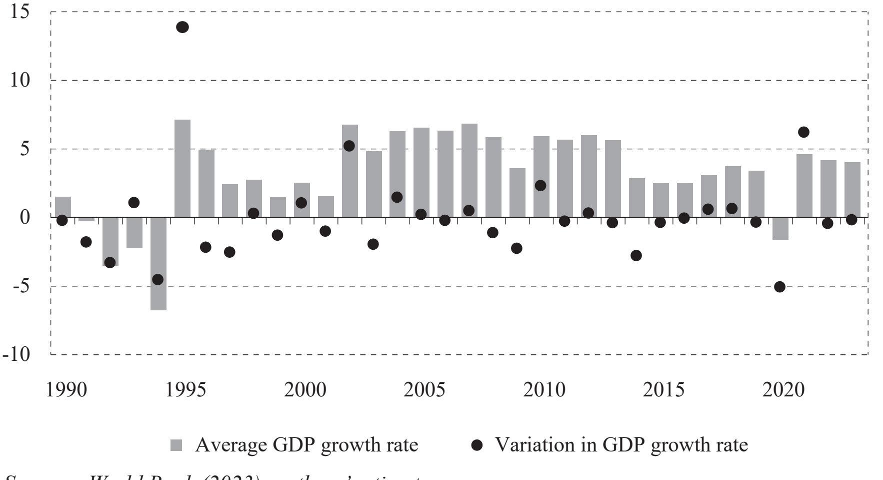
Other studies on balance found greater support for the structuralist view. Bouvet, Bower and Jones (2022) analysed the effects of currency depreciation in francophone West African countries induced by IMF conditionality that exchange rate be allowed to adjust before loans could be granted. They found that only three countries experienced significant GDP growth and could control inflation resulting from depreciation within a one-year period, but the majority of countries experienced no appreciable pickup in growth over 1994-2020. The contractionary effects of depreciation on growth were also reported for Nigeria over 1981-2020 (Dada et al., 2022). Ramoni-Perazzi and Romero (2022) analysed a panel of 194 countries over 1995-2019 and established significant negative effects of currency depreciation on economic growth, attenuated to some extent by central bank interventions in the foreign exchange market. Serena and Sousa (2017) studied the effects with firm-level data, and found that depreciation led to contraction of investment and growth in firms in 36 emerging market economies over 1998-2014; the effect could be attenuated by central bank FX interventions. Lavalliere, Molina and Chaudhary (2023) found similar effects in a sample of small and medium enterprises in Lebanon.

In sum, both neoclassical and structuralist theories assign currency depreciation a prominent role in open economies' growth dynamics, more so in developing than advanced economies. The primary difference is that neoclassical theory focuses on the interplay of market forces that enable depreciation to foster growth, while the structuralist theory emphasises systemic rigidities that impair market forces in developing economies and thereby result in negative effects of depreciation on growth. In the case of Sub-Saharan Africa, where currency depreciation has been persistent, the findings of existing studies on its growth impact have been mixed. Our paper contributes to that literature by looking at the concurrent impact of inflation on growth, and asking to what extent central bank interventions in foreign exchange markets can offset any negative effects of depreciation on growth.

3 STYLISED FACTS

Growth in Sub-Saharan Africa over the 1990-2023 period has been characterised by remarkable fluctuations. The average GDP growth rate declined from 1.5% in 1990 to a low of -6.8% in 1994, only to rise above 7% the following year and decline again to around 2% in the second half of the 1990s (graph 1). From 2002 until 2013 growth averaged over 6% per annum and was fairly stable. From 2014 until 2019, however, the average growth rate halved to around 3%. After a brief recession in 2020 due to the Covid pandemic, the average growth rate stabilised at above 4% per annum. Variations in the annual growth rate were mostly negative, indicating the lack of sustained growth dynamism in this region over the past 34 years. This lack has been explained in most analyses by a combination of internal and external forces: exchange rate instability, rising inflation, monetary and fiscal policy ineffectiveness, persistent weakness in global markets for primary commodity exports, and spillovers from the financial distress in advanced economies.

GRAPH 1
Growth performance of Sub-Saharan African countries, 1990-2023

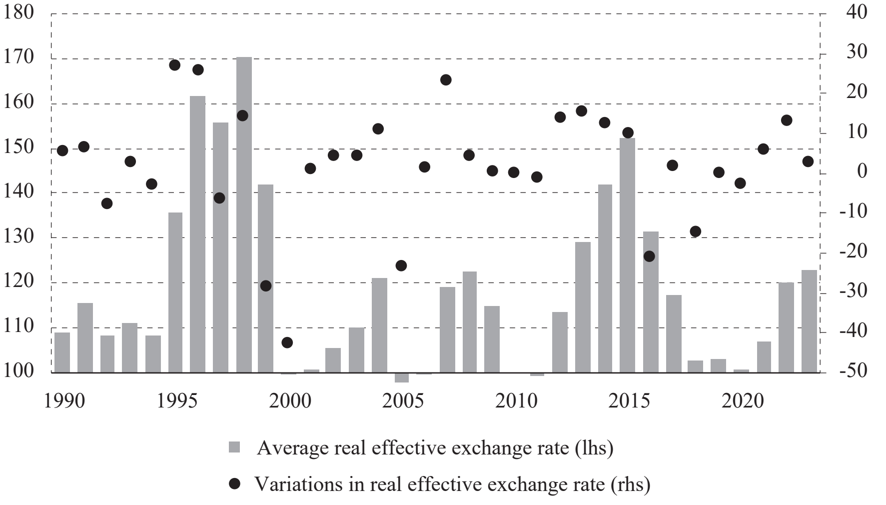


Sources: World Bank (2023); authors' estimates.

