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Nowcasting Peru's GDP with Machine Learning Methods

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Abstract

This paper explores the application of machine learning (ML) techniques to nowcast the monthly year-over-year growth rate of both total and non-primary GDP in Peru. Using a comprehensive dataset that includes over 170 domestic and international predictors, we assess the predictive performance of 12 ML models. The study compares these ML approaches against the traditional Dynamic Factor Model (DFM), which serves as the benchmark for nowcasting in economic research. We treat specific configurations, such as the feature matrix rotations and the dimensionality reduction technique, as hyperparameters that are optimized iteratively by the Tree-Structured Parzen Estimator. Our results show that ML models outperformed DFM in nowcasting total GDP, and that they achieve similar performance to this benchmark in nowcasting non-primary GDP. Furthermore, the bottom-up approach appears to be the most effective practice for nowcasting economic activity, as aggregating sectoral predictions improves the precision of ML methods. The findings indicate that ML models offer a viable and competitive alternative to traditional nowcasting methods.

JEL classification: C14, C32, E32, E52.
Keywords: GDP, Machine Learning, nowcasting.

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1 Introduction

Nowcasting, the estimation of an economy's current state in near real-time, is a critical tool in economic analysis, particularly for informing decision-making and policy formulation. Initially developed for meteorology, nowcasting has gained prominence in economics, as highlighted by seminal contributions from Giannone, Reichlin and Small (2008) and Bańbura et al. (2013). Recent advancements in machine learning (ML) have demonstrated significant potential for improving macroeconomic nowcasting, particularly by capturing nonlinear relationships that traditional models may overlook. Extensive research has examined ML applications for nowcasting GDP in advanced economies; however, studies focusing on developing economies, such as Peru, are increasing in number but remain relatively scarce.

This study builds upon the growing literature on ML-enhanced nowcasting by addressing two primary challenges: (i) identifying a robust set of high-frequency indicators capable of capturing real-time economic signals and (ii) selecting optimal predictive models to transform these indicators into reliable estimates. To address these challenges, we construct a comprehensive dataset spanning April 2015 to August 2024, integrating over 170 domestic and international predictors. This dataset combines structured macroeconomic variables with unstructured sources such as Google Trends to provide a holistic approach to nowcasting.

The primary objective is to evaluate the performance of various ML algorithms in nowcasting Peru's monthly year-over-year GDP growth rates—both total and non-primary GDP. Tested models include regularization techniques (Ridge and Lasso), tree-based methods (Random Forest and XGBoost), and advanced approaches such as Support Vector Regression and Neural Networks. Additionally, we benchmark these ML methods against a Dynamic Factor Model (DFM), a standard tool for time-series nowcasting in economic research.

We tested various model specifications, focusing on key aspects of the nowcasting process. Specifically, we examined the use of expanding versus rolling windows for the training sample, compared the performance of K-Fold cross-validation against Walk-Forward cross-validation, and assessed different strategies for dimensionality reduction and feature matrix rotations to optimize model performance. These evaluations enabled us to identify the most effective techniques for improving the accuracy of our ML models in nowcasting GDP.

A closely related study is Tenorio and Perez (2023), which also investigates ML applications for nowcasting Peruvian GDP. Our research stands out for using a broader set of predictors, extending the analysis to non-primary GDP, and adopting a bottom-up approach that predicts sectoral GDP growth before aggregating results into overall GDP estimates. Furthermore, we implement recursive hyperparameter optimization using the Tree-Structured Parzen Estimator and evaluate dimensionality reduction techniques to enhance model performance.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on GDP nowcasting and ML applications. Section 3 describes the dataset and estimation strategy, including preprocessing steps, sample splits, and hyperparameter optimization. Section 4 presents results comparing model performance across different methodological approaches. Finally, Section 5 concludes with implications for future research.

2 Literature Review

ML methods have become increasingly valuable for macroeconomic and financial forecasting due to their ability to capture nonlinear relationships between predictors and target variables, particularly in high-dimensional datasets, where traditional econometric models often fall short (Ahmed et al. (2010), Goulet Coulombe et al. (2022), Masini, Medeiros and Mendes (2023)). This paper contributes to the growing body of research evaluating the effectiveness of ML models for nowcasting real GDP growth. Numerous studies have demonstrated that ML techniques can either rival or surpass standard statistical methods in improving nowcasting accuracy.

Recent research has primarily focused on advanced economies. Soybilgen and Yazgan (2021), Babii, Ghysels and Striaukas (2022), and Hopp (2024) applied ML techniques to nowcast US GDP. Soybilgen and Yazgan (2021) employed bagged decision trees, random forests, and stochastic gradient tree boosting models, while Hopp (2024) built on this by incorporating long short-term memory (LSTM) networks and XGBoost alongside these models. Babii, Ghysels and Striaukas (2022) introduced a structured ML regression approach tailored for high-dimensional time series data sampled at varying frequencies, demonstrating its effectiveness in nowcasting US GDP growth. Similarly, Richardson, van Florenstein Mulder and Vehbi (2021) applied a range of ML techniques, including ridge, Lasso, elastic net, and support vector machine (SVM) regression, to nowcast New Zealand's GDP, showcasing the performance of these methods beyond gradient boosting and neural networks. Kant, Pick and de Winter (2022) conducted a comparable exercise for the Dutch economy, illustrating the adaptability of ML models across different economic contexts.

For developing economies, several studies have also explored the potential of ML techniques for nowcasting GDP. Zhang, Ni and Xu (2023) compared various ML algorithms with DFMs, static factor models, and MIDAS for short-term forecasting of China's annualized GDP growth. Ghosh and Ranjan (2023) evaluated these approaches for a group of emerging economies, while Dauphin et al. (2022) applied them to European countries. Muchisha et al. (2021) focused on Indonesia, Fornaro and Luomaranta (2020) on Finland, and Tiffin (2016) on Lebanon. Additionally, Buell et al. (2021) explored the use of ML models for nowcasting GDP in Sub-Saharan Africa.

In Latin America, several studies have applied ML models to nowcasting GDP. Bolivar (2024) utilized these methods for Bolivia, while León and Ortega (2018) employed artificial neural networks (ANNs) to nowcast monthly economic activity in Colombia using electronic payments data. Bravo Higuera et al. (2024) investigated regularization techniques to generate early estimates of agricultural GDP in Colombia. De Oliveira (2023) compared traditional statistical methods and ML techniques for nowcasting Brazilian GDP, concluding that combining ML predictions with traditional models yielded the best results. Miranda (2021) applied Lasso and deep neural networks to nowcast economic activity in Mexico.

In the case of Peru, research using ML techniques for nowcasting GDP remains limited. One of the few recent studies in this area is by Tenorio and Perez (2023), who applied ML methods to nowcast monthly Peruvian GDP using a large dataset that integrates both structured and unstructured data sources.

This growing body of literature underscores the increasing relevance and effectiveness of ML models in enhancing the accuracy and timeliness of GDP nowcasting across both advanced and developing economies.

3 Methodology

3.1 Models

This section provides an overview of the ML and benchmark models employed for nowcasting Peruvian GDP. Details are provided in the original citations. It focuses primarily on the selection of key hyperparameters and the out-of-sample exercise for evaluating nowcast performance. Let y_t and x_t denote the target variable and the set of d predictors, respectively.

Dynamic Factor Models: As a benchmark, we use a standard DFM based on the framework of Bańbura et al. (2013) and Mariano and Murasawa (2010), alongside a modified implementation in Python from Fulton (2020). DFMs assume that a reduced number of unobserved latent factors can capture variability in a large set of observable macroeconomic and financial variables. This model facilitates the extraction of common information from a high-dimensional dataset, which can then be used to predict key economic indicators like GDP.

The DFM is represented as:

$$z_t = Af_t + e_t$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + \ldots + u_t$$

where z_t is an $N \times 1$ vector of observable variables at time t; f_t is an $r \times 1$ vector of unobserved common factors; A is an $N \times r$ matrix of factor loadings; $A_1, A_2, \ldots$ are $r \times r$ autoregressive coefficient matrices; e_t is an $N \times 1$ vector of idiosyncratic disturbances, and u_t is an $r \times 1$ vector of factor innovations. In our setup, $z_t = [y_t \quad x_t']'$ with $N = d+1$. Detailed estimation procedures are provided in the Appendix.

Ridge, Lasso, and Elastic Net: These regularization techniques address model complexity and mitigate overfitting by introducing penalty terms into regression models.

Ridge regression ($L2$ Regularization) penalizes the sum of the squared magnitudes of the coefficients, shrinking them toward zero without eliminating any predictors:

$$\beta = \arg\min \left[\sum_{t=1}^{T} (y_t - \beta_0 - \sum_{i=1}^{d} x_{it}\beta_i)^2 + \lambda \sum_{i=1}^{d} \beta_i^2 \right]$$

Here, λ controls the degree of shrinkage, with larger values reducing the impact of less significant predictors.

Lasso regression ($L1$ regularization) penalizes the absolute values of coefficients, promoting sparsity by driving some coefficients to zero. This approach is particularly useful for feature selection when only a subset of predictors is relevant:

$$\beta = \arg\min \left[\sum_{t=1}^{T} (y_t - \beta_0 - \sum_{i=1}^{d} x_{it}\beta_i)^2 + \lambda \sum_{i=1}^{d} |\beta_i| \right]$$

Elastic Net combines $L2$ (Ridge) and $L1$ (Lasso) penalties to balance coefficient shrinkage and sparsity. The objective function is:

$$\beta = \arg\min \left[\sum_{t=1}^{T} (y_t - \beta_0 - \sum_{i=1}^{d} x_{it}\beta_i)^2 + \lambda \sum_{i=1}^{d} ((1-\alpha)\beta_i^2 + \alpha|\beta_i|) \right]$$

Here, λ governs overall regularization strength, and α (ranging from 0 to 1) determines the trade-off between Ridge ($L2$) and Lasso ($L1$) penalties. When $\alpha = 0$, Elastic Net behaves as Ridge; when $\alpha = 1$, it behaves as Lasso.

Support Vector Machine: The Support Vector Machine (SVM) algorithm for regression, commonly referred to as Support Vector Regression (SVR), was introduced by Cortes and Vapnik (1995).It aims to identify a function that predicts the target variable y_t with a maximum deviation of ϵ from the actual targets while keeping the function as flat as possible. The predicting model is expressed as:

$$y_t = b + w * g(x_t) + e_t$$

Here, b is the bias term, w is the weight vector, $g(.)$ is a vector function that maps the input feature vector into a high-dimensional feature space, x_t is the input feature vector, and e_t is the disturbance term. The concept of "flatness" involves minimizing the magnitude of the weight vector w, ensuring the decision function has the smallest possible slope. This approach promotes generalization to unseen data, thereby reducing the risk of overfitting.

In practice, finding a function that keeps all deviations within ϵ may not always be feasible. To accommodate this, the algorithm introduces slack variables ξ_i and ξ_i^*, which measure the degree to which predictions $f(x)$ fall outside the allowable error margin. The optimization problem for SVM regression is formulated as:

$$\min \frac{1}{2}||w||^2 + C\sum_{t=1}^{T}(\xi_t + \xi_t^*)$$

subject to:

$$\begin{aligned} y_t - w * g(x_t) - b \leq & \quad \epsilon + \xi_t \\ w * g(x_t) + b - y_t \leq & \quad \epsilon + \xi_t^* \end{aligned}$$

The regularization parameter C is critical in controlling the model's complexity. A larger C enforces stricter adherence to the ϵ-tube by penalizing slack variables, which can increase the risk of overfitting if the model becomes too complex. Conversely, a smaller C allows for more slack, enabling the model to tolerate greater error margins and improving generalization, though it may lead to underfitting.

K-Nearest Neighbors: K-Nearest Neighbors (KNN), introduced by Fix and Hodges (1951) and further developed by Cover and Hart (1967), is a simple, yet powerful non-parametric ML algorithm used for both classification and regression tasks. Unlike parametric models, KNN does not assume a predefined relationship between predictors and the dependent variable. Instead, it relies on the proximity of data points in the feature space, making predictions based on the values of the k-nearest neighbors.

In regression, KNN predicts the outcome for a query point x_q at time q by averaging the outcomes of the k-nearest observations in the training data. Distances between the query point x_q and each observation x_t in the training dataset are typically calculated using the Euclidean distance:

$$d(x_q, x_t) = \sqrt{\sum_{i=1}^{d} (x_{iq} - x_{it})^2}$$

Here, d represents the number of dimensions (features) in the dataset, and x_{ti} denotes the value of the i-th feature at time t. After identifying the k-nearest neighbors based on their proximity to x_q, the predicted value $\hat{y}_q$ is computed as:

$$\hat{y}_q = \frac{1}{K} \sum_{s \in N_k(x_q)} y_s$$

where $N_k(x_q)$ is the set of indices for the k-nearest neighbors.

Decision Tree: A decision tree (DT), introduced by Breiman et al. (1984), is a non-parametric model that recursively partitions the data space into subsets based on predictor values. Splits are chosen to minimize a given criterion, such as variance in regression tasks. The resulting tree structure consists of internal nodes representing decision rules and terminal nodes (leaves) representing subsets of the data where a simple prediction model, typically a constant value, is applied.

In regression, a DT divides the predictor space into disjoint regions R_m. The prediction for a new observation in region R_m is given by a constant c_m, the mean of the y-values within that region:

$$\hat{y}_t = \sum_{m=1}^{M} c_m 1_{(x_t \in R_m)}$$

where M is the total number of regions.

Gradient Boosting, Extreme Gradient Boosting and Adaptive Boosting: Gradient boosting (GBoosting) is an ensemble learning technique that builds a robust predictor by combining multiple weak learners, typically DTs. Weak learners are trained sequentially, with each iteration aiming to correct the errors of the previous one by minimizing a predefined loss function, such as least squares or least absolute deviation. The model is updated iteratively:

$$F_m(x) = F_{m-1}(x) + v\Delta_m(x)$$

Here, $F_m(x)$ represents the model at iteration m, $F_{m-1}(x)$ is the previous model, $\Delta_m(x)$ is the weak learner (a DT), and v is the learning rate, a hyperparameter that controls the contribution of each learner. The learning rate v serves as a shrinkage parameter, mitigating overfitting by controlling the influence of each model update. Setting v to a value less than 1 effectively slows the learning process, improving generalization beyond the training data.

