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Nowcasting GDP Growth for Kenya

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Antonio Spilimbergo

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Nowcasting GDP Growth for Kenya
Prepared by Nikolay Danov, Domenico Giannone, Alain Kabundi, Cedric Okou, and Antonio Spilimbergo*

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Nowcasting GDP Growth for Kenya*

Nikolay Danov Domenico Giannone Alain Kabundi Cedric Okou
Antonio Spilimbergo

February 14, 2026

Abstract

This paper develops a nowcasting model to produce timely estimates of quarterly GDP growth for Kenya. Nowcasting combines official monthly indicators with digital transaction data. Exploiting strong co-movement of macroeconomic time series, a few latent factors summarize aggregate dynamics and enhance forecasts. The model is updated with each data release, decomposing revisions into predictable and news components. Results demonstrate robust performance of the nowcasting model in data-constrained environments and show that nowcasting is applicable to low-income countries.

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1 Introduction

Monitoring a country’s current economic performance is challenging because comprehensive indicators, such as GDP, are released infrequently and with significant delay. This challenge is particularly severe in low-income countries (LICs), where GDP is often available only at annual frequency and published several months after the end of the year. As a result, policymakers must rely on outdated information, sometimes more than a year old, to assess recent economic developments. In many LICs, quarterly GDP data are not available at all, further complicating efforts to monitor short-term fluctuations and respond to shocks in a timely manner.

Kenya stands out among LICs for the relatively high quality of its macroeconomic statistics, having published quarterly GDP since 2009. However, the publication delay remains substantial: GDP is released more than three months after the end of the quarter, hindering the implementation of timely stabilization measures and the design of growth-friendly development policies. This delay is longer than in major emerging markets such as Brazil and India, where GDP is typically published within two months, and significantly longer than in advanced economies (AEs) such as the United States or the Euro Area, where the lag is about one month.

To address this challenge, nowcasting uses higher-frequency and more timely data to predict economic conditions in real time (Giannone et al., 2008). While this approach has been widely adopted in advanced and large emerging economies, little effort has been devoted to LICs—despite a greater need for timely assessment of economic activity due to data scarcity and even longer reporting lags.

In this paper, we develop a dynamic factor nowcasting model for Kenya, leveraging official data, including monthly traditional indicators and non-traditional data such as digital payments to produce real-time estimates of quarterly GDP growth. The model exploits the fact that business cycle fluctuations exhibit strong comovement across sectors and indicators, allowing a small number of latent factors to summarize the information contained in a broad set of time series (for recent surveys, see Stock and Watson, 2016; Luciani, 2017; Doz and Fuleky, 2020). We model jointly all macroeconomic indicators, including GDP, using a dynamic factor model. Inference is conducted using Kalman filtering techniques and quasi-maximum likelihood, following Doz et al. (2012), Bańbura and Modugno (2014), and Barigozzi and Luciani (2024). Predictions are continuously updated in real time as new macroeconomic indicators are released. The model decomposes each data release into a predictable component and a *news* (unpredictable) component. The latter is linked to the revision in the nowcast, offering a transparent

interpretation of how incoming information drives forecast updates.

Our main finding is that our fully automated framework produces predictions that are competitive with those generated by institutions such as the Central Bank of Kenya (CBK) and the International Monetary Fund (IMF). It is important to note that these institutional forecasts result from a process that combines prediction models and judgment, whereas our model is devoid of any judgment. This suggests that the same modeling approach that has proven successful in advanced and emerging economies also performs well in a low-income Sub-Saharan African country. The results highlight the robustness of comovement-based models and the regularity of macroeconomic dynamics even in data-constrained environments. Our data release decomposition also reveals that *news* in data releases on electricity and vehicle production, digital mobile payments, and exports and imports of goods, through their impacts on aggregate consumption and trade, are the main drivers of the GDP nowcast revisions in 2024 and 2025. Although we focus on traditional statistics, our framework is flexible enough to incorporate transactions and digital payments data from non-traditional or other high-frequency sources when available, making it a practical and extensible tool for real-time monitoring of economic activity.¹ We show that the model works well with arbitrary patterns of missing data, which allows us to incorporate and evaluate the marginal contribution of new data sources with typically short history without modifying our modeling framework. Our findings open the door to extend this methodology to other LICs where quarterly GDP data are not yet available, thereby enabling a formal econometric analysis of current economic conditions and informing development policy decisions in more challenging data environments.

Beyond well-documented data constraints, it is challenging to reliably characterize business cycles in LICs by a single common factor, as typically found in AEs. This is because business cycle fluctuations in LICs stem from a diverse mix of idiosyncratic and weakly synchronized shocks—including commodity price volatility, extreme weather events, aid and remittances swings, domestic supply side disturbances, policy reversals, and institutional shocks—which operate through shallow financial and structural channels (Di Pace et al., 2025; Cerra and Saxena, 2008; Aguiar and Gopinath, 2007). This contrasts sharply with AEs and major emerging markets, which feature mature economic structures and where business cycle fluctuations are underpinned primarily by domestic macroeconomic disturbances and financial cycle dynamics shaped by global integration

¹The results remain qualitatively unchanged when satellite-based port-level data on maritime trade from IMF [PortWatch](#) are incorporated, and these additional results are available from the authors upon request.

(Cascaldi-Garcia et al., 2024a; Dahlhaus et al., 2017; Burns and Mitchell, 1946). In LICs, trade shocks remain the dominant drivers of cyclical fluctuations: relative price movements in primary exports and in imported capital and intermediate goods account for roughly half of output volatility and generate large swings in investment and labor supply, while world interest rate shocks play only a moderate role (Kose and Riezman, 2001). As a result, multi-factor frameworks that accommodate multiple external and domestic latent factors could offer a more accurate representation of cyclical dynamics in LICs (Kose et al., 2003; Kim, 2021).

We contribute to the literature on nowcasting, which relies on higher-frequency indicators to predict near-term GDP growth. This approach has been successfully applied in a wide range of advanced and emerging market economies (for a survey on nowcasting, see Bańbura et al., 2011; Bańbura et al., 2013; Bok et al., 2018; Giannone et al., 2021; Cascaldi-Garcia et al., 2024b). To our knowledge, this is the first paper to implement and evaluate such a nowcasting model for a LIC. As such, it provides a blueprint for extending nowcasting tools to data-constrained environments and for adapting them to economies subject to recurrent and multifaceted shocks, thereby improving stabilization measures and development policies.

Our work also relates to a growing literature that uses new data sources, in particular transaction data, to nowcast economic activity (Galbraith and Tkacz, 2018; Gonçalves, 2022; Umar et al., 2024). The strong uptake of digital payment systems has enabled over 85% of Kenyan adults to access financial services mainly through digital platforms in 2025. This has significantly shifted Kenya’s economic landscape towards cashless transactions in both the formal and informal sectors, facilitated household consumption smoothing and risk sharing, deepened financial inclusion, thereby strengthening economic development and poverty alleviation (Aker and Mbiti, 2010; Suri et al., 2021; Adu and Hartarska, 2025). We leverage digital payments data that are becoming almost official, as they are routinely collected and published by the CBK. We study the marginal value of these new data, in addition to the readily available traditional data. Many earlier contributions, such as Varian (2014), have not fully leveraged the available official data. This entails a bias toward overemphasizing the predictive content of new data sources. Our framework allows us to quantify the marginal predictive value of each new data while accounting for its timeliness and controlling for all other data. It also enables us to evaluate in real time the estimation accuracy of the signal in these new data, which can be limited because of their short history. In contrast to D’Amuri and Marcucci (2017) and Ferrara and Simoni (2023), we only use data that are directly linked to economic activity because other data sources such as satellite night lights, pollution,

or search data might reflect many other socioeconomic trends, behaviors, and factors that can distort the economic signal.

Our findings underscore the robustness of dynamic factor models across a wide range of economic environments. The stability of comovement among key macroeconomic indicators—even in a low-income country—means that meaningful signals can be extracted from diverse and timely monthly series. This enables real-time tracking of economic conditions, providing policymakers, market participants, and analysts with an early read on the state of the economy while awaiting official GDP releases. The successful application of this approach in Kenya also demonstrates its potential for use in other LICs, including those where GDP is only available at annual frequency. In such settings, factor-based nowcasting can serve as a scalable and practical tool for monitoring economic activity in real time and supporting timely policy responses.

The rest of the paper is structured as follows. Section 2 describes the data and outlines the challenges of nowcasting GDP growth in Kenya. In Sections 3 we present our tailor-made dynamic factor model and unpack how the *news* components of incoming data drive GDP nowcast revisions. Section 4 discusses the empirical results and benchmarks the performance of our nowcasts to alternative forecasts. Section 5 concludes.

2 Data and nowcasting challenges

2.1 Data

2.1.1 GDP and economic activity data

To build our nowcasting predictions, we exploit traditional data that are routinely monitored by the CBK, markets, and media. The variables in Table 1 are transformed in year-on-year (y-o-y) log differences to induce stationarity and address seasonality, except for PMI and visitor arrivals series that are already stationary, and therefore, are left in level.² The predictor variables are selected based on the availability of data monitored by monetary and economic institutions and markets, economic sector coverage, ability to track activity in Kenya’s main economic sectors, as well as their comovement with GDP growth.

In addition to quarterly GDP series (our target variable), we use a combination of 11 hard and soft official input data recorded at the monthly frequency. Hard data measure

²Survey-based indicators are included in level because, typically, they already reflect changes in current macroeconomic conditions (e.g., producer confidence index) relative to a previous period. Annex A illustrates and provides detailed descriptions of the transformed high-frequency economic indicators and GDP growth.

Table 1: Selected economic indicators

Variable (y)	Frequency	Start — End Dates	Lag (days)	Unit	Transformation	Correlation ($\rho_{y,gdp}$)	Variance share of Common Component	Source
Stanbic Bank Kenya PMI	Monthly	Jan 2014 — Dec 2025	5	Index	Level	-0.01	0.000	S&P Global
Diaspora Remittances	Monthly	Jan 2004 — Nov 2025	11	NSA, Mil. USD	y-o-y % Δ	-0.02	0.210	CBK
Mobile Money	Monthly	Mar 2007 — Nov 2025	17	NSA, Bil. KES	y-o-y % Δ	0.02	0.254	KNBS/CBK
Exports of Goods	Monthly	Aug 1998 — Nov 2025	41	NSA, Mil. KES	y-o-y % Δ	0.19**	0.299	CBK
Imports of Goods	Monthly	Aug 1998 — Nov 2025	41	NSA, Mil. KES	y-o-y % Δ	0.36***	0.618	CBK
Exports of Coffee	Monthly	Aug 1998 — Nov 2025	41	NSA, Tonnes	y-o-y % Δ	-0.02	0.028	KNBS/CBK
Exports of Tea	Monthly	Aug 1998 — Nov 2025	41	NSA, Tonnes	y-o-y % Δ	-0.18**	0.104	KNBS/CBK
Money Supply (M2)	Monthly	Dec 1995 — Sep 2025	45	NSA, Mil. KES	y-o-y % Δ	0.11	0.018	CBK
Electricity Production	Monthly	Feb 2006 — Nov 2025	48	NSA, Mil. KWh	y-o-y % Δ	0.30***	0.073	KPLC/KNBS
Visitor Arrivals (Persons)	Monthly	Jan 2007 — Sep 2025	48	Number	Level	0.38***	0.069	KTB/KNBS
Vehicle Production	Monthly	Jan 2003 — Nov 2025	48	Number	y-o-y % Δ	0.35***	0.055	KNBS
Real GDP	Quarterly	2009 Q1 — 2025 Q3	99	NSA, Mil. KES	y-o-y % Δ	1.00	0.368	KNBS

Notes: CBK—Central Bank of Kenya; KPLC—Kenya Power & Lighting Company; KNBS—Kenya National Bureau of Statistics; KTB—Kenya Tourism Board. ***, **, * indicate statistical significance of contemporaneous correlations at 1%, 5%, 10% level, respectively. The variance share of common component is estimated over the in-sample period spanning January 2010 and September 2021.

actual economic activity outcomes. Soft data, on the other hand, are survey-based indicators that measure the sentiments, expectations, intentions, and perceptions of the state of the economy. In our dataset, hard data include real sector official agricultural variables on trade in goods (especially tea and coffee) and services (tourists arrivals), and production (vehicles produced, electricity generated). We add data on remittances which shape household disposable income for consumption and investment alongside a variable for money supply (M2) to reflect the amount of liquidity available to support economic growth, as higher money supply without a corresponding increase in the production of goods and services can lead to inflation.³ We also include soft data on purchasing managers’ sentiments (PMI) to capture the economic momentum in manufacturing and services perceived by supply chain professionals.

Coffee and tea exports are included in the set of predictors due to their significance in Kenya’s agricultural production and trade. Financial analysts, such as Trading Economics and the Economic Intelligence Unit, closely monitor these data. Kenya is known for its premium Arabica coffee, which is a crucial agricultural export and a major cash crop that provides subsistence revenues to many small-scale farmers. Key growing regions, including Central and Eastern Kenya and the Rift Valley, benefit from favorable climate conditions and fertile soils. Kenyan coffee is mainly exported to Europe, North America, and Asia, often fetching premium prices as a specialty product. However, challenges such as aging trees, climate change, and global competition persist. Efforts are ongoing to improve production, quality, and sustainability, with an increasing focus

³We do not include Consumer Price Index in the set of input variables because the volatility of price indicators in Kenya is substantially higher than that of GDP growth.

on direct trade and specialty markets. Kenya is also a leading global producer of high-quality black tea, recognized for its robust flavor and premium pricing. Tea exports are essential for the economy, with continuous initiatives to address challenges and maintain their contribution to the livelihoods and national income.

Diaspora remittances, Kenya’s largest source of foreign exchange, reached \$4.95 billion in 2024—18% higher than in 2023, amounting to 4.6% of the country’s GDP. The United States of America (USA) accounts for 51% of these inflows, followed by Europe at 18.1%. These funds support household needs, healthcare, education, and investments. Despite the assistance of mobile platforms like M-Pesa in facilitating transfers, high transaction costs (9.15% for \$200) remain a concern, exceeding global and Sustainable Development Goal (SDG) targets. As a tourist destination, visitor arrivals, which capture the number of visitors entering through major ports (air, land, sea), significantly contribute to the economy. Key tourist source markets include the USA, UK, India, and regional neighbors such as Tanzania and Uganda. Inflows from international tourism surpassed pre-coronavirus levels in 2023, with further improvements in 2024. Although visitor arrivals were stagnant in the first quarter of 2025, there was a 9.7% year-on-year increase in April.

Finally, important production variables for Kenya include electricity and vehicle production. Kenya’s electricity generation, crucial for economic growth, reached approximately 13,000 GWh in 2024. Installed capacity grew to 3.82 million kW in 2023, with demand peaking at 2,362 MW in July 2025, driven by urbanization and industrialization, leading to increased infrastructure investments. Production rose significantly between January and April 2024. Kenya’s vehicle production primarily involves assembling commercial vehicles (LCVs and HCVs) from Completely Knocked Down (CKD) kits, with 826 units produced in November 2024, a decrease from 978 in October. Major assemblers like Isuzu East Africa, KVM, and AVA operate below capacity, utilizing 40% local parts and supporting over 10,000 jobs. Challenges such as high costs, dependence on imports, and competition from used vehicles (94.3% sourced from Japan in 2023) persist. Policies are in place to boost production to 3,270 units by 2030, with increasing support for electric vehicles (EVs).

2.1.2 Transaction data

To better capture private demand, we use timely insights from non-traditional transaction data, which have proven highly effective in forecasting real-time economic activity during the COVID-19 pandemic (Chetty et al., 2024; Mishra et al., 2024). Specifically,

we complement data on remittances with data on digital payments (Total agent cash in cash out) from the CBK.⁴ To our knowledge, this is the first paper that uses digital payments data to nowcast GDP growth in Kenya. Unlike AEs (Giannone et al., 2021), non-traditional data can play a much bigger role in improving the accuracy and timeliness of economic monitoring in LICs because their official data tend to be less frequent, less accurate, and subject to greater revisions. Digital money data is a timely indicator of the Kenyan economy’s performance, with data published on the 17th of each month for the preceding month. Digital payment systems have enhanced financial inclusion in Kenya, particularly by expanding digital financial services.

We use mobile payments data compiled by the CBK from digital payment platforms. The digital payment sector’s reach continues to expand, thereby deepening Kenya’s financial inclusion. The number of active mobile money agents and registered mobile money accounts nearly doubled over the past 5 years, reaching 424,404 and 85.62 millions in May 2025, respectively. The recorded volume (number) of mobile money transactions also increased to 214.51 millions, rising by almost 60% during the same period. The value of mobile money transactions (Total agent cash in cash out) followed a similar upward trend until end-2024, before softening in the first half of 2025. While the number of transactions edged higher, the value of mobile money transactions dropped by 21.8% y-o-y to 636.21 billion Kenya Shillings (about 3.7% of 2025 GDP) in February 2025 and 713.25 billion Kenya Shillings (about 4.2% of 2025 GDP) in May 2025—still 1.2% lower than the same month in the previous year.⁵ The apparent divergence between mobile payment usage and transaction value in the first half of 2025 suggests a potential shift toward low-value payments and a retreat in large-scale use, reflecting higher living costs and slowing household spending.

Safaricom’s M-PESA has remained the dominant digital transaction platform in Kenya since its launch in 2007, although its market share edged down to 91% in 2025 Q1, amid increasing competition from other fintech service providers such as Airtel Money. With over 85% of Kenyan adults having access to financial services mainly through digital platforms in 2025, recent trends in consumption reveal a significant shift towards cashless transactions, driven by the growth of broadband internet, e-commerce, and mobile-money payment systems. Digital payment data reflect to some extent these consumption patterns in Kenya.

Kenya’s mobile money sector plunged in March–April 2020 in the wake of the COVID-

⁴Note that we use the terms digital payment, digital money, and mobile money interchangeably in this paper.

⁵According to the IMF’s April 2025 WEO report, Kenya’s 2025 GDP in current prices is projected at 131.67 billion USD or about 17 trillion Kenya Shillings.

19 outbreak, with transactions hitting multi-year lows. The recovery was swift and exceeded pre-pandemic levels, jumping by 84% from its trough in April 2020 to February 2021, driven by Central Bank measures—fee waivers, higher limits, and promotion of digital payments—alongside shifts to contactless transactions. Growth accelerated through expansion of services into credit, savings, and bill payments, plus increasing e-commerce and remote work. The network effects cemented mobile money as a core part of Kenya’s financial ecosystem, marking a structural shift in payment behavior.⁶

2.1.3 Sampling frequencies and correlations

With the exception of the quarterly GDP series, all indicators that we use are sampled at a monthly frequency and have a maximum delay (i.e., the time between the release date and the end of the period referred to) of about one and a half months (Figure 1). Nowcasting in full real time would entail the use of real-time vintages featuring a complete revision process for all the indicators included in the model. However, to the best of our knowledge, such detailed historical data sets do not exist for Kenya. To be able to assess the importance of timeliness in this setting we therefore reconstructed *pseudo* data vintages that, while disregarding the effects of data revisions, would nonetheless mimic the actual data flow and thus allow to evaluate our model in a *pseudo*-real-time setting. To do so, we rebuilt the history of data releases starting from September 2021, which also marks the beginning of our forecast evaluation sample, collecting the relevant dates from the Calendar of Economic Releases supplied to Haver Analytics.