Our analysis focuses on the role of persistent currency weakness and high inflation in this disappointing growth performance. Graph 2 shows the average real effective exchange rates of the ten Sub-Saharan countries over 1990-2023; index values above 100 indicate real effective depreciation. The mid-1990s saw a massive real depreciation of nearly 60% between 1994 and 1998. Domestic currency weakness during this period can be largely attributed to the policy shift from fixed to floating exchange rates (IMF, 2023). Depreciation pressures eased in the early 2000s, but resurfaced in 2004 and 2007-9. The mid-2010s saw another bout of real depreciation, cumulating to more than 50% from 2011 to 2015. A measure of stability returned in 2018-21, but rapid depreciation resumed in 2022-23. Currency weakness in this period has been attributed to a combination of factors, including trade imbalances, decline in foreign reserves, inadequate policies and further external reforms (Kemoe, Mama and Mighri, 2023). With few exceptions, annual variations in real effective rates have been mostly positive, confirming the persistent downward pressure on the value of domestic currencies in the region. This has led the IMF and the World Bank, among other institutions, to worry about when the Sub-Saharan countries would finally be able to stabilise their exchange rates (Kubota and Calderson, 2024).

Graph 2

Real effective exchange rates of Sub-Saharan African countries, 1990-2023
2000 = 100

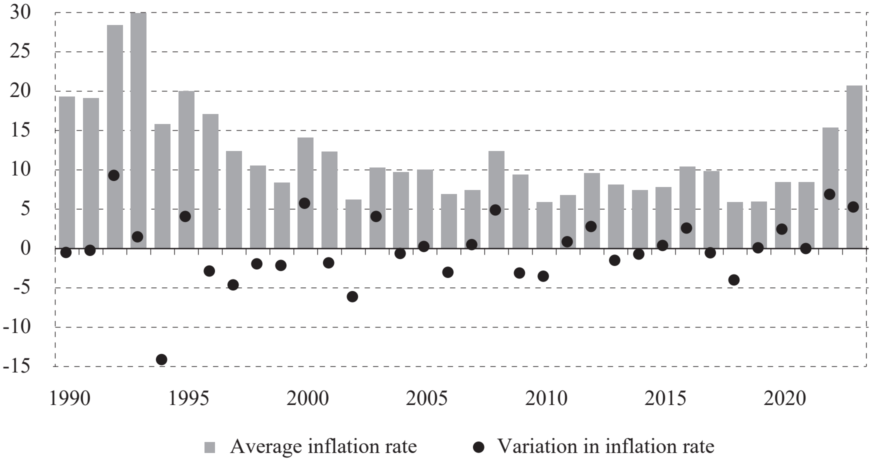


Sources: Federal Reserve Bank of St. Louis (2024); OECD (2023); authors' estimates.

Real depreciation has been accompanied by high inflation, averaging over 20% per year from 1990 to 1996, and about 10% from 1997 to 2021 (graph 3). Like elsewhere around the world, the pandemic led to a surge in inflation in 2022-23. The annual variations show the patchy record of bringing down inflation from the mid-1990s to the early 2020s: many years saw disinflation, but such efforts could not be sustained and average inflation often rebounded in subsequent years. In addition to currency weakness, persistent inflationary pressures have been attributed to supply shocks in agriculture, high production costs, and fiscal expansion (Nguyen et al., 2017).

Graph 3

Inflation rates in Sub-Saharan African countries, 1990-2023



Sources: World Bank (2023); authors' estimates.

4 EMPIRICAL FRAMEWORK

A regression equation of GDP growth as explained by currency depreciation, inflation, central bank FX interventions, and other explanatory variables can be specified as follows:

$$EG_{it} = f[CDP_{it}, INF_{it}, C^{F}_{it} MON_{it}, KAP_{it}, TRD_{it}] \tag{1}$$

$$EG_{it} = \alpha_0 + \sum_{j=1}^{6} \alpha_j X_{it} + \omega_i + \tau_t + \mu_{it} \tag{2}$$

where EG_{it} is the growth rate of GDP in country i in year t; CDP_{it} is the change in the real effective exchange rate (an increase indicates depreciation); INF_{it} is the rate of inflation; C^{F}_{it} is an interaction term between depreciation and inflation rates; MON_{it} is the size of central bank FX interventions (central bank gross sales of foreign currencies in the interbank FX market as a share of official foreign reserves); KAP_{it} is gross fixed capital formation as a share of GDP; TRD_{it} is a measure of trade openness (exports plus imports as a share of GDP); and X_{it} in equation (2) is a vector of the five exogenous variables. ω_i, τ_t, and μ_{it} are vectors of country fixed effects, time fixed effects, and random error terms, respectively. The signs of coefficients α_j that need to be estimated are *a priori* uncertain.

