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Nowcasting GCC GDP:

A Machine Learning Solution for Enhanced Non-Oil GDP Real-time Prediction

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ABSTRACT: This paper presents a machine learning–based nowcasting framework for estimating quarterly non-oil GDP growth in the Gulf Cooperation Council (GCC) countries. Leveraging machine learning models tailored to each country, the framework integrates a broad range of high-frequency indicators—including real activity, financial conditions, trade, and oil-related variables—to produce timely, sector-specific estimates. Advancing the nowcasting literature for the MENA region, this approach moves beyond single-model methodologies by incorporating a richer set of high-frequency, cross-border indicators. It presents two key innovations: (i) a tailored data integration strategy that broadens and automates the use of high-frequency indicators; and (ii) a novel application of Shapley value decompositions to enhance model interpretability and guide the iterative selection of predictive indicators. The framework's flexibility allows it to account for the region's unique economic structures, ongoing reform agendas, and the spillover effects of oil market volatility on non-oil sectors. By enhancing the granularity, responsiveness, and transparency of short-term forecasts, the model enables faster, data-driven policy decisions strengthening economic surveillance and enhancing policy agility across the GCC amid a rapidly evolving global environment.

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Executive Summary

This paper introduces a real-time nowcasting framework for estimating quarterly non-oil GDP growth in the GCC. Unlike traditional forecasts, which are released infrequently and often focus on overall GDP, this approach provides high-frequency, sector-specific estimates that offer policymakers a timely insight into GCC's non-oil economic activities and serve as a valuable real-time gauge for analysts, investors, and international community seeking to understand the region's underlying growth momentum and recent trends.

The paper extends the existing nowcasting literature for the MENA region by moving beyond single-model approaches and incorporating a richer set of high-frequency, cross-border indicators. This is the first time a nowcasting framework has been systematically applied across the GCC, combining a unified structure with country-specific models for non-oil GDP. Leveraging a flexible, machine learning-based approach, the framework incorporates a broad set of high-frequency indicators, spanning real activity, financial conditions, trade, and oil-linked variables sourced from both domestic and global datasets. Its design is tailored to the region's unique economic landscape, including the spillover effects of oil market volatility on non-oil sectors, accounting for evolving statistical systems and structural reforms aimed at diversification. By accounting for both cross-country heterogeneity and shared macroeconomic dynamics, the framework makes a novel contribution to the nowcasting literature and advances real-time monitoring tools in oil-exporting economies.

By enhancing granularity, responsiveness, and transparency of short-term forecasts, the framework facilitates faster and data-driven policy decisions. The paper identifies key high-frequency indicators that are strongly correlated with non-oil activities in the GCC, helping to bridge long-standing information gaps. It complements existing institutional forecasts and, in the case of Saudi Arabia, the model slightly outperformed official non-oil flash estimates in terms of sample average of forecast errors. The framework's scalable design further amplifies its value, offering a powerful tool that can be extended across the GCC to strengthen economic surveillance and policy agility in the face of a rapidly evolving global environment.

I. Introduction

Nowcasting, the practice of predicting the present or very near future of an economy using high-frequency indicators has become an essential tool for generating real-time insights, especially in the period preceding the release of official GDP figures. The literature has established that timely GDP nowcasts can reduce the lag between evolving economic conditions and policy responses (Banbura et al. 2013; Bok et al. 2018), enhance the agility of both monetary and fiscal policy (Banbura 2010; Giannone et al. 2008), and help mitigate the impact of economic downturns (Carriero et al. 2015).

This paper contributes to the existing literature by focusing specifically on nowcasting non-oil real GDP, rather than total real GDP. In oil-exporting economies, headline GDP is heavily influenced by fluctuations in oil prices and production volumes, often driven by external shocks or policy decisions. In contrast, the non-oil sector reflects more domestic economic dynamics and is influenced by a broader set of structural, financial, and consumption-related indicators. While non-oil GDP is not fully insulated from the oil sector, owing to fiscal spillovers, sentiment effects, and government-led investment channels, it provides a more meaningful signal of underlying economic activity relevant for medium-term growth and diversification efforts.

The relevance of nowcasting in the GCC and broader MENA region is further amplified by the dual challenge of oil market volatility and the economic transformation underway across these economies. Structural reforms aimed at reducing reliance on hydrocarbons introduce sectoral shifts and policy-driven dynamics that are often not well captured by traditional models. A flexible nowcasting framework ensures that economic monitoring remains timely, credible, and policy-relevant in these dynamic environments.

Importantly, our approach adopts a nowcasting framework that encompasses 22 candidate models (Annex II) rather than relying on a single-model specification. This model-agnostic setup aggregates estimates across a suite of methods, including factor-based regressions, bridge equations, and machine learning techniques. It offers improved robustness in the face of structural shifts and evolving data environments, reduces sensitivity to the idiosyncrasies or biases of individual models, and provides the flexibility to incorporate and reweight incoming information as new data is released. This approach is particularly critical for the GCC, where frequent data revisions and evolving statistical capacity require estimates that remain adaptable and responsive. Authorities across the region continue to improve the quality, frequency, and transparency of macroeconomic data, and a flexible nowcasting framework allows real-time integration of these improvements without the need to recalibrate models from scratch.

The framework draws on a broad set of high-frequency indicators capturing key aspects of economic activity. These include, but are not limited to, consumer prices and subcomponents for inflation and consumption, PMIs and industrial production for output momentum, and trade data to proxy domestic demand and external linkages. Financial conditions are tracked using point-of-sale transactions (which also capture private consumption), credit, deposit rates, and stock market indicators, which also reflect forward-looking sentiment and investment trends. The framework further incorporates global, cross-border, and regional signals, such as oil price benchmarks, interest rate spreads, and financial flows from key partners including the United States, China, Saudi Arabia, and the UAE, particularly relevant for the open, small economies of the GCC.

Table 1. Quarterly GDP Publication in GCC Countries

Country	Available Time Series (as of June 2025)	Publication Lag (from the reference quarter)
Bahrain	2008Q1 – 2024Q4	+90 days
Kuwait	2010Q1 – 2024Q4	+90 days
Oman	2010Q1 – 2024Q4	+105 days
Qatar	2011Q1 – 2024Q4	+90 days
Saudi Arabia	2011Q1 – 2025Q1	+68 days (1)
United Arab Emirates	2012Q1 – 2024Q3	+200 days [varies] (2)

Source: National Authorities.
Note: (1) Saudi Arabia authority (GASTAT) publishes flash estimates of quarterly GDP with a 30-day lag and the actual official data with a 68-day lag. The new rebased GDP published by GASTAT in May 2025 are not used for nowcasting in this paper, as we compare the out-of-sample performance against official estimates that were available at each respective point in time to ensure a fair comparison (see Figure 5). Data vintage as of end-April 2025 was used for Saudi Arabia, reflecting chain-linked methodology adopted by GASTAT in early 2024.

(2) UAE’s quarterly GDP publication lag varies by emirates.

The remainder of the paper is structured as follows. Section II discusses related literature. Section III presents the nowcasting framework, covering data selection, model evaluation, and Shapley value decompositions. Section IV reports the nowcasting results, Section V presents robustness checks and forecast performance. Section VI concludes.

II. Literature Review

A wide range of nowcasting models has been developed to enhance the accuracy and timeliness of real-time GDP estimates, which are generally classified into two distinct groups:

- The conventional **parametric models** assume a specific form for the underlying relationship between input variables and the output (i.e., GDP growth), which are characterized by a finite number of parameters that are independent on the numbers of instances of training data. The parametric models simplify estimation and inference but limits flexibility (Hastie, Tibshirani, & Friedman, 2009). Examples of parametric models commonly applied for GDP nowcasting include OLS (as in Bridge models), ARIMA/VAR (with mixed-frequency of Bayesian extensions), Dynamic Factor Models (DFM), State-Space Models etc. (Giannone et al. 2008; Jensen et al. 2016; Nakazawa 2022; Almuzara et al. 2023).

- In contrast, the **non-parametric models**, do not assume a fixed functional form for the underlying data distribution, makes them flexible and particularly useful when the data's structure is unknown or in high dimensions. This flexibility, however, often comes at the cost of requiring larger datasets for effective training and can lead to challenges such as overfitting (Breiman, 2001). In addition, interpretation and hypothesis testing of results are challenging in non-parametric framework, as the signs and relationship between variables are not based on structural models. Notable examples of non-parametric methods include Random Forests, Support Vector Regression (SVR), Gradient Boosting, etc. (Ahmed et al. 2010; Fornaro et al. 2020; Richardson et al. 2021).

For the MENA region, the nowcasting GDP literature remains limited. Alkhareif et al. (2022) developed a nowcasting model for Saudi Arabia's overall, oil, and non-oil real GDP growth using a single parametric specification (Generalized DFM). Al-Rawashdeh (2024) applied a machine learning approach (Extreme Gradient Boosting) to nowcast Jordan's GDP with limited data span and finds superior nowcast accuracy compared with traditional models such as ARIMA and DFM.

In this paper, we adopt non-parametric machine learning algorithms to nowcast non-oil GDP by using a set of high frequency indicators and several models. Given the generally sufficient input data available cross various sectors of the GCC economies, the presence of dynamic interactions among indicators (e.g., linkages between oil and non-oil, sovereign and financial sector)—especially in light of ongoing economic reforms—and the growing potential to integrate more high-frequency or alternative data sources, we consider non-parametric methods to be well-suited for the scope and objectives of this study. The ML models used in our nowcasting framework, as presented in Annex II, include Support Vector Machines (SVMs), Random Forests, Stochastic Gradient Boosting Trees, Elastic Net, Principal Component Regression (PCR), and so on. The diverse set of models highlights the flexibility and adaptability of ML approaches. These models can handle different data types and structures, mitigate issues like multicollinearity and overfitting, and improve prediction accuracy. Moreover, their ability to be continuously trained on new data enables them to adapt to changing economic conditions and improve their predictive performance over time.