Extreme Gradient Boosting (XGBoost) is an advanced implementation of GBoosting that incorporates optimizations to enhance performance and scalability (Chen and Guestrin (2016)). Key features include L1 and L2 regularization to control model complexity, efficient handling of missing data, parallelized tree construction, and early stopping, which halts further iterations when no significant improvement is detected. These enhancements make XGBoost suitable for large datasets, contributing to its widespread use in ML competitions and practical applications.

Adaptive Boosting (AdaBoost), another popular boosting algorithm, differs from GBoosting in its approach. Instead of fitting residuals, AdaBoost adjusts the weights of training instances at each iteration, emphasizing observations poorly predicted by previous models (Freund and Schapire (1997)). By increasing the influence of these "difficult" cases, AdaBoost forces subsequent models to correct earlier mistakes, enhancing accuracy. However, AdaBoost is sensitive to noise and outliers, which can be addressed through careful hyperparameter tuning.

Bagging: Short for bootstrap aggregating, is an ensemble learning technique that improves model robustness and accuracy by reducing variance and mitigating overfitting. It involves training multiple models independently on unique bootstrap samples of the dataset. By exposing each model to a distinct variation of the training data, bagging reduces dependency on any single dataset and lowers the variance associated with individual models.

After training, the predictions of all models are aggregated to produce a final output, leveraging the strengths of individual models while counteracting their errors. Bagging is particularly effective for high-variance models, such as DTs, as it mitigates overfitting by ensuring each model learns from different portions of the dataset. This results in an ensemble model with improved predictive performance, particularly in scenarios where variability in individual models could compromise accuracy.

Random Forest: Random Forest (RF), introduced by Breiman (2001), is an ensemble learning method that combines multiple DTs to create a robust and accurate predictive model. Building on the principles of bagging, RF introduces an additional layer of randomness by selecting a random subset of predictors (features) at each split in the DTs. This random selection prevents individual trees from overly relying on specific predictors and promotes diversity across DTs.

The final RF prediction is obtained by averaging the predictions of all DTs, which reduces the variance and improves generalization, making RF less prone to overfitting compared to a single DT. Mathematically, the RF prediction for a regression task is:

$$\hat{y}_t = \frac{1}{K} \sum_{k=1}^{K} \hat{y}_k(x_t)$$

where $\hat{y}_k(x)$ is the prediction from the k-th tree and K is the total number of trees in the forest.

Artificial Neural Network: A Multilayer Perceptron (MLP) is a type of artificial neural network designed to map a set of input features to a target output through multiple layers of nodes or neurons. The network comprises an input layer, one or more hidden layers, and an output layer. Each layer contains nodes representing weights and biases, which are adjusted during training to optimize predictions.

The process begins with the input layer, where the raw data is fed into the network. These inputs are then passed to the first hidden layer, where each node applies a linear combination of the input values using weights and biases, followed by a nonlinear activation function (e.g., sigmoid, ReLU). This enables the network to capture complex patterns and relationships within the data. In deeper networks, additional hidden layers can be added, with each layer building on the output of preceding layers, learning increasingly abstract data representations.

The output layer combines the learned features of the hidden layers to generate predictions. The activation function used in the output layer depends on the task. For regression, a linear activation is common, while classification tasks often employ a softmax function to generate probabilities for different classes. Mathematically, the MLP is represented as:

$$\hat{y} = f(W_2 \cdot g(W_1 \cdot x + b_1) + b_2)$$

where x is the input vector, W_1 and W_2 are weight matrices for the first and second layers, b_1 and b_2 are bias terms, g is the activation function for the hidden layer (e.g., sigmoid, ReLU), f is the activation function for the output layer (e.g., linear, softmax), and $\hat{y}$ is the predicted output.

The MLP is trained by adjusting weights W_1, W_2 and biases b_1, b_2 to minimize a chosen loss function, such as mean squared error (MSE) for regression. This optimization is achieved through backpropagation, which computes the gradient of the loss function with respect to the network's weights and biases, enabling iterative updates using methods like stochastic gradient descent (SGD). See Rumelhart, Hinton and Williams (1986) for further details.

3.2 Data

The dataset comprises a diverse range of macroeconomic and financial market variables, providing a comprehensive foundation for nowcasting Peruvian GDP. These variables encompass domestic activity indicators, such as electricity and oil production, cement consumption, baby chicken placements, and goods supplied to wholesale markets; consumer and producer price indices to reflect inflationary pressures; and surveys conducted by the Central Reserve Bank of Peru (BCRP) capturing sentiment and expectations across sectors. Additionally, the dataset incorporates domestic trade statistics and a variety of international macroeconomic variables, enabling the assessment of global influences on Peru's economy. Domestic financial market variables, including asset prices, interest rates, and currency fluctuations, are also included. Recognizing the vulnerability of specific sectors to natural phenomena, the dataset further integrates climate data.

Following Tenorio and Perez (2023), we augment the dataset with unstructured data from Google Trends, offering real-time insights into consumer behavior and economic sentiment. Keywords such as "economy," "visa," "huaico," and "Toyota", among others (see Section B of the Appendix).

The dataset spans April 2015 to August 2024, enabling the models to capture both short-term fluctuations and long-term trends in economic activity, thereby providing a robust foundation for nowcasting. Combining structured and unstructured data enhances the model's predictive power and adaptability to varying economic conditions.

3.3 Estimation Strategy

This section outlines the estimation strategy employed in this study. As emphasized by citecoulombe2021macroeconomic, the choice of data transformations significantly affects the accuracy of ML methods.

To evaluate the performance of ML techniques for nowcasting Peruvian GDP, the study examined various specifications. These included using variables in year-on-year (YoY) or month-on-month (MoM) percent changes (seasonally adjusted).[1] We also examined the use of expanding versus rolling windows for the training sample.[2] Further, we compared K-Fold to Walk-Forward cross-validation and assessed the appropriate lag structure. Feature matrix rotations and dimensionality reduction techniques were treated as hyperparameters, optimized during each nowcasting iteration.

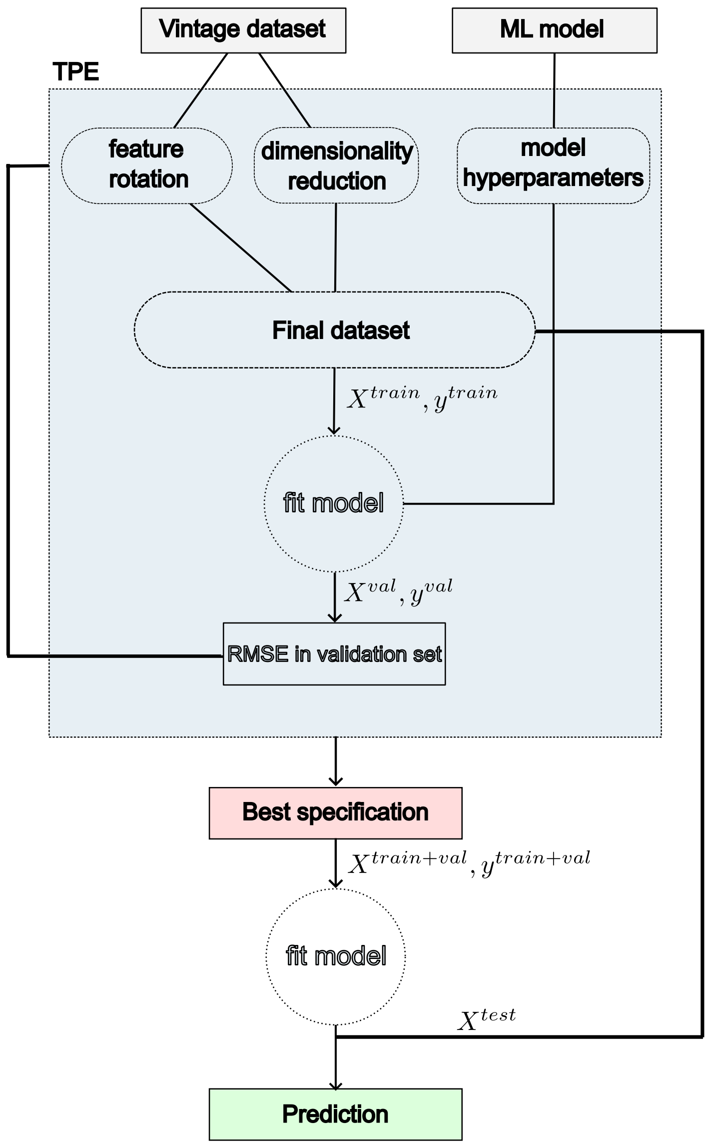
[1]Seasonal adjustment was performed using the TRAMO-SEATS algorithm in the RJDemetra package, applied to both the features and the target variable when seasonality was detected. As the target variable is expressed in YoY percent changes, forecasted factors were used to convert model predictions into this format.

[2]In the expanding window approach, the training set begins with an initial subset of observations, progressively incorporating new data with each nowcast iteration. The rolling window approach maintains a fixed-size training set, where the oldest data points are replaced with the most recent ones as time progresses.

Additionally, we assessed a bottom-up approach, nowcasting the individual sectors comprising total and non-primary GDP and aggregating the results externally. The sectors included services, commerce, primary industry, non-primary industry, and agriculture. Construction, mining, and fishing sectors were excluded from nowcasting as their data is available prior to the publication of total and non-primary GDP. For electricity, water, and gas distribution, we assumed electricity production growth, which accounts for approximately 80% of this sector.

The diagram in Figure 1 illustrates the estimation strategy adopted for point prediction, summarizing the methodology detailed below. This comprehensive approach ensures the deployment of the most effective model configuration, enabling precise and robust GDP nowcasting while effectively capturing its inherent complexities.

Figure 1: Estimation Strategy



Note: This procedure is employed to obtain point predictions using a given dataset and an ML model. Feature rotations and the dimensionality reduction technique are treated as hyperparameters and optimized alongside the ML model hyperparameters within the Tree-Structured Parzen Estimator framework.

Data Preprocessing: The dataset used in the analysis is sampled on a monthly basis. Each time series is individually evaluated to determine the optimal transformation for maximizing its predictive relevance for GDP growth. First, series are seasonally adjusted[3] to remove recur-

[3]Our analysis revealed that using seasonally adjusted variables yields better out-of-sample performance compared to applying YoY percent change transformations.

ring seasonal patterns that could introduce noise or distort the underlying trends relevant for GDP nowcasting. Depending on the characteristics of each series, transformations include converting to monthly percentage changes, taking first differences, or retaining the series in its level form. These transformations are selected based on their ability to enhance the signal related to GDP dynamics, ultimately improving model performance. To further optimize the model, we evaluate (i) the appropriate lag structure and (ii) feature matrix rotations to identify configurations that maximize predictive accuracy on the validation set. Given the temporal nature of economic data, lagged predictor values often hold significant information about future GDP behavior, making the determination of an optimal lag structure critical for capturing this temporal dependence. Moreover, Goulet Coulombe et al. (2021) demonstrate that certain feature rotations can enhance predictive performance. In this study, we introduce eight lags for each variable and allow the Tree-Structured Parzen Estimator to select the optimal feature matrix rotations from the hyperparameter space detailed in Table 1:

Table 1: Rotations - Hyperparameter Search Space

Rotation	Hyperparameter	Prior Distribution
X	Use	{True,False}
MARX	Use	{True,False}
	Order	DiscreteUniform(3,6)
MAF	Use	{True,False}
	N° Components	DiscreteUniform(1,3)

Note: X represents features in levels, while MARX and MAF denote the moving average rotation of X and moving average factors, respectively. See Goulet Coulombe et al. (2021) for further details.

COVID-19 Pandemic: To address the disruptions caused by the COVID-19 pandemic, we exclude observations from March 2020 to December 2021, following the recommendations of Schorfheide and Song (2021) and Lenza and Primiceri (2022). This exclusion is justified by the significant economic volatility and structural breaks that occurred during this period, which could distort model estimates and reduce predictive accuracy. Removing these observations ensures more stable and reliable model performance. While alternative techniques for nowcasting during the pandemic (e.g., citeforonietal2022) were not evaluated, such approaches could be explored in future research to extend the test set.

Finally, all time series are standardized to ensure comparability across variables with different scales and units, preventing predictors with larger magnitudes from dominating the ML algorithms.

Dimensionality Reduction: Dimensionality reduction techniques address high-dimensionality and multicollinearity issues, enabling more robust model estimation. This step is potentially important given the inclusion of feature matrix rotations, which may increase correlation among variables.

We treat dimensionality reduction methods as hyperparameters to be optimized. Following Ng (2013), we include Least Angle Regression (LARS) and Principal Component Analysis (PCA) in the hyperparameter search space defined in Table 2:

Table 2: Dimensionality Reduction - Hyperparameter Search Space

Model	Hyperparameter	Prior Distribution
Dimensionality reduction	Use	{None, LARS, PCA}
LARS	N° non-zero coefficients	DiscreteUniform$(30, 150)$
PCA	N° Components	Uniform$(0.5, 0.99)$

The LARs regression algorithm is particularly effective when the number of predictors is large relative to the number of observations. It constructs a parsimonious model by iteratively selecting variables based on their correlation with the response variable. At each step, LARs adjusts the estimated coefficients toward the least-squares solution. Unlike traditional stepwise selection, it halts when a new predictor becomes as correlated with the residual as the current predictor. This process continues until all predictors are incorporated or the model reaches a predefined level of sparsity (see Efron et al. (2004) for further details). PCA is a widely used dimensionality reduction method that transforms a set of correlated variables into a smaller set of uncorrelated variables called principal components. Each principal component is a linear combination of the original variables and captures the maximum variance in the data, effectively reducing the dimensionality of the dataset while preserving its most critical information.