Most of the contemporaneous correlations ($\rho_{y,gdp}$) in Table 1 are economically and statistically significant. About half of these contemporaneous correlations exceed 0.2, suggesting significant comovement between the selected predictor variables and GDP growth. Although the respective absolute contemporaneous correlations of PMI and remittances with GDP growth seem weak, these predictor variables are relatively timely—with only 5 and 11 days reporting lags—and lead GDP growth. This descriptive analysis lays the groundwork to apply our dynamic factor model to nowcast Kenya’s economic activity.

⁶Annex A provides additional details on the transactions.

2.2 Why nowcast Kenya’s GDP growth?

2.2.1 Main challenges to predict near-term GDP growth

One of the main challenges in tracking Kenya’s near-term economic activity is the long delay in GDP growth releases. GDP data is typically published with at least one quarter delay (Figure 1). The wait is even longer in many other LICs. In some cases, GDP is only available on an annual basis and subject to substantial revisions (Ley and Misch, 2014). This significantly limits forecasters’ ability to track economic activity in a timely manner.

Another challenge is the limited availability of data. Compared to AEs, Kenya and other LICs have far fewer macroeconomic indicators available at the monthly frequency. To put this data gap into perspective, we only found 11 monthly economic series that are publicly available for Kenya (Table 1) compared to the 190,000 monthly US economic series that are publicly accessible from the St. Louis Federal Reserve database.⁷ The historical data available is also shorter, which makes it more challenging to develop reliable models comparable to those used in AEs.

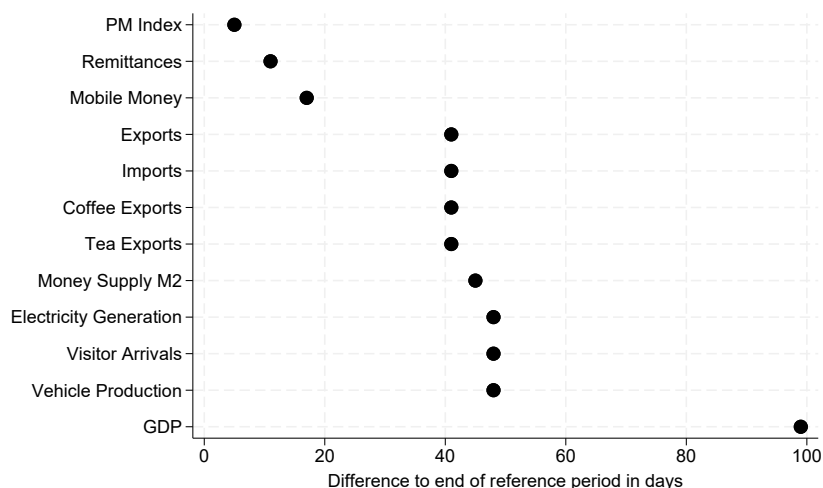
Moreover, many key economic variables have different frequencies (monthly, quarterly, annual). They are released infrequently, published on different dates (asynchronously), and often suffer from missing observations. The combination of mixed frequencies, publication delays, asynchronicity, and data gaps creates a sparse or *ragged-edge* dataset structure, which complicates the construction of a reliable nowcasting framework. These challenges are even more severe in developing and low-income countries, where data publication can be discontinued, statistical series may change frequency, and improvements in data collection gradually expand the range of available indicators. For example, in Kenya GDP was published only annually until 2009, when quarterly national accounts became available and the PMI business sentiment survey began in 2014. We treat mixed frequencies as arising from temporal aggregation and periodically missing observations, and the ragged edge as a special case of missing data. Following Giannone et al. (2008) and Bańbura and Modugno (2014), these issues are handled in our dynamic factor model through the Kalman filter, which interpolates and forecasts missing observations while accommodating aggregation in a unified way. Such specifications are *full-system models*, meaning that the target variable and its predictors are jointly modelled so that all aspects of the nowcasting problem are addressed simultaneously within a single coherent framework.

As discussed earlier, an important advantage of this framework is that it enables

⁷The St. Louis Federal Reserve database was accessed on July 30, 2025.

a transparent interpretation of the impact of each data release on the current assessment of economic conditions. Because the Kalman filter generates projections for all variables in the model, it is possible to compute a model-based surprise—the *news*—for each release. In this way, data releases are weighted in a rigorous, model-based manner, allowing the contribution of different categories of information—such as surveys, financial indicators, production, or labor market data—to be systematically evaluated.⁸ Our nowcasting framework addresses these challenges in an efficient, practical, and transparent way. By producing timely predictions of current economic conditions in Kenya and interpretable updates, the proposed framework provides an additional tool to help policy makers take informed decision concerning stabilization measures. Ultimately, it provides policymakers with reliable near-term forecasts of economic outcomes, enabling them to make informed decisions that promote economic stability, growth, and development.

Figure 1: Data release lags



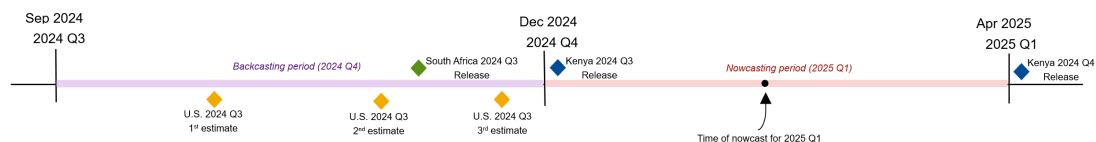
Notes: The black dots show the number of days between the end of the reference period and the release date of each economic activity indicator.

⁸*Partial models*—such as bridge equations and MIDAS regressions—forecast the target variable separately at each data vintage, without jointly modelling the predictors. They require auxiliary forecasts to fill missing values, cannot decompose forecast revisions into model-based news, and change specification as data availability evolves, making interpretation difficult. See [Bańbura et al. \(2013\)](#) for further discussion.

2.2.2 Data releases and nowcasting

To anchor our analysis, we now turn to the timing of macroeconomic data releases and near-term GDP predictions. Figure 2 shows the timing of GDP data publications in Kenya relative to the backcasting and nowcasting periods. The data release lag for Kenya GDP is at least one quarter, that is, about one month delay compared to South Africa GDP data release and two weeks after the third estimation of US GDP is published (Cascaledi-Garcia et al., 2024a; Giannone et al., 2021; Kabundi et al., 2016). Such a delay implies that many timely official indicators on Kenya’s economic activity become available between GDP releases.

Figure 2: Backcasting and nowcasting



Notes: This figure shows the timing of GDP data publication in Kenya compared to the U.S. and South Africa.

Due to large publication lag between Kenya GDP releases, we need to estimate not only current quarter GDP growth (nowcast), but also previous quarter GDP growth (backcast). Operationally, we run a nowcast of current quarter growth and a backcast of previous quarter growth on the 7th and 21st day of each month.

3 Nowcasting framework

Our goal is to build a tailor-made nowcasting framework for Kenya’s GDP growth based on data tracked by markets, policymakers, and media. To this end, we adapt a frontier nowcasting approach used in AEs. In this Section we provide a general overview of the modeling approach. More details are provided in Bańbura et al. (2013), Luciani (2017), Bok et al. (2018), and Cascaledi-Garcia et al. (2024b).

3.1 Dynamic factor model

To nowcast GDP growth in Kenya, we use a dynamic factor model (DFM) as in Giannone et al. (2008). Our DFM is a *full* forecast framework in the sense that both target (GDP) and predictor variables are endogenously and jointly determined and forecasted. This approach decomposes every economic indicator in the information set into two parts: (1) factors common to each indicator, and (2) an idiosyncratic component which is

specific to each indicator. The model assumes that the comovements between the high- and low-frequency indicators are summarized by a small set of unobserved common factors F_t , whereas idiosyncratic components are orthogonal to each other and to the common factors at each lead and lag period. The latter assumes that the idiosyncratic components are not cross-sectionally correlated. This assumption is necessary to ensure identification and preserve parsimony of the model. However, in practice this assumption is very restrictive especially with many predictors that have some correlation in the idiosyncratic noise. Fortunately, the model is robust to violation of this assumption, as shown by [Doz et al. \(2012\)](#), and [Barigozzi and Luciani \(2024\)](#).

Our nowcasting model is standard:

$$y_t = \Lambda F_t + \epsilon_t, \quad (1)$$

$$F_t = \Gamma F_{t-1} + u_t, \quad u_t \sim \text{i.i.d. } \mathcal{N}(0, \Xi), \quad (2)$$

$$\epsilon_t = \Theta \epsilon_{t-1} + \eta_t, \quad \eta_t \sim \text{i.i.d. } \mathcal{N}(0, \Sigma), \quad (3)$$

where y_t is a vector of $(M \times 1)$ standardized economic indicators, Λ is a matrix of $(M \times k)$ loadings of the economic indicators on the latent factors, F_t is a vector of $(k \times 1)$ common latent factors (with $k < M$), ϵ_t is a vector of $(M \times 1)$ idiosyncratic components. The motion of the common factors is governed by a vector autoregressive process, where Γ is a matrix of $(k \times k)$ autoregressive coefficients of the factors in companion form, and Ξ is the variance-covariance matrix of the common factors. The idiosyncratic components follow a similar dynamic where Θ is the associated $(M \times M)$ diagonal autoregressive matrix and Σ is the diagonal covariance matrix of the errors. Assuming that Θ and Σ are diagonal matrices allows to preserve the cross-orthogonality condition among the idiosyncratic components.

Our estimation strategy uses the expectation-maximization algorithm and the Kalman filter. This makes the estimation viable and efficient, since it can be computed iteratively starting from a simple estimation based on principal components ([Doz et al., 2012](#)). To run the Kalman filter, we re-cast the model in a state-space form:

$$y_t = \begin{bmatrix} \Lambda & \mathbf{I}_{M \times M} \end{bmatrix} \begin{bmatrix} F_t \\ \epsilon_t \end{bmatrix}, \quad (4)$$

$$\begin{bmatrix} F_t \\ \epsilon_t \end{bmatrix} = \begin{bmatrix} \Gamma & \mathbf{0}_{k \times M} \\ \mathbf{0}_{M \times k} & \Theta \end{bmatrix} \begin{bmatrix} F_{t-1} \\ \epsilon_{t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ \eta_t \end{bmatrix}, \quad (5)$$

where

$$\begin{bmatrix} u_t \\ \eta_t \end{bmatrix} \sim \text{i.i.d. } \mathcal{N} \left(\begin{bmatrix} \mathbf{0}_{k \times 1} \\ \mathbf{0}_{M \times 1} \end{bmatrix}, \begin{bmatrix} \Xi & \mathbf{0}_{k \times M} \\ \mathbf{0}_{M \times k} & \Sigma \end{bmatrix} \right). \quad (6)$$

We run the model with a number of factors k ranging from 1 to 5. In most nowcasting applications, a single factor model is sufficient to generate accurate nowcasts (see [Cascaldi-Garcia et al., 2024b](#)). Of course, performances can be improved by fine-tuning this hyperparameter k as well as others (see [Alessi et al., 2010](#); [Bok et al., 2018](#); [Feunou and Okou, 2018](#)). However, there is a danger of overfitting. For this reason, we keep the model simple, settling on a two-factor model ($k = 2$) as discussed in Section 4. In this sense, the results we show are a sort of lower bound of the potential in accuracy from a parsimonious specification.

3.2 Mixed frequencies

Nowcasting models are typically fitted to dataset containing mixed-frequency—in this case, quarterly and monthly—indicators. Therefore, we use a factor-based mixed-frequency aggregation to *bridge* the frequency gap between higher-frequency (monthly) predictors and lower-frequency (quarterly) GDP growth.⁹ To clarify the notations, we explicitly rewrite the vector of variables in Equation 1 as $y_t = [y_{t,gdp}^q; y_t^m]$. In practice, quarterly GDP growth $y_{t,gdp}^q$ is treated as a variable that is partially observed at the monthly frequency, with its quarterly release assigned to the last month of the respective quarter. We assume that this partially observed quarterly GDP growth is obtained by aggregating an unobserved monthly GDP growth rate $y_{t,gdp}^m$ —defined as the difference in log level GDP $Y_{t,gdp}^m - Y_{t-1,gdp}^m$, which features the same factor structure as the other monthly indicators:

$$y_{t,gdp}^m = \lambda_{gdp} f_t + \epsilon_{t,gdp}, \quad (7)$$

⁹The same approach could be applied in cases where GDP growth is available at an even lower frequencies (e.g., annual or biannual).

where

$$\epsilon_{t,gdp} = \rho_{gdp}\epsilon_{t-1,gdp} + \eta_{t,gdp}. \quad (8)$$

Let Y_t^q denote the log level of the quarterly GDP. We obtain the following aggregation formula, which maps $y_{t,gdp}^m$ to the quarterly year-on-year GDP growth rate $y_{t,gdp}^q$ that is partially observed at every third month of the quarter:

$$\begin{aligned} y_{t,gdp}^q &= y_{t,gdp}^m + y_{t-1,gdp}^m + y_{t-2,gdp}^m \\ &= \lambda_{gdp}(f_t + f_{t-1} + f_{t-2}) + \epsilon_{t,gdp} + \epsilon_{t-1,gdp} + \epsilon_{t-2,gdp}. \end{aligned} \quad (9)$$

Thus, the quarterly variables should load equally on the current and lagged values of the unobserved monthly factor.¹⁰ This representation can be viewed as *bridging the high-frequency (monthly) to low-frequency (quarterly) gap with factors* in the spirit of [Giannone et al. \(2008\)](#), as the monthly factor series extracted with the Kalman filter are plugged in Equation 9 to obtain the nowcast for quarterly GDP growth.

3.3 Estimation: Expectation-maximization algorithm

We employ an expectation-maximization (EM) approach to estimate our DFM. The algorithm was first developed by [Watson and Engle \(1983\)](#), and extended to handle large models by [Doz et al., 2012](#)). Let's stress that the standard EM algorithm needs to be adapted to handle the *ragged edge* structure of nowcasting panels, which stems from the mixed frequencies, different historical time spans, and asynchronous release dates of nowcasting datasets, as illustrated in Table 1 and Figure 1. We use an extension of the EM algorithm developed by [Bańbura and Modugno \(2014\)](#), which is suited to estimate our DFM on nowcasting panels with arbitrary patterns of missing data.

We denote by T_v the time index of the most recent observation in the information set Ω_v . The log-likelihood can be expressed as a function $\mathcal{L}(\underline{y}, \underline{F}, \Psi)$ of data $\underline{y} = (y_1, y_2, \dots, y_{T_v})$, factors $\underline{F} = (F_1, F_2, \dots, F_{T_v})$, and all parameters collected in $\Psi = (\Lambda, \Gamma, \Theta, \Sigma, \Xi)$. The EM algorithm is initialized in the iteration $\iota = 0$, by extracting the factors $F_t^{(0)}$ by Principal Component Analysis (PCA) and estimating the parameters

¹⁰[Modugno \(2013\)](#) and [Bańbura et al. \(2013\)](#) use a similar approach to derive aggregation formulas mapping daily and weekly data to quarterly predictions. See Section B in the Annex for details on the state-space representation of the factor-based bridging formulas.

$\Psi^{(0)}$ by ordinary least squares (OLS) regressions. It then proceeds iteratively between the following two consecutive steps until convergence:

(E-step) given the current set of parameter estimates, $\hat{\Psi}^{(\iota)}$, the algorithm computes the expectation of the log-likelihood conditional on the information contained in the data $\mathcal{L}(\Psi, \Psi^{(\iota)}) = \mathbb{E}_{\Psi^{(\iota)}} [\mathcal{L}(\underline{y}, \underline{E}, \Psi) | \Omega_v]$ and extracts the factors using the Kalman filter and smoother;

(M-step) given the extracted factors in the previous iteration, the parameters are re-estimated by maximizing of the expected log-likelihood $\Psi^{(\iota+1)} = \arg \max_{\Psi} \mathcal{L}(\Psi, \Psi^{(\iota)})$.¹¹

The simplicity of each step makes the algorithm computationally viable without any limitation on the size of the system, while ensuring at each step that the likelihood increases until convergence. It is worth noting that this does not guarantee convergence to a global maximum because the EM algorithm can reach a local maximum if the starting conditions are too far away from the maximum of the likelihood function. However, in most situations, the PCA provides a good starting point close to the maximum likelihood solution (see [Doz et al., 2012](#), for a detailed discussion).

Alternatively, Bayesian inference may be used to estimate DFMs ([D’Agostino et al., 2016](#); [Antolín-Díaz et al., 2024](#)). The Bayesian estimation is done using priors and Gibbs sampling techniques that alternate the following two steps: (1) given a draw of the parameters, the missing data and the latent factors are drawn conditional on the observations using the simulation smoother, and (2) given a draw of the full data and the latent factors, the parameters are drawn from their posterior distributions.

3.4 Real-time data flow and news decomposition

Our objective in nowcasting GDP growth for Kenya is to establish a framework that effectively utilizes the flow of real-time data releases. Whenever new data becomes available, the nowcasting model generates an estimate for the current quarter’s GDP growth rate, providing a series of updates for this specific event. By employing a state-space framework, the model can also produce forecasts for all variables within the database, facilitating the extraction of the *news* or *unexpected* component from the released data. By leveraging model-based *news* for all variables, we can estimate the GDP nowcast as a weighted sum of these *news*, with the weights determined by the model itself. This framework is crucial for understanding how estimates of current economic activity evolve over time and for evaluating the significance of each data publication.

¹¹We refer the reader to Annex Section C for more details on the EM algorithm.

Following Bańbura and Modugno (2010), Bańbura et al. (2011), and Bańbura et al. (2013), we derive the *news* update as follows. Let us consider two consecutive data vintages, Ω_v and Ω_{v+1} , corresponding to variables released in months v and $v + 1$, respectively. Disregarding data revisions, the information sets Ω_v and Ω_{v+1} may differ simply because Ω_{v+1} includes newly released data that was not present in Ω_v . We have the following:

$$\Omega_v \subset \Omega_{v+1} \text{ and } \Omega_{v+1} \setminus \Omega_v = y_{t_j, n_j}, \text{ for } j=1, \dots, J_{v+1}. \quad (10)$$

Thus, the information set is “expanding”. It is worth noting that different types of data come with varying publication delays, which typically results in $t_j \neq t_l$ for some $j \neq l$.