Table 2. High-frequency Determinants in GDP Nowcasting Literature [1]

Sector	Determinants	Importance and Expected Impact
Real (incl. non-commodity trade)	▪ Inflation ▪ Imports and exports of non-commodity goods and services ▪ Employment ▪ PortWatch trade ▪ Flights and hotels tracker	Stable macroeconomic conditions, increased activities of production, consumption, and labor market foster growth and contribute to higher GDP.
Commodity Sector	▪ Volume of commodity trade ▪ Price of commodity (energy, metal, agricultural products)	Higher prices and export volumes of commodities directly boost GDP; commodity sector often has spillover effects to non-commodity sector through fiscal and financial channels.
Manufacturing	▪ Industrial Production Index (IPI) ▪ Purchasing Mangers' Index (PMI)	Higher manufacturing outputs and business sentiment about future manufacturing and services increase GDP.
Monetary and Finance	▪ Exchange rate ▪ Interest rates ▪ Point-of-sales [2] ▪ Credit growth ▪ Stock market performance	Current movement can impact trade competitiveness and inflation; loose financial conditions can stimulate investments; higher stock market index signals investor's confidence of market prospects.
Unconventional data sources	▪ Satellite imagery ▪ Social media contents	Signal activities in production, consumption, and trade, where increased activities indicate higher GDP.

Note: (1) The distinction between domestic and global/regional variables are not specified here, as their selections and relevance depend on economic openness and data availability.
(2) point-of-sales data also captures private consumption.

High-frequency determinants commonly used in GDP nowcasting (Table 2) provide a foundation and insights for nowcasting non-oil GDP in the GCC. High-frequency data have become increasingly integral to nowcasting GDP, offering timely insights into economic activities across various sectors. They can be broadly grouped into four interrelated sectors: (i) Real sector indicators capture macroeconomic stability (i.e., inflation), activities of production, consumption, labor market dynamics, and external demand and supply of non-commodity goods. (ii) Commodity sector is particularly important for resource-dependent economies, such as the oil-exporting GCC countries. Commodity prices and volumes not only have a direct impact on the overall GDP, but also generate indirect spillovers to non-oil activities through fiscal and financial channels. Therefore, the oil sector remains an important category for nowcasting GCC's non-oil GDP. (iii) Manufacturing sector provides information on industrial production and business sentiment, both of which are closely linked to economic performance. (iv) Monetary and financial sectors, including the performances of government securities, reflect credits activity and overall liquidity conditions. A growing strand of literature has incorporated unconventional data sources to enhance the timeliness and granularity of GDP nowcasting. These include satellite-based data (e.g., nighttime lights, land cover, nitrogen dioxide concentration), PortWatch trade data, google search trends, their relevance and predictive power for nowcasting vary by country and depend on structural economic characteristics.[1]

III. Nowcasting Framework

This paper builds on the growing literature on nowcasting (Barhoumi et al., 2022; Akbal et al., 2023), while introducing two key innovations: (i) an advanced data collection and integration approach tailored to the GCC context, and (ii) a novel use of Shapley value decompositions to iteratively refine indicator selection and enhance the interpretability of non-oil GDP nowcasts. Together, these innovations strengthen the framework's analytical rigor and practical relevance for policymaking.

First, we introduce a new data collection strategy aimed at enhancing the accuracy and timeliness of economic forecasts. This approach broadens the scope of high-frequency indicators used in nowcasting, combining traditional economic metrics with real-time financial transactions and other unconventional data. By employing advanced data scraping techniques and leveraging partnerships with data providers, we ensure a continuous and up-to-date data pipeline into our models. This innovation improves the granularity and responsiveness of the nowcasting framework, narrowing the lag between economic developments and their reflection in model outputs.

Second, we apply Shapley value decompositions, borrowed from cooperative game theory, to improve the interpretability of complex machine learning models used in nowcasting. These decompositions systematically quantify the marginal contribution of each predictor, helping to explain variable importance within algorithms such as Random Forests and Gradient Boosting Machines. Crucially, the Shapley framework is used not only as a diagnostic tool but also to support an iterative, model-agnostic process for indicator selection. Across more than 30 model variants, we evaluate and reweight dozens of candidate indicators, testing multiple configurations over time, to identify the most predictive and robust set of inputs for each country. This allows the framework to adapt to data availability, structural changes, and country-specific dynamics, while preserving

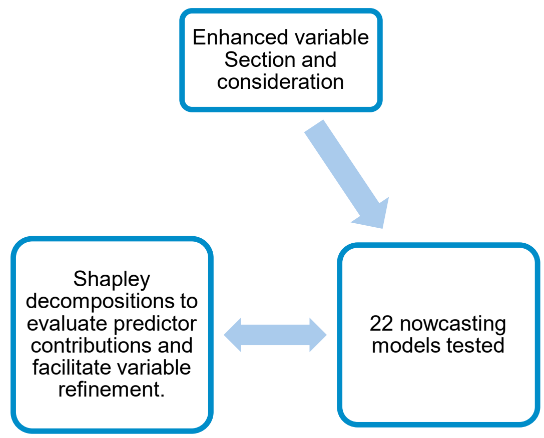
[1] In this study, we incorporate only a limited set of unconventional data sources, as their broader use is typically reserved for cases where conventional indicators are lacking or insufficient for nowcasting—particularly in the areas of trade and production—which is not the case for the GCC.

transparency and interpretability. The result is a lean, country-calibrated, and empirically validated set of high-frequency indicators that maximizes nowcast accuracy and policy relevance.

Main Components of the Nowcasting Framework

We present a comprehensive nowcasting framework designed to improve the prediction and monitoring of non-oil GDP growth, tailored to the economic characteristics of the GCC and other oil-exporting regions. This framework builds on prior IMF work (Barhoumi et al., 2022; Akbal et al., 2023) and follows a phased, modular approach.

Figure 1. Main Nowcasting Framework Components



The framework consists of three main components. First, we implement a rigorous variable selection process, drawing from a wide range of high-frequency indicators. These indicators are chosen based on their relevance and predictive power for non-oil GDP, ensuring coverage of both domestic economic activity and external influences. This step establishes a strong foundation for model accuracy by creating a meaningful and dynamic information set.

Second, the nowcasting stage applies advanced machine learning algorithms, drawing on tests of 22 models (Annex II) to generate real-time estimates of current economic conditions. These algorithms are calibrated to maximize predictive accuracy while adapting to the evolving data environment. The resulting nowcasts serve as timely inputs to inform policymaking and economic surveillance.

Third, we apply Shapley value decompositions to assess the marginal contribution of each predictor to the nowcast.[2] This enhances model transparency, identifies key drivers of forecast performance, and supports iterative model refinement. By quantifying the influence of each variable, the framework facilitates targeted improvements in both indicator selection and model specification.

Together, these components form a flexible and data-rich framework for real-time economic monitoring. The approach advances the state of nowcasting in the GCC context by combining methodological rigor, machine learning, and interpretability, addressing key challenges in forecasting non-oil GDP in resource-dependent economies.

Variable Consideration and Selection

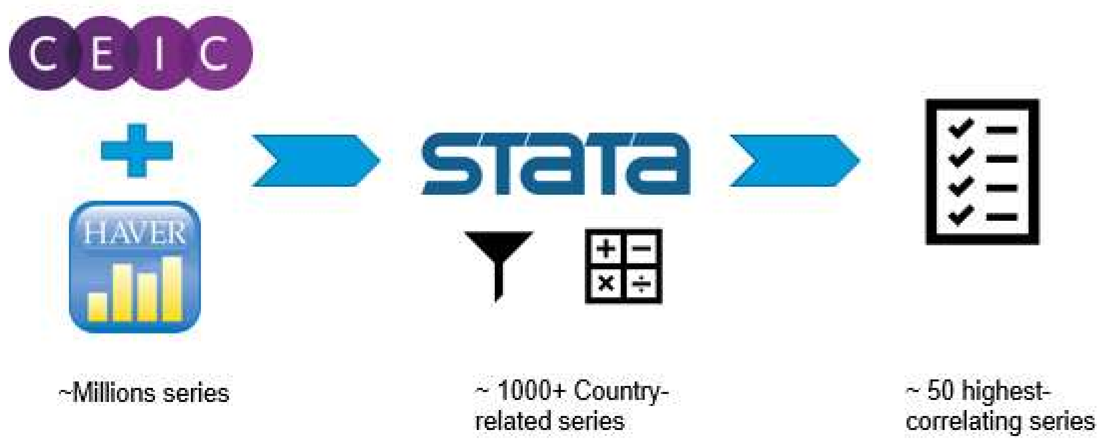
The selection of predictive variables is a critical step in building an effective nowcasting model. We introduce a new methodology that enables a comprehensive scan of both conventional indicators commonly used in the

[2] A Shapley value should be read as the indicator's contribution to the forecast, not as evidence that the series itself rose or fell. Thus, a negative Shapley value for broad money, for example, means the model interprets the recent liquidity build-up as signaling inflationary or tightening pressures that lower the predicted non-oil GDP, regardless of whether the money supply level increased.

literature (e.g., consumer price index) and nontraditional signals (e.g., financial transactions, high-frequency trade and consumption proxies). This approach covers a broad range of economic indicators, sourced not only from the domestic economy but also from neighboring and major trading partner countries, capturing relevant external spillovers.