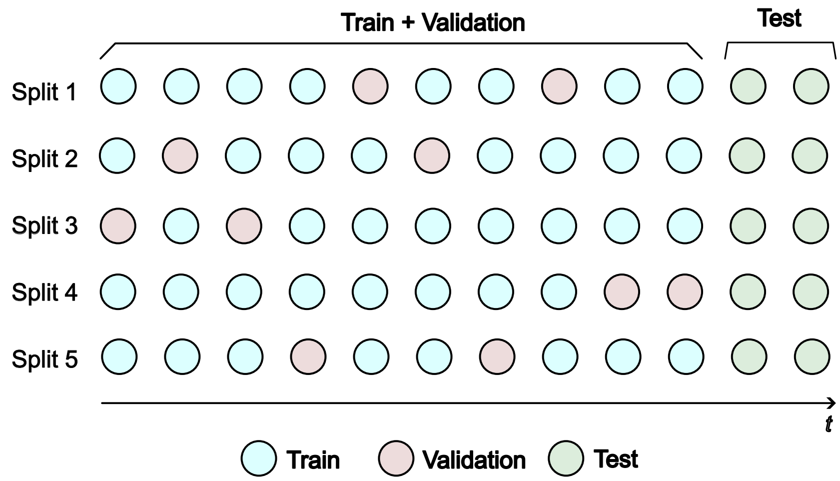
For a comprehensive mathematical treatment of PCA, see Jolliffe (2002).

Sample Split: We divided the dataset into training and test sets, experimenting with various split configurations to identify the most appropriate setup. Ultimately, the training set covers the period from April 2015 to February 2020, while the test set spans January 2022 to August 2024, deliberately excluding the pandemic period (March 2020 to December 2021), as previously noted. This approach ensures the model is trained on stable, pre-pandemic data and evaluated on post-pandemic economic conditions, providing a more reliable measure of performance unaffected by the unprecedented volatility during the COVID-19 pandemic.

Cross Validation: To fine-tune the model's hyperparameters, we conducted a cross-validation exercise using two methods: K-Fold and Walk-Forward cross-validation. Each method is suited to specific data characteristics, particularly in the context of time-series predictions.

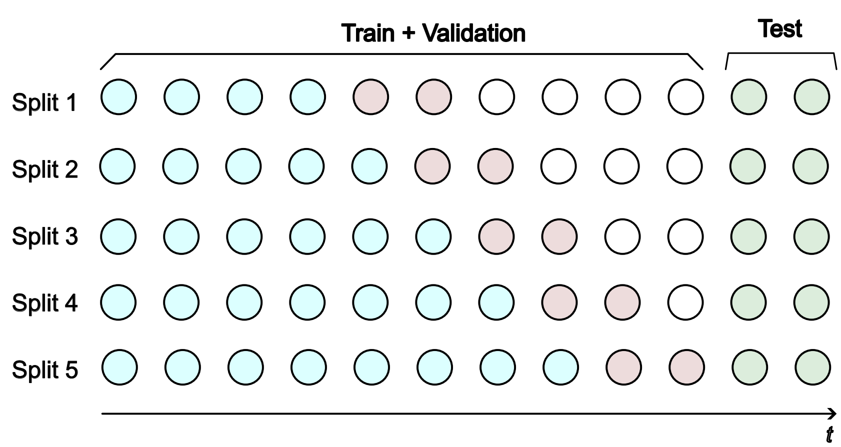
K-Fold cross-validation is a widely used technique that divides the training set into K equal-sized subsets or "folds". The model is trained on $K-1$ folds and tested on the remaining fold. This process is repeated K times, with each fold serving as the validation test set once. The performance is then averaged across all K iterations to produce a robust estimate of model accuracy. For $K = 5$, the dataset is split into five parts (Figure 2). In each iteration, four parts are used for training, while the remaining part is used for validation. This ensures all observations are used for both training and validation, providing a comprehensive assessment of the model's generalization ability.

Figure 2: K-Fold Cross-Validation (5 folds)



Walk-Forward cross-validation, also known as time-series cross-validation, is designed specifically for time-series data, where the temporal order of observations must be preserved. In this method, the training set starts with a small subset of data and grows sequentially as more data becomes available. After each training iteration, the model is validated using the next time period. This iterative process mimics real-world nowcasting, where models are trained on past data to predict future outcomes. However, walk-forward cross-validation is less efficient in terms of data usage, as each iteration uses only a portion of the dataset for training and another portion for validation. This can lead to higher variance in performance estimates, particularly in early iterations when the training set is smaller.

Figure 3: Walk Forward Cross Validation (5 folds)



In our analysis, we found that 5-Fold cross-validation outperformed Walk-Forward cross-validation, consistent with the findings of Goulet Coulombe et al. (2022). The K-Fold method provided more stable and reliable results for hyperparameter tuning, likely because it fully utilizes the data in a balanced manner and is less sensitive to the temporal dependencies that Walk-Forward cross-validation seeks to preserve.

Hyperparameter Optimization: We explored two widely used techniques for hyperparameter optimization: Grid Search and the Tree-Structured Parzen Estimator. These methods play a critical role in enhancing model performance by identifying the most effective hyperparameter configurations.

Grid Search systematically evaluates all possible combinations of hyperparameters within a predefined range of values. For each hyperparameter, a set of candidate values is specified, and the algorithm tests every possible combination, training and validating the model for each case. While Grid Search guarantees that the best combination within the defined grid is found, it can be computationally expensive, particularly when the number of hyperparameters and their respective value ranges is large.

The Tree-Structured Parzen Estimator (TPE) is a Bayesian optimization technique that leverages probabilistic models to guide the search for optimal hyperparameters. Unlike Grid Search, which explores the hyperparameter space without incorporating prior results, TPE constructs a probabilistic model of the objective function based on past evaluations. This model is then used to predict the most promising regions of the hyperparameter space to explore next, enabling a more targeted and efficient search.

TPE is particularly advantageous for complex models, such as deep learning architectures (see Watanabe (2023) for further details), where the hyperparameter space is vast and non-linear. By focusing on the most promising regions, TPE significantly reduces the number of evaluations required to identify the optimal configuration. This makes it especially effective in scenarios involving complex and non-intuitive hyperparameter interactions. For each model, let $\mathbf{h}$ represent the set of hyperparameters and s denote the corresponding objective function values. TPE operates through the following steps:

1. Given an initial number of evaluations (N^{init}) of an objective function, define $D := \{(\mathbf{h}_n, s_n)\}_{n=1}^{N^{init}}$ as the set containing all pairs of hyperparameter configurations and their corresponding objective function values..

2. Divide set D in two subsets: a "good" group (D^l) and a "bad" group (D^g), based on a quantile $s^\gamma, \gamma \in [0,1)$.

3. Construct probability density functions (PDFs) $p(\mathbf{h}|D^l), p(\mathbf{h}|D^g)$ using a prior distribution for each hyperparameter and kernel density estimators (KDEs).

4. Sample from the PDF of the "good" group: $S := \{\mathbf{h}_i\}_{i=1}^{N_i} \in p(\mathbf{h}|D^l)$.

5. Optimize a surrogate function to identify the best candidate for evaluating the objective function:

$$\mathbf{h}^*_{\mathbf{N+1}} = \underset{\mathbf{h} \in S}{\operatorname{argmax}}\, r(\mathbf{h}|D)$$

$$r(\mathbf{h}|D) = p(\mathbf{h}|D^l)/p(\mathbf{h}|D^g)$$

6. Evaluate the objective function at the optimal candidate: $\mathbf{s}^*_{\mathbf{N+1}} = f(\mathbf{h}^*_{\mathbf{N+1}})$

7. Update set $D \leftarrow D \cup \{(\mathbf{h}^*_{\mathbf{N+1}}, \mathbf{s}^*_{\mathbf{N+1}})\}$.

8. Repeat steps 1–7 until the maximum number of objective function evaluations is reached.

9. Select the hyperparameter configuration that optimizes the objective function.

After assessing the performance and efficiency of all three methods, we selected TPE as our preferred technique for hyperparameter optimization. Its iterative refinement based on previous results significantly enhances efficiency compared to Grid Search, especially for complex models. The search space for hyperparameters across models is detailed in Table 3:

Table 3: ML Models - Hyperparameter Search Space

Model	Hyperparameter	Prior Distribution
Lasso	Alpha	Uniform($10^{-3}, 3*10^{-1}$)
Ridge	Alpha	Uniform($10^{-1}, 10^{2}$)
Elastic Net	Alpha	Uniform($10^{-3}, 3*10^{-1}$)
	L1 ratio	Uniform($10^{-4}, 1$)
SVR	Gamma	Uniform($10^{-7}, 0.5$)
	C	Uniform($1, 10^{5}$)
Decision Tree	Max. Depth	Discrete Uniform(3,100)
	Min. samples for leaf	DiscreteUniform(1,20)
	Min. samples for split	DiscreteUniform(2,20)
	Max. leaf nodes	DiscreteUniform(5,20)
KNN	N Neighbors	DiscreteUniform(2,30)
	Weights	{uniform,distance}
Random Forest	Max. Depth	DiscreteUniform(3,100)
	Min. samples for leaf	DiscreteUniform(4,10)
	Min. samples for split	DiscreteUniform(4,10)
	N. Estimators	DiscreteUniform(30,200)
AdaBoost	Learning Rate	Uniform($10^{-4}, 1$)
	Loss	{linear,squared,exponential}
	N. Estimators	DiscreteUniform(30,200)
GBoost	Learning Rate	Uniform($10^{-4}, 1$)
	Max. Depth	DiscreteUniform(3,100)
	Min. samples for leaf	DiscreteUniform(4,10)
	Min. samples for split	DiscreteUniform(4,10)
	N. Estimators	DiscreteUniform(30,200)
XGBoost	Columns per tree	Uniform($10^{-2}, 0.99$)
	Gamma	Uniform($10^{-3}, 0.99$)
	Learning Rate	Uniform($10^{-4}, 1$)
	Subsample	Uniform($0.5, 0.99$)
	Max. Depth	DiscreteUniform(3,100)
	N. Estimators	DiscreteUniform(30,200)
Bagging	N. Estimators	DiscreteUniform(5,20)
	Max. Samples	Uniform($10^{-2}, 1$)
	Max. Features	Uniform($3*10^{-2}, 1$)
	Bootstrap	{True,False}
	Bootstrap Features	{True,False}
MLP	N. Layers	DiscreteUniform(1,7)
	Neurons per layer	DiscreteUniform(1,15)
	Activation	{Identity, Logistic, Tanh, ReLU}
	Alpha	Uniform($10^{-8}, 0.99$)
	Batch size	DiscreteUniform(10,20)
	Beta 1	Uniform($10^{-2}, 0.99$)
	Beta 2	Uniform($10^{-2}, 0.99$)

Model Evaluation: Following established practices in GDP nowcasting literature, we assess model performance using the Root Mean Square Error (RMSE), a widely recognized metric for evaluating prediction accuracy. RMSE directly measures the average magnitude of prediction errors, with larger errors penalized more heavily, making it a robust tool for model comparison.

For a given model m, the RMSE is computed as the square root of the mean of squared differences between actual values y_t and the predicted values $\hat{y}_t$:

$$RMSE^m = \sqrt{\frac{1}{32}\sum_{t=T-32}^{T}(y_t - \hat{y}_t^m)^2}$$

where y_t denotes actual GDP values at time t, $\hat{y}_t^m$ is the nowcast generated by model m at time t, T corresponds to August 2024, and the 32-observation window refers to the test period (the last 32 months).

4 Results

To evaluate and compare the performance of various ML methods, we conducted an out-of-sample nowcasting exercise from January 2022 to August 2024. Four analyses were performed: one for each target variable (total and non-primary GDP) and for each approach (direct and bottom-up).

Tables 4 and 5 present point nowcasts for YoY total GDP growth using the bottom-up and direct approaches, respectively. The first column lists actual GDP values, while subsequent columns display predictions for each ML model, the mean prediction across ML models (Mean ML), and the DFM benchmark.

From Table 4, all ML models achieved lower RMSE values than the DFM. Models such as XGBoost and Elastic Net consistently performed well, with RMSE values around 0.6, showcasing their ability to capture non-linear patterns in GDP data.

Comparing tables 4 and 5, the bottom-up approach yielded lower RMSE values across all ML models. By assembling sectorial nowcasts, this approach captured episodes of high volatility more precisely. For example, in Q2 2024, agriculture and fisheries experienced a significant rebound, which the direct approach failed to capture. This suggests that identifying sector-specific movements may be easier than forecasting total GDP, an aggregate of all sectors.