Now, let us focus on the two consecutive nowcast updates, $E[y_{t_n, n} | \Omega_v]$ and $E[y_{t_n, n} | \Omega_{v+1}]$, where $y_{t_n, n}$ is the variable of interest, that is, GDP growth. The new available figures will generally provide additional information about the GDP growth rate, which will, in turn, necessitate a revision of the nowcast. Based on the properties of conditional expectation as an orthogonal projection operator, specifically $\Omega_{v+1} \perp \Omega_v$, we conclude that:

$$\underbrace{\mathbb{E}[y_{t_n, n} | \Omega_{v+1}]}_{\text{new forecast}} = \underbrace{\mathbb{E}[y_{t_n, n} | \Omega_v]}_{\text{old forecast}} + \underbrace{\mathbb{E}[y_{t_n, n} | I_{v+1}]}_{\text{revision}}. \quad (11)$$

where $I_{v+1} = [I_{v+1, 1} \dots I_{v+1, J_{v+1}}]'$ and $I_{v+1, j} = y_{t_j, n_j} - \mathbb{E}[y_{t_j, n_j} | \Omega_v]$ for $j = 1, \dots, J_{v+1}$. The term I_{v+1} refers to the portion of the release that is “orthogonal” to the information already available in Ω_v . In essence, this represents the *unexpected* component of the release, leading us to label I_{v+1} as the “*news*”. It is crucial to understand that it is the *news*—not the release itself—that drives the nowcast revision. If the figures in Ω_{v+1} perfectly align with predictions based on the information in Ω_v , indicating “*no news*,” the nowcast will remain unchanged. We can rewrite Equation 11 to express the nowcast revision as a weighted sum of *news* from the new data releases

$$\underbrace{\mathbb{E}[y_{t_n, n} | \Omega_{v+1}] - \mathbb{E}[y_{t_n, n} | \Omega_v]}_{\text{Revision from } v \text{ to } v+1} = \sum_{j \in J_{v+1}} \delta_{v+1, j} \underbrace{\left(y_{t_j, n_j} - \mathbb{E}[y_{t_j, n_j} | \Omega_v] \right)}_{\text{News for } n_j \text{ from } v \text{ to } v+1} \quad (12)$$

where J_{v+1} is the set of newly released variables y_{t_j, n_j} at time $v + 1$ and $\delta_{v+1, j}$ are the associated weights.

This implies that the revision can be expressed as a weighted average of the *news* in the latest release. The significance of the revision is determined by both the magnitude of the *news* and its relevance to the variable of interest, represented by the weight $\delta_{v+1,j}$. Thus, Equation 12 can be viewed as a generalization of the standard Kalman filter update equation for situations where “*new*” data arrives asynchronously. Finally, it is important to note that filter uncertainty for $y_{t_n,n}$ diminishes with the release of new data, and this reduction can be broken down in a similar manner.

Equation 12 allows us to identify the sources of forecast revisions. Specifically, when multiple variables (or groups of variables) are released simultaneously, we can break down the resulting forecast revision into contributions from the *news* associated with each individual series (or group of series). Additionally, we can make statements such as, “following the release of PMI, the GDP forecast increased because the indicators were, on average, higher than anticipated.” This framework offers a clean and straightforward computation of nowcast revisions that is intuitive because it is based on the dynamic updating logic of the Kalman filtering. The model is always the same, which allows to seamlessly handle the information flow as new data become available and trace the sources of forecast revisions back to each predictor, mimicking how markets continuously digest predictable changes and surprises in incoming data (Caruso, 2019). Our full prediction model facilitates the interpretability of the dynamic updating because a single model predicts all variables in real time. By contrast, partial forecast models do not produce such complete model-based impacts of *news* because they only predict the target variable, whereas all variables in the system should be predicted to construct transparent *news* decomposition of forecast revisions. Another limitation of partial models is that they change every time to adapt to the pattern of data availability, thereby mixing the effects of new information and new model specification, and complicating the comparison between subsequent updates.¹²

The *news* decomposition formula in Equation 12 assumes that model parameters are fixed while the information set Ω_v expands only because new data is released. In practice however, the past data in the information set often changes due to historical data revisions. Therefore, the model parameters are reestimated iteratively, as discussed in Section 3.3 and Annex Section C. The Kalman smoother output gives the news I_{v+1} and the expectations needed to compute the *news* weight $\delta_{v+1,j}$ in Equation 12 (Bańbura

¹²Among the partial prediction models, the Mixed Data Sampling (MIDAS) model is a computationally convenient approximation of the Kalman filter approach used in this paper (Bai et al., 2013). However, our Kalman filter-based estimation is computationally efficient, inexpensive, and viable even with very large dataset (Doz et al., 2012). Overall, the advantages of the MIDAS model are limited while the drawbacks remain significant compared to our framework.

and Modugno, 2010; Bańbura et al., 2011, 2013).

4 Empirical results

We start by summarizing the estimation results of the dynamic factor model described earlier. Next, we examine the model’s real-time performance, focusing on its forecasting accuracy and ability to track and integrate incoming data as it arrives. A key prerequisite of the model is the presence of strong comovement among macroeconomic indicators while minimizing idiosyncratic differences. The model with a single common factor has proven to be particularly robust for nowcasting in both advanced and emerging economies (Cascaldi-Garcia et al., 2024a; Dahlhaus et al., 2017). Its success reflects a fundamental empirical regularity—first documented by Burns and Mitchell (1946)—that business cycles are characterized by significant comovement across a wide range of economic indicators.

However, Panel A in Figure 3 shows that a DFM with only one factor fails to capture the unprecedented depth, speed, and sectoral shifts observed during the COVID-19 recession and recovery. This finding is consistent with Stock and Watson (2025), who provide compelling empirical evidence and economic rationale for augmenting standard DFMs with an additional factor specifically designed to capture the unique macroeconomic features of the COVID-19 pandemic shock. Traditionally, the comovements of U.S. macroeconomic time series have been well described by a single common factor, which is sufficient to capture business cycles before and after the COVID-19 pandemic period.

Stock and Watson (2025) demonstrate that the anomalous macroeconomic dynamics during the COVID-19 period can be attributed to a new unobserved aggregate shock termed as the “COVID shock”, which is closely linked to pandemic related deaths. The predictive importance and macroeconomic effects of this “COVID shock” taper off during the recovery as self-protective measures, widespread vaccination, and pandemic fatigue take hold. Empirically, this COVID factor explains the vast majority of the variation in key macroeconomic indicators during the pandemic, then subsides rapidly as economic fluctuations return to normal. This suggests that an additional factor is needed to capture adequately the unique features of the transitory “COVID shock” and its macroeconomic implications. This modeling approach allows for a parsimonious yet effective decomposition of economic activity, distinguishing between conventional business cycle dynamics and the extraordinary and temporary impact of the pandemic.

The results in Panel A suggest that multi-factor models are able to capture the

dynamics of the pandemic recession better than models with a single factor. Notably, models with more than one factor are virtually indistinguishable from each other. In addition, all models perform similarly in the pre-COVID period, with the main differences emerging only during the COVID period. Based on these findings, we proceed with the model featuring two common factors, extracted from our macroeconomic dataset spanning the entire sample period from January 2010 to September 2021, as Kenya’s macroeconomic indicators also exhibit substantial comovement. For comprehensiveness, the estimated results for the DFMs featuring one and three factors are presented in Annexes E—I, while nowcasts from 4- and 5-factor models are available from the authors upon request.

Panel B shows comovement between the common component from the two-factor model, GDP growth and its predictors, in line with the correlations and variance shares of common components in Table 1. The common component, which subsumes sectoral indicators, closely tracks GDP growth. Specifically, it captures both normal-cycle expansions and contractions as well as large swings, such as the sharp decline in 2020 and the subsequent recovery in 2021. The key takeaway from Figure 3 is straightforward yet compelling, strongly supporting our proposed approach: the pronounced comovement in Kenyan data provides a robust basis for constructing a model to formally and promptly assess Kenya’s growth performance by capitalizing on these shared dynamics.

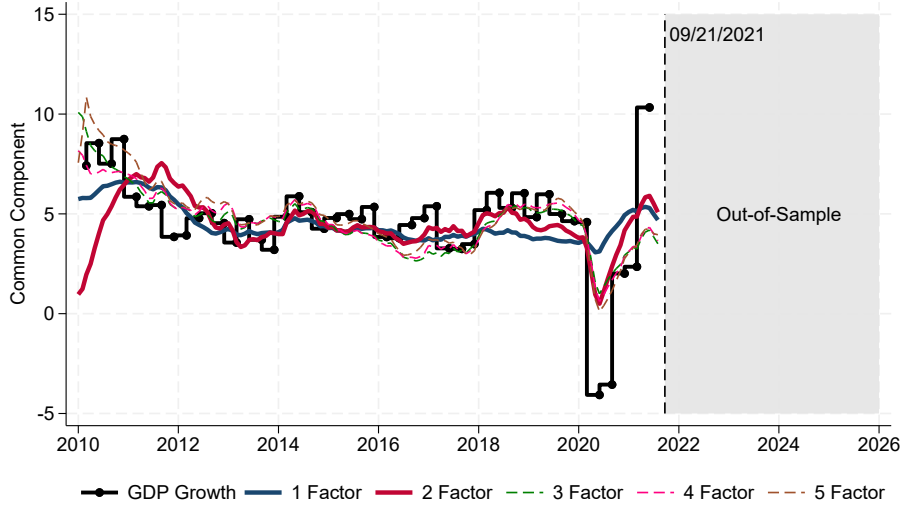
This good in-sample fit indicates that, despite possible limitations in individual data series, extracting a common signal from all indicators yields forecasts for GDP growth of a quality comparable to those in more AEs. Building on this result, we next analyze how individual data releases contribute to revisions in the nowcast through the model’s *news* decomposition.

4.1 Real time performance of quarterly nowcasts and data releases

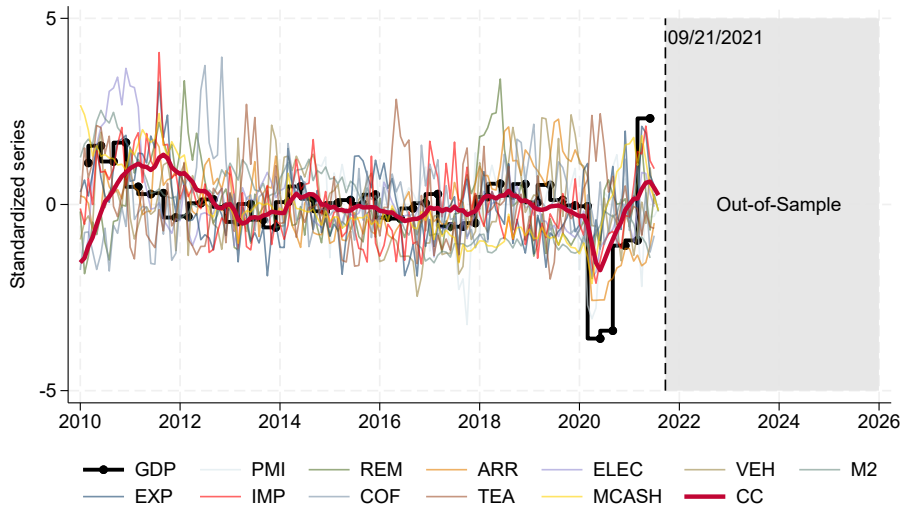
We nowcast the two-factor model by simulating the perspective of a forecaster running it in real time every two weeks, beginning on September 21, 2021. The exercise is conducted in real time in the sense that we use only the information that would have been available at the time each nowcast was produced. At each forecast origin, model parameters are recursively re-estimated using the data available up to that point. Predictions are generated solely from the variables that would have been released by that time, following the stylized data availability calendar described in Section 3.4. The exercise is considered pseudo real-time because we do not have access to actual historical data vintages. Instead, we construct pseudo-vintages that mimic the timing and flow of real-

Figure 3: Estimated common component

(A) Common components of different factor models



(B) Standardized variables and common component of 2-factor model



Notes: Panel A plots a stepwise monthly representation of quarterly GDP growth alongside the estimated monthly common components from one- to five-factor models. Panel B displays the estimated monthly common component using the two-factor model, together with the standardized monthly variables. The estimation horizon spans from January 2010 to September 2021. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP; CC = Common Component of two-factor model.

time data based on the calendar. Model parameters are re-estimated at the start of each quarter using the most recent 12 years of data. Re-estimated model parameters are fixed for the nowcast prediction exercise within each quarter. We generate nowcasts for all quarters and present the nowcasts for 2024 Q3 — 2025 Q4 as examples. Nowcasts for all other quarters are available in Annex F.

We use real-time data vintages for the series listed in Table 1 to assess the performance of our nowcasting framework primarily along two dimensions. First, we estimate the model for the period from January 2010 to August 2021. Subsequently, we run sequentially the *pseudo* real-time forecast from September 2021 to March 2024, while the *true* real-time forecast extends from April 2024 to December 2025. This enables us to analyze how GDP growth nowcasts change as increasingly richer information from incoming high-frequency indicators is incorporated until the publication of GDP data.¹³ Second, we assess how the uncertainty around our nowcast evolves over the consecutive prediction rounds.

The *pseudo* real time quarterly predictions are constructed for a period running from 2021 Q3 to 2024 Q1, while the *true* real-time forecasts span 2024 Q2 to 2025 Q4. In each quarter, we estimate six nowcasts of the current quarter GDP growth, that is, two nowcasts on the 7th and 21st day of each of the three months in that quarter. Concurrently, we also produce six backcasts of the previous quarter GDP growth, mimicking at every point in time what a forecaster using our model would have predicted. This allows to reconstruct recent historical data that were available at the time of the predictions. It is important to note that the model estimations and predictions are performed recursively when the information flow expands, as discussed in Sections 3.3 and 3.4.

The solid black line in Figure 4 illustrates the evolution of quarterly nowcast updates of y-o-y GDP growth (at an annualized rate) for 2024 Q3 — 2025 Q4. The progression of *pseudo* real-time predictions for the preceding quarters (2022 Q4 to 2024 Q2), as well as predictions from models incorporating one and three factors, are shown in figures reported in Annex F. Each black diamond on the line represents the nowcast for a specific week. Additionally, Figure 4 displays the contribution of the *news* component from all 12 variables to the nowcast revision for the week indicated on the x-axis by the colored bar corresponding to that diamond. The black triangle represents the impact as described in Equation 12. Panel A presents the nowcast updates for the third quarter of 2024. We produce bimonthly updates of nowcasts, forecasts, and backcasts, resulting in

¹³We focus on GDP nowcast since it subsumes the information of all other macroeconomic variables, and therefore, best reflects the current state of Kenya’s economy.

12 predictions for each quarter. The nowcast, which begins at the start of the quarter, covers the three months of the reference quarter plus the three months following it, up to the GDP publication date.

The first update takes place on July 7, coinciding with the release of the PMI data, M2, and first-quarter GDP growth figures. The revision of GDP growth is driven mainly by negative contributions from the second-quarter growth rate, PMI, and M2. This negative signal is reinforced by the subsequent nowcast update on July 21, which shows a decrease in the projected growth rate from 4.06% to 3.57%. The downward revision is broad-based, affecting most indicators, with the notable exceptions of visitor arrivals and tea exports. Among the contributing factors, trade variables—namely imports and exports—and digital money account for the largest downward adjustments, followed by electricity production and remittances.

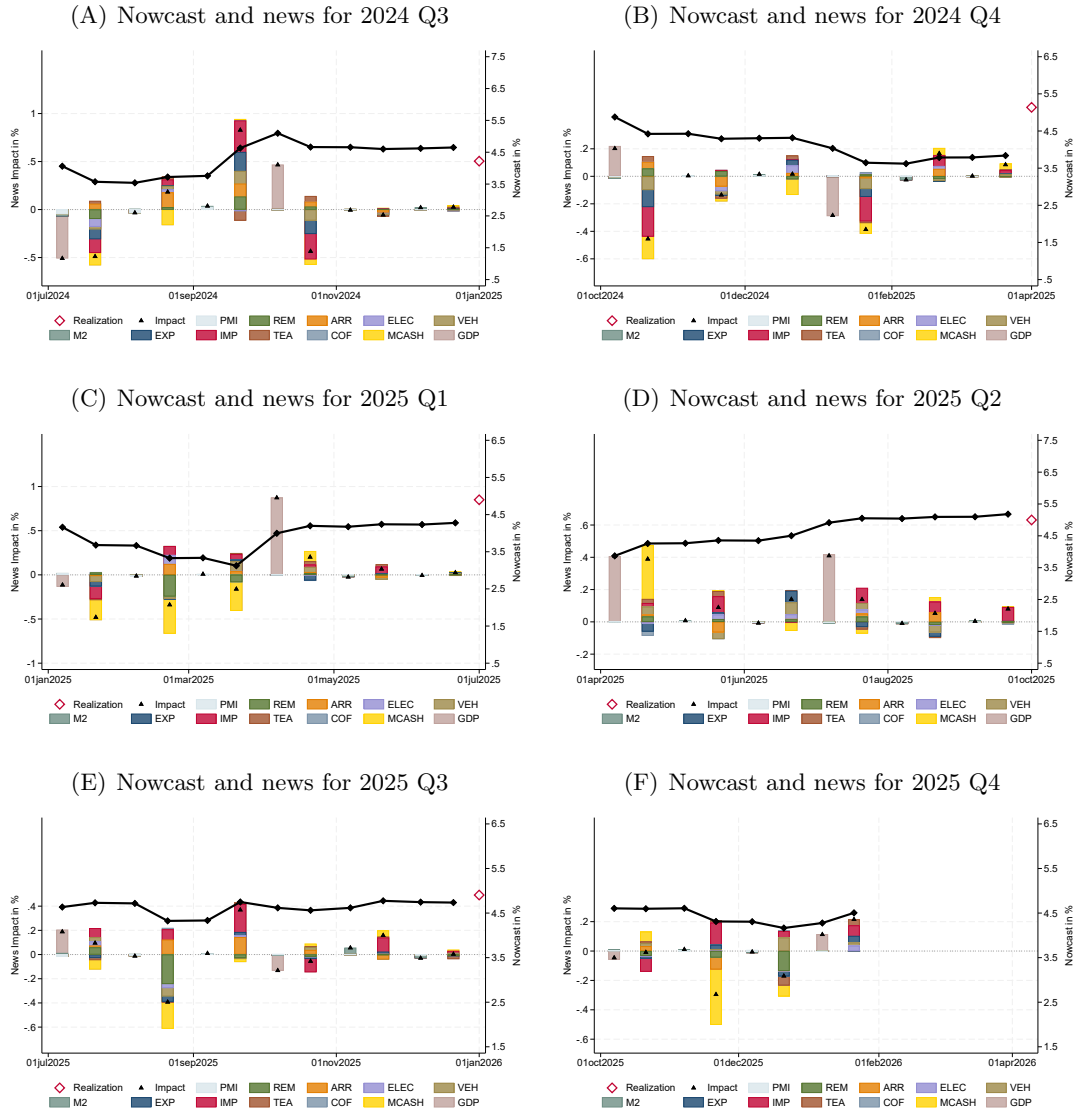
The decline in GDP growth, which begins in July stabilizes in August before picking up in September and October. This improvement is driven primarily by positive readings in imports, exports, vehicle production, visitor arrivals, and remittances, followed by second-quarter GDP growth. Subsequently, GDP growth is revised down as most macroeconomic indicators are released, mainly reflecting weak performance in digital money figures, trade, and vehicle production. It is important to note that backcasting for third-quarter GDP growth in 2024 begins at the start of the fourth quarter in October 2024. Subsequent revisions keep GDP growth steady at around 3.87% through the end of December 2024. Notably, the backcasted growth rate exhibits a smoother pattern than the nowcast updates. The predicted GDP growth rate of 4.65% slightly exceeds the actual growth of 4.2% recorded in 2024 Q3.