The data sample consists of annual observations for the ten Sub-Saharan African countries noted above over the period 1990-2023. Data sources for the variables are the World Bank's *Open Database* (GDP growth and inflation), *World Development Indicators* (gross fixed capital formation and trade openness), St. Louis Federal Reserve Bank's *FED statistics* and OECD Statistics (for real effective exchange rates), and central bank and national statistical databases (for central bank foreign exchange sales and foreign reserves). Foreign exchange sales are calculated from the annual data series on central bank weekly interventions via auctions and direct sales in individual countries' interbank markets.

Equation (2) can be transformed into a dynamic ordinary least squares (DOLS) model:

$$EG_{it} = \partial_0 + \sum_{j=1}^{6} \partial_j X_{it} + \Delta \sum_{j=1}^{6} \sum_{k=(-1,+1)}^{6} \pi_j X_{it-k} + \omega_i + \tau_t + \mu_{it} \tag{3}$$

where Δ is the first difference operator, and ∂_j are long-run coefficients of exogenous variables that need to be estimated. First differences are included to control for time-invariant, country-specific factors. The leads and lags are introduced to address potential issues with autocorrelation and endogeneity of variables.

Equation (3) describes a long-run equilibrium relationship between economic growth and the set of selected explanatory variables. It is a specification dating back to Stock and Watson (1993) that is commonly used to analyse long-run relationships between endogenous and exogenous variables. We complement it with an error-correction model that describes short-run growth adjustment to shocks in explanatory variables:

$$EG_{it} = \beta_0 + \sum_{j=1}^{6} \beta_j Z_{it-1} + \omega_i + \tau_t + \mu_{it} \tag{4}$$

$$\Delta EG_{it} = \beta_0 + \sum_{j=1}^{6} \beta_j Z_{it-1} + \Delta \sum_{j=7}^{12} \beta_j Z_{it-1} + \theta EC_{it-1} + \tau_t + \mu_{it} \tag{5}$$

where Z_{it} is a vector of lagged exogenous variables with coefficients β_j (j = 1,…,6); Z_{it-1} is a vector of lagged exogenous variables in first differences with coefficients β_j (j = 7,…,12), and EC_{it} is an error-correction term with adjustment coefficient θ.

We perform standard preliminary tests to check that all variables in the model are stationary and co-integrated. The stationary tests are complemented with three unit-root tests: the Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), and Hadri (HD) tests. Co-integration between variables is assessed using Pedroni, Kao, and Westerlund tests as applied for instance in Andrei, Mieila and Panait (2017) and Taghizadeh-Hesary et al. (2019). Structural stability of the model is tested by employing the maximum likelihood technique proposed by Yu, Jong and Lee (2008), followed by a test of prediction capacity using the procedure adopted by Kuo (2016).

5 PRELIMINARY ASSESSMENT OF VARIABLES

5.1 DESCRIPTIVE STATISTICS

The average annual growth rate for the ten countries in the sample over 1990-2023 was a moderate 3.3%, with a minimum of -6.4% and a maximum of 7.8%. The high standard deviation and kurtosis indicate significant fluctuations in growth rates across countries and over time. The average real effective exchange rate index indicates significant real depreciation of nearly 12% per year.[1] It fluctuated between 1% and 77% relative to the base year (2010 = 100), which highlights pronounced currency instability. The average inflation rate was also very high, 13% per annum, ranging from 5.5% to over 31%. Central banks sold on average close to 23% of their reserves in the FX market each year to limit the weakening of domestic currency. The size of FX interventions was relatively stable across the sample. Gross fixed investment averaged 18% of GDP per annum and was also stable. Sub-Saharan African countries are quite open, with an average share of exports and imports in GDP of 62%. This points to a relatively high potential to generate foreign currency, which unfortunately has yet to realise, hence domestic currencies remain weak.

Table 1

Descriptive statistics[1]

Variable	Mean	Median	Max	Min	Std. dev.	Skewness	Kurtosis
Real GDP growth[2]	3.3	6.7	7.8	-6.6	5.8	-1.60	3.36
REER index[2]	111.5	126.2	176.9	101.2	19.7	0.92	4.07
Inflation rate[2]	13.1	7.2	31.3	5.5	6.2	2.40	3.93
Central bank FX sales[3]	22.8	16.1	41.4	14.7	3.1	0.83	2.52
Gross investment[4]	17.9	14.7	21.6	12.1	2.9	0.96	2.96
Trade openness[4]	62.3	29.7	71.2	27.2	17.6	1.21	3.62

[1]The sample includes 340 annual observations for ten Sub-Saharan countries over 1990-2023. [2]2010 = 100. [3]In percent of total international reserves of central bank. [4]In percent of GDP.

Source: Authors' calculations.

5.2 PANEL UNIT ROOT AND COINTEGRATION TESTS

The panel unit root tests indicated that economic growth and gross investment were stationary in levels, and all other variables were stationary in first differences (table 2). By rejecting the null hypothesis that the variables are non-stationary, the tests suggest that the six model variables are suitable for DOLS and ECM estimation.

The Pedroni, Kao and Westerlund panel cointegration tests further confirmed that the model variables were co-integrated, i.e. they tend to converge to their long-run equilibrium values after being temporarily disturbed by exogenous shocks. The test statistics shown in table 2 are all estimated to be statistically significant at the 5% level. This indicates that the panel ECM can be used to estimate the dynamic relationship between growth and the selected five explanatory variables.

[1] Averages for the REER index and inflation in table 1 are slightly different from those shown in graphs 2 and 3 because the former were calculated for all 340 observations, while the latter were, for easier interpretation of regional trends, first averaged over individual countries and then over all the ten countries for a given year.