Table 4: Nowcast of YoY GDP (bottom-up)

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	2.8	4.2	4.0	4.0	4.0	3.2	4.1	3.9	3.6	3.4	3.5	3.4	4.3	3.8	4.0
Feb-22	4.7	5.4	5.5	5.6	5.6	5.1	5.2	5.3	5.3	5.2	5.2	5.2	5.8	5.4	5.9
Mar-22	3.8	3.9	4.2	4.1	4.4	3.7	3.8	3.5	3.6	3.5	3.7	3.6	4.3	3.9	4.0
Apr-22	4.0	3.6	3.3	3.6	3.6	3.3	3.8	3.5	3.5	3.3	3.6	3.6	3.4	3.5	4.3
May-22	2.6	2.5	2.6	2.6	2.2	2.0	2.1	2.4	2.5	2.6	2.2	2.1	2.4	2.3	1.7
Jun-22	3.5	2.9	3.0	3.1	2.9	3.6	3.2	3.4	3.4	3.6	3.4	3.6	3.2	3.3	3.6
Jul-22	1.8	2.6	2.4	2.4	2.4	3.1	2.4	2.6	2.6	2.7	2.5	2.6	2.4	2.6	2.8
Aug-22	2.0	1.8	2.0	1.8	1.8	2.0	1.7	2.0	1.9	1.9	2.2	1.9	1.9	1.9	1.9
Sep-22	2.1	1.5	1.7	1.6	1.3	1.5	1.6	1.6	1.5	1.6	1.7	1.5	1.7	1.6	1.7
Oct-22	2.3	3.1	2.9	3.0	3.1	3.0	3.3	2.9	3.0	2.8	2.8	2.9	3.0	3.0	3.5
Nov-22	2.1	2.6	2.6	2.7	2.6	2.1	2.4	2.8	2.4	2.4	2.5	2.4	2.7	2.5	2.7
Dec-22	1.0	2.1	2.4	2.1	2.3	3.1	2.4	2.2	2.2	2.2	2.5	2.5	2.4	2.4	1.8
Jan-23	-0.9	0.1	0.3	0.3	0.5	0.7	0.5	0.4	0.5	0.5	0.5	0.5	0.2	0.4	0.4
Feb-23	-0.6	-0.9	-1.0	-1.0	-1.0	-0.9	-0.7	-0.7	-0.9	-1.1	-1.0	-1.1	-0.9	-0.9	-1.0
Mar-23	0.3	0.5	0.1	0.3	-0.1	0.2	0.6	0.4	0.3	0.4	0.2	0.4	-0.4	0.2	-0.2
Apr-23	0.4	0.6	0.8	0.5	0.8	0.6	1.1	1.2	0.9	0.7	0.7	0.9	0.5	0.8	1.1
May-23	-1.3	-0.9	-1.0	-1.1	-1.1	-0.5	-0.2	-0.4	-0.5	-0.7	-0.7	-0.7	-1.1	-0.7	-0.9
Jun-23	-0.6	-0.5	-0.3	-0.5	-0.1	-0.8	-0.7	-0.7	-1.0	-1.0	-0.8	-0.8	-0.2	-0.6	-1.5
Jul-23	-1.2	-0.2	-0.5	-0.4	-0.1	-0.1	-0.2	-0.3	-0.3	-0.1	-0.2	0.1	-0.3	-0.2	-0.4
Aug-23	-0.4	-0.8	-0.8	-0.6	-0.9	-0.5	-1.1	-1.0	-0.5	-0.6	-0.7	-0.2	-0.8	-0.7	-1.2
Sep-23	-1.2	-1.0	-1.1	-1.0	-1.1	-0.7	-0.8	-0.8	-0.9	-0.8	-0.8	-0.7	-1.2	-0.9	-0.3
Oct-23	-0.7	-0.3	-0.4	-0.4	-0.5	-0.6	-0.7	-0.6	-0.4	-0.8	-0.5	-0.5	-0.4	-0.5	-0.4
Nov-23	0.3	-0.5	-0.4	-0.5	-0.6	-0.4	-0.2	-0.2	-0.2	-0.2	-0.3	-0.1	-0.5	-0.3	0.4
Dec-23	-0.7	-0.9	-0.9	-0.9	-0.8	-1.5	-0.6	-0.6	-0.9	-1.3	-0.9	-1.1	-1.0	-0.9	-0.5
Jan-24	1.5	1.3	1.2	1.4	1.3	1.3	1.0	1.0	1.1	1.3	1.4	0.8	1.3	1.2	0.8
Feb-24	3.2	3.3	3.1	3.1	3.4	2.9	3.3	3.3	3.0	3.2	3.1	3.0	3.2	3.2	3.6
Mar-24	-0.4	-0.7	-0.4	-0.5	-0.7	-1.0	-0.9	-0.7	-0.7	-0.5	-0.6	-0.6	-0.6	-0.7	-0.7
Apr-24	5.4	4.6	4.2	4.4	4.5	4.9	3.5	3.8	4.7	4.8	4.6	4.4	4.3	4.4	3.4
May-24	5.3	5.1	5.0	5.1	5.3	5.6	6.1	5.8	5.4	5.3	5.4	5.4	5.0	5.4	6.2
Jun-24	0.3	1.4	1.4	1.6	1.5	1.4	2.0	1.7	0.9	1.0	1.0	1.0	1.4	1.4	1.8
Jul-24	4.6	3.4	3.4	3.4	3.8	3.2	3.5	3.4	3.5	3.4	3.3	3.5	3.7	3.5	3.7
Aug-24	3.7	3.4	3.6	3.4	3.6	3.4	3.4	3.5	3.5	3.7	3.4	3.4	3.5	3.5	2.9
RMSE		0.637	0.643	0.629	0.682	0.740	0.804	0.720	0.588	0.586	0.608	0.631	0.673	0.628	0.840

Table 5: Nowcast of YoY GDP (direct)

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	2.8	2.9	2.8	2.9	2.8	3.2	2.3	2.4	2.3	2.6	2.8	2.6	2.5	2.7	3.6
Feb-22	4.7	3.0	3.1	3.1	3.9	3.4	3.6	3.4	3.6	3.4	3.6	3.3	3.2	3.4	4.6
Mar-22	3.8	5.0	5.3	4.4	4.9	4.9	4.7	4.3	4.3	4.1	4.3	4.4	5.2	4.6	3.9
Apr-22	4.0	3.8	4.1	4.4	4.1	3.2	4.0	4.0	4.2	3.6	4.2	4.2	4.2	4.0	5.2
May-22	2.6	3.4	3.2	3.4	3.2	3.8	2.6	3.3	3.1	3.8	3.0	3.5	3.3	3.3	2.0
Jun-22	3.5	2.7	2.6	2.6	2.7	2.3	2.5	2.5	2.7	3.0	2.5	2.4	2.6	2.6	3.6
Jul-22	1.8	3.1	3.1	3.0	2.9	3.2	2.9	3.3	3.7	3.7	2.8	3.5	3.0	3.2	4.0
Aug-22	2.0	1.9	1.9	1.6	2.1	2.3	2.5	1.9	2.2	2.3	1.5	1.6	1.7	2.0	1.1
Sep-22	2.1	1.1	1.1	1.1	1.2	1.9	1.5	1.2	1.5	0.7	1.2	1.0	0.9	1.2	1.1
Oct-22	2.3	2.4	2.3	2.3	2.6	2.0	2.4	2.6	2.7	2.7	2.7	2.4	2.3	2.4	3.7
Nov-22	2.1	2.0	2.5	2.5	2.3	2.7	3.1	2.6	2.4	2.6	2.1	2.7	2.6	2.5	2.7
Dec-22	1.0	2.0	1.9	2.0	2.3	2.1	1.8	1.8	2.0	2.4	2.0	1.9	1.9	2.0	1.0
Jan-23	-0.9	0.5	0.5	0.4	0.5	1.2	1.1	1.6	1.5	1.0	1.5	2.0	0.7	1.1	2.4
Feb-23	-0.6	-2.4	-2.0	-2.3	-1.7	-1.3	-1.7	-1.1	-1.2	-1.8	-0.8	-0.9	-2.4	-1.6	-1.3
Mar-23	0.3	-0.1	1.1	0.1	0.1	0.0	-0.7	0.3	0.2	0.3	0.0	0.4	-0.1	0.1	-1.3
Apr-23	0.4	-0.1	-0.3	-0.3	-0.1	0.1	0.7	0.1	0.1	-0.6	0.0	-0.2	-0.2	-0.1	-0.1
May-23	-1.3	0.3	0.2	0.1	0.2	0.9	0.5	0.7	0.6	0.4	0.5	0.8	0.3	0.4	0.2
Jun-23	-0.6	-1.6	-1.7	-1.6	-1.6	-0.9	-1.2	-1.3	-1.2	-1.0	-1.3	-1.3	-1.7	-1.4	-1.5
Jul-23	-1.2	-0.1	-0.1	-0.2	-0.3	0.3	-0.4	-0.3	-0.5	-0.7	-0.5	-0.7	-0.3	-0.3	1.4
Aug-23	-0.4	-0.7	-0.4	-0.5	-0.4	-0.1	-0.6	-0.8	-0.8	-0.5	-0.7	-1.0	-0.3	-0.6	-1.5
Sep-23	-1.2	-1.3	-0.8	-0.6	-0.7	-1.0	-0.9	-0.6	-0.6	-0.5	-1.0	-0.5	-0.7	-0.8	-0.4
Oct-23	-0.7	-0.8	-0.9	-0.9	-0.7	-0.5	-0.2	-0.4	-0.8	-0.8	-0.6	-0.3	-0.7	-0.6	-0.8
Nov-23	0.3	-0.9	-1.0	-0.9	-0.9	-0.6	-0.8	-0.7	-0.8	-0.5	-0.7	-0.7	-0.9	-0.8	-0.1
Dec-23	-0.7	0.5	0.5	0.3	0.6	0.7	0.5	0.3	0.5	0.5	0.5	0.1	0.3	0.4	-0.8
Jan-24	1.5	1.8	2.0	2.0	1.4	1.3	1.6	1.0	1.0	0.8	0.8	1.1	2.0	1.4	1.3
Feb-24	3.2	2.5	2.5	2.6	2.3	1.3	2.3	1.9	2.3	1.6	2.0	1.9	2.3	2.1	3.3
Mar-24	-0.4	-1.0	-1.1	-0.8	-1.0	-0.3	-0.2	-0.3	-1.0	-1.2	-0.2	-0.3	-0.7	-0.7	0.1
Apr-24	5.4	3.2	3.3	3.3	3.0	3.0	2.8	2.7	2.7	3.2	3.0	2.9	3.4	3.1	2.8
May-24	5.3	3.2	3.1	3.1	3.2	4.6	3.4	4.1	3.9	3.4	3.7	4.2	3.2	3.6	4.9
Jun-24	0.3	2.4	2.4	2.7	2.0	2.9	3.9	3.0	3.1	3.0	3.5	3.0	2.7	2.9	2.6
Jul-24	4.6	3.2	3.2	3.1	2.9	2.9	2.9	2.9	2.7	3.2	2.9	2.9	3.1	3.0	4.4
Aug-24	3.7	3.3	3.0	3.1	3.6	2.2	3.5	3.2	3.1	3.1	3.2	3.0	3.1	3.1	3.0
RMSE		1.107	1.105	1.099	1.039	1.207	1.208	1.156	1.163	1.173	1.148	1.202	1.128	1.101	1.245

Tables 6 and 7 provide monthly nowcasts of YoY non-primary GDP growth for the bottom-up and direct approaches, respectively. Non-primary GDP is particularly significant due to the relative lack of real-time information, making accurate nowcasts critical for policymakers and analysts.

ML models demonstrated strong performance in capturing non-primary GDP movements during economic downturns (e.g., H2 2023) and periods of volatility (e.g., H1 2024), with RMSE values around 0.7–0.8. Notably, the DFM performed comparably, achieving an RMSE of 0.7.

However, ML models struggled to capture the rapid slowdown in January 2023 caused by social conflicts. Although the bottom-up approach mitigated errors to some extent, the DFM provided superior predictions for this period, accurately reflecting non-primary GDP dynamics.

Table 6: Nowcast of YoY Non-Primary GDP (bottom-up)

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	2.9	4.1	4.0	4.0	4.0	3.9	4.1	4.1	3.9	3.9	4.0	4.0	4.0	4.0	3.9
Feb-22	6.1	6.5	6.4	6.6	6.6	6.2	6.4	6.4	6.4	6.3	6.5	6.2	6.5	6.4	7.1
Mar-22	5.3	4.9	5.1	5.3	5.0	4.8	4.7	4.8	4.8	4.8	4.8	4.8	5.1	4.9	5.3
Apr-22	5.1	4.7	4.4	4.5	4.6	4.5	4.4	4.6	4.5	4.6	4.8	4.8	4.5	4.6	4.9
May-22	4.4	4.6	4.5	4.5	4.4	4.2	4.4	4.5	4.6	4.7	4.5	4.4	4.5	4.5	4.3
Jun-22	3.7	3.6	3.7	3.8	3.9	4.0	3.9	4.0	3.9	4.0	4.1	4.1	3.9	3.9	4.0
Jul-22	2.1	3.2	3.2	3.1	3.1	3.4	3.0	3.1	3.1	3.1	3.0	3.0	3.2	3.1	2.9
Aug-22	2.8	2.3	2.4	2.4	2.4	2.7	2.4	2.6	2.5	2.4	2.6	2.6	2.3	2.5	2.6
Sep-22	2.7	2.0	2.1	2.1	2.0	1.7	2.0	2.0	2.0	2.0	2.2	1.8	2.1	2.0	2.0
Oct-22	2.1	3.1	3.0	2.9	3.0	2.8	3.1	2.9	2.8	2.6	2.7	2.8	2.9	2.9	2.8
Nov-22	2.1	2.5	2.5	2.5	2.4	2.5	2.3	2.5	2.4	2.5	2.3	2.5	2.4	2.4	2.3
Dec-22	-0.2	1.3	1.3	1.3	1.4	1.4	1.6	1.4	1.3	1.3	1.5	1.3	1.5	1.4	1.3
Jan-23	-1.9	-0.1	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.2	-0.2	0.0	0.0	-0.7
Feb-23	-1.6	-1.8	-1.9	-2.0	-1.9	-1.8	-1.9	-1.8	-1.8	-2.0	-2.0	-2.1	-1.8	-1.9	-2.2
Mar-23	-1.9	-2.3	-2.3	-2.3	-2.2	-2.1	-2.0	-2.0	-2.1	-2.0	-2.0	-1.9	-2.4	-2.1	-2.3
Apr-23	-1.1	-1.9	-1.7	-1.8	-1.9	-1.5	-1.7	-1.6	-1.8	-1.9	-1.8	-1.5	-1.9	-1.8	-1.8
May-23	-1.4	-1.2	-1.2	-1.2	-1.4	-1.2	-1.1	-1.1	-1.1	-1.3	-1.1	-1.0	-1.2	-1.2	-1.1
Jun-23	-0.7	-1.3	-1.3	-1.3	-1.3	-1.2	-1.1	-1.3	-1.3	-1.4	-1.4	-1.2	-1.3	-1.3	-1.2
Jul-23	-2.0	-0.5	-0.6	-0.6	-0.2	-0.8	-0.6	-0.6	-0.5	-0.7	-0.5	-0.4	-0.6	-0.5	-0.6
Aug-23	-1.8	-2.0	-2.0	-1.8	-2.1	-1.9	-1.6	-1.8	-1.9	-1.9	-1.9	-1.7	-2.0	-1.9	-1.8
Sep-23	-2.5	-2.7	-2.7	-2.6	-2.6	-2.4	-2.4	-2.4	-2.4	-2.4	-2.3	-2.2	-2.7	-2.5	-2.1
Oct-23	-1.5	-1.3	-1.0	-1.2	-1.3	-1.5	-1.2	-1.3	-1.4	-1.5	-1.3	-1.4	-1.2	-1.3	-1.1
Nov-23	-1.6	-1.5	-1.5	-1.5	-1.6	-1.9	-1.5	-1.5	-1.5	-1.6	-1.6	-1.5	-1.6	-1.6	-1.0
Dec-23	0.3	-1.0	-1.0	-1.0	-0.9	-1.0	-0.8	-0.8	-0.8	-0.8	-0.7	-0.8	-1.0	-0.9	-0.2
Jan-24	2.3	2.2	2.2	2.3	2.4	2.5	2.2	2.1	2.1	2.4	2.4	2.1	2.2	2.3	1.9
Feb-24	2.7	2.2	2.2	2.2	2.1	2.0	2.3	2.2	2.1	2.2	2.2	2.1	2.2	2.2	2.5
Mar-24	-0.3	-0.7	-0.6	-0.6	-0.6	-0.7	-0.6	-0.6	-0.6	-0.5	-0.6	-0.5	-0.6	-0.6	-0.6
Apr-24	3.9	3.9	3.8	3.9	3.9	3.7	3.6	3.6	3.8	3.8	3.6	3.8	3.8	3.8	3.8
May-24	2.5	2.3	2.3	2.3	2.6	2.5	2.4	2.5	2.3	2.4	2.3	2.4	2.4	2.4	3.1
Jun-24	1.1	1.4	1.2	1.3	1.2	1.2	1.1	1.0	1.0	1.0	1.1	1.0	1.2	1.1	1.2
Jul-24	5.1	3.7	3.7	3.8	4.0	3.8	3.8	3.8	3.8	3.7	3.9	3.9	4.0	3.8	3.8
Aug-24	3.6	3.2	3.1	3.2	3.1	3.4	3.4	3.3	3.4	3.3	3.2	3.3	3.2	3.2	3.0
RMSE		0.766	0.742	0.737	0.754	0.744	0.746	0.731	0.728	0.721	0.732	0.695	0.738	0.727	0.672