In sum, we first find that trade variables make a significant contribution to the nowcast revisions. Exports and imports exert the largest downward influence in July 2024, while the upward revision observed in August and September is driven mainly by the contribution of imports. Second, digital money plays a crucial role in growth updates for the July and August revisions, with its negative contribution particularly notable in August. Third, timely variables provide early signals regarding the direction of growth revisions. While PMI does not strongly contribute overall to the nowcast updates, it acts as a leading indicator early in the nowcast quarter, with little to no effects toward the end. Thus, it is useful to include variables that can signal the direction of output growth alongside those that exhibit strong comovement. Fourth, the increase in vehicle production observed in September led to an upward revision of GDP growth, which was subsequently revised downward in October.

Turning to Panels B-F, we see the real-time revisions to GDP growth and contribu-

tions of various variables for 2024 Q4 to 2025 Q4. In Panel B, the downward revisions of GDP growth for 2024 Q4 continued until January 2025, driven by disappointing readings in trade and digital money indicators, before stabilizing through March 2025. Panel C shows that the 2024 Q4 GDP data release on May 6, 2025, led to a substantial upward revision, with the estimate increasing from 3.12% to 4.00%. This highlights the importance of hard data—particularly lagged GDP growth—in improving nowcasts of economic growth for current and upcoming periods. A similar pattern can be observed in Panel D for the nowcast of 2025 Q2. The GDP growth rate is gradually revised upward, increasing from 3.87% in April to 5.18% in September, bringing the estimate closer to the actual growth rate of 5.0%. In contrast to the significant effect of 2024 Q4 GDP release on our GDP growth update for the first quarter of 2025, the GDP publication for 2025 Q1 contributed moderately to the revision in the second quarter of 2025. Imports emerged as the primary driver of this upward adjustment, followed by vehicle production, while digital money provided an initial and substantial contribution at the onset of the nowcasting process in April 2025. Our final prediction for 2025 Q3 GDP growth is 4.74%, which is very close to the actual growth rate of 4.90% published by the Kenya National Bureau of Statistics (KNBS) on December 31, 2025 (Panel E). In the last Panel F, GDP growth forecast edged down from 4.61% on October 7 to 4.16% on December 21, 2025, primarily due to weak digital money readings, before recovering to 4.50% in January 2026.

Figure 4: Quarterly predictions for 2024 Q3 – 2025 Q4



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

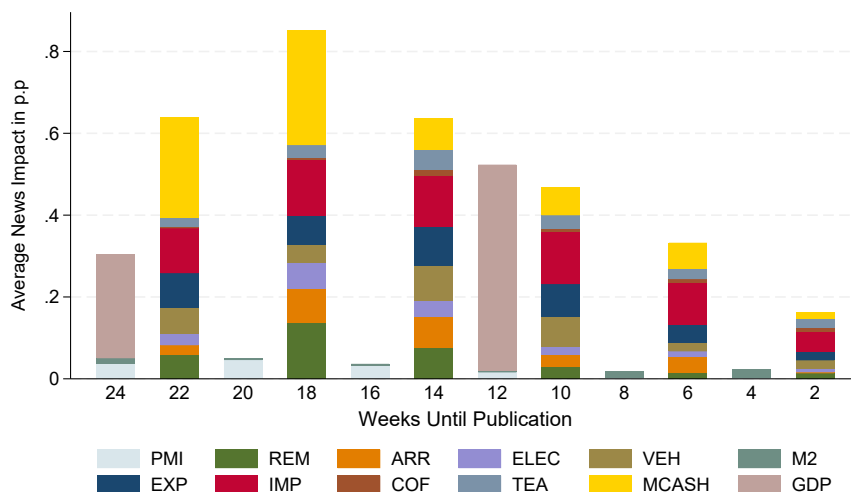
The following question arises from the analysis of the news decomposition: which variables are the most important drivers of the nowcast? Figure 5 shows the average absolute weekly impact of each series, computed in real time over the 2022 to 2025 sample. Four key insights emerge from this figure. First, the publication of GDP growth significantly affects nowcast updates. The release of the previous quarter’s GDP growth is consistently followed by a notable jump in the nowcast revision. This holds true for both nowcasts and backcasts. Second, the most important sectors include trade (exports and imports), production (electricity and vehicle), and consumption (digital money). These results are consistent with the literature (Di Pace et al., 2025; Kose and Riezman, 2001), which highlights the importance of trade shocks for explaining business cycle fluctuations in developing countries.

It is important to highlight the positive association between imports and GDP growth. Similar to other Sub-Saharan African countries (Asaana and Sakyi, 2021; Abdel-Latif et al., 2025), Kenya’s imports are not merely leakages in the GDP identity—they are active catalysts for economic growth. The findings presented in this paper reveal that Kenya’s economic growth is closely linked to import activity. Imports of technology-embedded capital goods and intermediate inputs play a pivotal role in enhancing productivity, accelerating industrialization, and strengthening export competitiveness—particularly in key sectors such as agriculture, manufacturing, and infrastructure. They enable access to advanced technologies and essential inputs that domestic industries rely on to innovate and scale-up production. Moreover, imports contribute to structural transformation by fostering economic diversification and improving the quality and variety of goods and services available in the domestic market.

The substantial contribution of non-traditional digital money data is also noteworthy. Digital money not only facilitates economic activity in the formal sector, but also enables a wide range of business opportunities for informal enterprises, especially in agriculture and services sectors (Aker and Mbiti, 2010; Suri et al., 2021). Moreover, it boosts financial inclusion and significantly contributes to households consumption smoothing and risk-sharing as well as poverty alleviation (Jack and Suri, 2014; Yao et al., 2023; Adu and Hartarska, 2025). Digital money figures are published 15 to 17 days after the end of the month. PMI, the timeliest variable, contributes mainly at the beginning of the sample, with its influence gradually fading over time. Finally, the almost bell-shaped pattern of Figure 5 indicates that the most useful information for the nowcast arrives in the middle of the nowcasting period, when data for the reference period first become available. In contrast, surprises have less impact on the nowcast at both the beginning and the end of the period: early on, because signals for GDP growth are still weak, and

later, because by then most useful information has already been incorporated, leaving little room for further revision. This pattern was also observed by Bok et al. (2018) in their analysis of nowcasting U.S. GDP growth.

Figure 5: The impact of macroeconomic data releases



Notes: The colored bars represent the average absolute impact of each macroeconomic variable on the nowcast estimated based on the two-factor model. The x-axis indicates the timing of the nowcasts within the quarter, measured by the number of bimonthly updates prior to the first official GDP release. These impacts are calculated in real time and averaged over the evaluation period from 2021 Q1 to 2025 Q4. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

4.2 Predictive performances

This section summarizes the nowcasting results to evaluate the model’s performance. First, we perform a qualitative assessment by presenting forecasts all together in a chart before inspecting the nowcasting errors. Figure 6 displays the evolution of the quarterly real-time predictions of y-o-y GDP growth at an annualized rate until the official publication of GDP data. The dots represent the official GDP data publication, while each line tracks how the nowcast changes as new information accumulates over time until the eve of the official GDP data release. As time progresses, the model is efficient in tracking quite closely the actual GDP growth, including, to some extent, the economic slowdown in 2022 and the subsequent rebound in 2023.

Zooming in on the end of the sample period, the yellow line shows the progression of GDP growth predictions performed in the first two quarters of 2024. The first half of the yellow line shows the six nowcasts for 2024 Q1 (two nowcasts per month in January, February, and March 2024), which are revised up from 5.06% to 6.40%.

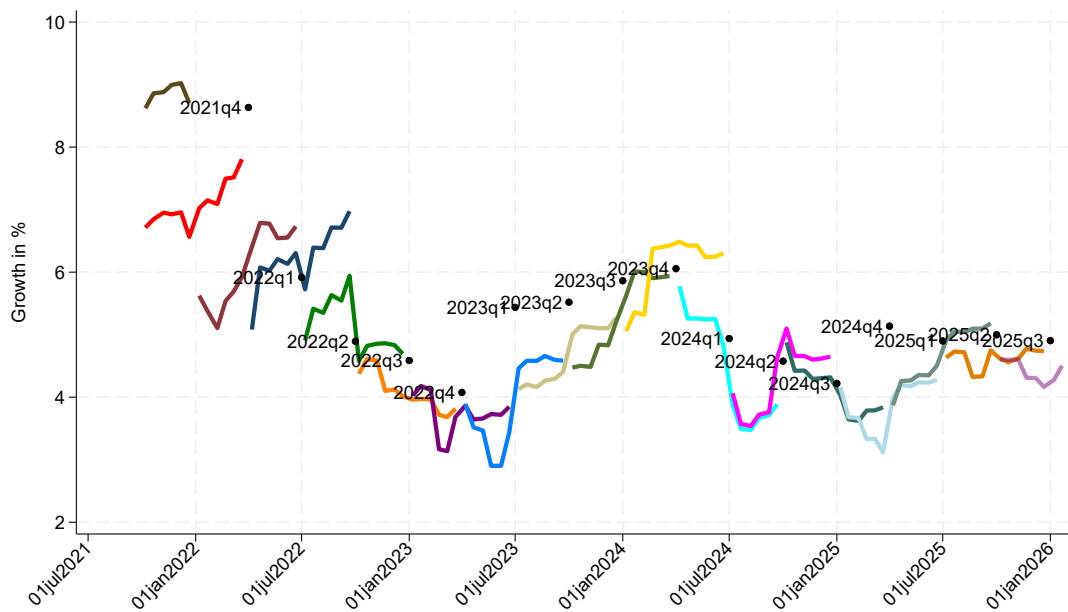
In the second half of the yellow line, we see that the six backcasts for 2024 Q1 (two backcasts per month in April, May, and June 2024) remain stable at around 6.30% until the official GDP growth data for 2024 Q1 is released in early July 2024 at 4.94%, which is lower than the predicted value. Visually, the backcasts for 2024 Q1 are illustrated by the part of the yellow line which overlaps the cyan line before the official GDP publication for 2024 Q1.

The six nowcasts for 2024 Q2 (two nowcasts per month in April, May, and June 2024) are shown in the first part of the cyan line before the official GDP data release for 2024 Q1, with values ranging from 5.78% to 4.83%. The respective backcasts are updated to values between 3.47% and 3.89% (segment of the cyan line which overlaps the purple line before the 2024 Q2 official data release) until the 2024 Q2 GDP growth data of 4.6% is published on October 2, 2024.

The nowcasts and backcasts for the subsequent quarters (2024 Q3, 2024 Q4, and 2025 Q1 to 2025 Q4) are updated the same way. For 2025 Q1, the nowcasts are revised downward from 4.16% to 3.12%, driven by negative *news* in mobile money figures, while 2024 Q4 GDP data release partly offset this negative effects—see the news contributions of the variables to nowcast revisions in Panel C of Figure 4. The GDP growth predictions for the second and third quarters of 2025 hovered around 5%, in line with realized figures (Panels D-E of Figure 4). The nowcasting process for 2025 Q4 is still ongoing, as illustrated by the downward edging light purple line at end of the period in Figure 6. This quasi out-of-sample exercise confirms a key appeal of the *joint* predictions that our DFM produces: the nowcast accuracy improves as we get closer to the GDP publication date, thanks to richer information from new data releases.

To further ascertain the accuracy of our model, Figure 7 plots the nowcast errors in real time relative to the most recent GDP data in the evaluation sample. Basically, it is the difference between each black diamond (prediction) in the black line progression and the red hollow diamond (released GDP growth data) in Figure 4. The dots at horizon one show the revision error as of one day before the GDP data release date. Then we take an average across all 15 quarters we evaluate from 2021Q4 to 2025Q3. The nowcasts errors are computed as the difference between the nowcasts and actual GDP growth data. We see that the nowcast errors, denoted by $Error_t = \hat{\mathbb{E}}[y_{t,gdp}|\Omega_T] - y_{t,gdp}$ for $T_0 \leq t \leq T$, shrink toward zero as time progresses closer to the official GDP data release (Figure 7).

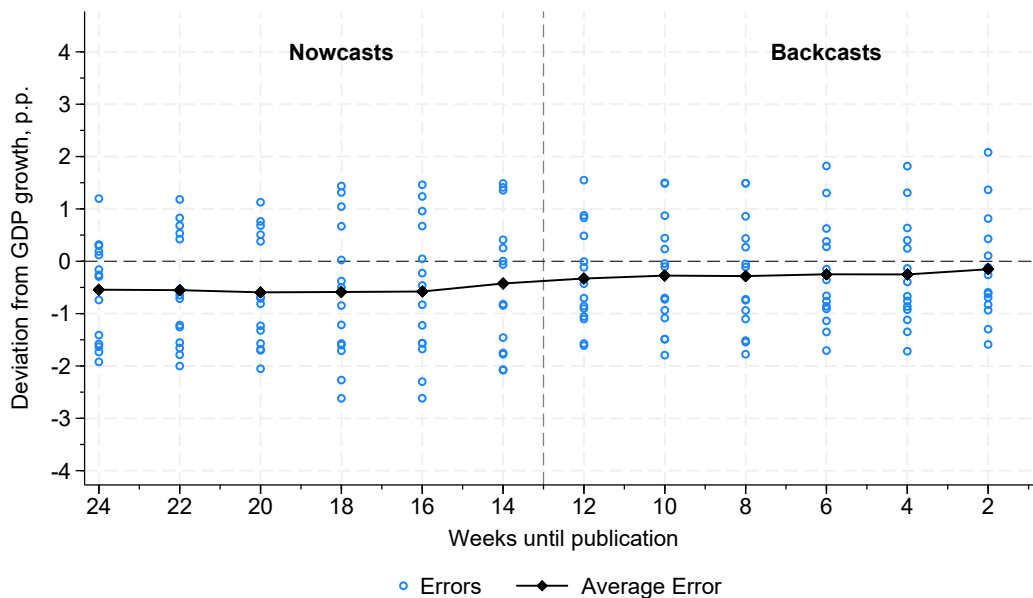
Figure 6: Evolution of annualized quarterly nowcast in 2021 Q3–2025 Q4



Notes: Solid lines depict the evolution of GDP growth nowcasts for different quarters using our model (Section 3). GDP release dates follow the official release calendar. The dots indicate the publication of official GDP data, and each line traces how the nowcast evolves as new information becomes available.

This further confirms the good out-sample performance of our model.

Figure 7: Nowcast errors relative to realized GDP growth



Notes: Forecast errors are computed in the out-of-sample exercise described in Section 4.1 using our nowcasting model (Section 3.1). Dots represent revision errors for all 15 quarters (2021Q4 to 2025Q3). The x-axis denotes the number of weeks until GDP publication within the forecast quarter. Specifically, 24 to 14 weeks before GDP publication indicates the nowcast period while the remaining weeks (12 to 2) at the right of the vertical black dotted line correspond to the backcast period.

4.3 Predictions for the calendar year

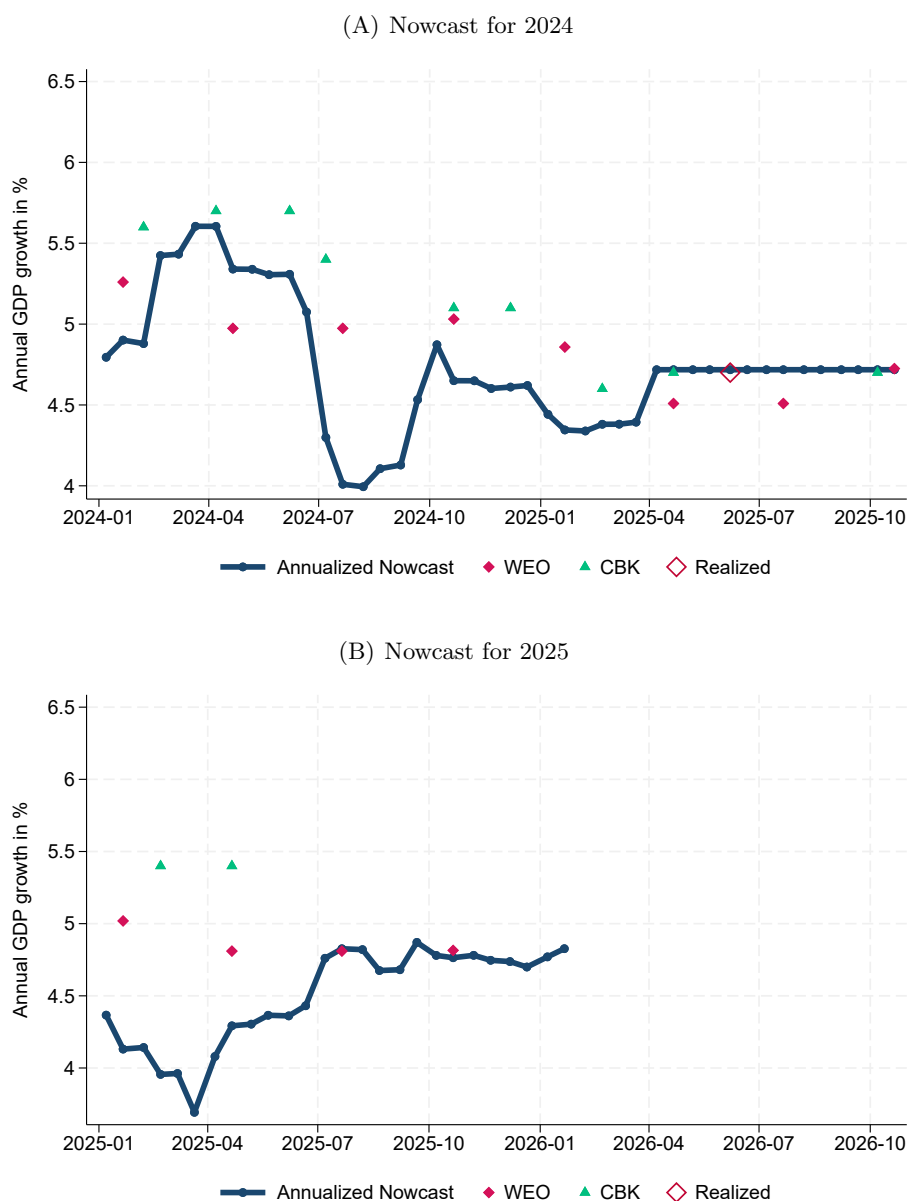
We now conduct an out-of-sample assessment of our DFM nowcasting framework, benchmarking its performance against that of the Central Bank of Kenya (CBK) predictions and World Economic Outlook (WEO) forecasts produced by the IMF. Figure 8 illustrates the evolution of y-o-y GDP growth estimates for 2024 and 2025, updated as new information becomes available. We analyze nowcast predictions using annual growth rates, as many institutions—including the CBK and IMF—focus on forecasting economic performance over the calendar year. Our annual nowcasts are constructed by aggregating quarterly forecasts, which are updated bimonthly, to produce consistent annual growth estimates that align with official statistics. We present results for the years 2022, 2023, 2024, and 2025. For the first three years, we show both the progression of nowcasts

throughout the year and the realized annual growth figures. For 2025, however, data collection is still ongoing, and the official annual GDP figures will only be released in Spring 2026.