Table 2
Panel unit root and cointegration test

	Panel unit root test					
Variable	Level			First difference		
	LLC	IPS	HD	LLC	IPS	HD
EG	3.02*	2.97*	0.99*	–	–	–
CDP	0.96	1.12	2.85	2.93*	2.99*	1.01*
INF	1.02	0.86	2.76	2.89*	3.04*	0.97*
MON	0.88	1.01	3.13	3.33*	3.10*	0.89*
KAP	2.99*	2.55*	1.06*	–	–	–
TRD	0.98	1.03	3.10	3.02*	2.91*	104*

	Panel cointegration test							
Test	Statistic							
	Var	Rho	PP	ADF	Gt	Ga	Pt	Pa
Pedroni	-7.05*	-6.23*	-8.08*	-5.54*	–	–	–	–
Kao	-5.48*	-4.96*	-9.31*	-6.03*	–	–	–	–
Westerlund	–	–	–	–	-11.07*	-5.97*	-7.99*	5.91*

* *Variable is stationary.*

Note: The sample includes 340 annual observations for ten Sub-Saharan African countries over 1990-2023. LLC = Levin-Lin-Chu test; IPS = Im-Pesaran-Shin test; HD = Hadri test. For LLC and IPS tests, larger statistics indicate more stationary variables. In HD test, smaller statistics indicate more stationary variables. Var = cointegration rank statistic; Rho = stationarity statistic; PP = Phillips-Perron test statistic for co-integration; ADF = Augmented Dickey Fuller test statistic for co-integration; Gt and Ga = Westerlund test statistics for cointegration; Pt and Pa = Westerlund test statistics for adjustment speed in cointegration.

Source: Authors' calculations.

6 ESTIMATION RESULTS

6.1 DYNAMIC ORDINARY LEAST SQUARES (DOLS) ESTIMATION

Estimates of the DOLS model after controlling for country and time specific effects are shown in table 3. The estimation was done by entering the indices of variables in log form. Currency depreciation had a statistically significant negative impact on growth. The estimated coefficient suggests that a 1% real depreciation, other things being equal, depressed GDP growth rate on average by 0.61%. In other words, the average annual growth rate in the sample would have been 5.4% instead of 4.2%, other things being equal, if domestic currencies in Sub-Saharan Africa had been stable instead of depreciating. Inflation also had a significant negative impact on growth: a 1% higher inflation depressed the real GDP growth rate of the countries in the sample by 0.52%. The average annual growth rate would thus have been 6.3%, other things equal, if domestic prices had been stable. The interaction between currency depreciation and inflation compounded these effects – the two variables had appreciable negative synergistic effects on growth.

Table 3
DOLS long-run estimation results
Endogenous variable: Real GDP growth (EG)

Exogenous variables	**Coefficient**	**SEE**	**t-statistic**	**Prob.**
Intercept	2.43**	0.266	9.14	0.001
REER change (CDP)	-0.61*	0.158	-3.84	0.011
Inflation rate (INF)	-0.52*	0.228	-2.28	0.014
REER and inflation interaction (C^F)	-0.74**	0.106	6.97	0.003
Cent.bk FX sales (MON)	0.32	0.233	1.37	0.142
Gross investment (KAP)	0.66*	0.166	3.96	0.009
Trade openness (TRD)	0.51*	0.225	2.26	0.011
ΔCDP_{-1}	-0.55*	0.228	2.41	0.014
ΔINF_{-1}	-0.46*	0.234	-1.96	0.027
ΔC^F_{-1}	-0.67*	0.167	-3.99	0.008
ΔMON_{-1}	0.37	0.263	1.39	0.122
ΔKAP_{-1}	0.58*	0.195	2.97	0.019
ΔTRD_{-1}	0.22	0.209	1.05	0.184
ΔCDP_{+1}	-0.51*	0.227	-2.22	0.017
ΔINF_{+1}	-0.49*	0.246	-1.99	0.021
ΔC^F_{+1}	-0.53*	0.235	-2.25	0.012
ΔMON_{+1}	0.39	0.274	1.42	0.129
ΔKAP_{+1}	0.50	0.420	1.19	0.151
ΔTRD_{+1}	0.26	0.234	1.11	0.163
Adjusted R^2 = 0.88; F-statistic = 14.26; Durbin's h = -1.96; log likelihood = 57.81				

Phillips-Perron unit root test on DOLS residuals		
Residual series	**Drift**	**Drift with trend**
Level	-5.04	-6.13
First difference	-9.86	-11.02
Critical value = -7.96		

** Significant at 5% level, **significant at 1% level.*
The sample includes 340 annual observations for ten Sub-Saharan African countries over 1990-2023.
Source: Authors' estimates.

Central bank interventions in the foreign exchange market had positive but statistically insignificant effects on growth, which suggests that they could not effectively contain the negative growth effects of depreciation and inflation.

Gross fixed capital formation and trade openness were positively correlated with growth, helping to offset partly the adverse effects of depreciation and inflation. The estimated coefficients suggest that a 1% rise in capital formation and trade openness were associated with 0.66% and 0.51% higher growth rates, respectively, thus providing cushioning effects against the adverse effects of depreciation and inflation on growth.