Table 7: Nowcast of YoY Non-Primary GDP (direct)

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	2.9	2.9	2.9	2.9	2.9	3.0	3.0	3.1	3.1	2.9	3.1	3.1	2.9	3.0	2.8
Feb-22	6.1	6.5	6.4	6.4	6.6	6.7	6.8	6.9	6.9	6.8	6.6	7.0	6.4	6.7	7.1
Mar-22	5.3	5.3	5.5	5.4	5.5	5.7	5.6	5.5	5.6	5.7	5.5	5.7	5.7	5.6	5.6
Apr-22	5.1	4.3	4.3	4.3	4.4	4.6	4.7	4.6	4.6	4.6	4.6	4.7	4.3	4.5	5.4
May-22	4.4	5.1	5.1	4.9	4.9	5.1	4.8	5.0	5.0	5.2	5.0	5.0	5.1	5.0	4.3
Jun-22	3.7	4.0	4.1	3.9	3.9	4.3	4.2	4.2	4.3	4.2	4.1	4.1	3.9	4.1	4.1
Jul-22	2.1	2.9	3.1	3.3	2.9	3.5	3.3	3.5	3.2	3.5	3.5	3.4	3.1	3.3	3.0
Aug-22	2.8	2.3	2.2	2.3	2.1	2.4	2.5	2.5	2.3	2.4	2.3	2.5	2.2	2.3	2.3
Sep-22	2.7	1.9	1.9	1.8	1.9	2.1	1.9	1.9	1.9	2.0	2.0	1.9	1.9	1.9	1.9
Oct-22	2.1	3.0	2.9	2.9	2.9	2.9	2.8	2.7	2.7	2.5	2.7	2.8	2.9	2.8	2.6
Nov-22	2.1	2.2	2.1	2.0	2.2	1.9	1.9	2.0	2.1	1.8	2.0	2.1	2.1	2.1	1.6
Dec-22	-0.2	1.1	1.1	1.2	1.1	1.5	1.5	1.3	1.2	1.3	1.4	1.3	1.1	1.3	0.5
Jan-23	-1.9	0.5	0.5	0.7	0.7	1.0	0.8	0.9	1.0	0.8	0.9	0.9	0.6	0.8	0.3
Feb-23	-1.6	-1.3	-1.4	-1.4	-1.3	-1.3	-1.6	-1.6	-1.6	-1.5	-1.8	-1.6	-1.3	-1.5	-2.2
Mar-23	-1.9	-1.6	-1.7	-1.6	-1.6	-0.7	-1.4	-1.4	-1.4	-1.4	-1.2	-1.3	-1.6	-1.4	-2.2
Apr-23	-1.1	-2.2	-2.2	-2.3	-2.3	-2.3	-2.3	-2.2	-2.1	-2.2	-2.3	-2.2	-2.2	-2.2	-2.2
May-23	-1.4	-0.2	-0.6	-0.4	0.0	-0.1	-0.4	-0.2	-0.2	-0.4	-0.3	-0.2	-0.6	-0.3	-0.4
Jun-23	-0.7	-1.5	-1.4	-1.5	-1.4	-1.4	-1.3	-1.4	-1.4	-1.4	-1.5	-1.4	-1.5	-1.4	-1.5
Jul-23	-2.0	-0.1	0.0	-0.2	-0.4	-0.7	-0.3	-0.7	-0.8	-0.8	-0.7	-0.9	0.0	-0.5	-0.3
Aug-23	-1.8	-1.6	-1.7	-1.6	-1.6	-0.9	-1.5	-1.6	-1.6	-1.5	-1.5	-1.5	-1.6	-1.5	-1.9
Sep-23	-2.5	-2.1	-2.2	-2.1	-2.1	-1.6	-2.0	-2.0	-2.1	-2.0	-2.1	-2.1	-2.1	-2.1	-1.8
Oct-23	-1.5	-1.6	-1.5	-1.5	-1.4	-1.6	-1.5	-1.5	-1.4	-1.5	-1.4	-1.6	-1.5	-1.5	-1.2
Nov-23	-1.6	-1.9	-1.9	-1.9	-1.9	-1.3	-1.8	-1.7	-1.7	-1.7	-1.7	-1.6	-1.8	-1.7	-1.1
Dec-23	0.3	-1.5	-1.6	-1.6	-1.6	-1.5	-1.4	-1.4	-1.5	-1.4	-1.5	-1.5	-1.6	-1.5	-1.0
Jan-24	2.3	2.4	2.3	2.6	2.0	1.2	2.0	1.6	1.5	1.7	1.8	1.6	2.4	1.9	1.3
Feb-24	2.7	2.3	2.3	2.3	2.2	2.0	2.5	2.2	2.3	2.2	2.0	2.1	2.3	2.2	2.5
Mar-24	-0.3	-0.3	-0.3	-0.3	-0.1	-0.2	-0.1	0.0	-0.1	-0.2	-0.2	-0.1	-0.3	-0.2	0.1
Apr-24	3.9	3.3	3.3	3.3	3.5	3.5	3.4	3.5	3.4	3.4	3.5	3.6	3.3	3.4	3.6
May-24	2.5	2.1	2.0	2.0	1.9	2.6	2.0	2.1	1.9	1.6	1.8	2.1	2.3	2.0	3.0
Jun-24	1.1	1.6	1.4	1.5	1.5	1.1	1.5	1.4	1.4	1.3	1.4	1.3	1.4	1.4	1.6
Jul-24	5.1	3.0	3.1	3.1	3.2	3.0	3.1	3.0	3.0	3.2	3.1	3.1	3.1	3.1	3.4
Aug-24	3.6	3.6	3.5	3.3	3.4	3.0	3.3	3.4	3.4	3.6	3.4	3.4	3.5	3.4	2.9
RMSE		0.916	0.909	0.933	0.924	1.021	0.938	0.943	0.944	0.912	0.949	0.926	0.915	0.921	0.841

Interesting patterns emerged regarding hyperparameter choices. Dimensionality reduction techniques were predominantly selected by TPE across target variables and ML models. Notably, LARS consistently outperformed PCA for all ML models, except for Decision Tree, which occasionally performed better with PCA. Feature matrix rotations showed mixed results. While TPE tended to favor MARX over MAF or X for most out-of-sample nowcasts, this preference was less pronounced compared to LARS dominance in dimensionality reduction. LARS was chosen 95.6% of the time (2,570 out of 2,688 cases), compared to 69.9% for MARX. Table 8 presents the relative frequency of hyperparameter usage in the out-of-sample exercises:

Table 8: Hyperparameters - Frequency of usage in Out-of-Sample exercises (Percentage points)

Dimensionality reduction			**Rotations**		
LARS	PCA	None	MARX	MAF	X
95.6	4.1	0.3	69.9	51.5	45.0

5 Conclusion

This paper applied ML techniques to nowcast total and non-primary Peruvian GDP. By testing a wide range of model specifications, we compared the accuracy of ML methods against the DFM, a standard benchmark for nowcasting. Our findings demonstrate that ML models performed well, achieving lower RMSE values than the DFM for total GDP and comparable RMSE values for non-primary GDP.

A key contribution of this study is the implementation of a bottom-up approach for nowcasting, which involved nowcasting disaggregated sectoral components of total and non-primary GDP. This approach reduced RMSE by approximately 45% and 22% for total and non-primary GDP, respectively. Additionally, we explored the value of incorporating new features and reducing the dimensionality of the feature matrix to enhance predictability. The inclusion of moving averages of features and the use of LARS for dimensionality reduction were the most frequently effective procedures.

An important avenue for future research involves expanding the focus from nowcasting to forecasting. While nowcasting assesses the current state of the economy, incorporating forecasting could provide valuable insights into future economic trends, further enhancing the utility of ML techniques for economic decision-making.

Besides, we plan to address the interpretability of ML models, often criticized due to their algorithmic complexity. Techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) could make ML results more transparent, boosting their reliability and acceptance among policymakers and economists, who often require a clear understanding of the drivers behind predictions.

In conclusion, while ML techniques have proven highly effective in nowcasting Peruvian GDP, there are significant opportunities to expand and refine their application. By extending into forecasting and enhancing interpretability, future research can further advance the role of ML in economic prediction.

A Dynamic Factor Model for Nowcasting Monthly GDP in Peru

The methodology in this paper follows the theoretical framework established by Bańbura et al. (2013) and Mariano and Murasawa (2010), with a modified implementation in Python based on Fulton (2020). The DFM assumes that a small number of unobservable factors can explain a significant portion of the variation and dynamics of a large set of observable variables. These observable variables often comprise dozens or even hundreds of series, making the estimation of dynamic factors an effective dimensionality reduction technique. The estimated factors are then utilized for forecasting and nowcasting. The model is specified as follows:

$$z_t = \Lambda f_t + \epsilon_t$$
$$f_t = A_1 f_{t-1} + \ldots + A_p f_{t-p} + u_t,$$

where $z_t = (y_{1t}, x_{1t}, \ldots, x_{dt})'$ represents monthly series, transformed to achieve stationarity. Here, ϵ_t denotes idiosyncratic disturbances at time t, f_t is an $r \times 1$ vector of unobservable common factors modeled as a VAR process of order p, and $u_t \sim N(0, Q)$ are the disturbances associated with the dynamic factors. Additionally, Λ is the matrix of factor loadings, and A_i are the autoregressive coefficient $r \times r$ matrices. The idiosyncratic component of the monthly series follows an AR(1) process:

$$\epsilon_{it} = \alpha_i \epsilon_{it-1} + e_{it}, \text{ with } e_{it} \sim i.i.d.N(0, \sigma_i^2) \text{ and } \mathbb{E}[e_{it}, e_{jt}] = 0, \forall i \neq j$$

The model allows for the decomposition of unobserved factors into two categories: (i) global factors, capturing cross-sectional comovement across all groups of explanatory variables (e.g., coincident/leading economic indicators, employment, credit, fiscal accounts), and (ii) group-specific factors for each group of variables.

To achieve this, we restrict Λ, A_1, A_2, ..., A_p and Q, to partition f_t into mutually independent global (g) and m group-specific (s) factors:

$$\Lambda = \begin{pmatrix} \Lambda_{g,s_1} & A_{s_1,s_1} & 0 & \dots & 0 \\ \Lambda_{g,s_2} & 0 & A_{s_2,s_2} & \dots & 0 \\ \vdots & \vdots & \dots & \ddots & \vdots \\ \Lambda_{g,s_m} & 0 & \dots & 0 & A_{s_m,s_m} \end{pmatrix}$$

$$f_t = \begin{pmatrix} f_t^g \\ f_t^{s_1} \\ \vdots \\ f_t^{s_m} \end{pmatrix}, \quad A_i = \begin{pmatrix} A_{i,g} & 0 & \dots & 0 \\ 0 & A_{i,s_1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & A_{i,s_m} \end{pmatrix}, \quad Q = \begin{pmatrix} Q_g & 0 & \dots & 0 \\ 0 & Q_{s_1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & Q_{s_m} \end{pmatrix}$$

This framework accounts for cross-sectional correlation within group-specific blocks while allowing for the efficient estimation of global factors. Importantly, A_i, g is not necessarily diagonal, permitting the presence of multiple correlated global factors.