Starting with real-time predictions, Panel A in Figure 8 illustrates updates to annualized quarterly GDP growth nowcast for 2024. Our nowcasts decreased from 5.60% to 5.07% in the first half of 2024, reflecting negative developments in trade, before rebounding and stabilizing to 4.72% in 2025 Q1, matching actual GDP growth before the official GDP data release. Although the nowcasts were significantly lower than the other institutional predictions in 2024 Q1, they gradually converged toward the CBK and WEO forecasts, surpassing them in 2025 Q2 slightly by 2 and 21 basis points, respectively. Panel B illustrates the nowcasting process for 2025 GDP growth, with 10 data points still missing from the required 33. On December 7, the model predicted an increase in growth to 4.72% in 2025, up from 4.37% in January. Our nowcasts for 2025 are substantially lower than institutional predictions in Q1 but converge toward WEO projections in Q3 and Q4, as additional data become available, indicating strong out-of-sample performance.

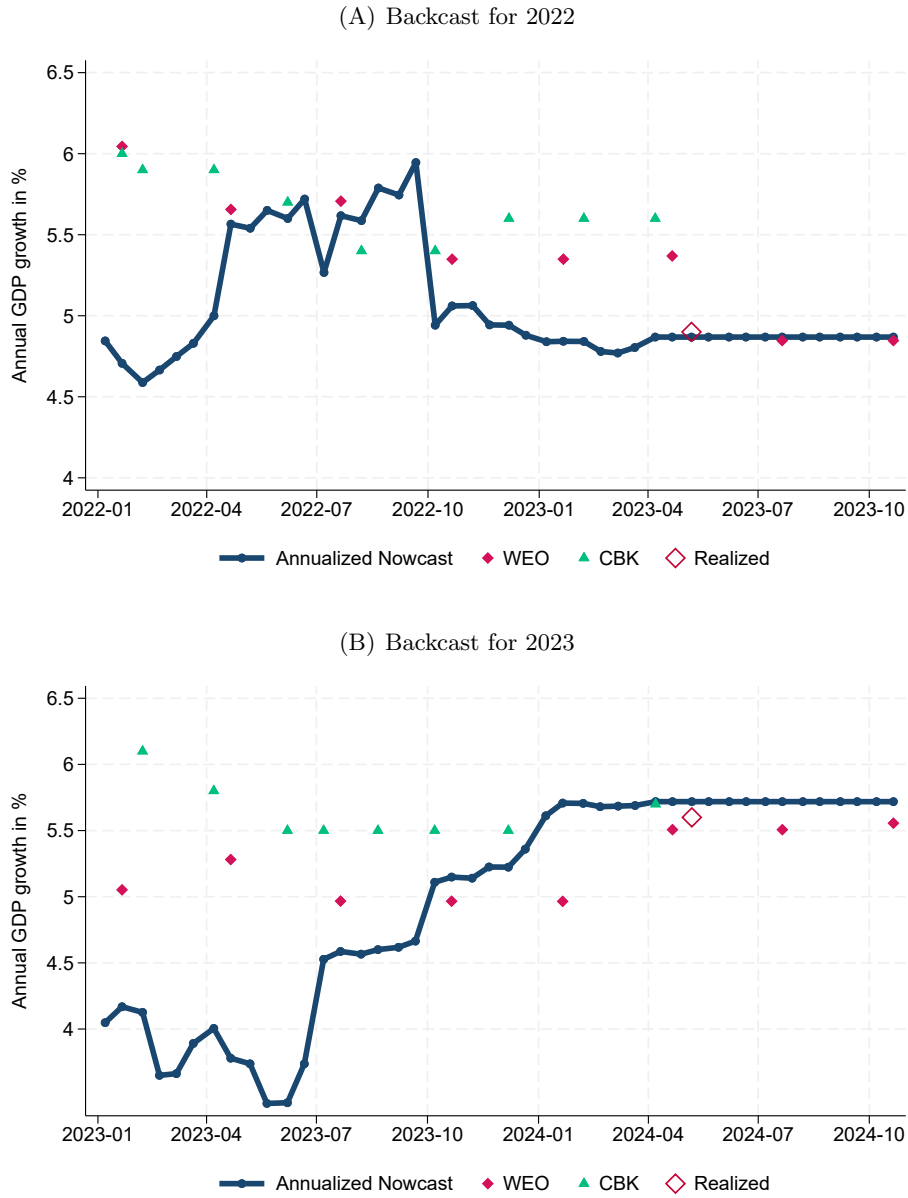
Turning to backtesting, Figure 9 shows how successive rounds of backcast revisions have evolved alongside WEO and CBK estimates in 2022 and 2023. Panel A indicates that our backcasts for 2022 dropped from 5.94% to 4.94% in 2022 Q3—close to CBK and WEO forecasts—before gradually declining to 4.87% in 2023 Q1, nearly matching the realized (actual) GDP growth of 4.90%. In contrast, CBK and WEO forecasts remained higher in 2023 Q1, at around 5.6 % and 5.37%, respectively. Panel B shows that the backcasts for 2023 rose from 3.44% in 2023 Q1 to 5.72% in 2024 Q1, while CBK and WEO forecasts ranged between 5% and 6.1%. This suggests stronger inertia in CBK and WEO forecasts, whereas our DFM nowcasts are more flexible, tracking actual GDP growth more closely by incorporating increasingly rich information as official data releases approach.

Figure 8: Real time prediction of annual GDP growth



Notes: The solid line depicts the evolution of annualized quarterly GDP growth nowcasts using the model in Section 3. GDP release dates follow the official calendar. Growth is measured as the year-over-year change. Annual nowcasts are constructed by aggregating quarterly forecasts, which are updated on a bimonthly basis. CBK = Forecasts from the Central Bank of Kenya; WEO = Forecasts from the IMF World Economic Outlook. CBK forecasts from 2025 Q3 and Q4 are not publicly available.

Figure 9: Backtesting annual GDP growth



Notes: The solid line depicts the evolution of annualized quarterly GDP growth backcasts using the model in Section 3. GDP release dates follow the official calendar. Growth is measured as the year-over-year change. Annual nowcasts are constructed by aggregating quarterly forecasts, which are updated on a bimonthly basis. CBK = Forecasts from the Central Bank of Kenya; WEO = Forecasts from the IMF World Economic Outlook.

5 Conclusion

Our paper contributes to the literature on business cycles in low-income countries by examining whether a single common component drives cyclical fluctuations in Kenya. While this assumption is well established for AEs, its validity in low-income contexts has been less clear; for example, Kose et al. (2003) shows that business cycles in LICs tend to be less synchronized than in AEs. The strong and robust performance of our nowcasting model suggests, however, that the single-factor framework can be meaningfully extended to low-income countries as well.

Nowcasting offers an important tool to assess the current state of the economy in LICs, where measures of economic activity are published infrequently and with significant delay. Although Kenya has been publishing quarterly GDP since 2009—which underscores the relatively high quality of its macroeconomic data among LICs, the reporting delay typically exceeds three months after the end of the quarter. This complicates the design and timely implementation of conjunctural macroeconomic policies.

Our paper builds a dynamic factor model tailored to Kenya’s economic conditions to nowcast GDP growth before the official data release. The modeling framework uses monthly indicators of activity in key Kenyan economic sectors and Kalman filtering techniques to produce early estimates of quarterly GDP growth. The model offers a practical way to continuously update near-term GDP growth predictions as new macroeconomic data become available. Thus, it informs timely stabilization policies and helps calibrate development policies with sound data-driven insights. It also elicits how the incoming information flow shapes nowcast updates, by decomposing each data release into a predictable part and a *news* component. We find that both quarterly and annual GDP predictions from our nowcasting framework perform well out-of-sample compared to alternative forecasts by the CBK and the IMF. Our estimation results also suggest that the *news* from data releases on electricity and vehicle production, digital money, exports and imports of goods are key factors that have affected GDP nowcast updates since 2024. The framework enables us to seamlessly include new predictors, as the set of high-frequency variables and non-traditional indicators grows. This paves the way for applying our nowcasting approach to other LICs with infrequent or annual GDP series.

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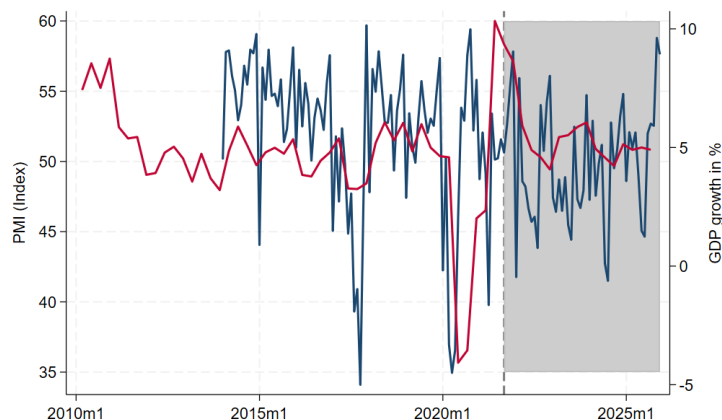
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Annex

A Time series of selected economic indicators

A.1 Stanbic Bank Kenya PMI

Figure A1: PMI (Index)

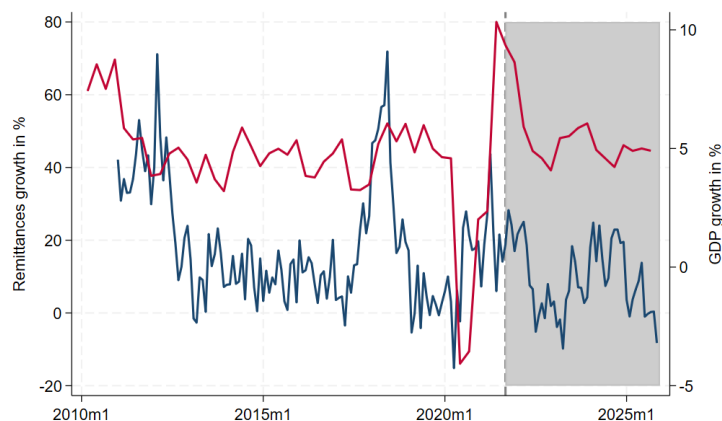


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

The Stanbic Bank Kenya Manufacturing PMI, compiled by Stanbic Bank, reflects the performance of the manufacturing and services sectors in Kenya. It is based on surveys conducted with purchasing managers across various industries. The PMI is released monthly, within the first 5 days of the month for the previous month, providing timely insights into economic conditions. The index was initiated in January 2014 and is constructed from five main components: new orders, production, employment, supplier deliveries, and inventories. Data may be subject to revisions, which are communicated in subsequent PMI reports, ensuring that stakeholders are aware of any adjustments to previously published figures. The PMI enters the model at levels. The data is updated on the 7th of each month.

A.2 Diaspora Remittances

Figure A2: Diaspora Remittances (Growth, %)



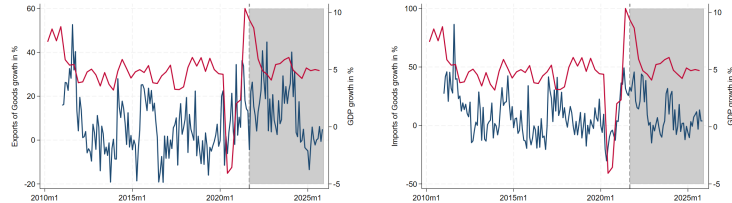
Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Diaspora Remittances data is released by the Central Bank of Kenya (CBK) on the 11th day of each month for the preceding month. This information is presented in millions of USD and is seasonally adjusted. Analysis of diaspora remittances is featured in prominent domestic and international publications such as Trading Economics, the Economist Intelligence Unit, and The Kenyan Wallstreet. In 2024, remittances surged by 18 percent to US\$4.9 billion and are anticipated to remain a crucial source of foreign exchange, contributing an average of 3.5 percent to GDP from 2025 to 2029 (Economist Intelligence Unit, July 21st, 2025). The data enters the nowcasting model using y-o-y growth rates to accommodate seasonality and is updated on the 21th of each month.

A.3 Exports and Imports of Goods

Figure A3: Exports and Imports of Goods (Growth, %)

(A) Exports of Goods (Growth, %) (B) Imports of Goods (Growth, %)

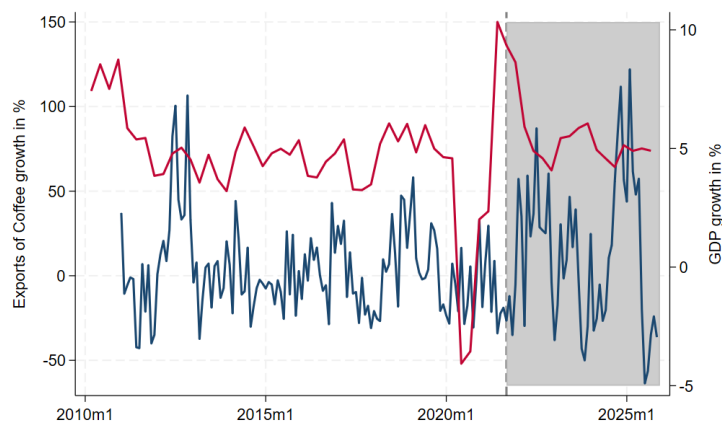


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Export and Import data are collected and reported by the CBK within the first 41 days of each month for the previous month. The data is presented in hundreds of millions of Kenyan Shillings (KES) and is not seasonally adjusted. It follows International Merchandise Trade Statistics (IMTS) definitions. Major financial commentators worldwide, including Trading Economics and Bloomberg, closely monitor these variables. Both imports and exports data are subject to revision and are incorporated into the model using monthly y-o-y growth rates to adjust for seasonality. This series is updated on the 21th day of the month for the previous two months.

A.4 Exports of Coffee

Figure A4: Exports of Coffee (Growth, %)

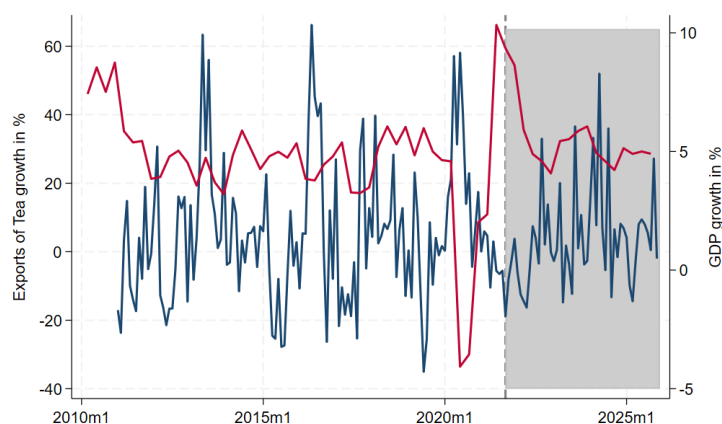


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

The data on Exports of Coffee is released by the KNBS and CBK 41 days from the previous publication. It is reported in Tonnes and is not seasonally adjusted. It follows International Merchandise Trade Statistics (IMTS) definitions. Financial commentators such as Trading Economics and the Economist Intelligence Unit track this data closely. The coffee export figures are subject to revision and are entered into the model using monthly y-o-y growth rates to account for seasonality. This series is updated on the 21th day of the month for the previous two months.

A.5 Exports of Tea

Figure A5: Exports of Tea (Growth, %)

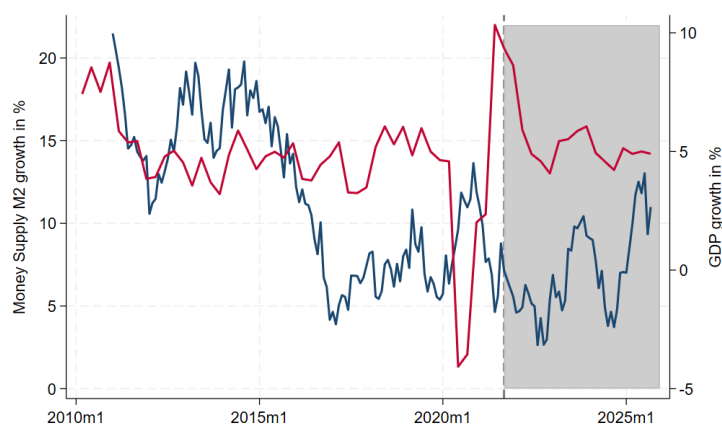


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Similarly, Exports of Tea data is published by KNBS and the CBK 41 from the last publication. It is reported in Tonnes and remains non-seasonally adjusted. It follows International Merchandise Trade Statistics (IMTS) definitions. This data is also monitored by major financial commentators like Trading Economics and the Economist Intelligence Unit. The tea export figures are subject to revision and are included in the model using monthly y-o-y growth rates to address seasonality. The series is updated on the 21th day of the month for the previous two months.