The process begins with the extraction of millions of time series from CEIC and Haver databases. These are filtered using Stata to retain approximately 1,000 country-relevant series per economy. From this refined set, the top ~50 indicators are selected based on their historical correlation with non-oil GDP growth. Figure 2 summarizes this multi-stage filtering process, where indicators are progressively narrowed based on economic relevance and statistical significance.

Figure 2. Data Collection Components



To ensure comparability and usability across models, all daily and weekly indicators are converted to monthly frequency using aggregation or end-of-period selection techniques. Variables are then transformed into year-on-year growth rates to standardize across units and frequencies, enabling consistent statistical analysis.

Candidate variables are evaluated based on three core criteria:

1. **Predictive Capability** – The degree to which a transformed series exhibits historical correlation with non-oil GDP growth. A typical threshold for inclusion is a correlation coefficient greater than ±0.7. This benchmark is adjusted based on data availability and correlation strength across countries.
2. **Historical Coverage** – Indicators are expected to have at least 10 years of historical data to support robust model training and ensure sufficient temporal variation for detecting predictive relationships.
3. **Timeliness (Latency)** – Indicators must be released with minimal lag to ensure nowcasts reflect the most recent developments. On average, we target series with publication lags of no more than ±45 days.

These criteria are applied iteratively. For predictive capability, the year-on-year transformation allows consistent evaluation across frequencies. The correlation threshold is country-specific, based on how many candidate series exceed the statistical cut-off. These thresholds were chosen based on empirical testing to strike a balance between predictive power and data availability; they are flexible in practice, with documented country-specific exceptions when justified by the overall model performance. For historical coverage, exceptions are rare and only allowed when a variable adds material predictive power. Regarding latency, indicators are prioritized if they provide sufficient lead time to predict the current quarter based on already-available information.

A critical modeling consideration is the trade-off between the number of predictors and the number of observations. Because all predictors must align temporally, the training sample is constrained by the start date of the series with the shortest history. While adding predictors generally improves in-sample fit, it may lead to overfitting when the sample size is limited. To manage this trade-off, we carefully choose the training window to balance the breadth of information with sufficient sample size. Previous studies (e.g., Xie 2023), together with our own robustness analyses, indicate that nowcasting models incorporating 10–15 indicators and spanning at least 10 years of data tend to perform best in terms of both accuracy and generalizability. The final list of selected variables per country is provided in Annex I.

This indicator basket is typically locked for the following iterations. However, we revisit a series if Shapley/LIME diagnostics show two or more consecutive quarters of negligible contribution, in which case we test a sector-analogous substitute under the same cross-validation protocol.

Data Input Description

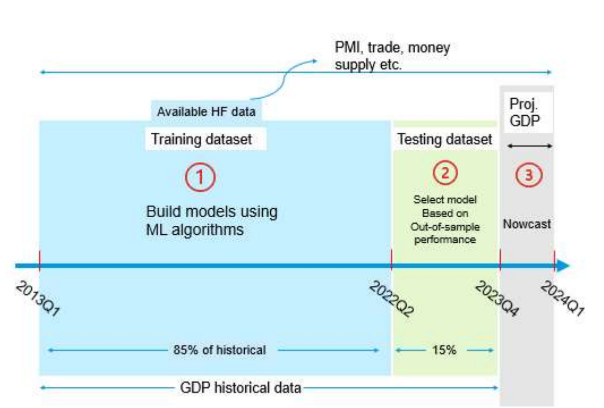
The nowcasting framework for non-oil GDP growth in the GCC leverages a rich set of high-frequency indicators that capture both domestic and global economic dynamics. These include data on trade (imports and exports), financial market conditions (loans, credit growth, and equity market performance), consumer prices, and sector-specific indicators such as air transport, etc.

The selection also extends to high-frequency global indicators that affect the region, including oil prices, international trade flows, and macroeconomic policy uncertainty indices. This broad coverage ensures that the models account for both domestic dynamics and external shocks influencing these open, oil-exporting economies.

By systematically integrating high-frequency data across these dimensions, the nowcasting models provide a comprehensive and timely view of current economic conditions. The goal is to support real-time monitoring and evidence-based policymaking by uncovering data-driven patterns that inform short-term economic forecasts.

Nowcasting Model Evaluation and Selection

Figure 3. Example Dataset Division



The evaluation and selection of machine learning models for accurate nowcasting follows a structured, three-stage process. The first stage involves training each model on a historical dataset, using a selected set of 10–15 high-frequency predictors and at least 10 years of data. The target variable is non-oil real GDP. A diverse set of algorithms is fitted during this phase to capture the complex relationships that drive short-term economic fluctuations.

In the early stages of model development, multiple combinations of indicator sets are tested iteratively over time using historical data. This allows for empirical evaluation of which groups of predictors consistently yield the best performance, enabling the refinement of a country-specific set of indicators that balances relevance, data availability, and predictive power.

In the second stage, we assess the predictive performance of each model on a holdout test set. Predictions are compared to actual outcomes using the Root Mean Squared Error (RMSE)[3], which is calculated as the square root of the average squared differences between predicted and observed values. RMSE serves as the key metric for evaluating out-of-sample accuracy, providing a clear measure of average forecast error. Emphasis is placed on minimizing out-of-sample RMSE, which indicates a model's ability to generalize beyond the training data and avoid overfitting. The second stage serves as a preliminary filter: model and indicator combinations are assessed on a fixed holdout to screen out poorly performing candidates, after which the surviving configurations undergo the rolling-window cross-validation in stage three to evaluate temporal stability and finalize selection.

The third stage involves cross-validation and final model selection. We use a rolling window approach, typically reserving the final 15 percent of the data as a holdout set and training on the initial 85 percent. Over 30 model types are tested, each fine-tuned using the training set and evaluated on the holdout set. The best-performing model, based on out-of-sample RMSE, is then re-estimated using the full dataset and used to generate the final nowcasts. This process ensures robust performance, model stability, and responsiveness to real-time data. Model selected using alternative statistics (e.g., MAE and MBE) consistently produce closely aligned results.

The models employed in our analysis encompass a broad spectrum of machine learning algorithms, each selected for their specific strengths and suitability for various tasks. This diverse array includes algorithms capable of processing different types of data, identifying complex relationships, and overcoming common data analysis challenges, such as overfitting, high dimensionality, and collinearity. For instance, Support Vector Machines (SVMs) are employed for their versatility in both classification and regression tasks, adept at managing high-dimensional data and capturing both linear and non-linear relationships. Similarly, Random Forest algorithms are chosen for their robustness and ability to handle large datasets, while Stochastic Gradient Boosting Trees offer enhanced performance through the addition of randomness, reducing the risk of overfitting. Elastic Net model is utilized for its efficacy in dealing with high-dimensional and collinear features,

[3] In addition to RMSE, model outputs provide alternative statistics for in-sample and out-of-sample MAE (Mean Absolute Error) and MBE (Mean Bias Error), which can be utilized to adjust evaluation as needed.

offering automatic feature selection capabilities. Principal Component Regression (PCR) is another key algorithm in our arsenal, useful for addressing multicollinearity by transforming predictors into a new set of uncorrelated variables. All models are fully described in Annex II.

Our approach is deliberately model agnostic, allowing us to select the most appropriate algorithm for each country and data environment. This flexibility ensures that our nowcasting tools are both accurate and adaptive—capable of reflecting country-specific economic structures while maintaining generalizability and interpretability. Through this rigorous selection process, we provide a robust and scalable solution for real-time prediction of non-oil GDP growth across the GCC region.

Iterations With Shapley Value Decompositions

In our nowcasting framework, Shapley value decompositions play a central role in refining model accuracy and interpretability. Derived from cooperative game theory, Shapley values provide a principled method for attributing the predictive contribution of each indicator in a multivariate model. By decomposing the overall model output into marginal contributions of individual predictors, we can identify which variables are most influential in driving forecast performance, an essential capability given the high dimensionality and complexity of economic data.

The iterative process begins with an initial indicator set selected based on traditional criteria, including correlation with non-oil GDP and data timeliness. Shapley values are then computed to quantify each variable's marginal contribution to predictive accuracy. Indicators with consistently low contributions are flagged for potential exclusion, allowing the model to be re-estimated with a more targeted set of predictors.[4] This cycle of model estimation, decomposition, and targeted refinement is repeated extensively, across dozens of model structures and input configurations, until a convergence is achieved on a country-specific set of indicators that yields both accuracy and stability.

In practice, each country's final model reflects numerous rounds of re-specification, often involving more than 30 modeling variants and hundreds of predictor permutations. The result is a tailored set of approximately 10–15 indicators per economy, each of which demonstrates a consistent and substantial contribution to model performance as measured by Shapley values. This refined set forms the foundation of the final nowcasting model: lean, interpretable, and robust.

Importantly, this approach improves forecast precision and also enhances economic insight. By isolating the drivers of non-oil GDP growth in a transparent and data-driven manner, Shapley-based iterations support more informed, timely, and targeted policy analysis. The methodology strengthens the technical rigor of the forecast and elevates its operational relevance for real-time surveillance.

[4] Shapley values remain valid in the presence of correlated variables. In such case, the marginal contribution to predictive accuracy is shared, rather than uniquely attributed, among correlated variables. Accordingly, Shapley values should be interpreted in terms of shared predictive influence, rather than causal effects.

IV. Nowcasting Results for GCC

Indicator Selection and Comparison Amongst The GCC

GCC country data draw on a broad spectrum of indicators reflecting both shared regional characteristics and country-specific economic structures. While there is a common emphasis on core sectors (real, oil, manufacturing, and monetary and financial) the mix of leading indicators identified in the nowcasting results (Annex I) reveals important differences in economic structure, policy priorities, and statistical maturity.