A.1 Data

The initial dataset comprises up to 182 series spanning January 2006 to September 2024. These include structured data such as industrial activity indicators, prices, fiscal accounts, trade balance, terms of trade, employment statistics, expectations survey indices, financial system data, and equity market information. Non-structured data is represented by Google Trends search volumes related to crises, expenditure, government transfers, and other topics.

To refine the dataset, a LASSO model was applied, optimizing hyperparameters for the period 2011–2019. This procedure yielded a preselected subset of 155 variables.

Lastly, we transform the variables as follows. First, we apply seasonal adjustment to the entire reduced dataset, using the software JDemetra+. Next, variables originally expressed in levels are converted to month-on-month variations to meet the stationarity assumption. Finally, we remove observations that are more than 10 times the Interquartile Range (IQR = $Q_3 - Q_1$, where Q_i is the i-th quartile) from the mean. This outlier removal implicitly excludes most of the COVID-19 period.

A.2 Estimation

The details of the state-space representation can be found in Mariano and Murasawa (2010) and Bańbura et al. (2013). The literature on nowcasting with DFM estimates $\theta = (\Lambda, A, Q, \sigma^2)$ using maximum likelihood, through the Expectation-Maximization (EM) algorithm, which accommodates missing observations. This algorithm roughly consists of iterating a two-step approach, while treating the unobserved factors as latent variables: (i) given a current estimate of θ, we compute the expected value of the log-likelihood function of the complete data (observed data and latent factors); and then (ii) we maximize the expected log-likelihood with respect to the parameters θ, yielding new estimates of the parameters.

The algorithm works as follows: we begin with an initial guess for θ. In the first step (Expectation Step), we use a Kalman Filter and Smoother to compute the conditional expectation of the latent factors f_t and their covariances, in order to calculate the expected value of the complete data log-likelihood, which depends on the latent factors. In the second step (Maximization Step), the expected log-likelihood from the previous step is maximized with respect to the parameters. We repeat the process until convergence; i.e., until the changes in the log-likelihood between iterations become sufficiently small.

The algorithm is implemented using the DynamicFactorMQ class from the statsmodels library in Python. After evaluating several model specifications, we identified the best-performing DFM configuration as one with two global factors modeled as a VAR process of order 4. Additionally, we specified three group-specific factors for economic activity, employment, and expectations indicators, each following a VAR process with 3 lags. The remaining four groups of variables were each modeled with a single factor following AR(1) processes.

B Dataset Description

Variable	Definition	Frequency	Aggregation
PBI_pesca	Fishery GDP	Monthly	-
PBI_mineria	Mining GDP	Monthly	-
elec	Total electricity generation	Monthly	-
elec_sm	Total electricity generation excluding demand from mining companies	Monthly	-
elec_resto	Electricity generation excluding demand from mining and manufacturing companies	Monthly	-
elec_manuf	Electricity demand from manufacturing companies	Monthly	-
cic	Domestic cement consumption	Monthly	-
unacem	UNACEM cement shipments	Monthly	-
afo	Public Construction	Monthly	-
anchoveta	Anchovy landings	Monthly	-
pet	Oil production	Daily	Sum
lgn	Liquefied natural gas production	Daily	Sum
gn	Natural gas production	Daily	Sum
colocac	Baby chicken placements	Monthly	-
ipc_tot	Consumer Price Index	Monthly	-
ipc_sae	CPI without Food and Energy	Monthly	-
ipm	Wholesale Price Index	Monthly	-
ipc_aa	Food CPI	Monthly	-
ipc_comb	Fuel CPI	Monthly	-
ipc_ele	Electricity CPI	Monthly	-
ipc_core	Core CPI	Monthly	-
precio_pollo	Wholesale chicken price	Monthly	-
arroz	Rice supply to wholesale markets	Monthly	-
papa	Potato supply to wholesale markets	Monthly	-
cebolla	Onion supply to wholesale markets	Monthly	-
igv_int_real	Real Domestic VAT	Monthly	-
ir	Real Income Tax	Monthly	-
fbk	Gross Capital Formation	Monthly	-
ingtrib	Real tax revenues	Monthly	-
ingnotrib	Real non-tax revenues	Monthly	-
volexp_trad	Traditional export volume	Monthly	-
volexp_notrad	Non-traditional export volume	Monthly	-
volimp_insum_plast	Import volume of plastic inputs	Monthly	-
volimp_insum_hierro	Import volume of iron	Monthly	-
volimp_insum_text	Import volume of textiles	Monthly	-
volimp_insum_papel	Import volume of paper	Monthly	-
volimp_insum_pquim	Import volume of chemical products	Monthly	-
volimp_insum_qorg	Import volume of organic chemicals	Monthly	-
volimp_bbk	Import volume of capital goods without construction materials	Monthly	-
volimp_cons	Import volume of durable consumer goods	Monthly	-
tdi	Terms of Trade	Monthly	-
desempleo	Unemployment Rate	Monthly	-
peao	Employed Economic Active Population	Monthly	-
expti_12m	BTS: Inflation expectations 12 months ahead	Monthly	-
exppbi_12m	BTS: GDP expectations 12 months ahead	Monthly	-
sitactneg_indice	BTS: Current business situation	Monthly	-
ventasn_indice	BTS: Sales index with respect to the previous month	Monthly	-
producn_indice	BTS: Production index with respect to the previous month	Monthly	-
nivdda_indice	BTS: Demand level with respect to expected	Monthly	-
ordcompran_indice	BTS: Purchase orders	Monthly	-
inv_nd	BTS: Unwanted inventories	Monthly	-
eco3prox_indice	BTS: Economy 3 months ahead	Monthly	-
ecoañoprox_indice	BTS: Economy 12 months ahead	Monthly	-
sec3prox_indice	BTS: Sector 3 months ahead	Monthly	-
secañoprox_indice	BTS: Sector 12 months months ahead	Monthly	-
emp3prox_indice	BTS: Company situation 3 months ahead	Monthly	-

empañoprox_indice	BTS: Company situation 12 months ahead	Monthly	-
dda3prox_indice	BTS: Demand 3 months ahead	Monthly	-
ddaañoprox_indice	BTS: Demand 12 months ahead	Monthly	-
cont3prox_indice	BTS: Hiring 3 months ahead	Monthly	-
contañoprox_indice	BTS: Hiring 12 months ahead	Monthly	-
invr3prox_indice	BTS: Investment 3 months ahead	Monthly	-
invrañoprox_indice	BTS: Investment 12 months ahead	Monthly	-
preinstresfor_indice	BTS: Price of inputs 3 months ahead	Monthly	-
prevtatresfor_indice	BTS: Sales price 3 months ahead	Monthly	-
indicca_p	COS: Consumer confidence - Present	Monthly	-
indicca_f	COS: Consumer confidence - Future	Monthly	-
credito_cons	Private sector credit balance - Consumption	Monthly	-
credito_hipo	Private sector credit balance - Mortgage	Monthly	-
credito_emp	Private sector credit balance - Companies	Monthly	-
circulante	Currency in circulation	Monthly	-
banc_actextlp	Long-Term Net External Assets of banking companies	Monthly	-
banc_liqmn	Liquidity in domestic currency of banking companies	Monthly	-
banc_obligvistamn	Demand deposits in domestic currency of banking companies	Monthly	-
banc_obligahorrmn	Savings deposits in domestic currency of banking companies	Monthly	-
banc_obligplazomn	Fixed-Term Liabilities in domestic currency of banking companies	Monthly	-
banc_liqme	Foreign currency liquidity of banking companies	Monthly	-
emisionprim	Monetary base - End of Period	Monthly	-
credito_mn	Credit in domestic currency (millions S/)	Monthly	-
credito_me	Credit in foreign currency (millions US$)	Monthly	-
banc_creditomn	Credit in domestic currency to the Private Sector of banking companies	Monthly	-
banc_cajamn	Cash in domestic currency of banking companies	Monthly	-
banc_cdbcrpmn	BCRP Certificates of deposit of banking companies	Monthly	-
banc_creditome	Credit in foreign currency to the Private Sector of banking companies	Monthly	-
banc_depbcrpme	Deposits in foreign currency in the BCRP of banking companies	Monthly	-
banc_pasextcp	Short-Term External Liabilities in foreign currency of banking companies	Monthly	-
banc_pasextlp	Long-Term External Liabilities in foreign currency of banking companies	Monthly	-
banc_obligme	Liabilities in foreign currency with the Private Sector of banking companies	Monthly	-
rin	Net International Reserves	Monthly	-
lbtr_mn_tot	Payments through LBTR in domestic currency	Monthly	-
lbtr_mn_cheq	Payments through LBTR in domestic currency with Checks	Monthly	-
lbtr_mn_transf	Payments through LBTR in domestic currency with Credit Transfers	Monthly	-
lbtr_me_tot	Payments through LBTR in foreign currency	Monthly	-
lbtr_me_cheq	Payments through LBTR in foreign currency with Checks	Monthly	-
lbtr_me_transf	Payments through LBTR in foreign currency with Credit Transfers	Monthly	-
tasa_pm	Monetary Policy Reference Rate	Monthly	-
tasa_over	National currency overnight deposit rate	Monthly	-
tasa_bonosper10mn	Peruvian 10-year Government Bond Yield in S/	Monthly	-
tasa_bonosper10me	Peruvian 10-year Government Bond Yield in US$	Monthly	-
tasa_encaje	Reserve ratio	Monthly	-
tasa_amn	Average lending interest rate in domestic currency	Monthly	-
tasa_pmn	Average borrowing interest rate in domestic currency	Monthly	-
tasa_interbanc	Interbank Average Interest Rate in domestic currency	Monthly	-
tasa_ame	Average lending interest rate in foreign currency	Monthly	-
tasa_ipme	Average borrowing interest rate in foreign currency	Monthly	-
tasa_hipomn	Mortgage Loan Interest Rate in domestic currency	Monthly	-
mcdocap_bonos	Bonds - Private sector	Monthly	-
mdocap_bonos_fin	Bonds - Financial Institutions	Monthly	-
mdocap_bonos_nofin	Bonds - Non-Financial Institutions	Monthly	-
mdocap_valpub	Public Sector Securities	Monthly	-
igbvl	General BVL Index	Monthly	-
isbvl	Selective BVL Index	Monthly	-
valorafp	Value of AFP Funds	Monthly	-

tc_us_interbvta	Interbank Exchange Rate	Monthly	-
tc_euro	Euro Exchange Rate	Monthly	-
tc_realbil	Bilateral Real Exchange Rate Index	Monthly	-
tc_realmult	Multilateral Real Exchange Rate Index	Monthly	-
embig_peru	EMBIG Peru	Monthly	-
gt_recesion	Google Trends: recession	Monthly	-
gt_kia	Google Trends: kia	Monthly	-
gt_toyota	Google Trends: toyota	Monthly	-
gt_cine	Google Trends: movies	Monthly	-
gt_restaurantes	Google Trends: restaurants	Monthly	-
gt_creditos	Google Trends: credits	Monthly	-
gt_prestamos	Google Trends: loans	Monthly	-
gt_casas	Google Trends: houses	Monthly	-
gt_departamentos	Google Trends: apartments	Monthly	-
gt_ofertas	Google Trends: offers	Monthly	-
gt_empleo	Google Trends: employment	Monthly	-
gt_trabajo	Google Trends: work	Monthly	-
gt_bloqueos	Google Trends: blockades	Monthly	-
gt_crisis_peru	Google Trends: peru crisis	Monthly	-
gt_quiebra	Google Trends: bankruptcy	Monthly	-
gt_economia	Google Trends: economy	Monthly	-
gt_crisis_economica	Google Trends: economic crisis	Monthly	-
gt_terrenos	Google Trends: land	Monthly	-
gt_inmuebles	Google Trends: real estate	Monthly	-
gt_elecciones	Google Trends: elections	Monthly	-
gt_viajes	Google Trends: travel	Monthly	-
gt_vuelos	Google Trends: flights	Monthly	-
gt_visa	Google Trends: visa	Monthly	-
gt_machu_picchu	Google Trends: machu picchu	Monthly	-
gt_hoteles	Google Trends: hotels	Monthly	-
gt_alojamientos	Google Trends: lodging	Monthly	-
gt_vacaciones	Google Trends: vacations	Monthly	-
gt_bonos	Google Trends: bonds	Monthly	-
gt_cts	Google Trends: cts	Monthly	-
gt_afp	Google Trends: afp	Monthly	-
gt_lluvias	Google Trends: rains	Monthly	-
gt_el_niño	Google Trends: el niño	Monthly	-
gt_sequias	Google Trends: droughts	Monthly	-
gt_heladas	Google Trends: frosts	Monthly	-
gt_huaicos	Google Trends: huaicos	Monthly	-
gt_inflacion	Google Trends: inflation	Monthly	-
gt_delivery	Google Trends: delivery	Monthly	-
gt_pollo_a_la_brasa	Google Trends: pollo a la brasa	Monthly	-
atsm	Sea surface temperature (dummy variable)	Monthly	-
pmi_usa	PMI USA	Monthly	-
pmi_china	PMI China	Monthly	-
sentimiento	Sentiment indicator	Daily	Average
vehiculos_livianos	Number of Light Vehicules sold	Monthly	-
vehiculos_pesados	Number of Heavy Vehicules sold	Monthly	-
vehiculos_menores	Number of Small Vehicules sold	Monthly	-
temp_media	Average national temperature	Daily	Average