Durbin's h and log-likelihood statistics indicate minimal serial correlation, and thus suggest that estimates are reliable and highly unlikely to be spurious. The Phillips-Perron test of residuals further confirms that all variables have a unit root. The drift statistics are statistically insignificant in levels but significant in first differences, so the null hypothesis of non-stationary residuals can be rejected.

6.2 ERROR-CORRECTION MODEL (ECM) ESTIMATION

Table 4 reports coefficient estimates from the error-correction model. The long-run coefficients on currency depreciation (CDP_{-1}), inflation (INF_{-1}), and their interaction are all negative and statistically significant at the 5% level or higher. They are slightly larger in size than the DOLS estimates, confirming the strong negative effect of unstable exchange rates and high inflation on growth. The estimated coefficient on central bank FX interventions is positive and statistically insignificant, suggesting that they were ineffective in offsetting the negative growth effects of currency depreciation and inflation. Coefficient estimates on gross investment and trade openness are positive, statistically significant, and similar in size to those obtained from the DOLS estimates. Reflecting high year-to-year volatility of growth, the estimated long-run coefficient on lagged growth is not statistically significant.

Among the short-run coefficient estimates, only those on currency depreciation (ΔCDP_{-1}) and its interaction with inflation (ΔC^{F}_{-1}) are significant, with the expected negative sign. The error-correction term (EC_{-1}) is likewise negative and statistically insignificant, suggesting that adjustment to the long-run steady state after a temporary disturbance is relatively slow.

The regression diagnostics indicate a robust goodness of fit (the Pearson statistic is significant at the 5% level), reliable and consistent estimates (the Sargan AR(1) and AR(2) statistics fall within the critical range of p-values), and optimality of the one-lag structure (based on the Akaike criterion).

Long run coefficient estimates can be useful for policy analysis if they are structurally stable. To check this property, we split the sample into two sub-periods using the structural break test of Yu et al. (2008). The test identified a break in 2007, a year before the onset of the Global Financial Crisis (GFC), which led to economic downturn in most African countries. However, the test statistics (structural break parameter rho, normalised bias statistic, standard deviation, and root mean square error) indicated insignificant variation between the two subperiods. In addition, maximum likelihood estimates of coefficients in the DOLS specification were not statistically significant for either the entire period or the pre- and post-GFC subperiods. The long-run estimates in table 3 can thus be considered suitable for policy analysis.

Table 4
ECM estimation results
Endogenous variable: ΔEG

Exogenous variables	Coefficient	SEE	t-statistic	Prob.
Intercept	2.74**	0.25	10.96	0.001
CDP_{-1}	-0.64*	0.17	-3.69	0.010
INF_{-1}	-0.56*	0.21	-2.59	0.021
C^F_{-1}	-0.79**	0.11	-7.17	0.008
MON_{-1}	0.28	0.27	1.01	0.119
KAP_{-1}	0.62*	0.17	3.63	0.012
TRD_{-1}	0.53*	0.23	2.29	0.013
EG_{-1}	0.33	0.25	1.28	0.094
ΔCDP_{-1}	-0.57*	0.21	-2.62	0.020
ΔINF_{-1}	-0.39	0.28	-1.37	0.073
ΔC^F_{-1}	-0.55*	0.22	-2.51	0.023
ΔMON_{-1}	0.14	0.19	0.73	0.116
ΔKAP_{-1}	0.28	0.24	1.16	0.102
ΔTRD_{-1}	0.17	0.19	0.86	0.139
ΔEG_{-1}	0.22	0.23	0.97	0.131
EC_{-1}	-0.29	0.24	-1.21	0.097
Pearson test = 2.08*, Sargan test = 4.97, AR(1) correlation test = 2.02, AR(2) correlation test = 1.99, Akaike criterion = 12.03				

*Note: * significant at 5 percent, **significant at 1 percent.*

Source: Authors' estimates.

We further tested the predictive capacity of the DOLS model by estimating it for the first subperiod and validating it for the second. Specifically, we evaluated the prediction errors in the two subperiods: for the prediction capacity to be considered strong, prediction errors in the two sub-periods should be negligible (Kuo, 2016). The values of prediction errors are reported in table 5: they are all negligible and less than unity, which suggests that the model possesses strong prediction capacity and can be relied upon to forecast growth in this sample of countries.

Table 5
Prediction errors

Measures of prediction error	Subperiod 1 (1990-2007)	Subperiod 2 (2008-2023)
MAE	0.122	0.129
MAPE	0.799	0.901
RMSE	0.130	0.126
Theil-T	0.007	0.008

Note: The test is based on the dynamic ordinary least squares (DOLS) model.

MAE = mean absolute error; MAPE = mean absolute prediction error; RMSE = root mean square error; Theil-T = Theil's coefficient of inequality.

Source: Authors' estimates.