Several common indicators consistently emerge as key predictors of non-oil GDP growth across the GCC, reflecting broad regional patterns. These indicators provide a unifying foundation for nowcasting models, anchoring country-specific variations within shared macroeconomic framework:

- **Oil price indicators**, including various regional crude spot prices and the OPEC reference basket price, remain important given their direct impact on external balances, strong spillover effects on fiscal revenues and domestic liquidity, and broader influence on non-oil sector growth.
- **Price and retail indicators**, such as the CPI and Point-of-Sales (POS) transactions, capture domestic consumption trends and inflationary pressures that are central to short-term economic activity.
- **Manufacturing and business sentiment indicators**, notably the PMI, captured through domestic PMI as well as PMI of main trading partners or regional/global indices, serve as leading signals of production momentum and private sector confidence.
- **Monetary and financial sector variables**, including stock market indices, credit measures, and interest rate spreads, help track liquidity conditions, investor sentiment, and financial flows, reflecting the role of investor confidence and financial market dynamics in shaping GCC economic landscapes.

Beyond the common factors discussed above, each GCC economy's nowcasting results incorporate indicators that reflect its unique structural features and data availability:

- **Bahrain**: The model results places greater emphasis on POS transactions and the CPI, reflecting the importance of domestic consumption and retail activity in its relatively small, service-oriented economy, which has a more limited oil exposure compared to its GCC peers.
- **Kuwait**: The results feature a distinct set of indicators such as the national valuation of gold, consistent with its wealth-management and oil-dependent economic profile. The inclusion of India's intermediate goods production and Indian's PMI highlights Kuwait's production and trade linkages with key partners.
- **Oman**: Likely due to limited coverage of high-frequency domestic data, the model relies more on external indicators, such as import measures, oil price inverse index, Saudi Arabia's PMI, U.S. industrial production, and U.S. Treasury yields, which collectively capture domestic demand, fiscal space, regional/global linkages that affect its non-oil economy.
- **Qatar**: The results reflect the interplay between domestic demand and external linkages. CPI, imports, and money supply capture domestic consumption, while the external indicators, such as Dubai's total economy output, India's PMI, and U.S. consumer credit, capture regional and global demand spillovers.
- **Saudi Arabia:** The model employs a broad set of indicators beyond oil, including non-oil exports, CPI, cement deliveries, and granular financial market measures such as the stock market indices, banking system's liquidity (proxied by 3-month SIBOR and 4-week SAMA bill). They underscore Saudi Arabia's

broad-based economic transformation under Vision 2030 and its leading position in data quality and statistical provision within the region.

- **UAE:** The model emphasizes the UAE's deep integration with global trade, transport, and energy markets. International cargo and passenger traffic complement standard domestic indicators, reflecting the importance of logistics and tourism as key drivers of non-oil activity. Industrial production indicators from the U.S., U.K., and Germany signal external demand conditions for trade and re-exports, while the global volatility index (VIX) captures shifts in global risk sentiment affecting capital flows and market confidence.

Nowcasting Statistics

Table 3 summarizes the performance of the top three models for each country in forecasting non-oil GDP growth for Q2 2024, based on out-of-sample RMSE. The results reflect the outcome of an extensive model evaluation process, which tested over 30 algorithms per country. The RMSE values provide a comparable measure of forecast accuracy across models and countries, with lower values indicating better out-of-sample predictive performance. Notably, Support Vector Machines and Elastic Net models consistently rank among the top performers across several economies, highlighting their adaptability to the high-dimensional, nonlinear nature of the input data.

Table 3. Latest Nowcasting Statistics (Q1 2025)

Country	Top 3 Performing Models	Out-of-Sample RMSE Metric
Bahrain *(as of June 12, 2025)*	1. Stochastic Gradient Boosting Trees (oneSE) 2. Stochastic Gradient Boosting Trees 3. Random Forest (oneSE) with Variable Selection	0.72 1.07 1.35
Kuwait *(as of June 12, 2025)*	1. Support Vector Machine (RBF) 2. Support Vector Machine (RBF) with Variable Selection 3. Support Vector Machine (Linear)	2.50 2.59 2.70
Oman *(as of June 12, 2025)*	1. Support Vector Machine (Polynomial) with Variable Selection 2. Principle Component Regression with Variable Selection 3. Support Vector Machine (RBF) (oneSE)	2.03 2.29 2.37
Qatar *(as of June 12, 2025)*	1. Support Vector Machine (RBF) (oneSE) 2. Random Forest (oneSE) 3. Multivariate Adaptive Regression Spline with Variable Selection	2.36 3.44 3.77
Saudi Arabia *(as of April 23, 2025)*	1. Support Vector Machine (RBF) 2. Support Vector Machine (Polynomial) with Variable Selection 3. Multivariate Adaptive Regression Spline	0.73 1.14 1.76
United Arab Emirates *(as of June 12, 2025)*	1. Random Forest with Variable Selection 2. Random Forest (oneSE) 3. Random Forest	0.79 0.85 0.93

Note: (1) We also include more traditional methods like OLS, which in some instances also perform well in comparison to the various machine learning models.
(2) In addition to RMSE, model outputs provide alternative statistics of MAE and MBE. The top two to three models demonstrate robustness across various fitness statistics, consistently yielding closely aligned results.

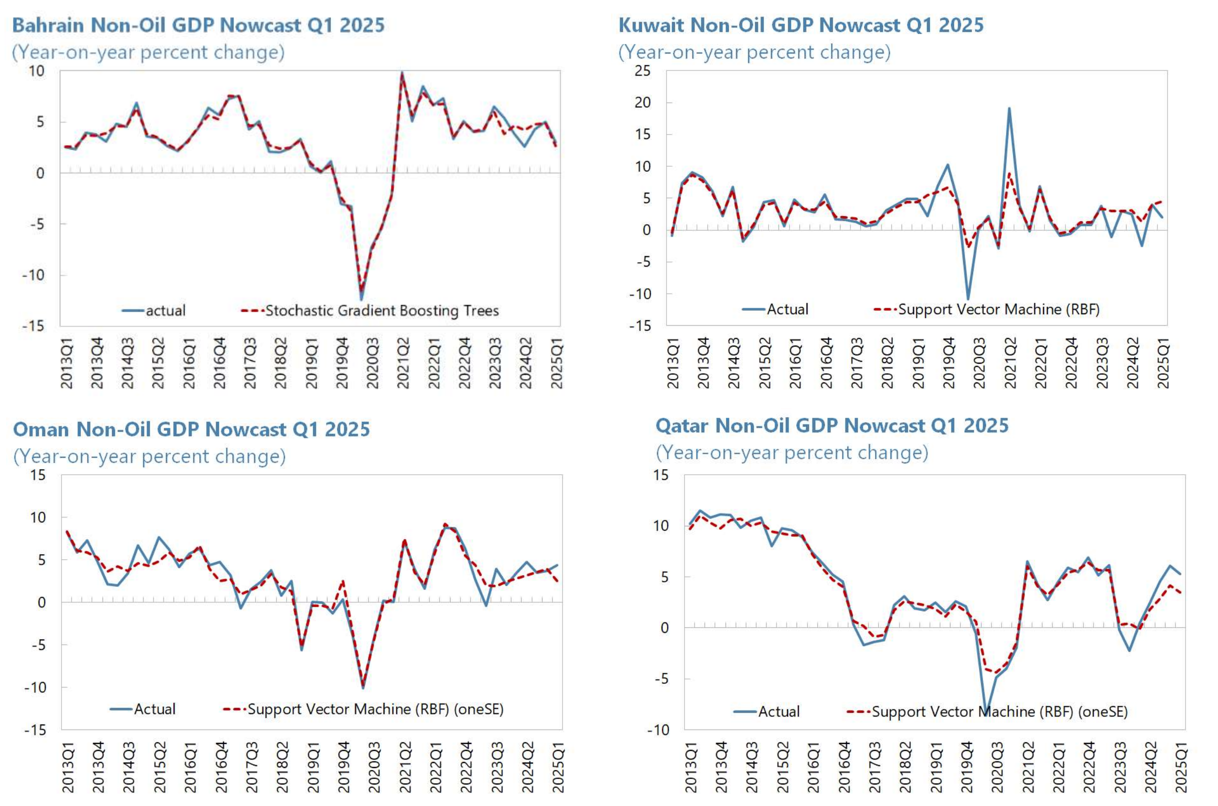
(3) Kuwait's higher RMSE largely reflects the country's comparatively sparse set of high-frequency domestic indicators; to preserve sample length we relied more on external and region-wide predictors, which inevitably track local non-oil fluctuations less tightly.

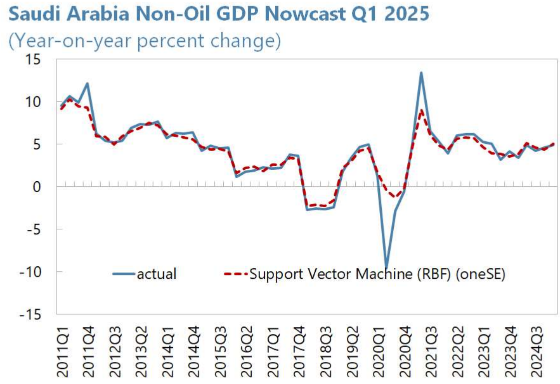
Nowcasting Estimations

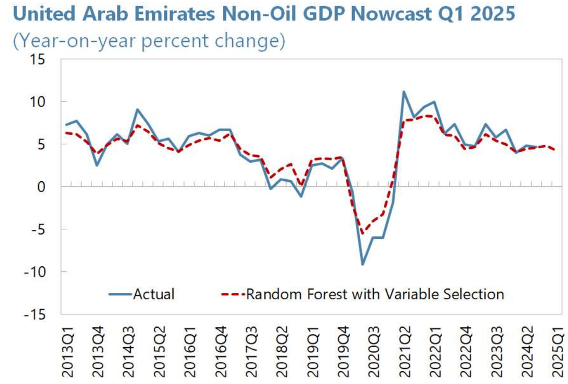
The panel below presents historical nowcasting results for non-oil GDP growth across GCC countries, including actual outcomes and model-based estimates through Q1 2025. Each panel shows year-on-year percent changes and includes the top-performing models identified through out-of-sample RMSE evaluation. The charts illustrate both the alignment of model estimates with realized GDP data and the responsiveness of the models to turning points and shocks, including the COVID-19 period. This historical view highlights the models' ability to track short-term dynamics in non-oil activity and underscores their value as real-time monitoring tools.