C Primary Industry

Table 9: Nowcast of YoY Primary Industry

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	-6.6	4.7	0.4	0.1	0.2	-17.5	3.5	-0.6	-7.7	-12.3	-12.4	-13.6	5.9	-4.1	2.2
Feb-22	-7.1	-1.7	7.2	4.0	2.6	3.2	-2.9	0.5	1.5	1.0	-7.2	-0.5	10.9	1.5	-0.1
Mar-22	-14.9	5.4	10.5	2.7	13.8	-6.9	-0.2	-11.2	-7.4	-7.8	-6.5	-8.5	12.1	-0.3	-12.7
Apr-22	-9.7	0.0	-0.3	2.2	3.3	-7.8	9.4	-3.9	-5.0	-7.8	-5.1	-4.3	-0.3	-1.6	6.2
May-22	-11.4	-12.0	-8.5	-8.1	-15.1	-15.2	-17.1	-12.6	-13.5	-15.0	-16.5	-16.6	-13.1	-13.6	-25.6
Jun-22	5.2	-2.8	-4.2	-3.3	-7.2	3.6	-3.4	-2.0	1.3	2.8	-2.3	1.6	-2.6	-1.5	0.4
Jul-22	12.7	14.9	9.5	11.2	12.7	24.1	17.1	19.3	19.6	20.9	19.6	21.9	9.9	16.7	32.8
Aug-22	-2.1	10.6	14.7	10.1	10.1	0.3	-1.7	7.6	4.8	3.3	14.4	2.2	15.3	7.7	0.7
Sep-22	-1.1	3.6	5.3	4.7	-4.1	4.6	1.7	6.3	3.9	4.4	3.6	5.7	4.5	3.7	3.3
Oct-22	2.3	-0.8	-8.4	-2.1	0.7	4.6	7.6	-0.3	5.2	3.2	0.1	1.1	-1.7	0.8	17.1
Nov-22	-1.7	-4.9	-3.6	-4.9	-0.7	-16.6	-2.7	0.9	-9.3	-11.9	-5.6	-10.9	-4.0	-6.2	1.9
Dec-22	4.8	1.7	7.2	4.0	4.3	18.9	2.4	-0.3	1.1	2.9	6.2	10.4	6.9	5.5	-9.1
Jan-23	12.7	1.9	3.5	3.4	13.5	15.7	12.6	8.2	9.0	8.0	8.7	16.4	2.2	8.6	25.3
Feb-23	23.0	13.8	12.5	14.1	15.2	12.1	20.0	18.7	13.3	9.3	14.8	11.0	15.0	14.2	17.5
Mar-23	29.3	44.0	32.4	39.4	21.2	32.5	42.7	33.8	32.4	35.2	27.3	31.4	14.5	32.2	23.1
Apr-23	12.4	14.7	16.1	7.1	19.7	4.2	22.4	28.1	21.2	15.4	12.9	15.3	8.9	15.5	28.5
May-23	-28.1	-16.4	-14.3	-18.9	-14.3	-1.2	0.8	-4.4	-6.6	-7.4	-9.3	-13.9	-15.6	-10.1	-2.2
Jun-23	-29.9	-24.3	-19.6	-23.9	-19.6	-25.0	-23.4	-22.5	-25.6	-23.5	-23.4	-24.8	-17.8	-22.8	-41.1
Jul-23	-18.1	-21.2	-23.2	-22.0	-20.8	-12.1	-17.9	-22.1	-18.2	-16.9	-20.2	-12.0	-21.3	-19.0	-23.9
Aug-23	16.4	7.9	6.2	6.8	5.5	7.8	-18.0	-11.0	10.3	16.3	2.0	15.4	5.9	4.6	-21.6
Sep-23	8.9	8.6	6.4	10.0	3.7	10.3	9.4	9.6	7.8	4.5	8.7	5.0	6.3	7.5	18.6
Oct-23	9.6	18.2	11.8	18.4	12.7	11.9	4.4	7.8	14.9	7.7	11.3	11.8	13.5	12.0	4.0
Nov-23	10.9	-6.1	-3.3	-6.1	-7.3	6.0	-1.4	2.2	1.8	1.0	-0.9	6.4	-2.2	-0.8	6.8
Dec-23	-28.1	-12.3	-10.6	-11.7	-9.9	-23.6	-5.2	-5.4	-12.0	-23.6	-15.8	-17.8	-12.8	-13.4	-11.8
Jan-24	-16.0	-24.1	-25.4	-25.4	-25.0	-29.4	-28.9	-28.4	-24.6	-27.3	-25.1	-29.0	-24.5	-26.4	-30.0
Feb-24	-22.7	-11.9	-13.7	-14.7	-8.4	-20.5	-15.1	-10.8	-18.4	-15.9	-14.8	-17.0	-12.2	-14.4	-12.1
Mar-24	-13.6	-17.4	-9.8	-11.7	-17.8	-17.0	-23.1	-18.7	-16.0	-17.2	-14.1	-17.4	-16.7	-16.4	-17.6
Apr-24	30.7	26.6	18.0	20.4	23.2	41.8	-1.4	9.3	34.9	38.6	34.9	26.8	18.6	24.3	-6.0
May-24	68.5	65.0	59.9	66.1	66.1	69.1	85.0	77.0	65.9	69.3	67.7	62.6	57.8	67.6	75.9
Jun-24	12.0	37.1	38.5	40.0	41.7	33.2	58.9	50.0	25.4	32.3	22.2	29.2	37.1	37.1	47.4
Jul-24	12.6	5.9	6.6	5.8	8.5	-0.8	9.1	7.0	3.8	5.1	0.4	0.9	8.9	5.1	13.1
Aug-24	-1.0	-1.6	1.9	-2.7	2.0	-6.5	-7.2	-7.1	-3.5	-5.7	-0.9	-5.5	1.4	-2.9	-11.0
RMSE		9.903	11.010	9.974	11.244	9.688	15.597	12.590	7.592	7.938	7.871	7.461	11.317	8.799	15.526

D Agriculture

Table 10: Nowcast of YoY Agriculture

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	6.2	7.4	8.7	9.1	8.4	7.8	6.1	7.7	7.8	7.8	8.6	7.5	9.5	8.0	8.5
Feb-22	3.1	6.2	5.6	6.4	6.7	4.2	5.5	6.0	5.3	5.3	6.9	5.7	7.4	5.9	7.9
Mar-22	4.7	1.1	0.0	-0.1	2.2	5.4	4.5	3.5	3.6	3.3	4.2	3.8	1.1	2.7	7.4
Apr-22	7.5	1.5	1.7	2.1	1.5	3.5	4.0	3.1	3.8	2.2	2.7	2.5	1.8	2.5	6.8
May-22	8.2	4.8	4.9	4.8	4.4	4.5	5.3	5.2	5.1	7.0	4.7	4.9	4.8	5.0	5.0
Jun-22	-0.7	-2.1	-2.0	-1.5	-2.4	-0.9	-1.0	-1.3	-0.9	0.1	-1.9	-0.9	-1.1	-1.3	0.1
Jul-22	4.8	2.6	2.5	2.6	2.4	3.2	1.1	1.9	1.9	3.4	1.9	1.9	2.1	2.3	2.5
Aug-22	7.4	4.1	4.9	4.2	3.4	7.0	7.0	6.3	6.3	9.4	5.8	5.6	5.2	5.8	6.2
Sep-22	4.3	2.0	1.8	0.9	0.0	5.5	3.5	2.6	2.5	2.0	2.5	2.2	2.2	2.3	4.1
Oct-22	6.0	7.3	7.3	7.4	7.2	5.4	6.5	5.4	5.4	5.6	5.6	5.9	7.6	6.4	8.8
Nov-22	3.1	8.1	7.6	9.1	6.9	5.3	6.8	8.8	8.9	8.9	9.4	8.0	9.4	8.1	9.6
Dec-22	0.3	-0.2	0.6	-0.5	-0.4	4.2	1.8	1.8	1.9	0.3	1.6	1.9	0.1	1.1	1.0
Jan-23	3.5	1.9	2.0	2.3	0.8	1.4	0.7	1.9	1.7	3.0	2.0	1.9	2.3	1.8	2.1
Feb-23	0.3	3.1	3.6	4.5	3.0	5.6	5.1	4.6	4.7	5.2	4.3	5.0	3.8	4.4	4.9
Mar-23	0.4	2.2	1.2	1.0	1.8	0.4	1.1	1.8	1.3	1.9	2.3	1.1	1.3	1.5	1.0
Apr-23	-11.0	-0.1	-0.2	0.4	0.2	-0.7	0.6	-0.6	0.0	0.0	-0.4	-1.2	0.0	-0.2	-1.1
May-23	-4.3	-7.8	-9.2	-7.8	-9.3	-8.5	-7.3	-7.7	-8.2	-8.0	-8.0	-7.6	-9.2	-8.2	-15.0
Jun-23	-2.1	2.3	2.2	1.4	4.4	-1.6	-2.8	-2.1	-3.0	-3.4	-1.1	-1.7	2.0	-0.3	-2.7
Jul-23	-0.2	-2.3	-3.4	-3.0	-3.7	-1.0	-1.9	-2.5	-3.6	0.0	-2.1	-2.7	-1.8	-2.3	-2.2
Aug-23	-2.5	-3.2	-3.8	-3.6	-3.6	-1.0	-2.1	-2.3	-2.4	-5.2	-1.8	-1.1	-3.3	-2.8	-0.5
Sep-23	-7.5	-1.1	-1.4	-2.6	-1.0	0.3	-2.0	-1.6	-2.8	-0.3	-1.9	-1.4	-3.4	-1.6	-0.6
Oct-23	-5.3	-5.2	-7.0	-7.2	-5.1	-5.1	-6.3	-5.3	-4.8	-5.3	-5.5	-5.0	-6.5	-5.7	-3.2
Nov-23	3.2	-4.6	-4.4	-3.8	-4.0	-3.5	-1.5	-2.5	-3.0	-1.2	-1.6	-3.0	-4.4	-3.1	-2.0
Dec-23	0.7	5.7	4.5	5.1	3.7	3.4	4.3	4.5	3.5	4.0	3.7	3.6	5.1	4.2	1.5
Jan-24	-2.4	-0.1	0.5	1.1	0.0	-0.8	-1.0	-0.6	0.3	0.4	0.7	-1.7	0.8	0.0	0.5
Feb-24	-0.2	2.3	1.1	0.7	4.1	2.1	2.4	1.3	1.2	2.2	0.4	1.7	1.3	1.7	2.8
Mar-24	1.2	2.5	2.2	2.2	2.0	-2.4	1.3	1.3	0.5	4.8	1.9	1.5	2.7	1.7	0.7
Apr-24	24.0	12.8	13.0	13.1	13.3	13.4	13.1	12.7	12.6	12.5	12.4	11.9	13.0	12.8	11.9
May-24	4.8	6.5	6.5	6.1	5.1	8.5	10.5	8.7	9.7	5.9	8.5	9.4	6.6	7.7	7.9
Jun-24	-0.8	2.1	2.3	3.0	3.4	5.6	2.9	3.4	3.1	2.0	3.6	2.6	3.0	3.1	3.5
Jul-24	-3.4	-2.7	-2.6	-2.4	0.3	-3.1	-2.6	-2.3	-1.3	-0.8	-3.2	0.0	-1.7	-1.9	-1.2
Aug-24	-1.8	0.1	1.3	0.2	1.6	-1.0	-0.8	1.0	-0.8	6.1	-0.7	-0.9	-0.1	0.5	-0.9
RMSE		4.255	4.227	4.263	4.469	4.026	3.852	3.921	3.968	4.234	3.982	3.974	4.257	3.961	4.414

E Retail Trade

Table 11: Nowcast of YoY Retail Trade

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	2.3	3.3	3.2	3.1	3.1	2.7	2.9	2.8	2.8	2.5	3.0	2.9	3.1	3.0	3.4
Feb-22	7.5	8.2	8.2	8.3	8.2	8.4	8.3	8.2	8.3	8.2	8.4	8.3	8.4	8.3	9.0
Mar-22	8.1	5.3	5.0	4.9	5.2	5.1	5.0	4.9	4.9	4.9	4.7	4.9	5.0	5.0	6.0
Apr-22	2.6	3.9	3.7	3.8	3.9	3.9	3.9	3.9	3.9	4.0	4.0	3.9	3.7	3.9	3.9
May-22	2.8	2.9	3.1	3.0	3.0	2.9	2.9	3.0	3.1	3.0	3.0	2.9	3.0	3.0	3.6
Jun-22	2.5	2.0	2.0	1.9	2.0	2.0	2.0	2.1	2.1	2.2	2.1	2.0	2.0	2.0	2.8
Jul-22	2.8	1.6	1.7	1.6	1.6	1.6	1.7	1.6	1.8	1.7	1.7	1.6	1.6	1.7	2.3
Aug-22	2.3	2.2	2.2	2.2	2.1	2.3	2.2	2.2	2.2	2.1	2.2	2.1	2.2	2.2	2.2
Sep-22	2.1	2.1	2.1	2.1	2.1	2.2	2.1	2.1	2.1	2.1	2.1	2.1	2.0	2.1	2.4
Oct-22	2.8	2.1	2.0	2.0	2.1	2.1	2.0	2.0	2.0	2.0	1.9	2.0	2.0	2.0	2.5
Nov-22	3.0	2.5	2.5	2.5	2.5	2.5	2.4	2.3	2.2	2.2	2.3	2.3	2.5	2.4	2.4
Dec-22	1.8	2.1	2.0	2.0	2.0	2.5	2.3	2.3	2.2	2.3	2.3	2.3	2.1	2.2	2.3
Jan-23	1.2	2.7	2.9	2.8	2.7	2.7	2.6	2.6	2.6	2.7	2.7	2.7	2.7	2.7	2.6
Feb-23	2.4	1.7	1.7	1.6	1.7	1.6	1.6	1.7	1.7	1.8	1.6	1.7	1.6	1.7	2.0
Mar-23	3.0	1.9	1.9	1.8	2.0	2.2	2.1	2.3	2.2	2.2	2.2	2.2	1.9	2.1	2.3
Apr-23	3.2	2.3	2.3	2.3	2.3	2.4	2.4	2.3	2.3	2.1	2.2	2.3	2.3	2.3	2.4
May-23	3.2	2.6	2.6	2.4	2.5	2.4	2.6	2.6	2.5	2.7	2.5	2.6	2.6	2.6	2.6
Jun-23	3.1	2.9	3.0	3.0	3.1	2.7	3.0	2.9	3.0	2.9	3.0	3.0	3.1	3.0	2.8
Jul-23	3.0	3.0	3.0	3.1	3.0	3.0	3.1	3.0	3.0	2.9	3.0	3.0	3.1	3.0	2.7
Aug-23	2.8	2.8	2.9	2.9	2.8	2.8	2.6	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.3
Sep-23	1.9	2.8	2.7	2.8	2.7	2.9	2.8	2.8	2.8	2.7	2.9	2.8	2.7	2.8	2.5
Oct-23	1.4	2.3	2.4	2.4	2.3	2.6	2.4	2.4	2.5	2.4	2.3	2.5	2.4	2.4	2.2
Nov-23	1.3	2.1	2.0	2.0	2.1	1.8	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.3
Dec-23	2.0	1.2	1.3	1.3	1.4	1.1	1.3	1.3	1.3	1.3	1.4	1.3	1.3	1.3	1.7
Jan-24	2.4	2.0	2.0	2.0	2.0	2.2	1.8	1.9	1.9	1.9	1.9	1.9	2.0	1.9	2.2
Feb-24	3.0	2.3	2.4	2.3	2.3	2.1	2.3	2.4	2.4	2.4	2.4	2.4	2.3	2.3	2.6
Mar-24	1.8	1.7	1.9	1.8	1.8	1.9	2.0	1.9	1.9	1.9	1.8	1.9	1.9	1.9	2.0
Apr-24	3.1	3.7	3.7	3.7	3.6	4.0	3.8	3.7	3.6	3.7	3.6	3.7	3.7	3.7	3.7
May-24	2.1	2.4	2.3	2.3	2.4	2.1	2.3	2.2	2.2	2.3	2.3	2.1	2.4	2.3	2.5
Jun-24	2.3	2.0	2.0	2.0	2.0	2.1	2.0	2.0	1.9	1.9	2.0	2.0	1.9	2.0	2.2
Jul-24	3.4	2.1	2.1	2.1	2.1	2.2	2.2	2.2	2.2	2.1	2.2	2.1	2.1	2.2	2.5
Aug-24	2.9	3.0	2.9	2.9	2.9	2.8	2.8	2.8	2.9	2.9	2.8	2.8	2.9	2.9	2.6
RMSE		0.871	0.883	0.913	0.866	0.890	0.881	0.884	0.879	0.898	0.924	0.896	0.892	0.885	0.768