6.3 ROBUSTNESS CHECKS AND CAUSALITY ANALYSIS

We checked the robustness of estimates in tables 3 and 4 by excluding some explanatory variables, following Matemilola, Bany-Ariffin and Azman-Saini (2012). In the DOLS model, we excluded the interaction term between currency depreciation and inflation and obtained the same pattern of coefficient signs and statistical significance as in table 3. In the ECM model, we excluded gross investment and trade openness, and likewise obtained the same pattern of coefficient signs and statistical significance, as well as parameter estimates of similar size, as in table 4.[2]

To further assess the direction of association between economic growth and exogenous variables, we conducted pairwise causality test. Table 5 reports the results of tests for bidirectional and unidirectional causalities. The F-statistics for the first pair of variables suggest a bidirectional causality between economic growth and currency depreciation, with depreciation having a somewhat stronger impact on growth than the other way around. The F-statistics for the second pair of variables suggest a unidirectional and significantly larger causality between inflation and growth than the other way around. There is also a unidirectional relationship between economic growth and central bank FX interventions, gross investment and economic growth, while bidirectional relationship exists between growth and trade openness. These results are not surprising. One would not expect the FX interventions to have a lasting impact on growth, but stronger growth on the other hand helps replenish foreign reserves and central bank's intervention capacity. Similarly, investment is expected to lead to higher growth, but not necessarily vice versa. The bidirectional causality between growth and trade openness largely conforms to economic intuition.

Table 6

Pairwise Granger causality tests

Direction of causality	F-statistic	Prob.	Causality status
CDP → EG	9.21	0.0002	Bidirectional
EG → CDP	8.70	0.0004	
INF → EG	8.11	0.0005	Unidirectional
EG → INF	1.39	0.2940	
MON → EG	2.91	0.1020	Unidirectional
EG → MON	7.88	0.0012	
KAP → EG	9.03	0.0003	Unidirectional
EG → KAP	2.31	0.1140	
TRD → EG	9.50	0.0002	Bidirectional
EG → TRD	7.07	0.0016	

Source: Authors' estimates.

The negative effects of currency depreciation on growth in this study are different from those obtained by Rodrik (2008), Habib, Mileva and Stracca (2016), Huong

[2] Details of these robustness checks are available from the authors upon request.

(2019), and Han (2020), who found depreciation to have a positive effect on growth in the long run. We also show that the negative effects hold even if the central bank intervenes to limit rising exchange rate, a structuralist policy channel that was not considered in the past studies of Serena and Sousa (2017), Dada et al. (2022), and Ramoni-Perazzi and Romero (2022), although they also found negative effect of depreciation on growth. The high adjusted R^2 indicates that even with this limited set of exogenous variables the model could account for 88 percent of the large variation in Sub-Saharan countries' economic growth.

7 CONCLUSION

This study has shown that the Sub-Saharan African countries have been unable to benefit from the improved price competitiveness of their exports that greater exchange rate flexibility was expected to generate. The reasons may include inelastic supply, high import dependency of exports, shocks in global demand for primary exports, high cost of capital, weak fixed investment (Kandil and Mirzaie, 2003), as well as the general failure to control inflation (Bandaogo, 2021). The adverse effect of depreciation supports the structuralist view of exchange rate flexibility (van Wijnbergen, 1989), and suggests that economies in Sub-Saharan Africa remain burdened by pronounced structural rigidities and market imperfections that prevent depreciation from fostering trade and growth.

Central bank intervention in foreign exchange markets could not ameliorate the negative effects of depreciation and inflation on growth. This may partly reflect limited reserves at the disposal of the central bank, and partly the limitations of intervention to offset currency weakness in economies with weak fundamentals. That said, the perceived inability of central banks in African countries adequately to deploy monetary policy measures to manage depreciation and inflation, which has raised concerns in the IMF and the World Bank, has played a role as well.

A key policy implication of these findings is the need for structural reforms to enable the Sub-Saharan economies to exploit their potential by raising exports and reducing imports on a sustained basis. Strong positive growth effects of gross fixed investment and trade openness confirm the need for such a policy orientation. A more restrained fiscal policy would certainly contribute to these efforts as well, by reducing domestic and import demand pressures and pressures on public debt financing, as well as by releasing resources for fixed investment. Likewise, a more effective monetary policy would help reduce inflation and improve domestic price competitiveness.

Disclosure statement

The authors have no conflict of interest to declare.

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Our Dollar, Your Problem

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In his newest book, the renowned economist Kenneth Rogoff reflects on the causes and effects of the global dominance of the US dollar and discusses whether the dollar's privileged status could be challenged in the future. The author is the IMF's former chief economist and a leading scholar in the field of international economics, who has published several seminal articles on dollarisation, exchange rates regimes, debt and currency crises.

The topic of the book is highly relevant in the current environment characterised by elevated uncertainty, fading globalisation and rising fragmentation. These trends could have a negative impact on the international role of the dollar and thereby reduce the economic benefits that the United States enjoys as its issuer. Some major economies from the opposite geopolitical bloc have already taken steps to reduce their reliance on the US dollar, notably by replacing the dollar as the invoicing currency in their bilateral trade.

The book is composed of an introduction and six parts, each containing several chapters.

In the introduction the author presents the historical and economic factors that have contributed to the US dollar's key role in the global economy. Rogoff reminds readers that the United States emerged from World War II as the only economic superpower, as other major economies had suffered severe devastation during the war. This gave US officials significant leverage in negotiations about the post-war international monetary system.

At the conference held in Bretton Woods in 1944 it was agreed that the US dollar would be the anchor currency of the international monetary system: its value would be pegged to gold, while other countries would be obliged to maintain fixed parities of their currencies against the dollar. Rogoff points out that such a system was advantageous for the United States, as it kept full autonomy in the conduct of monetary policy, unlike all other countries which were constrained by the need to maintain their dollar parities. In addition, demand for US Treasury debt was strong under this framework because other countries had to hold sufficient dollar assets to be able to conduct foreign exchange interventions if needed.