A.6 Money Supply M2

Figure A6: Money Supply M2 (Growth, %)

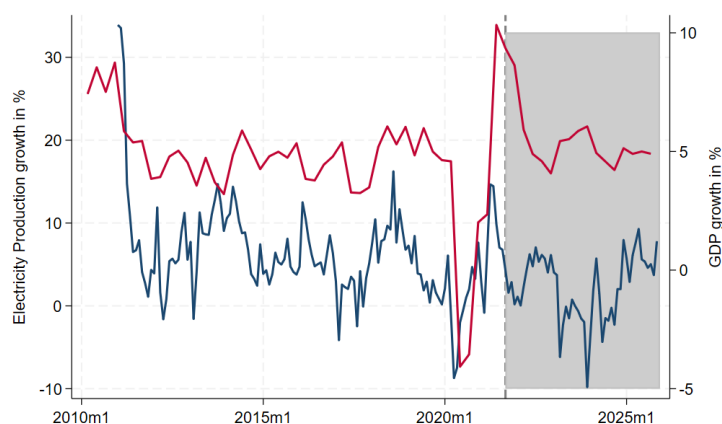


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

The Money Supply M2 data is released by the CBK within 45 days of the previous publication and is published in the monthly Financial Statistics Bulletin. This bulletin provides details on all physical cash, demand deposits, savings accounts, and other short-term deposits held by the public, as well as KES-denominated cross-border financial activities. The official release unit is KES Million, and the data enters the model using y-o-y growth rates to accommodate seasonality. This series is monitored by numerous domestic and international financial commentators, including Trading Economics and Bloomberg, and is updated on the 7th day of the month for the previous two months.

A.7 Electricity Production

Figure A7: Electricity Production (Growth, %)

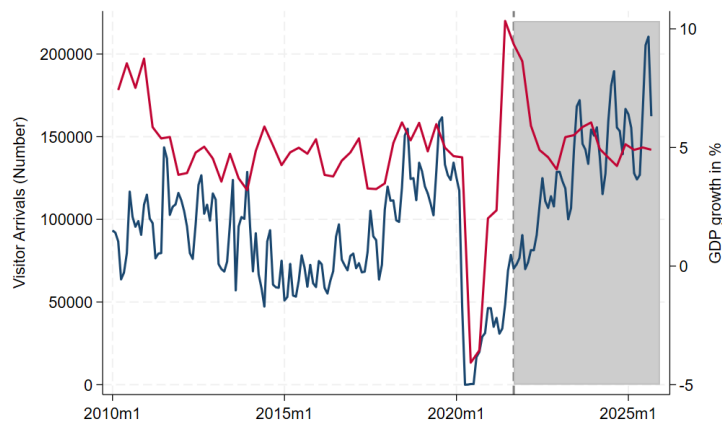


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Electricity Production data, a crucial component of Kenya's energy sector, is released by the Kenya Power & Lighting Company (KPLC) and the KNBS 48 days following the previous publication. It is reported under the category of energy production, which encompasses overall electricity generation statistics broken down by sources such as geothermal, hydropower, wind, solar, and thermal. The official release unit is million kWh, and the data is used in monthly y-o-y growth rates to address seasonality. The total installed electricity generation capacity in Kenya has been steadily rising, driven by a combination of renewable and non-renewable energy sources. Rising demand for electricity, fueled by population growth, urbanization, and industrialization, has led to ongoing infrastructure investments. Data for January-April indicates significant increases in electricity production, with updates occurring on the 21th of each month for the previous two months.

A.8 Visitor Arrivals

Figure A8: Visitor Arrivals

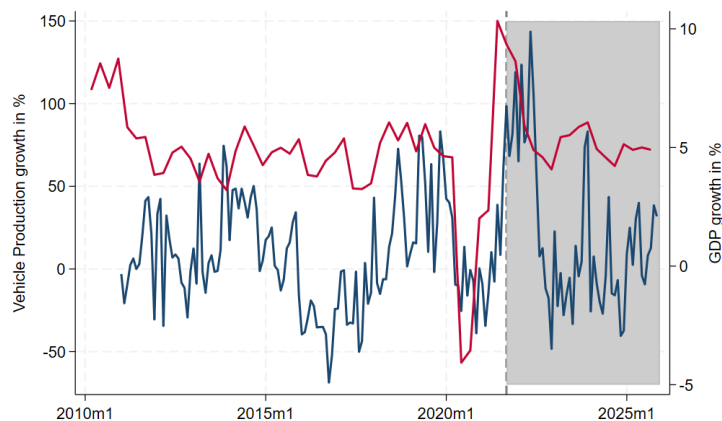


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Visitor Arrivals data is published by the Kenya Tourism Board and the KNBS, capturing the number of visitors entering through major ports (air, land, sea) within 48 days from the previous publication. Key source markets typically include countries such as the USA, UK, India, and regional neighbors like Tanzania and Uganda. Inflows from international tourism exceeded pre-coronavirus levels in 2023, with further improvements expected in 2024. Although visitor arrivals were flat in the first quarter, there was a 9.7% year-on-year increase in April. This series is closely monitored by domestic analysts and major financial commentators such as Trading Economics and Bloomberg and enters the model at level, with updates on the 21th of each month for the past two months.

A.9 Vehicle Production

Figure A9: Vehicle Production (Growth, %)

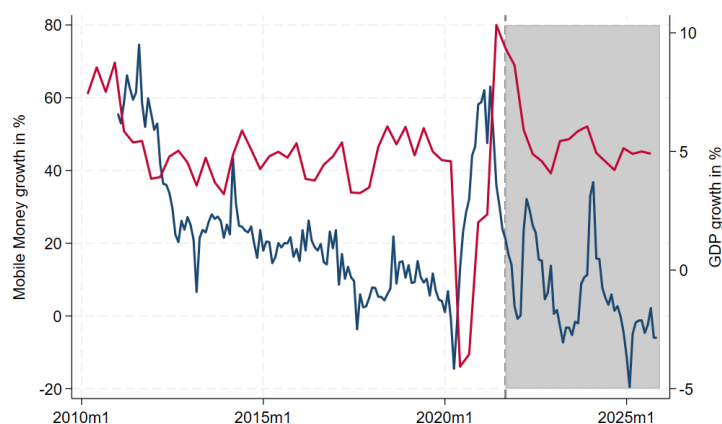


Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Vehicle Production data, released by the KNBS, is published 48 days after the previous release and is integrated into the model using y-o-y growth rates to account for seasonality. Updates occur on the 21st of each month for the previous two months. Prominent domestic and international commentators, including Trading Economics and Bloomberg, track vehicle production data closely. Data for January-April indicates strong increases in vehicle production, which is incorporated into the model using y-o-y growth rates.

A.10 Mobile Payments

Figure A10: Total agent cash in cash out (Growth, %)



Notes: The blue lines (left-hand side y-axis) show the monthly series of the transformed high-frequency economic indicators and the red line (right-hand side y-axis) shows GDP growth. The shaded area represents the out-of-sample period from September 2021 onwards.

Monthly mobile payments data, including the widely used Safaricom’s M-PESA payment system, are compiled by the CBK from digital payment platforms and published until February 2025. Data for the most recent months (March to May 2025) are released with a 17-day delay in the latest KNBS’ leading economic indicators monthly report (May 2025) which was published in late July 2025. Thus, we update the data on the 21st of each month to account for corrections and checks. Total agent cash in cash out data indicates the overall value of mobile money transactions, which grew steadily until end-2024. In the first half of 2025 however, the value of digital payments fell by 21.8% y-o-y to 636.21 billion Kenya Shillings in February 2025 and by 1.2% y-o-y to 713.25 billion Kenya Shillings in May 2025, even as the number of transactions increased. The widening gap between mobile payment usage and transaction value in the first half of 2025 points to a potential shift toward low-value payments.

The World Bank’s Findex reports position Kenya as a global pioneer in mobile money usage, with 82.3% of adults engaged with mobile money accounts in 2024. These reports highlight M-PESA’s pivotal role in fostering financial inclusion, particularly in rural regions, where adoption stands at 77%, and in communities lacking traditional banking infrastructure. Furthermore, services such as Airtel Money and Equitel are acknowledged for their contributions to increased accessibility.

Kenya’s mobile money sector experienced a sharp decline in March and April 2020

due to the economic slowdown triggered by COVID-19, with transaction volumes and values dropping to multi-year lows. However, the rebound was swift and robust, surpassing pre-pandemic levels and continuing on an upward trajectory to date. This strong recovery was driven by decisive policy measures from the Central Bank of Kenya, including waiver of fees on small transactions, raising wallet and transaction limits, and promoting digital payments to reduce cash handling. These interventions, combined with behavioral shifts toward contactless payments, accelerated digital adoption during lockdowns. The growth was further reinforced by the expansion of mobile money services into credit, savings, and bill payments, as well as the rise of e-commerce and remote work. The effects of the network amplified usage, making mobile money an indispensable part of the Kenyan financial ecosystem and cementing a structural change in the payment behavior.

B Details on bridging the frequency gap with factors

Here, we present the aggregation formula in Equation 9, which bridges the frequency gap between the quarterly year-on-year GDP growth rate $y_{t,gdp}^q$ —that is partially observed at every third month of the quarter—and the monthly year-on-year GDP growth rate $y_{t,gdp}^m$:

$$\begin{aligned}
 y_{t,gdp}^q &= Y_{t,gdp}^q - Y_{t-12,gdp}^q \\
 &= (1 - L^{12})Y_{t,gdp}^q \\
 &\approx (1 - L^{12})(1 + L + L^2)Y_{t,gdp}^m \\
 &= (1 + L + L^2)(1 - L^{12})Y_{t,gdp}^m \\
 &= (1 + L + L^2)y_{t,gdp}^m \\
 &= y_{t,gdp}^m + y_{t-1,gdp}^m + y_{t-2,gdp}^m,
 \end{aligned} \tag{13}$$

We can re-express the quarterly GDP growth as

$$y_{t,gdp}^q = \lambda_{gdp}(f_t + f_{t-1} + f_{t-2}) + \epsilon_{t,gdp} + \epsilon_{t-1,gdp} + \epsilon_{t-2,gdp}, \tag{14}$$

or in state-space form as

$$\begin{bmatrix} y_{t,gdp}^q \\ y_t^m \end{bmatrix} = \begin{bmatrix} \lambda_{gdp} & \lambda_{gdp} & \lambda_{gdp} & 1 & 1 & 1 & \mathbf{0}' \\ \Lambda_m & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_m \end{bmatrix} \begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ \epsilon_{t,gdp} \\ \epsilon_{t-1,gdp} \\ \epsilon_{t-2,gdp} \\ \boldsymbol{\epsilon}_t^m \end{bmatrix}, \tag{15}$$

where Λ_m is an $((M-1) \times 1)$ vector of factor loadings for the monthly predictor variables, $\mathbf{0}$ is an $((M-1) \times 1)$ vector of zeros, and \mathbf{I}_m is an $((M-1) \times 1)$ vector of ones.

C Details on the expectation-maximization algorithm

This section gives additional details on the expectation-maximization (EM) estimation. In the $(\iota + 1)^{th}$ iteration in the M-step, the re-estimated new parameters are given by

$$\hat{\Lambda}^{(\iota+1)} = \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [y_t F_t' | \Omega_v] \right) \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_t F_t' | \Omega_v] \right)^{-1}, \quad (16)$$

$$\hat{\Gamma}^{(\iota+1)} = \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_t F_{t-1}' | \Omega_v] \right) \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_{t-1} F_{t-1}' | \Omega_v] \right)^{-1}, \quad (17)$$

$$\begin{aligned} \hat{\Theta}^{(\iota+1)} &= \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [y_t y_{t-1}' | \Omega_v] - \hat{\Lambda}^{(\iota+1)} \sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_t y_{t-1}' | \Omega_v] \right) \\ &\quad \times \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [y_{t-1} y_{t-1}' | \Omega_v] - \hat{\Lambda}^{(\iota+1)} \sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_{t-1} y_{t-1}' | \Omega_v] \right)^{-1}, \end{aligned} \quad (18)$$

$$\hat{\Sigma}^{(\iota+1)} = \text{diag} \left(T_v^{-1} \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [y_t y_t' | \Omega_v] - \hat{\Lambda}^{(\iota+1)} \sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_t y_t' | \Omega_v] \right) \right), \quad (19)$$

$$\hat{\Xi}^{(\iota+1)} = T_v^{-1} \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_t F_t' | \Omega_v] - \hat{\Gamma}^{(\iota+1)} \sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_{t-1} F_t' | \Omega_v] \right). \quad (20)$$

The EM algorithm converges when the increase in the likelihood between two consecutive iterations falls below an arbitrarily small threshold. Assuming there is no missing data in y_t would imply that

$$\mathbb{E}_{\Psi^{(\iota+1)}} [y_t y_t' | \Omega_v] = y_t y_t' \quad \text{and} \quad \mathbb{E}_{\Psi^{(\iota+1)}} [y_t F_t' | \Omega_v] = y_t \mathbb{E}_{\Psi^{(\iota+1)}} [F_t' | \Omega_v], \quad (21)$$

could be plugged into the parameter estimation formulas in the M-step, enabling to compute $\mathbb{E}_{\Psi^{(\iota+1)}} [F_t F_t' | \Omega_v]$, $\mathbb{E}_{\Psi^{(\iota+1)}} [F_t F_{t-1}' | \Omega_v]$, and $\mathbb{E}_{\Psi^{(\iota+1)}} [F_t | \Omega_v]$ using the Kalman filter and smoother. However, the formulas above indicate that the EM algorithm, in its standard form, is not suited to address the issues arising from datasets with different frequencies, different historical availability, and asynchronous reporting times.

Following [Bańbura and Modugno \(2014\)](#), we use a modified version of the expectation-maximization algorithm that is suited to estimate the parameters of a state-space model on *ragged edge* datasets. When the vector of data y_t contains missing observations,

we re-express it as :

$$y_t = (I_{M \times M} - \mathcal{S}_t) y_t + \mathcal{S}_t y_t, \quad (22)$$

where \mathcal{S}_t is a diagonal selection matrix with diagonal values of ones corresponding to the non-missing observations in y_t and zeros otherwise. This modified representation of the EM-algorithm facilitates the computation of the expectations in equation 21 and the associated part of the estimates when the data are available. Thus, the formulas in equations 16 and 19 can be rewritten as

$$\text{vec} \left(\hat{\Lambda}^{(\iota+1)} \right) = \left(\sum_{t=1}^{T_v} \mathbb{E}_{\Psi^{(\iota)}} [F_t F_t' | \Omega_v] \otimes \mathcal{S}_t \right)^{-1} \text{vec} \left(\sum_{t=1}^{T_v} \mathcal{S}_t y_t \mathbb{E}_{\Psi^{(\iota)}} [F_t' | \Omega_v] \right), \quad (23)$$

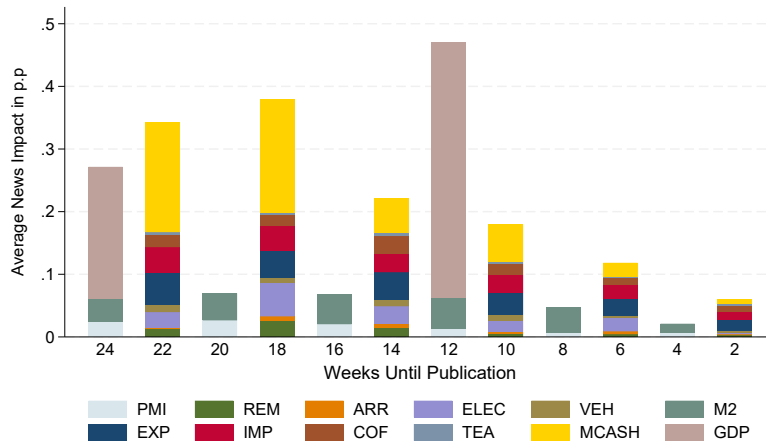
and

$$\begin{aligned} \hat{\Sigma}^{(\iota+1)} = & \text{diag} \left(T_v^{-1} \sum_{t=1}^{T_v} \left(\mathcal{S}_t y_t y_t' \mathcal{S}_t' - \mathcal{S}_t y_t \mathbb{E}_{\Psi^{(\iota)}} [F_t' | \Omega_v] \hat{\Lambda}^{(\iota+1)'} \mathcal{S}_t \right. \right. \\ & - \mathcal{S}_t \hat{\Lambda}^{(\iota+1)} \mathbb{E}_{\Psi^{(\iota)}} [F_t | \Omega_v] y_t' \mathcal{S}_t + \mathcal{S}_t \hat{\Lambda}^{(\iota+1)} \mathbb{E}_{\Psi^{(\iota)}} [F_t F_t' | \Omega_v] \hat{\Lambda}^{(\iota+1)'} \mathcal{S}_t \\ & \left. \left. + (I_{M \times M} - \mathcal{S}_t) \hat{\Sigma}^{(\iota)} (I_{M \times M} - \mathcal{S}_t) \right) \right). \end{aligned} \quad (24)$$

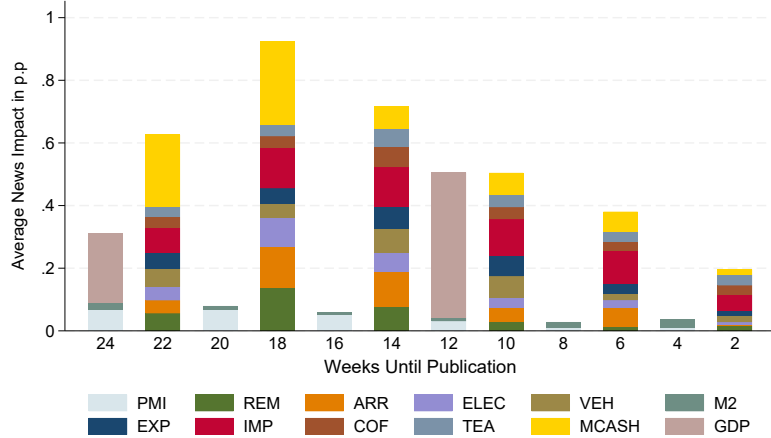
D News Impacts

Figure D11: The impact of macroeconomic data releases

(A) News impacts, 1-factor model



(B) News impacts, 3-factor model

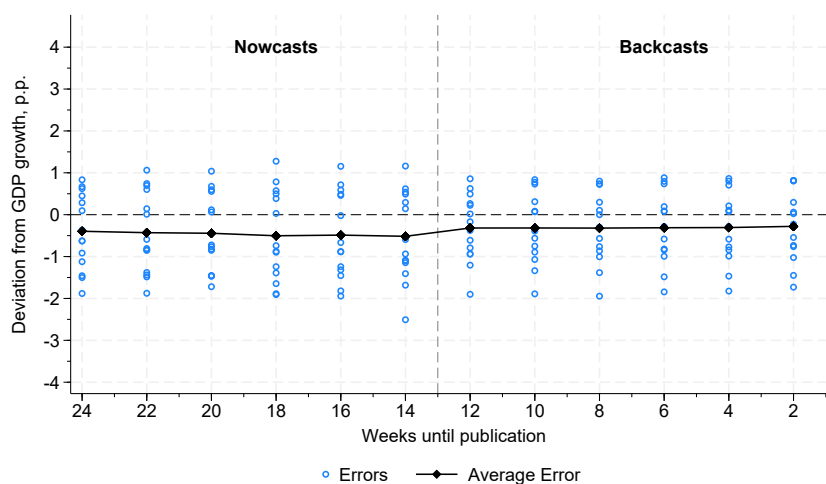


Notes: The colored bars represent the average absolute impact of each macroeconomic variable on the nowcast based on one- and three-factor models. The x-axis indicates the timing of the nowcasts within the quarter, measured by the number of bimonthly updates prior to the first official GDP release. These impacts are calculated in real time and averaged over the evaluation period from 2021 Q1 to 2025 Q4. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