Figure 4. Nowcasting Results by Country Q1 2025[(4)]

(Out-of-sample predictions from training dataset: 2011Q1—2023Q1; testing dataset: 2023Q2-2024Q4)

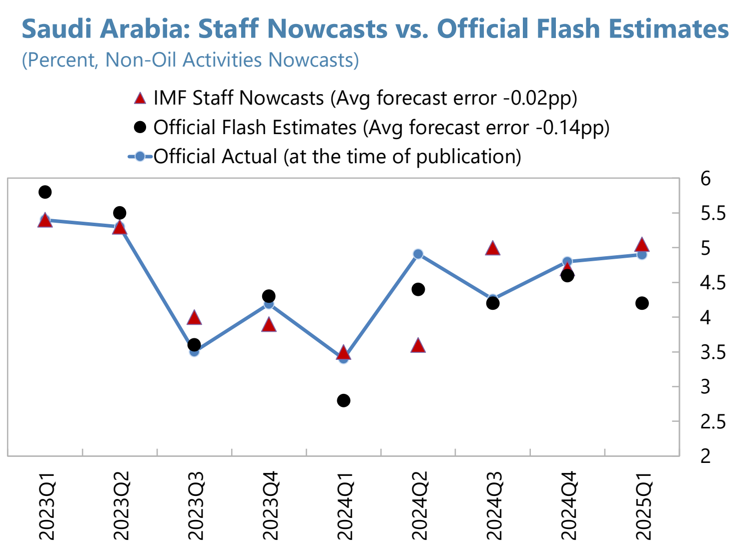






Sources: Haver Analytics, CEIC, Country Authorities, and IMF staff calculations.
Note: (1) Nowcasts for Saudi Arabia are applied to real non-oil activities (excluding government activities) to ensure consistency with the official data releases and comparability with official flash estimates. For the other GCC countries, nowcasts are applied to the real non-oil GDP (e.g., non-hydrocarbon sector GDP) published by the authorities.
(2) Saudi Arabia's nowcasts results above are based on the previous official data published by GASTAT (data vintage as of end-April 2025) prior to the new rebased GDP in May 2025. The actual data shown above also refer to the previous official series, except for 2025Q1, which is only avilable under the new rebased GDP. See Figure 5 for comparison.
(3) The nowcasts plotted are generated out-of-sample. Each estimate uses a model trained only on data available up to the start of the test window (2023Q2), with performance evaluated on the subsequent holdout period.
(4) The nowcasts for Q1 of 2025 are as of the timline indicated in Table 3, April/June estimations, which have now been plotted against Q1 actuals available as of August 18, 2025.

Figure 5. Saudi Arabia: Comparison of Staff Nowcasts with Official Flash Estimates



Sources: GASTAT and IMF staff calculations.
Note: (1) The official actual data refer to Saudi Arabia's initial official release of quarterly real non-oil acticvities grow for each respective quarter. These figures may differ slightly from the current official data, which incorporate hisotrical revision (e.g., GASTAT's methodolocal enhancement to national accounts statistic in 2024 and 2025).
(2) The comparision for 2025Q1 should be interpreted with caution, as the official actual data (4.9 percent) is from GASTAT's newly rebased GDP (published in May 2025), whereas the official flash estimates (4.2 percent) and staff nowcasts (5.05 percent) were based on the previous series.
(3) Average forecast errors are calculated as the sample average of the projection minus the actual values, expressed in percentage points (pp).

Regional Comparison

The nowcasting results reveal both convergence and divergence across GCC economies, shaped by their shared macroeconomic characteristics and country-specific features. Countries such as Saudi Arabia and the UAE, which benefit from broader economic diversification and stronger statistical systems, show more robust nowcast performance driven by financial market indicators, point-of-sale transactions, and global trade variables. In contrast, Oman and Kuwait rely more heavily on a narrower set of high-frequency indicators, such as import values, credit aggregates, and regional oil prices, reflecting more limited data availability and slower reporting cycles. By grouping features into country-specific blocks and applying Shapley-based weighting with rolling-window validation, the framework flexibly captures the GCC's distinctive structural patterns.

Despite differences in model inputs, several regional patterns emerge. Oil prices, even when the focus is on non-oil GDP, remain important predictors across the GCC due to fiscal transmission channels and government (or quasi-government) led investment cycles. Global PMI, regional equity indices, and trade activity in neighboring countries often serve as useful external signals, capturing the open and interlinked nature of GCC economies. However, the marginal predictive value of these variables varies significantly by country, depending on structural reforms, diversification progress, and data maturity.

Compared to other MENA countries, GCC economies generally benefit from more consistent macroeconomic reporting and a relatively wider set of high-frequency indicators, particularly on financial conditions. Yet they also face unique challenges not as prevalent in non-oil MENA peers, namely, more acute sensitivity to oil production adjustments, broader fiscal policy swings, and heavier dependence on external capital flows. These dynamics introduce greater volatility into short-term activity and require models that can adapt to both market-driven and policy-induced inflections.

Relative to non-oil emerging markets in other regions, such as Southeast Asia or Latin America, GCC countries often experience higher data latency and more frequent historical revisions, especially for national accounts. Moreover, the structure of non-oil GDP in the GCC is often more state-driven and less responsive to private sector sentiment than in more market-oriented EMs, reducing the predictive power of consumer confidence or retail indicators commonly used elsewhere. In this context, the need for tailored, country-specific nowcasting models becomes clear. A one-size-fits-all approach proves inadequate, underscoring the importance of both indicator flexibility and adaptive modeling to capture the distinct rhythms of GCC economies within the broader EM landscape.

V. Robustness Checks and Forecasting Performance

Robustness checks are critical for validating the reliability and generalizability of the nowcasting models across GCC economies. Given the structural complexity of these economies and the significant role of oil revenues, it is essential to ensure that models are both stable and adaptable to different assumptions, subcomponents, and data configurations. To this end, we conduct a range of tests, including cross-validation, out-of-sample prediction, bottom-up decomposition, external composite index construction, and external validation to verify the consistency and precision of nowcasting estimates.

Bottom-Up Decomposition: Oman's Non-Oil GDP

A key robustness test was applied to Oman's non-oil GDP through a bottom-up nowcasting approach, in which we separately nowcasted two key subcomponents, services GDP and tradables GDP, before aggregating the forecasts and comparing them to the overall non-oil GDP nowcast. This approach enabled a more granular analysis of sectoral behavior and tested whether aggregate model results are consistent with disaggregated forecasts.

The process began by constructing a nowcasting model for the services sector, which plays a significant role in Oman's economic activity. The model was designed to capture sector-specific dynamics using targeted indicators, including air transport data (e.g., flight arrivals and departures), money supply metrics (M2 and quasi money), consumer prices, and financial aggregates such as government deposits and private sector liabilities. External variables, such as U.S. interest rates and mortgage rates, as well as monetary and credit aggregates from Saudi Arabia and the UAE, were also incorporated to reflect cross-border linkages.

A parallel model was developed for the tradables sector, which includes export- and import-oriented goods. Predictors for this model emphasized external trade data (e.g., exports in INR and USD, imports of mineral products), financial system indicators (e.g., commercial bank deposits, resident bank balances), and monetary aggregates related to private sector and foreign currency time deposits. Regional indicators from Saudi Arabia, such as PMI purchase prices, domestic claims, and private credit, were included to account for regional spillovers affecting trade dynamics.

<table>
<tr><th colspan="2">Table 4. Oman Robustness Check Indicators</th></tr>
<tr><td>Tradable GDP Indicators</td><td>Services GDP Indicators</td></tr>
<tr><td>

Exports:
Exports: INR: Oman
Exports: USD: Oman
Imports:
Imports: Mineral Products
Banking and Financial Indicators:
Deposits: Commercial Banks: Rial Omani: Over 2% to 3%
Commercial Banks: Assets: Balances Due from Banks: Resident
Deposits: Private Sector: Time: Foreign Currency
Saudi Arabia Financial Metrics:
Saudi Arabia PMI: Total Economy Purchase Prices
Saudi Arabia: Monetary Survey: Domestic Claims
Saudi Arabia: Private Sector Credit
Other Indicators:
Domestic Assets: Other Net Items
Number of Subscribers: Internet

</td><td>

Air Transport: Muscat International Airport:
Num. of Flights: Abroad: Departures
Num. of Flights: Abroad: Arrivals
Banking and Money Supply:
Oman: Conventional Bank Liabilities: Government Deposits
Oman: Private Sector Deposits: Total
Oman: Money Supply: M2
Oman: Money Supply: Quasi Money
Inflation and Consumer Prices:
Oman: Consumer Prices
Interest Rates and Mortgage Rates:
U.S.: 5-Year Treasury Note Yield at Constant Maturity
U.S.: 30-Year Fixed Mortgage Rate
Saudi Arabia and UAE Financial Metrics:
Saudi Arabia: Monetary Base [Reserve Money]
UAE: Government Domestic Credit to Residents

</td></tr>
</table>

After estimating both subcomponent models, we aggregated their forecasts and compared the combined estimate to the original nowcast of total non-oil GDP. The high degree of alignment between the two provided a strong internal validation of the model's structure and inputs, while also shedding light on the relative contribution of each sector to short-term economic fluctuations. This decomposition revealed that the services sector accounts for a significant portion of the volatility and growth in Oman's non-oil GDP, whereas the tradables sector showed greater sensitivity to external shocks and global demand conditions.