The monetary system established in Bretton Woods operated smoothly for almost three decades, but it eventually collapsed as overly expansionary economic policy in the United States undermined the confidence in the convertibility of the dollar into gold. Despite the collapse of the dollar-based monetary system in the early 1970s, the dollar has remained at the centre of the global economy, with many central banks keeping their currencies stable against the dollar.

Rogoff provides several strong economic reasons why the dollar significantly outperforms all other major currencies. The global dominance of the dollar reflects in particular the size of the US economy and the depth and liquidity of its financial

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markets. While the United States accounts for a smaller share of global output today than it did in the past, it is still the largest economy in the world. Moreover, the United States is home to the largest market of safe assets in the world. Rogoff explains why the US Treasury securities are considered the safest and most liquid sovereign assets, which makes them not only a key part of central banks' foreign exchange reserves, but also a core component of safe assets for financial institutions around the world.

In Part I, entitled "Past challengers to dollar dominance", Rogoff explores the economic performance of the United States' main global competitors in the decades after World War II. The discussion focuses on the Soviet Union, Japan and the euro area. In the 1950s and 1960s, the Soviet Union was a real threat for the United States, not only militarily, but also economically. In that period of massive investment in infrastructure and military equipment, the centrally planned Soviet economy was able to compete very well in growth terms with the market-based US economy. Its growth rates were so impressive that many prominent economists predicted at that time that the Soviet Union would fully catch up with the United States. However, by the early 1970s, productivity gains from massive public investment had waned and the Soviet Union started to fall behind the United States.

Japan emerged as a major global contender somewhat later, in the late 1970s and the 1980s. Rogoff notes that, unlike the Soviet Union, Japan grew rapidly based on its highly advanced manufacturing sector. Strong competitive pressure from Japan gradually began to inflict serious harm on the US automotive industry and the consumer electronics sector. This prompted US officials to explore options to curb the inflow of highly competitive Japanese products. These efforts eventually led to the Plaza Accord of 1985, under which Japan agreed to revalue its currency significantly to help the US reduce its large current account deficit. The strong appreciation of the yen after 1985 turned out detrimental to the Japanese economy, as it triggered a chain of events that led to the boom and subsequently collapse of the real estate sector, a banking crisis, and a prolonged period of stagnation. Rogoff observes that the yen has never really challenged the US dollar on the global stage. While it is considered a safe currency, it does not play a major role in international trade and finance. No country in the world maintains stability by pegging its currency to the yen.

The euro is a much stronger global competitor to the dollar than the yen. It accounts for about 20% of global foreign exchange reserves, second only to the US dollar with its 58% share. The third and fourth most important currencies, the yen and pound sterling, account for only 6 and 5% of total global reserves, respectively. The euro is also a major invoicing currency because the vast majority of intra-EU trade is conducted in euros. However, compared with the US dollar, the euro appears to be primarily a regional currency. It is not regularly used for settling trade transactions between non-EU countries and very few countries outside Europe peg their currencies to the euro. Rogoff argues that one of the obstacles preventing the euro from challenging the dollar more seriously on the international scale is the fragmented nature of the euro area's financial markets. Achieving further integration in the banking sector, including a common deposit insurance scheme, and establishing a capital market union would be essential to strengthen the euro's global reach.

When comparing the share of the US dollar in total global reserves with the shares of the euro and other major currencies, Rogoff focuses on the most recent data and does not take into consideration the important changes observed over time, which are well documented in the ECB's report on the international role of the euro (ECB, 2025). Importantly, the report shows that the share of the US dollar declined by more than 10 percentage points in the last decade, while the euro's share remained almost unchanged. The same report also shows that non-traditional reserve currencies, such as the Canadian dollar, the Australian dollar and the Korean won, have seen their cumulative shares increase noticeably since the pandemic.

Part II, "China: the present-day challenger", examines China's recent economic performance and the potential impact of efforts taken by its authorities to decouple from the US dollar. Rogoff acknowledges the success that China's economy has achieved in the last four decades, but doubts it can sustain high growth rates and surpass the United States in terms of per capita GDP. Rogoff is one of the first well-known researchers to have recognised that China's export- and infrastructure investment-led growth model has been largely exhausted. After decades in which it has expanded export-oriented manufacturing and invested heavily in public infrastructure and private housing, there are clear signs of overcapacity in these sectors. In addition, China already holds a significant share of world exports, so a further expansion of its export-oriented industries would be difficult even in the absence of the high tariffs recently imposed by the United States and the EU on some of its most competitive export products.

Despite China's large size and global influence, the renminbi lags significantly behind the dollar and the euro according to all major metrics. China has made efforts to promote the use of the renminbi as an invoicing currency in trade with its Asian partners. However, the renminbi is rarely a part of central banks' foreign exchange reserves. This reflects the restrictions on foreign participation in China's debt markets and the insufficient depth and liquidity of these markets. Rogoff does not mention other factors highlighted in the ECB (2025) report that have negatively affected central banks' demand for the renminbi in recent years – geopolitical concerns, transparency issues, and weaker growth outlook. Rogoff argues that the renminbi's prospects as a reserve currency crucially depend on whether steps are taken to make its debt markets more open and liquid. However, if China decided to switch to a more flexible exchange rate, this could indirectly weaken the dollar's global role, as China's trading partners in Asia might loosen their ties to the dollar and focus on the renminbi exchange rate instead.