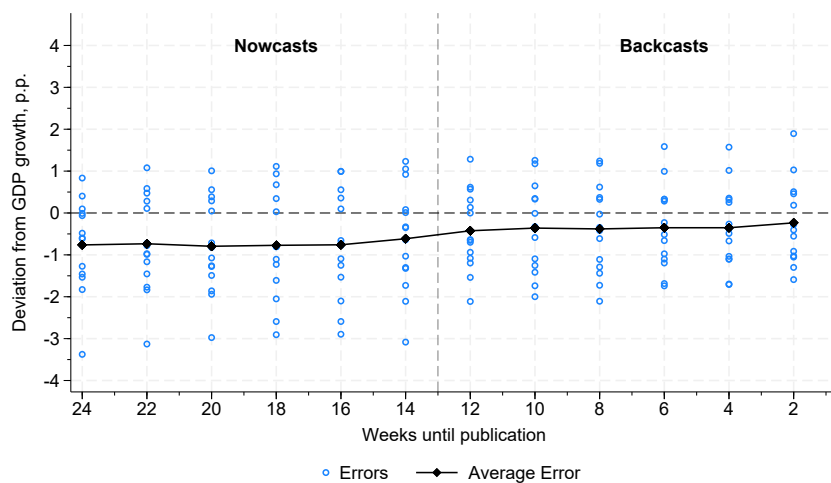
E Nowcast errors for 1-factor and 3-factor models

Figure E12: Nowcast errors relative to realized GDP growth

(A) Nowcast errors, 1-factor model



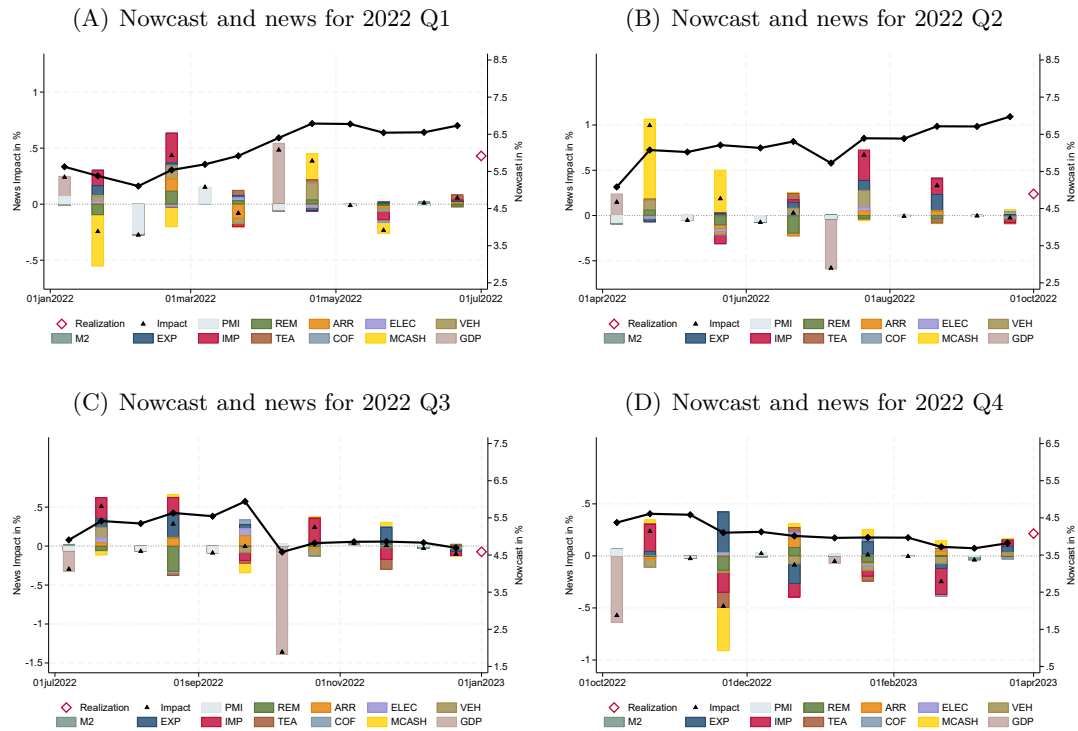
(B) Nowcast errors, 3-factor model



Notes: Forecast errors are computed in the out-of-sample exercise described in Section 4.1 using our nowcasting model (Section 3.1). Dots represent revision errors for all 14 quarters (2021Q4 to 2025Q3). The x-axis denotes the number of weeks until GDP publication within the forecast quarter. Specifically, 24 to 14 weeks before GDP publication indicates the nowcast period while the remaining weeks (12 to 2) at the right of the vertical black dotted line correspond to the backcast period.

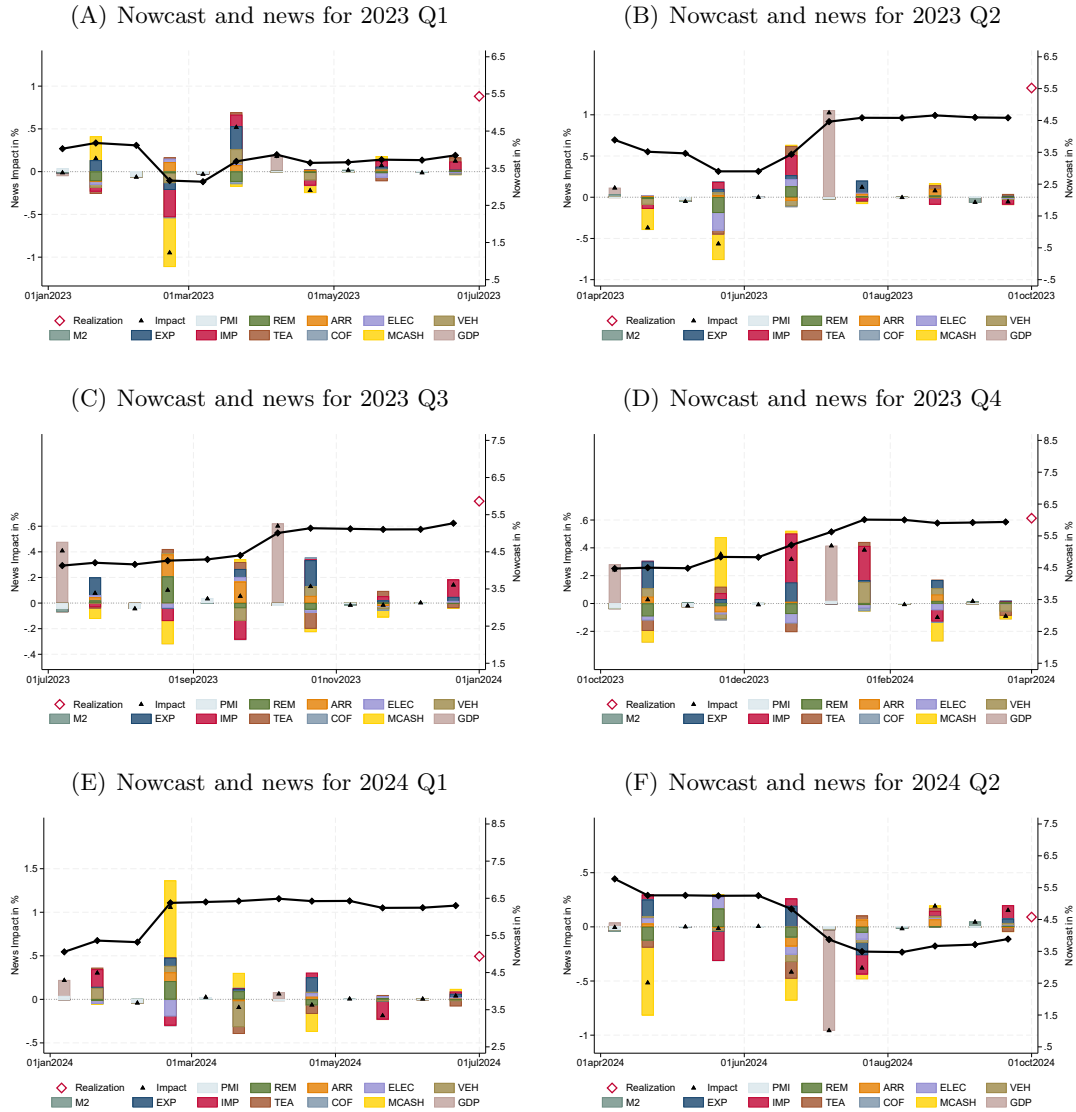
F Real time predictions and news decomposition for the remaining quarters 2022 Q1–2025 Q4, 2-factor model

Figure F13: Quarterly predictions and news decomposition for 2022 Q1–Q4, 2-factor model



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

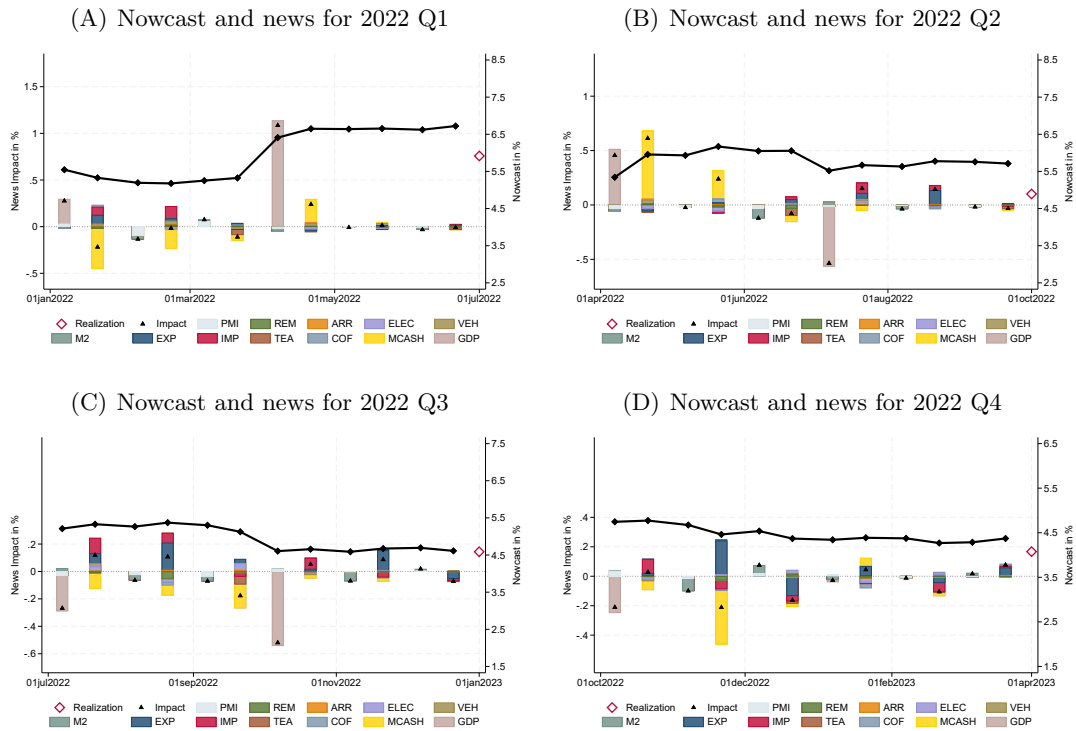
Figure F14: Quarterly predictions and news decomposition for 2023 Q1 – 2024 Q2, 2-factor model



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

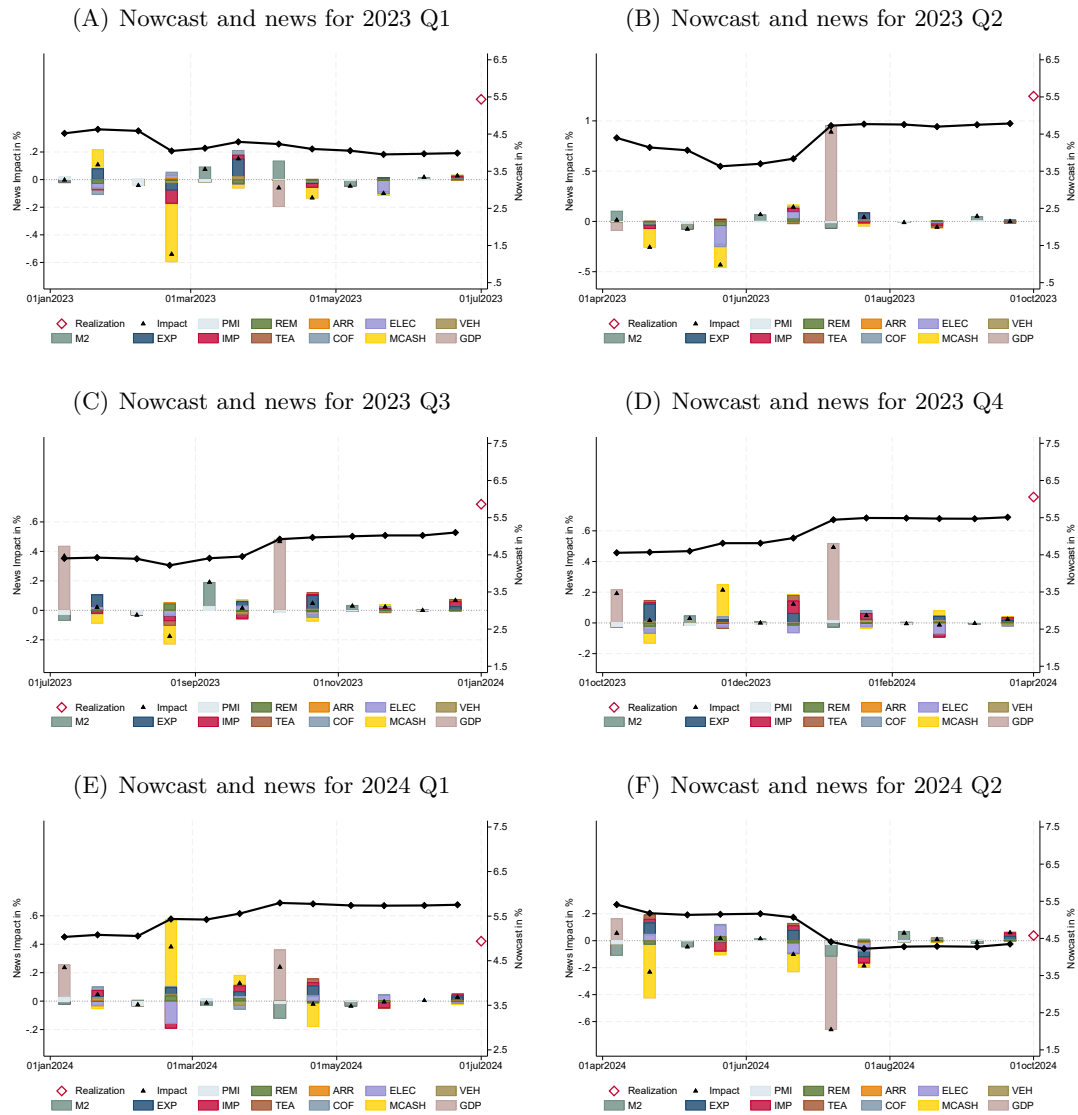
G Real time predictions and news decomposition for the remaining quarters 2022 Q1 – 2025 Q4, 1-factor model

Figure G15: Quarterly predictions and news decomposition for 2022 Q1 – Q4, 1-factor model



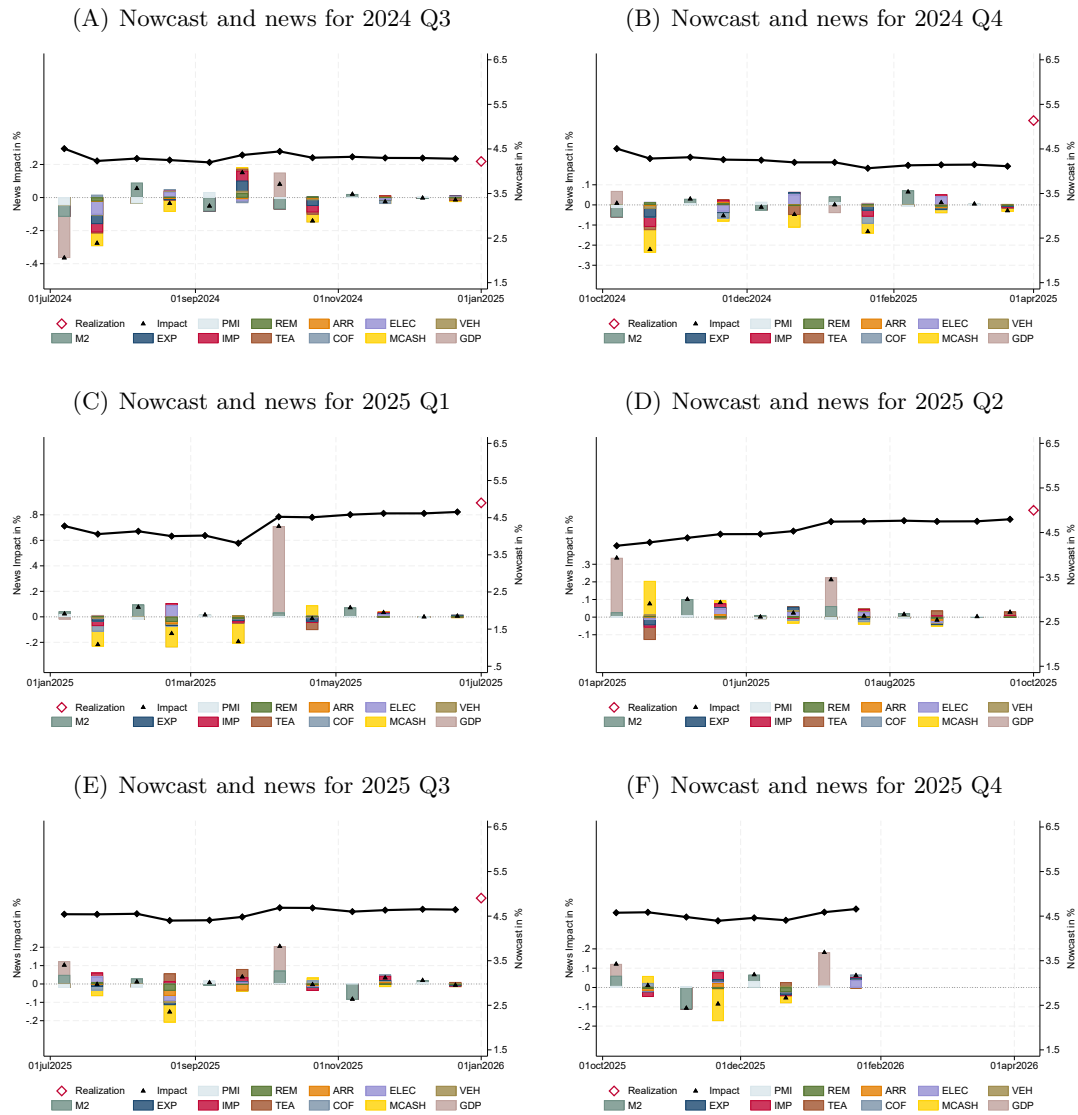
Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