This bottom-up robustness checks not only confirmed the model's predictive integrity but also deepened our understanding of sectoral interdependence and structural features of the economy, insights valuable for both policy formulation and sectoral monitoring.

External Composite Index Validation

To further test the resilience and efficiency of the nowcasting framework, a second robustness check was conducted using a composite index approach. For each of the three Oman models, Services GDP, Tradables GDP, and General Non-Oil GDP, we constructed a tailored external composite index comprising only those international variables that had demonstrated consistent influence on model performance.

For example, the composite index for the services model included selected indicators from the United States, Saudi Arabia, and the UAE, reflecting the influence of external financial and monetary conditions on domestic consumption and liquidity. For the tradables model, the index captured external demand and trade financing conditions, while the general non-oil GDP index combined broader cross-border influences into a single metric.

This approach served three purposes:

1. **Model simplification:** By consolidating multiple external variables into a single composite input, the model becomes more parsimonious and easier to interpret without sacrificing essential external information.
2. **Robustness validation:** Comparing the predictive accuracy of models using disaggregated external variables versus composite indices allows us to assess the sufficiency of the aggregated signal.
3. **Sectoral sensitivity mapping:** The degree to which each model responds to the composite index offers a clearer view of how external conditions impact each segment of the economy.

Our findings suggest that while composite indices slightly reduce the fine-grained explanatory power of specific indicators, they are effective in maintaining overall model performance, especially for real-time tracking and streamlined policy monitoring. The results also highlight differential sectoral sensitivity to external shocks, tradables GDP, for instance, shows a stronger response to regional financial conditions than services GDP, which is more affected by domestic liquidity and U.S. interest rate changes.

Forecast Performance Benchmarking: Model vs. Consensus

While our nowcasting framework focuses on quarterly estimates of non-oil GDP, most available consensus forecasts, whether from private institutions or international organizations, are published on an annual basis and refer to total GDP. As such, a direct statistical comparison between the model and consensus is not feasible. Nevertheless, a qualitative benchmarking exercise still offers valuable insights.

We assess whether our quarterly nowcasts are directionally consistent with the broader economic outlook reflected in the annual consensus, particularly at key turning points in the growth cycle. For all countries, model estimates for the latter half of 2024 are generally aligned with the directional trends in annual consensus projections. In periods of heightened uncertainty, the nowcasting model can also provide an early signal of changes in economic momentum, especially in the non-oil economy, before these are fully incorporated into institutional or market forecasts.

In the case of Saudi Arabia, we also compare our nowcasts against the official flash estimate of quarterly non-oil GDP published by GASTAT. Our model demonstrates close alignment with these flash estimates and, in several quarters, has matched or slightly outperformed them in terms of final-revised accuracy. This underscores the potential of model-based nowcasting to serve as a robust, timely complement to official early-release figures, particularly where comprehensive revisions follow initial estimates.

In addition, the higher frequency and sectoral focus of our framework allow for more timely and granular insights, complementing consensus forecasts that often depend on slower-moving data and structural models. While consensus forecasts tend to cluster around a central estimate, particularly in countries with infrequent GDP reporting, the nowcasting model responds dynamically to high-frequency indicators, capturing shifts in real activity related to consumption, trade, and financial conditions in near real-time. Thus, even in the absence of fully aligned forecast targets, the nowcasting framework serves as a useful early-warning tool and a complementary input into broader forecast discussions. Over time, the use of real-time nowcasts could help improve the calibration and timeliness of consensus forecasts, especially in data-constrained environments such as the GCC.

VI. Conclusion

This paper proposes a machine learning–based nowcasting framework tailored to the specific needs of GCC economies, where oil price volatility, delayed GDP reporting, and evolving statistical capacity present unique forecasting challenges. By focusing on non-oil GDP at a quarterly frequency, our approach aims to deliver more timely, granular, and sector-specific insights to support economic monitoring and policy formulation. This approach directly responds to the region's growing need for high-frequency data tools that align with its economic diversification objectives and enhance real-time decision-making.

The framework demonstrates that integrating a wide range of high-frequency domestic and international indicators, transformed and evaluated through a structured filtering process, can yield robust nowcasts that align closely with official data and consensus expectations. By relying on model-agnostic methods, the approach strikes a balance between flexibility and interpretability, adapting to country-specific conditions while remaining transparent. The application of Shapley value decompositions further enhances usability by helping policymakers identify the key drivers behind forecast revisions. The framework's credibility is reinforced through iterative testing across more than 30 model variants and rigorous out-of-sample validation, ensuring that its forecasts are not only accurate but also reliable and generalizable across different contexts. Robustness checks, including a sectoral decomposition for Oman's non-oil GDP and a novel composite index test, confirm the model's adaptability and policy relevance. Although direct comparisons with annual consensus forecasts are limited, our framework provides a complementary view of economic conditions. In the case of Saudi Arabia, nowcasts track official flash estimates of non-oil GDP closely and sometimes anticipate revisions, underscoring their operational utility.

More broadly, this paper presents the first region-wide application of machine learning-based nowcasting models tailored to the unique economic structures and data environments of the GCC. It sets a precedent for systematic, high-frequency economic surveillance in oil-exporting and emerging market contexts. The framework introduces key methodological innovations, including an automated, scalable data integration process and the novel use of Shapley value decompositions to enhance model transparency and policy relevance. Designed with operational utility in mind, the framework offers the flexibility to evolve alongside statistical capacity and can be readily embedded into institutional workflows, making it a practical tool for strengthening real-time monitoring and evidence-based policymaking across the region.

As the region continues to strengthen its statistical infrastructure, this nowcasting framework offers a scalable and replicable tool for monitoring real-time economic activity, enabling faster responses to shocks and more informed policy decisions. Future research could build on this foundation by integrating sentiment indices, mobility data, or supply chain disruptions, further enhancing the responsiveness of nowcasts in rapidly evolving policy environments.

Annex I. Nowcasting Leading Indicators

This annex documents the leading indicators used in the nowcasting framework to predict quarterly non-oil GDP growth across the GCC. These indicators serve as timely signals of underlying economic activity and are selected based on their predictive relevance, frequency, and availability. The annex provides a country-specific overview of the final variables retained in the models after undergoing rigorous filtering, transformation, and evaluation. Indicators span multiple sectors, including trade, prices, financial conditions, consumer behavior, and external variables, capturing both domestic and global dynamics relevant to short-term growth. Their inclusion reflects a balance between empirical correlation, economic intuition, and practical considerations such as data latency and update frequency.

While the annex lists only the input indicators, the underlying model diagnostics make extensive use of Shapley value decomposition to gauge each variable's marginal impact on the nowcast. A Shapley value should be read as the indicator's contribution to the forecast, not as evidence that the series itself rose or fell. Thus, a negative Shapley value for broad money, for example, means the model interprets the recent liquidity build-up as signaling inflationary or tightening pressures that lower the predicted non-oil GDP, regardless of whether the money supply level increased. This distinction helps separate statistical influence from the raw direction of the economic data.

Annex Table 1: GCC Leading Nowcasting Indicators

	Real Sector	Oil Sector	Manufacturing	Monetary and Financial
Bahrain	• Consumer Price Index • CPI: Recreation and Culture • Non-oil Imports	• OPEC Reference Basket Price • Saudi Arabian Light: Spot Crude Price	▪ Global PMI ▪ Developed Markets PMI	▪ Public Debt: Conventional Instruments ▪ Public Debt: Development Bonds ▪ Money Supply: M2 ▪ Monetary Survey: Other Domestic Assets ▪ One Month Deposit Rate ▪ Stock Exchange: All Share Index ▪ POS Transaction Value ▪ POS Transaction Number
Kuwait	• National Valuation of Gold	▪ Export Spot Crude Price	• India IP: Intermediate Goods • India PMI: Manufacturing Output Prices	• Global excl. Mainland China PMI: Future Services Activity • Saudi Arabia: General Share Price Index • U.S. Stock Price Index: NYSE Composite • U.S. Commercial Bank Credit to the Private Sector • China: Terms of Trade • UAE: Deposits • Oman: Exchange Buying Rate: Kuwait • Kuwait: Credit Facility Agt. W Res: Consumer Loans • Kuwait: Boursa Kuwait Shares Traded Bought by Kuwaiti Co/Estab • Kuwait: Exchange Rate with USD