In Part III, "Everyone else's problem: living with the dollar", Rogoff provides an overview of several past episodes of currency crises to illustrate how difficult it can be to maintain financial stability in a global economy dominated by the US dollar. He shows that dealing with dollar dominance is particularly challenging for countries that peg their currencies to the dollar. Adopting a fixed exchange rate regime can bring significant benefits to countries suffering from persistently high inflation and low institutional credibility. But such a regime also makes the economy more exposed to external shocks and currency speculation, especially if its capital account is fully liberalised.

Rogoff points out that the Federal Reserve runs its monetary policy to fulfil its dual mandate of full employment and price stability in the US economy, and that it is typically not concerned with possible spillover effects of its policy on other countries. The exposure to US monetary shocks can therefore be a major challenge for policymakers in other countries, especially in times of sudden shifts in the Fed's policy stance. Rogoff refers here to an influential strand of the literature suggesting that, regardless of exchange rate regime, countries would be well advised to deploy macro-prudential measures to insulate their economy from the global financial cycle emanating from the United States. The Fed is willing to consider explicitly the spillovers of its policy actions on other countries only in times of global financial turmoil. During the last two major crises – the Global Financial Crisis of 2008-09 and the Covid pandemic of 2020-22 – the Fed injected a substantial amount of dollar liquidity into global markets through its swap lines with other central banks. This helped restore stability in dollar funding markets, preventing a further deepening of the crisis that would have affected the United States as well.

Part IV, entitled "Alternative currencies", examines whether cryptocurrencies such as bitcoin and central bank digital currencies (CBDCs) developed by other major economies pose a threat to the US dollar's dominance. Rogoff argues that despite the advanced technology involved, cryptocurrencies are not capable of outcompeting the US dollar, at least not as a means of payment in the official economy. He notes that, throughout history, government-backed currencies have always prevailed over private sector monetary inventions. The reason is that only the government has the power to regulate the use of means of payment, and this power is exercised every time the official currency and the financial system are at risk. While being sceptical about the ability cryptocurrencies to overtake the US dollar, Rogoff stresses that some of them, notably bitcoin, have a fundamental value due to their widespread use in the underground economy. In that regard, he disagrees with some prominent economists who claim that bitcoin is essentially worthless and merely a vehicle for speculation. Rogoff argues that a more material threat to the dollar's central global role could come from government-backed CBDCs. The reason is that the United States lags significantly in this area, and other countries could use their advantage in developing CBDCs to increase the global reach of their currencies at the expense of the dollar. While the digital euro and the digital renminbi are in an intermediate or advanced stage of development, the Fed only recently started exploring the possible effects of introducing its own retail CBDC.

Part V, "The perks and burdens of being the dominant currency", discusses in detail the effects of the dollar's global status on the US economy. Rogoff emphasises that being the issuer of the key global reserve currency is very beneficial to the United States. Given that US Treasury securities are considered the safest and most liquid debt instruments in the world, there is an underlying strong demand for these securities from foreign central banks, sovereign wealth funds, and private investors around the world. US Treasury securities are also widely used as collateral in global financial transactions, which makes them even more attractive to investors. This enables the US government to borrow on very favourable terms, including during severe global crises. The capacity of the US government to provide stimulus during crises is thereby greater than that of other sovereign issuers.

Rogoff considers the costs of being the issuer of the dominant currency lower today than in the first decades after World War II, when the Bretton Woods monetary system was in place. That system depended crucially on the United States pursuing responsible economic policies, with low inflation and healthy public and external balances. Otherwise, confidence in the US dollar and the entire system would have deteriorated, prompting other countries to demand the conversion of their dollar reserves into gold – which France, for example, regularly practiced. In today's monetary system, such a scenario is not possible, but a destabilising run on the US dollar could still occur, particularly if China suddenly decided to reduce its large holdings of US Treasury securities.

Part VI, "Peak dollar dominance", concludes with reflections on current US policy issues that could negatively affect the dollar's global role. One of these is the threat to the Fed's independence, stemming from political pressure on the Fed to put more weight on objectives other than price stability. Rogoff argues that these pressures cannot be resisted forever, and that over time they could impair the Fed's ability to deliver on price stability, which is crucial for the US dollar's global reputation.

Another major domestic issue potentially undermining the credibility of the dollar is the rapidly rising US public debt. In recent decades, both political parties in the United States have been prone to running large fiscal deficits, in line with the widely accepted view that, as the largest advanced economy, the United States did not have to worry about the level of its public debt, particularly in times of very low interest rates. Rogoff argues that such a view is wrong, not least because persistently low interest rates seen after the Global Financial Crisis will not be seen again anytime soon. Irresponsible fiscal policy, if left unaddressed, can damage the reputation of the United States in financial markets and result in a much higher inflation risk premium than is currently the case. It is worth noting that, after the book was published, the new US administration implemented a major tax reform providing substantial tax relief, without corresponding spending cuts to offset the impact on the budget. The outlook for the US public debt has deteriorated significantly as a result.

Taking into account these domestic vulnerabilities, but also efforts taken by competitors to promote the use of their own currencies, Rogoff concludes that dollar dominance has probably reached its peak and could decline in the future. That said, the transition to a more decentralised global monetary system is likely to be gradual and orderly.

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