F Services

Table 12: Nowcast of YoY Services

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	4.0	4.6	4.5	4.5	4.5	4.4	4.7	4.6	4.5	4.3	4.6	4.5	4.5	4.5	4.2
Feb-22	7.0	8.3	8.3	8.3	8.2	8.3	8.2	8.2	8.2	8.2	8.3	8.1	8.4	8.2	8.6
Mar-22	4.5	5.6	5.6	5.7	5.5	5.3	5.2	5.2	5.2	5.2	5.2	5.2	5.5	5.4	5.9
Apr-22	5.2	4.1	4.0	4.1	4.1	4.3	4.0	4.0	4.1	4.0	4.2	4.1	4.1	4.1	4.8
May-22	4.6	4.7	4.6	4.6	4.6	4.4	4.5	4.6	4.7	4.8	4.7	4.6	4.6	4.6	4.5
Jun-22	3.6	3.6	3.7	3.7	3.9	3.7	3.9	3.9	3.8	3.8	4.0	4.1	3.7	3.8	3.9
Jul-22	2.4	3.3	3.3	3.2	3.2	3.2	3.1	3.0	3.1	3.1	3.1	3.0	3.2	3.2	2.8
Aug-22	2.9	2.3	2.3	2.3	2.4	2.7	2.5	2.6	2.6	2.7	2.5	2.5	2.3	2.5	2.6
Sep-22	3.0	2.3	2.4	2.4	2.3	2.1	2.4	2.3	2.3	2.4	2.6	2.2	2.4	2.3	2.3
Oct-22	2.1	3.0	2.9	2.9	2.9	2.7	2.9	2.8	2.8	2.7	2.9	2.7	2.9	2.8	2.6
Nov-22	1.7	2.5	2.4	2.5	2.5	2.4	2.3	2.4	2.4	2.6	2.3	2.4	2.4	2.4	2.0
Dec-22	-0.1	1.5	1.5	1.5	1.4	1.6	1.5	1.5	1.4	1.3	1.6	1.4	1.6	1.5	1.6
Jan-23	-1.2	1.0	1.1	1.1	1.0	1.5	1.2	1.2	1.2	1.3	1.4	0.8	1.1	1.2	0.1
Feb-23	-0.3	-0.7	-0.8	-0.8	-0.9	-0.8	-0.8	-0.7	-0.7	-1.0	-0.9	-0.9	-0.7	-0.8	-1.0
Mar-23	-0.6	-0.4	-0.5	-0.4	-0.2	-0.4	-0.2	-0.2	-0.3	-0.2	-0.2	-0.1	-0.6	-0.3	-0.5
Apr-23	-0.5	-1.3	-1.1	-1.2	-1.3	-0.8	-1.2	-1.0	-1.1	-1.1	-1.3	-0.9	-1.1	-1.1	-1.1
May-23	0.2	0.1	0.1	0.2	0.0	0.0	0.2	0.1	0.1	0.0	0.1	0.2	0.1	0.1	0.0
Jun-23	0.3	0.0	-0.1	0.0	-0.1	0.4	0.1	0.0	0.0	0.0	-0.1	0.1	-0.1	0.0	0.0
Jul-23	-0.6	0.4	0.3	0.5	0.6	0.1	0.3	0.3	0.2	0.3	0.3	0.4	0.4	0.3	0.3
Aug-23	-0.8	-0.5	-0.5	-0.3	-0.6	-0.7	-0.2	-0.4	-0.5	-0.5	-0.5	-0.6	-0.5	-0.5	-0.4
Sep-23	-0.7	-1.1	-1.1	-0.9	-1.0	-0.7	-0.9	-0.8	-0.8	-0.6	-0.9	-0.7	-1.0	-0.9	-0.6
Oct-23	-0.3	0.1	0.2	0.0	0.1	-0.2	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.1	0.4
Nov-23	-1.2	-0.4	-0.3	-0.3	-0.5	-0.6	-0.1	-0.3	-0.3	-0.4	-0.4	-0.3	-0.4	-0.4	0.4
Dec-23	0.8	-1.1	-1.0	-1.1	-1.1	-0.9	-1.0	-1.0	-1.0	-1.0	-0.8	-0.9	-1.1	-1.0	0.2
Jan-24	1.5	1.7	1.6	1.7	1.7	1.9	1.5	1.6	1.5	1.6	1.9	1.6	1.7	1.7	1.1
Feb-24	1.9	1.6	1.6	1.6	1.5	1.4	1.8	1.5	1.6	1.5	1.6	1.5	1.6	1.6	2.0
Mar-24	1.3	0.5	0.6	0.6	0.6	0.3	0.5	0.5	0.5	0.5	0.4	0.5	0.5	0.5	0.5
Apr-24	3.5	3.4	3.2	3.3	3.4	3.2	3.3	3.3	3.3	3.2	3.2	3.5	3.3	3.3	3.5
May-24	2.5	2.0	2.0	2.1	2.4	2.3	2.3	2.2	2.1	2.1	2.1	2.3	2.1	2.1	3.1
Jun-24	2.2	2.5	2.4	2.4	2.3	2.1	2.2	2.0	2.1	2.0	2.2	2.0	2.3	2.2	2.3
Jul-24	4.5	3.3	3.2	3.3	3.6	3.3	3.3	3.4	3.4	3.4	3.3	3.5	3.6	3.4	3.2
Aug-24	3.6	3.2	3.2	3.2	3.2	3.1	3.3	3.3	3.4	3.2	3.2	3.3	3.3	3.2	2.7
RMSE		0.868	0.863	0.872	0.842	0.861	0.855	0.841	0.816	0.838	0.864	0.778	0.855	0.839	0.784

G Non-Primary Industry

Table 13: Nowcast of YoY Non-Primary Industry

	GDP	Lasso	Ridge	Elastic Net	SVR	DT	KNN	RF	AdaBoost	GBoost	XGBoost	Bagging	MLP	Mean ML	DFM
Jan-22	0.1	5.5	5.2	5.6	5.5	5.1	5.9	5.6	5.0	6.1	4.6	6.0	5.7	5.486	5.8
Feb-22	5.8	1.9	0.8	1.8	2.4	-1.8	1.4	1.1	0.7	0.5	1.4	0.4	0.9	0.9	3.6
Mar-22	10.4	3.9	6.1	6.6	5.8	4.9	4.8	5.5	5.4	5.6	5.9	5.6	6.6	5.6	5.2
Apr-22	7.7	9.5	7.2	8.2	8.2	6.6	7.6	9.0	8.0	9.0	9.3	9.7	7.9	8.3	7.7
May-22	8.9	9.9	9.5	9.2	8.5	8.2	8.9	9.1	10.1	10.1	9.6	8.6	9.5	9.3	7.9
Jun-22	5.2	4.6	5.2	5.5	5.2	7.5	5.3	6.4	5.5	6.7	6.4	6.1	6.2	5.9	5.5
Jul-22	-1.1	4.4	4.5	4.3	4.5	6.8	4.3	4.8	4.7	4.8	4.1	4.4	4.5	4.7	3.8
Aug-22	1.5	0.5	0.9	0.9	0.9	1.6	0.5	1.1	0.7	-0.5	2.3	2.2	0.5	1.0	1.9
Sep-22	1.0	-1.1	-0.7	-1.2	-0.8	-2.3	-1.4	-1.2	-1.7	-1.4	-1.2	-2.0	-0.9	-1.3	-1.4
Oct-22	-0.9	3.1	3.2	2.7	2.8	2.8	3.5	2.7	2.3	1.1	1.4	2.7	2.7	2.6	2.7
Nov-22	-1.6	-1.6	-1.7	-1.7	-2.8	-0.9	-2.4	-0.9	-1.9	-1.7	-1.6	-1.0	-1.7	-1.7	-0.8
Dec-22	-8.4	-4.6	-4.3	-4.7	-3.5	-4.6	-2.6	-3.8	-3.5	-3.4	-3.5	-4.6	-3.3	-3.9	-5.2
Jan-23	-4.2	-2.6	-2.6	-2.3	-2.3	-4.2	-2.7	-2.9	-2.1	-3.5	-2.8	-3.2	-2.9	-2.8	-2.9
Feb-23	-8.8	-8.0	-8.6	-8.5	-8.0	-7.7	-8.3	-8.3	-8.5	-8.4	-8.6	-9.1	-7.9	-8.3	-9.4
Mar-23	-7.2	-11.3	-10.8	-11.2	-11.9	-10.1	-10.1	-10.3	-10.6	-10.2	-10.8	-9.8	-11.0	-10.7	-11.5
Apr-23	-8.3	-10.0	-9.6	-9.9	-10.1	-9.4	-8.8	-9.0	-9.6	-10.8	-9.2	-9.0	-10.5	-9.7	-9.7
May-23	-10.2	-7.7	-7.6	-7.9	-8.3	-7.4	-7.4	-6.7	-6.8	-8.1	-7.4	-6.8	-7.9	-7.5	-6.0
Jun-23	-7.9	-11.1	-10.6	-10.7	-10.6	-12.1	-10.4	-10.9	-11.0	-11.7	-11.1	-10.9	-10.4	-11.0	-9.9
Jul-23	-11.1	-3.8	-5.3	-5.4	-2.3	-5.6	-4.7	-4.3	-3.8	-5.2	-3.9	-3.2	-5.4	-4.4	-4.7
Aug-23	-8.6	-11.6	-11.4	-10.9	-11.8	-9.3	-9.9	-10.4	-10.8	-10.7	-10.8	-9.1	-11.3	-10.7	-9.6
Sep-23	-12.9	-13.5	-13.5	-13.9	-13.2	-13.2	-12.3	-12.2	-12.2	-13.1	-11.6	-11.4	-14.1	-12.9	-10.9
Oct-23	-7.6	-8.5	-7.2	-7.9	-8.7	-8.8	-7.9	-8.8	-9.4	-9.9	-8.1	-9.3	-8.0	-8.5	-8.1
Nov-23	-4.4	-8.1	-8.2	-8.8	-8.8	-10.1	-9.7	-8.8	-8.3	-8.9	-8.8	-8.9	-8.8	-8.8	-8.6
Dec-23	-3.7	-4.3	-4.1	-3.7	-3.0	-5.1	-2.5	-3.0	-2.7	-2.9	-2.9	-2.9	-4.2	-3.4	-4.5
Jan-24	0.5	-1.0	-0.6	-0.1	0.1	0.1	0.0	-1.1	-1.0	0.6	-0.4	-1.5	-0.5	-0.5	-0.8
Feb-24	3.1	1.9	1.2	1.9	1.8	1.4	1.9	1.8	1.1	2.1	1.9	1.4	1.9	1.7	1.7
Mar-24	-9.1	-7.9	-7.8	-7.8	-7.6	-6.8	-7.2	-7.0	-7.1	-6.7	-6.6	-6.9	-7.5	-7.2	-7.2
Apr-24	5.5	6.1	5.2	6.0	5.7	4.0	2.7	3.6	4.7	5.1	4.0	4.1	5.1	4.7	3.5
May-24	0.8	1.3	1.9	1.5	2.5	2.3	1.1	2.3	1.3	2.3	1.1	1.8	1.8	1.8	2.5
Jun-24	-4.1	-3.4	-3.6	-3.3	-3.7	-2.7	-3.3	-3.5	-4.0	-3.6	-3.2	-3.6	-3.5	-3.5	-3.6
Jul-24	10.3	6.3	6.5	6.7	6.5	7.2	6.6	5.9	6.6	5.2	7.4	6.6	7.2	6.6	6.8
Aug-24	4.2	2.5	2.2	2.4	2.1	5.2	3.9	3.6	3.5	3.5	3.1	3.3	2.3	3.1	3.8
RMSE		3.058	2.804	2.730	3.128	3.307	3.057	3.028	3.032	3.076	2.853	3.092	2.847	2.930	2.822

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