				• Kuwait: Time Deposits of Res & Non-Res: Over 1-3 months
Oman	• Imports: Electrical Machinery, Mechanical Equipment and Parts • Imports: Food and Food Preparation Beverages and Tabacco • Air Transport: Muscat International Airport: No of Flights: Abroad • Bank Clearance: No of Items • Consumer Price Index • Exports: SITC: Middle East and North Africa: Oman	• U.S. Spot Oil Price: WTI • Oil Price Inverse Index Oman	• Saudi Arabia PMI: Total Economy Output • U.S. Industrial Production excluding Construction	• Loans: Commercial Banks: Over 0-5% • Market Capitalization MSX • MSX Index: Banking and Investment • U.S. 10 year Treasury Bond Yield • U.S. News Based Economic Policy Uncertainty Index
Qatar	• Consumer Price Index • Dubai Total Economy Output	• International Rig Count: Land: Qatar • Import Price: Crude Oil, Qatar	• India PMI: Services Employment	• Imports: Qatar • Deposit Rate: Weighted Average: 3 months • Money Supply: Currency in Circulation • Qatar Stock Exchange: shares Traded: Value: Real Estate • Liabilities: Banks: Domestic: Due to Qatar Central Bank • US Consumer Credit Outstanding • Saudi Arabia Imports
Saudi Arabia	• Consumer Price Index • Non-oil Exports	▪ Crude Oil Production: Saudi Arabia ▪ Saudi Arabian Light: Spot Crude Price	▪ Global Manufacturing PMI ▪ Cement Deliveries	▪ 3 Month SIBOR (Average, %) ▪ Stock Market: Number of Transactions (Number) ▪ Stock Market: Number of Shares Traded (Mil) ▪ Stock Market: Tadawul All Share Index (EOP) ▪ Foreign Reserves: Investment in Foreign Securities (EOP) ▪ 4 Week SAMA Bill (Average, %)
UAE	• Cargo Traffic: International • Passenger Traffic: International	• European Brent Spot Price • Dubai Fateh: Spot Crude Price • United Arab Emirates Murban: Spot Crude Price	▪ UAE PMI Total Economy ▪ Global PMI: Composite Output ▪ Global PMI: Composite New Orders ▪ Global PMI: Services Business Activity ▪ Saudi Arabia PMI: Total Economy New Orders ▪ Saudi Arabia PMI: Total Economy ▪ UK: Index of Production ▪ U.S. Industrial Production excluding Construction ▪ Germany Industrial Production, Total Industry	▪ CBOE Market Volatility Index: VIX ▪ CBOE Vix Volatility Index

Indicator definitions

Bahrain

1. Real Sector
   - Bahrain: Consumer Price Index (NSA, Apr-19=100)
     - Measures changes in the price level of a basket of consumer goods and services purchased by households.
   - Bahrain: CPI: Recreation and Culture (NSA, Apr-19=100)
     - A subset of the Consumer Price Index, focusing on recreation and culture expenses.
   - Bahrain: Non-oil Imports (NSA, Thous.Dinars)
     - Reflects the value of goods imported into Bahrain excluding oil, which can include manufactured goods.
2. Oil Sector
   - OPEC Reference Basket Price ($/BBL)
     - Represents a weighted average of prices for petroleum blends produced by OPEC members.
   - Saudi Arabian Light: Spot Crude Price ($/BBL)
     - The price of light crude oil from Saudi Arabia in the spot market.
3. Manufacturing
   - Global PMI: Composite Output (SA, 50+=Expansion)
     - A key indicator of the economic health of the manufacturing sector; a PMI above 50 indicates expansion.
   - Developed Markets PMI: Composite (SA, 50+=Expansion)
     - Similar to the Global PMI but focuses on developed markets.
4. Monetary and Financial
   - Bahrain: Public Debt: Conventional Instruments (EOP, NSA, Mil.Dinars)
     - The total amount of conventional financial instruments issued by the Bahraini government to finance its activities.
   - Bahrain: Public Debt: Development Bonds (EOP, NSA, Mil.Dinars)
     - Specifically focuses on bonds issued for financing development projects.
   - Bahrain: Money Supply: M2 (SA, EOP, Mil.Dinars)
     - A measure of the money supply that includes cash, checking deposits, and easily convertible near money.
   - Bahrain: Monetary Survey: Other Domestic Assets [Net] (NSA, EOP, Mil.Dinars)
     - Reflects other domestic assets, adjusted for liabilities, held by the monetary authorities.
   - Bahrain: One Month Deposit Rate (AVG, %)
     - The average interest rate on one-month deposits in Bahraini banks.
   - Bahrain: Stock Exchange: All Share Index (EOP, Feb.02-Dec.02=1000)
     - Indicates the performance of all shares listed on the Bahrain Stock Exchange.
   - Bahrain: Point of Sale Transaction Value (NSA, Dinars)
     - The total value of goods and services purchased through point of sale transactions.
   - Bahrain: Point of Sale Transactions Number (NSA, Number)
     - The total number of transactions made through point of sale systems.

Kuwait

1. Real Sector

- Kuwait: Gold, National Valuation (EOP, Mil.US$)
    - The valuation of Kuwait's national gold reserves, which can reflect the country's wealth and economic stability.

2. Oil Sector

- Kuwait Export: Spot Crude Price ($/BBL)
    - The spot price of crude oil exported from Kuwait, a critical indicator given the country's economy heavily depends on oil exports.

3. Manufacturing

- India: IP: Intermediate Goods (NSA, Apr.11-Mar.12=100)
    - While specific to India, this indicator of industrial production for intermediate goods can give insights into global manufacturing trends, including those that might affect Kuwait indirectly.
- India PMI: Manufacturing Output Prices (NSA, 50+=Expansion)
    - Similar to the above, this provides insight into manufacturing sector health and price trends, which can have global implications, including on Kuwait's economy.

4. Monetary and Financial

- Global excl Mainland China PMI: Services Future Activity (NSA, 50+=Expansion)
    - Indicates global services sector future activity expectations, which can impact financial markets and investment flows, including those in Kuwait.
- Saudi Arabia: General Share Price Index [TASI] (EOP, 1985=1000)
    - Reflects stock market performance in Saudi Arabia, relevant for regional financial stability and investor sentiment that also affects Kuwait.
- U.S.: Stock Price Index: NYSE Composite (EOP, Dec-31-02=5000)
    - The performance of the NYSE Composite Index, which can influence global financial markets and investment climates, including in Kuwait.
- U.S.: Commercial Bank Credit to the Private Sector (NSA, Bil.$)
    - Reflects credit availability in the U.S., which can have global financial implications, including effects on Kuwait's financial sector.
- China: Terms of Trade (NSA, 2010=100)
    - While specific to China, changes in terms of trade can impact global economic dynamics and thereby affect Kuwait's economy, especially in terms of trade.
- UAE: Deposits (EOP, NSA, Mil.AED)
    - The volume of deposits in UAE banks, indicating regional banking health that can affect financial flows into Kuwait.
- Oman: Exchange Buying Rate: Kuwait (EOP, Omani Rial/Kuwaiti Dinar)
    - Exchange rates between Oman and Kuwait can reflect bilateral trade and investment conditions.
- Kuwait: Credit Facility Agt. w Res: Consumer Loans (NSA, EOP, Mil.Dinars)
    - Consumer loans in Kuwait, indicating domestic credit conditions and consumer confidence.
- Kuwait: Boursa Kuwait Shares Traded Bought by Kuwaiti Co/Estab (EOP, Thous)
    - Activity on the Boursa Kuwait, specifically shares bought by Kuwaiti companies or establishments, reflecting market confidence and investment trends.
- Kuwait: Exchange Rate with US$ (EOP, Kuwaiti Dinar/US$)
    - The exchange rate between the Kuwaiti Dinar and US Dollar, a critical indicator for international trade and investment.
- Kuwait: Time Deposits of Res & Non-Res: Over 1 to 3 Months (NSA, EOP, Mil)

  - Short-term time deposits in Kuwait, reflecting liquidity and short-term investment preferences in the financial sector.

Oman

1. Real Sector
   - Imports: Electrical Machinery, Mechanical Equipment and Parts
     - Reflects the importation of electrical and mechanical equipment, indicating industrial and consumer demand within Oman.
   - Imports: Food and Food Preparation Beverages and Tobacco
     - Indicates the value of food, beverages, and tobacco products imported, reflecting consumption trends.
   - Air Transport: Muscat International Airport: No of Flights: Abroad
     - The number of international flights at Muscat International Airport, indicating connectivity and economic activity levels.
   - Consumer Price Index
     - Measures changes in the price level of a basket of consumer goods and services purchased by households, indicating inflation levels.
   - Exports: SITC: FA: Middle East & North Africa: Oman
     - Reflects the value of goods exported from Oman to Middle Eastern and North African countries, indicating trade activity.
2. Oil Sector
   - U.S.: Spot Oil Price: West Texas Intermediate [Prior'82=Posted Price] ($
     - The spot price of WTI crude oil, relevant for global oil market trends affecting Oman's economy.
   - LEI: BOT: sa: Oil Price Inverse Index (Oman)
     - An inverse oil price index specific to Oman, indicating the impact of global oil prices on the Omani economy.
3. Manufacturing
   - Saudi Arabia PMI: Total Economy Output (NSA, 50+=Expansion)
     - While specific to Saudi Arabia, this indicator provides context for regional manufacturing and economic health that can affect Oman.
   - U.S.: Industrial Production excluding Construction (NSA, 2017=100)
     - Reflects the level of industrial production in the U.S., which can have implications for global economic trends and Oman's manufacturing sector.
4. Monetary and Financial
   - Bank Clearance: Number of Items
     - The number of items cleared through banks, which can reflect the overall economic activity.
   - Loans: Commercial Banks: Over 0% to 5%: Over 4% to 5%
     - Indicates the interest rate range for loans provided by commercial banks in Oman, reflecting monetary conditions.
   - Market Capitalization: MSX: ow Financial
   - Index: Muscat Stock Exchange (MSX): Banking and Investment
     - These indicators reflect the performance and capitalization of the Muscat Stock Exchange, particularly focusing on the financial and banking sectors, indicating investor sentiment and financial market health within Oman.
   - United States: 10 Year Treasury Bond Mid Yield (EOP, % p.a.)

    - The yield on 10-year U.S. Treasury bonds, an important global financial indicator that can influence investment flows and interest rates worldwide, including in Oman.
- United States: News-Based Economic Policy Uncertainty Index (1985-09=101)
    - An index measuring economic policy uncertainty based on news media coverage in the U.S., which can impact global financial markets and investor sentiment, including in Oman.