Figure G16: Quarterly predictions and news decomposition for 2023 Q1 – 2024 Q2, 1-factor model



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

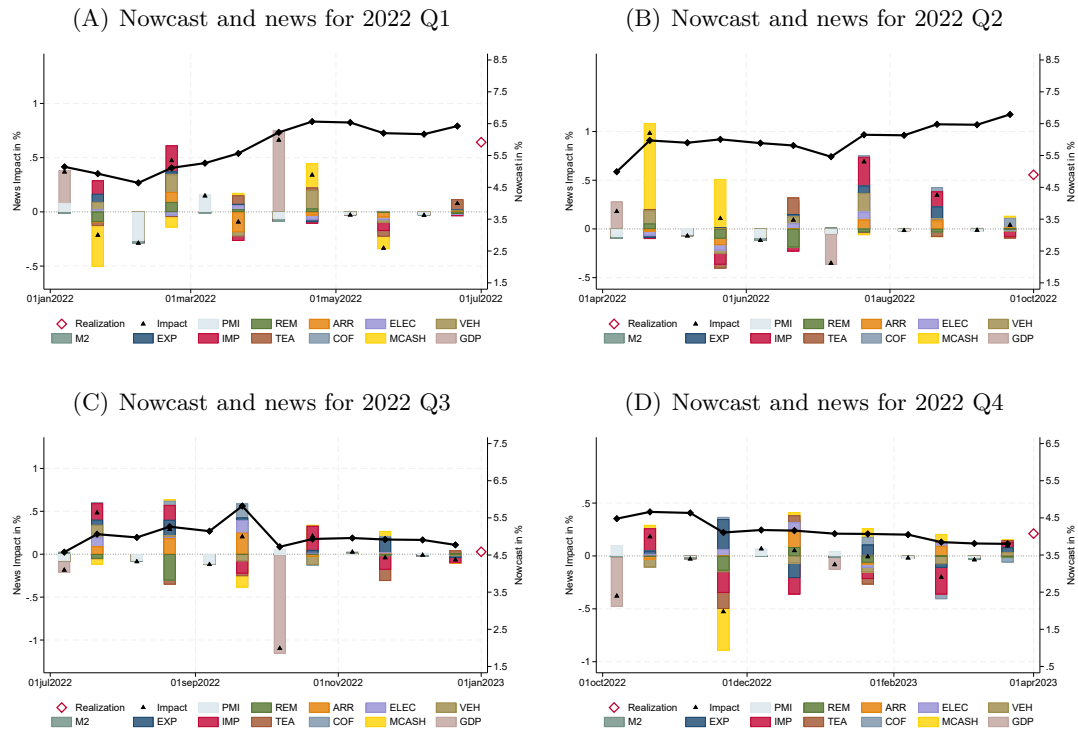
Figure G17: Quarterly predictions and news decomposition for 2024 Q3 – 2025 Q4, 1-factor model



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

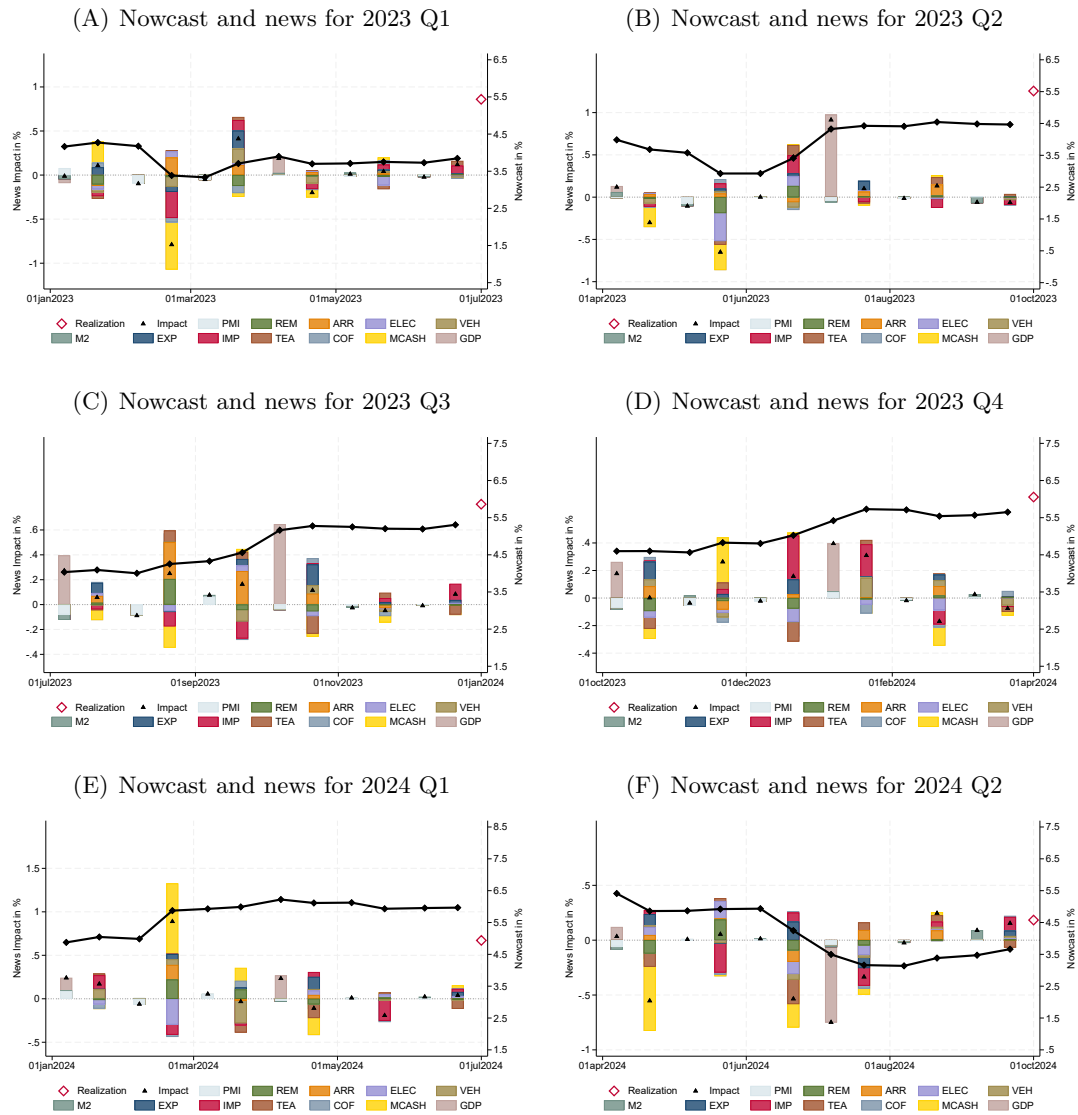
H Real time predictions and news decomposition for the remaining quarters 2022 Q1 – 2025 Q4, 3-factor model

Figure H18: Quarterly predictions and news decomposition for 2022 Q1 – Q4, 3-factor model



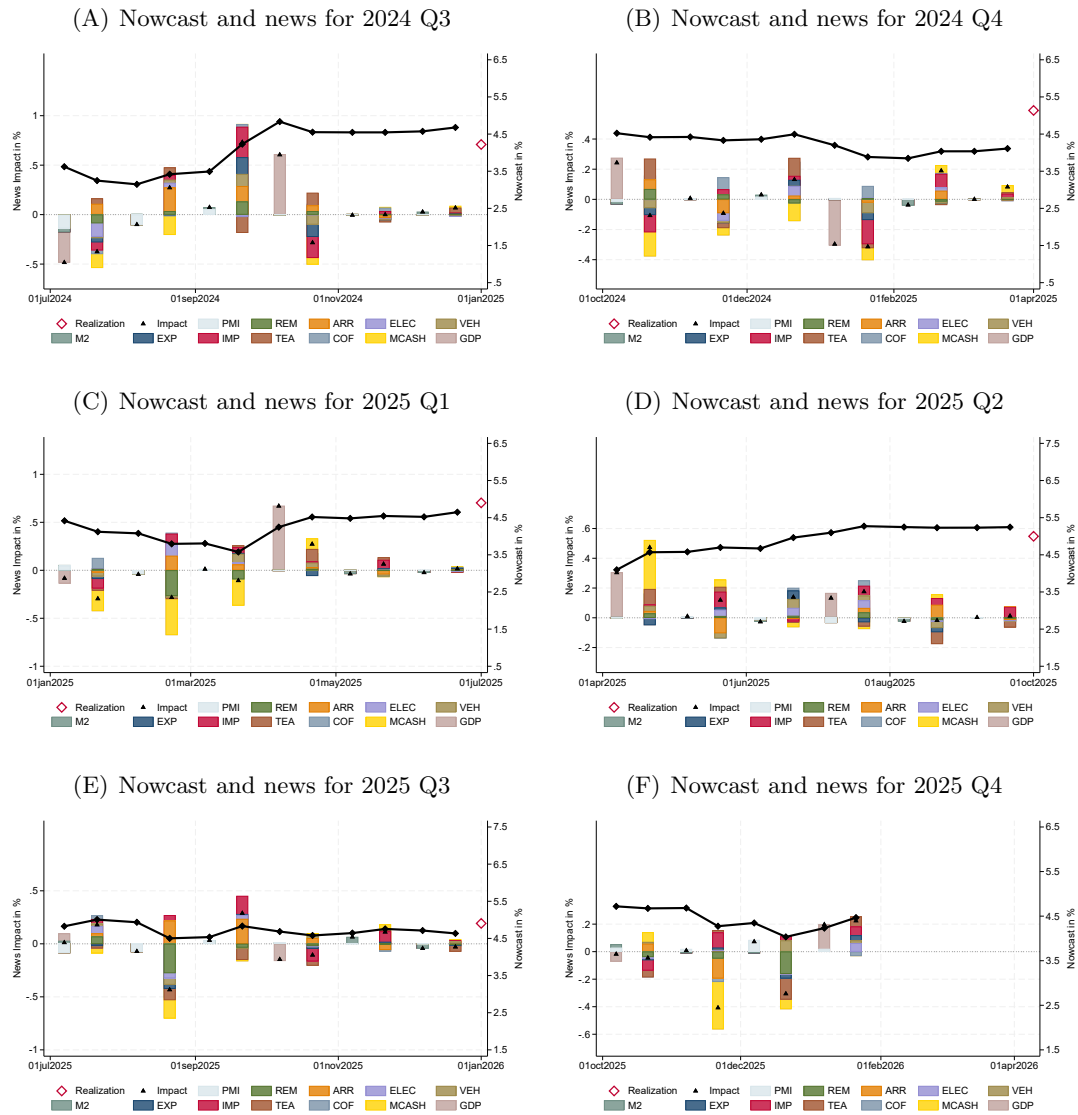
Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

Figure H19: Quarterly predictions and news decomposition for 2023 Q1 – 2024 Q2, 3-factor model



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

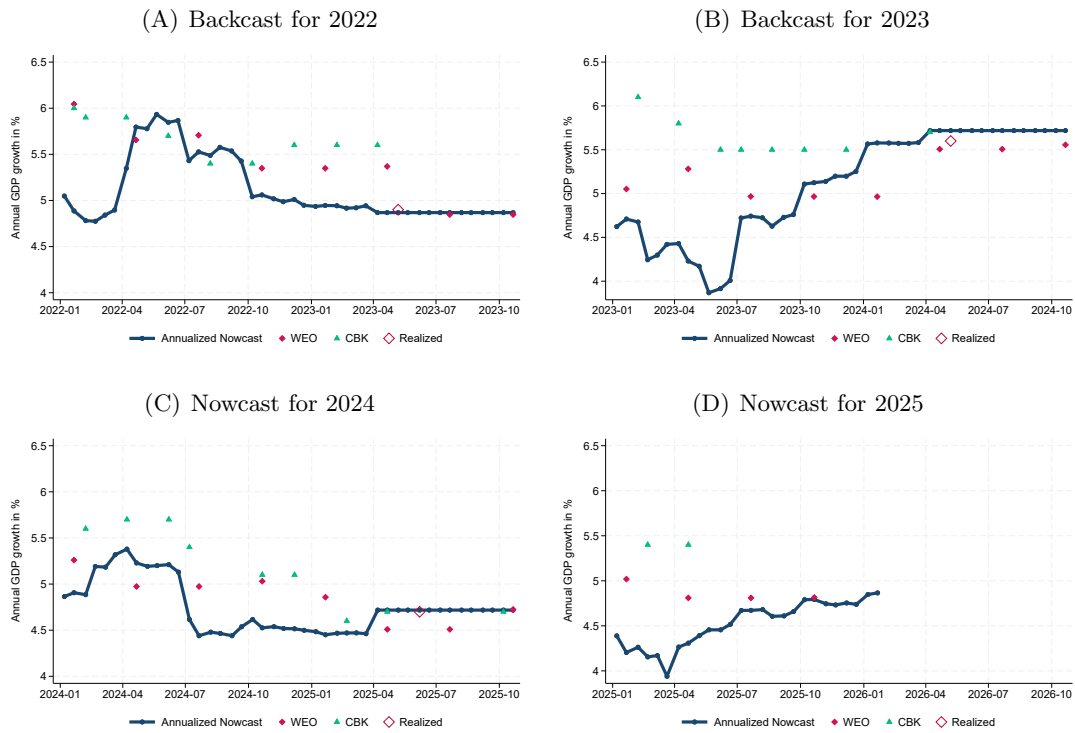
Figure H20: Quarterly predictions and news decomposition for 2024 Q3 – 2025 Q4, 3-factor model



Notes: The black solid line (right-hand side y-axis) shows the quarterly nowcasts of GDP growth and the red hollow diamond represents the published actual GDP growth. The black triangle marks (left-hand side y-axis) show the changes in two consecutive quarterly nowcasts of GDP growth while the bars show the contribution of each predictor to the nowcast updates. PMI = Stanbic Bank Kenya PMI; REM = Diaspora Remittances; ARR = Visitor Arrivals; ELEC = Electricity Production; VEH = Vehicle Production; M2 = Money Supply; EXP = Exports of Goods; IMP = Imports of Goods; COF = Exports of Coffee; TEA = Exports of Tea; MCASH = Mobile Money; GDP = Real GDP.

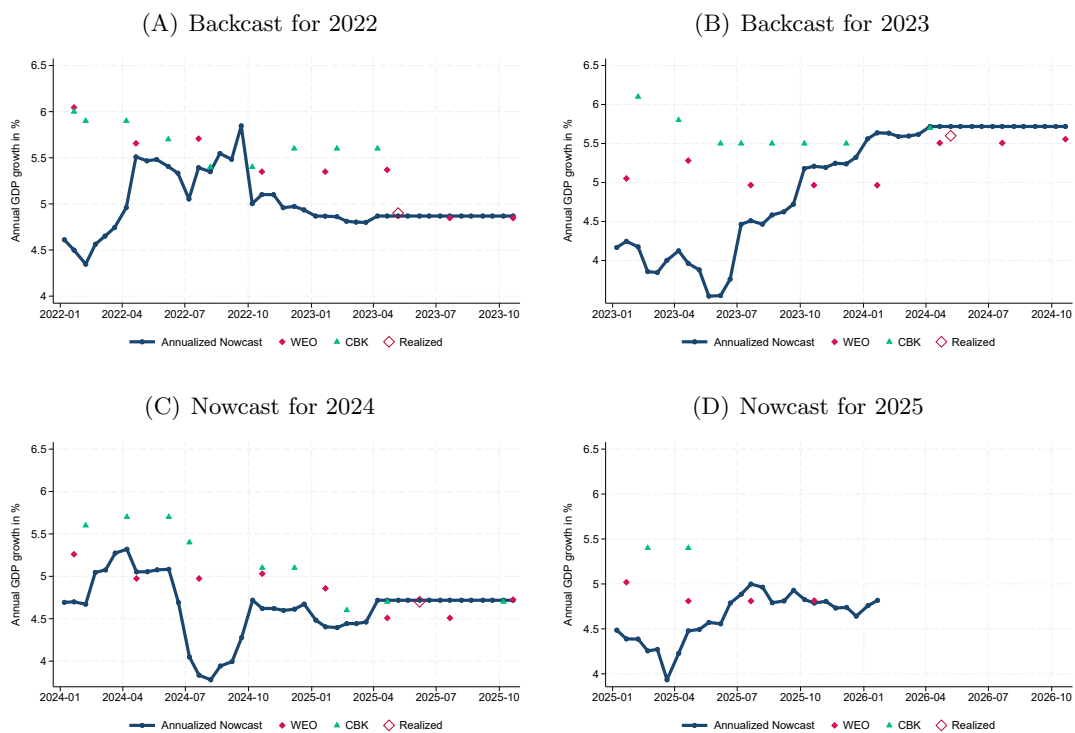
I Annual nowcasts and backcasts with 1-factor and 3-factor models

Figure I21: Nowcasting and backcasting annual GDP growth, 1-factor model



Notes: The solid line depicts the evolution of annualized quarterly GDP growth backcasts using the model in Section 3. GDP release dates follow the official calendar. Growth is measured as the year-over-year change. Annual nowcasts are constructed by aggregating quarterly forecasts, which are updated on a bimonthly basis. CBK = Forecasts from the Central Bank of Kenya; WEO = Forecasts from the IMF World Economic Outlook. CBK forecasts from 2025 Q3 and Q4 are not publicly available.

Figure I22: Nowcasting and backcasting annual GDP growth, 3-factor model



Notes: The solid line depicts the evolution of annualized quarterly GDP growth backcasts using the model in Section 3. GDP release dates follow the official calendar. Growth is measured as the year-over-year change. Annual nowcasts are constructed by aggregating quarterly forecasts, which are updated on a bimonthly basis. CBK = Forecasts from the Central Bank of Kenya; WEO = Forecasts from the IMF World Economic Outlook. CBK forecasts from 2025 Q3 and Q4 are not publicly available.



PUBLICATIONS

Nowcasting GDP Growth for Kenya

Working Paper No. WP/2026/032