Qatar

1. Real Sector
- Qatar: Consumer Price Index (NSA, 2018=100)
    - Measures changes in the price level of a basket of consumer goods and services purchased by households.
- Dubai: Total Economy Output (SA, 50+=Expansion)
    - Although it specifies Dubai, this indicator reflects general economic health and can be relevant for understanding regional economic trends affecting Qatar.
- Imports: Qatar
    - Reflects the value of goods and services imported into Qatar, which can impact monetary policy and exchange rates.

2. Oil Sector
- NN: BHGE: International Rig Count: Land: Middle East: Qatar
    - Reflects the number of active drilling rigs in Qatar, indicating exploration and production activity in the oil sector.
- CN: Import Price: Crude Oil: Asia: Qatar
    - The price of crude oil imported from Qatar to Asian markets.

3. Manufacturing
- India PMI: Services Employment (NSA, 50+=Expansion)
    - While focused on India, this indicator reflects the health of the service sector, which can have manufacturing implications due to service-sector employment being indicative of broader economic health. IMEC signed in 2023 includes India which further enhances the choice of this indicator.

4. Monetary and Financial
- Qatar: Deposit Rate: Weighted Average: Time: 3 Months
    - The average interest rate for three-month deposits in Qatari banks, indicating monetary and financial conditions.
- Qatar: Money Supply: M3: M2: M1: Currency in Circulation
    - Measures the total amount of currency in circulation and deposits in Qatari banks, indicating the liquidity in the economy.
- Qatar Stock Exchange: Shares Traded: Value: Real Estate (f8)
    - The value of real estate shares traded on the Qatar Stock Exchange, providing insight into the financial market’s sentiment towards the real estate sector.
- Qatari Banks: Traditional: Liabilities: Domestic: Due to Qatar Central BU
    - Liabilities of traditional Qatari banks towards the Qatar Central Bank, indicating the banking sector's stability and health, albeit small.
- U.S.: Consumer Credit Outstanding (NSA, EOP, Bil.$)
    - Although this is a U.S. indicator, it can impact global financial markets and thus have indirect implications for Qatar's financial sector.
- Saudi Arabia: Imports (NSA, Mil.Riyals)

  - This indicator, while specific to Saudi Arabia, can reflect regional trade dynamics that may affect Qatar's monetary and financial landscape.

Saudi Arabia

1. Real Sector

- Saudi Arabia: Consumer Price Index (NSA, 2018=100)
  - Measures changes in the price level of a basket of consumer goods and services purchased by households.
- Saudi Arabia: Nonoil Exports (NSA, Mil.Riyals)
  - Reflects the value of goods exported from Saudi Arabia excluding oil, which can include manufactured goods.

2. Oil Sector

- Production: Crude Oil: Saudi Arabia (Thous. Barrels per Day)
  - Reflects the daily production volume of crude oil in Saudi Arabia.
- Saudi Arabian Light: Spot Crude Price ($/BBL)
  - The price of light crude oil from Saudi Arabia in the spot market.

3. Manufacturing

- Global Manufacturing PMI (SA, 50+=Expansion)
  - A key indicator of the economic health of the manufacturing sector worldwide; a PMI above 50 indicates expansion.
- Saudi Arabia: Cement Deliveries (NSA, Thous.Ton)
  - Indicates the amount of cement delivered within Saudi Arabia, which can reflect construction activity and economic health.

4. Monetary and Financial

- Saudi Arabia: 4 Week Treasury Bill (Average, %)
  - The average interest rate on 4-week treasury bills issued by the Saudi government.
- Saudi Arabia: 3 Month SIBOR (Average, %)
  - The average interest rate for the Saudi Interbank Offered Rate over three months.
- Saudi Arabia: Stock Market: Number of Transactions (Number)
- Saudi Arabia: Stock Market: Number of Shares Traded (Mil)
- Saudi Arabia: Stock Market: Tadawul All Share Index {TASI} (EOP, 1985=1000)
  - These indicators reflect the activity and performance of the Saudi stock market, providing insights into investor sentiment and financial market conditions.
- Saudi Arabia: Foreign Reserves: Investment in Foreign Securities (EOP, Mil.Riyals)
  - The total value of foreign securities held by Saudi Arabia as part of its foreign exchange reserves.

United Arab Emirates

1. Real Sector

- Cargo Traffic: International
  - Reflects the volume of cargo transported internationally, indicating trade activity levels.
- Passenger Traffic: International
  - Indicates the volume of international passenger traffic, which can signal economic health and tourism levels.

2. Oil Sector

- European Brent Spot Price FOB ($/Barrel)
    - The price of Brent crude oil, a major trading classification of sweet light crude oil.
- Dubai Fateh: Spot Crude Price ($/BBL)
    - The spot price of Dubai Fateh crude oil, used as a benchmark for Middle Eastern crude oil exports to Asia.
- United Arab Emirates Murban: Spot Crude Price ($/BBL)
    - The spot price of Murban crude oil, a light crude oil produced in Abu Dhabi.

3. Manufacturing

- U.A.E. PMI: Total Economy (SA, 50+=Expansion)
    - A measure of the economic health of the manufacturing and service sectors in the UAE.
- Global PMI: Composite Output (SA, 50+=Expansion)
- Global PMI: Composite New Orders (SA, 50+=Expansion)
- Global PMI: Services Business Activity (SA, 50+=Expansion)
    - These PMI indicators reflect the global manufacturing and services business activity levels and new orders.
- Saudi Arabia PMI: Total Economy New Orders (NSA, 50+=Expansion)
- Saudi Arabia PMI: Total Economy (NSA, 50+=Expansion)
    - PMI measures for Saudi Arabia's total economy, indicating manufacturing and service sector health.
- UK: Index of Production (SA, 2019=100)
    - Reflects the total output of the production industries in the UK.
- U.S.: Industrial Production excluding Construction (NSA, 2017=100)
- Germany: Industrial Production: Total Industry incl Construction (NSA, 2015=100)
    - These indicators show the level of industrial production in the respective countries, including the UAE's major trading partners.

4. Monetary and Financial

- CBOE Market Volatility Index: VIX (Index)
    - A real-time market index representing the market's expectation of 30-day forward-looking volatility.
- CBOE VIX Volatility Index [VVIX] (AVG, Index)
    - Represents the volatility of the VIX itself, providing a measure of the market's expectation of the future volatility of the VIX.

Please note that the indicators selected are part of an exhaustive list that spans all sectors and available data. For example, in the case of Qatar, natural gas indicators were tested but not chosen given their performance in the models.

Annex II. Summary of Nowcasting Models

This annex provides a comprehensive overview of the 22 models evaluated in the nowcasting framework. The selection spans a range of linear, regularized, dimension-reduction, tree-based, and kernel-based machine learning algorithms, applied both with and without variable selection techniques. Models marked "(oneSE)" follow the one-standard-error rule for optimal complexity. All models were assessed based on out-of-sample Root Mean Squared Error (RMSE) to determine predictive performance.

1. Linear and Regularized Regression Models

- **Step.Model**: Stepwise regression using forward, backward, or both directions to select features.
- **Elastic Net**: Regularized linear model combining L1 and L2 penalties to manage collinearity.
- **Elastic Net (oneSE)**: Simpler Elastic Net variant selected via cross-validation using the one-standard-error rule.
- **Elastic Net with Variable Selection / Elastic Net (oneSE) with Variable Selection**: Elastic Net models incorporating pre-screening of variables based on predictive importance.

2. Dimension Reduction Models

- **Principal Component Regression (PCR)**: Regression using principal components of the predictors.
- **PCR with Variable Selection**: PCR applied to a subset of variables selected prior to transformation.
- **Partial Least Squares Regression (PLS)**: Dimension-reduction technique that maximizes covariance between predictors and target.
- **PLS with Variable Selection**: PLS model applied to a reduced set of predictors.

3. Tree-Based Models

- **Multivariate Adaptive Regression Splines (MARS)**: Nonlinear regression that models interactions and nonlinearities via piecewise linear basis functions.
- **MARS with Variable Selection**: MARS model applied to a filtered subset of predictors.
- **Random Forest**: Ensemble of decision trees using bootstrap aggregation and random feature selection.
- **Random Forest (oneSE)**: Random Forest with a reduced number of trees selected under the one-standard-error rule.
- **Random Forest with Variable Selection / Random Forest (oneSE) with Variable Selection**: Random Forests trained on a selected set of predictors.
- **Stochastic Gradient Boosting Trees (GBM)**: Boosting method that sequentially fits shallow trees to residuals.
- **GBM (oneSE)**: Parsimonious boosting model tuned using the one-standard-error rule.

4. Support Vector Machines (SVMs)

- **SVM (Linear)**: Linear-kernel SVM used for regression (SVR).
- **SVM (Linear) (oneSE)**: Linear SVM with regularization selected using the one-standard-error rule.
- **SVM (Polynomial)**: SVR using polynomial kernel to model nonlinear relationships.
- **SVM (Polynomial) (oneSE)**: Polynomial-kernel SVR with reduced complexity.
- **SVM (RBF)**: SVR with radial basis function kernel for capturing nonlinearities.
- **SVM (RBF) (oneSE)**: Simpler variant of RBF-kernel SVR.

- **SVM (Linear/Polynomial/RBF) with Variable Selection**: Kernel-based models trained on pre-selected variable sets.

Each model was tested on a consistent training sample with harmonized input variables. Models with variable selection were trained on indicator subsets chosen via Shapley value decompositions or correlation screening. Full hyperparameter tuning procedures and model specifications are available upon request.

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