Nowcasting Peruvian GDP with Machine Learning Methods

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Motivation

- Nowcasting involves estimating the current economic state in real-time, which is crucial for decision-making and policy formulation.
- The increasing relevance of machine learning (ML) in macroeconomic prediction has shown potential in capturing non-linear relationships that traditional models may miss.
- Previous studies have focused on developed economies, with limited research on using machine learning to nowcast GDP in developing countries like Peru.

Literature Review

- Studies like Soybilgen and Yazgan (2021) and Hopp (2024) have applied ML models, such as decision trees, LSTMs, and XGBoost, for nowcasting in the U.S.
- Kant et al. (2022) applied various ML techniques for nowcasting the Dutch economy, demonstrating the versatility of these methods.
- ML techniques have also been employed in emerging economies, such as Indonesia, Brazil, and Sub-Saharan Africa.

- For Peru, Tenorio and Perez (2023) applied ML techniques to nowcast monthly GDP, using both structured and unstructured data.
- This growing body of literature emphasizes the relevance of machine learning models for improving GDP nowcasting accuracy across different economic contexts.

What We Do...

- This research aims to apply ML methods to nowcast the year-over-year growth rate of Peruvian total and non-primary GDP, comparing various models' performance.

- We explore the usefulness of i) applying rotations to original feature matrix, ii) applying dimensionality reduction techniques and iii) using a bottom-up approach for nowcasting our objective variables.

What We Found...

- LARs was the preferred dimensionality reduction technique for virtually all models and target variables.
- Adding rotations such as moving averages and variables in levels can improve models' performance.
- A bottom-up approach delivers more precise nowcasts' than the usual direct approach, with gains up to 45 and 22 percent for each target variable, respectively.

What We Found...

- ML models consistently delivered strong predictions, with RMSE values around 0.6 for total GDP and around 0.7 for non-primary GDP.

- ML models performed better than the benchmark-DFM for total GDP, and delivered a similar average error than this benchmark for non-primary GDP.

ML Models

- We employ a battery of 12 ML models for nowcasting Peruvian GDP:

Machine Learning Models

Shrinkage	Non-Linear	Ensemble
LASSO	Decision Tree	Random Forest
Ridge	Support Vector Machine	GBoost
Elastic Net	K-Nearest Neighbors	XGBoost
	MLP	AdaBoost
		Bagging

- We use a Dynamic Factor Model (DFM) as a benchmark.

Data

- **Variables**: Around 170 predictors sampled mostly at monthly frequency, including:
  - Structured data: Macroeconomic indicators (e.g., economic activity, prices, trade, survey data, financial and climate variables)
  - Unstructured data: Google Trends search terms
- **Time span**: Data covers the period from April 2015 to August 2024. The intial out-of-sample (OOS) exercise includes information until February 2020 and corresponds to the nowcast of January 2022, and new observations are added in an expanding window fashion.

Preprocessing

1. If seasonality is present, we seasonally adjust variables using the RJDemetra package in RStudio.
2. Time series are individually evaluated and transformed: retained in level form, month over month percentage changes or first differences.
3. Include 8 lags for both GDP growth and predictors to capture temporal dependencies.

4. Adding feature matrix rotations, recommended in Coulombe et al. 2021, is treated as an hyperparameter to be optimized in each vintage. In particular, we consider three possible rotations:

    - MARX: Adding moving averages of original features.
    - X: Adding features in levels.
    - MAF: Adding factors that summarize the information contained in every tuple of feature,lags.

5. Apply Z-transformation to prevent predictors with larger magnitudes from dominating ML algorithms.

Cross Validation Strategy

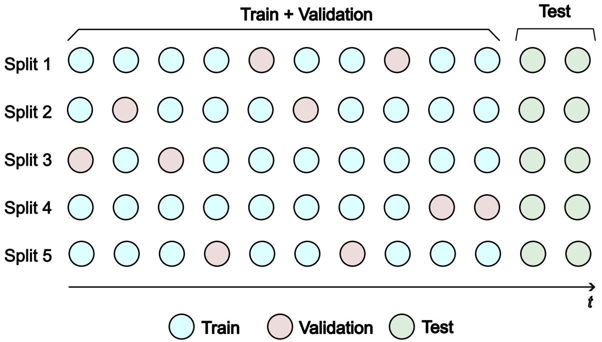
ML models rely on a set of hyperparameters, whose optimum values usually depend on the problem at hand.

- Suppose a hyperparameter space $\boldsymbol{\mathcal{X}} = \boldsymbol{\mathcal{X}}_1, \boldsymbol{\mathcal{X}}_2, \ldots, \boldsymbol{\mathcal{X}}_d \in \mathbb{R}^d$ and $\mathbf{x} \in \boldsymbol{\mathcal{X}}$ a hyperparameter configuration.
- An objective function $y = f(\mathbf{x})$

The goal is to find a hyperparameter configuration $\mathbf{x}^*$ that minimizes the objective function (usually a measure of error in the validation set):

$$\mathbf{x}^* = \operatorname*{argmin}_{\mathbf{x} \in \boldsymbol{\mathcal{X}}} f(\mathbf{x})$$

Our objective function $f(\mathbf{x})$ is the RMSE in the validation set of a 5-Fold cross validation strategy, as in Goulet Coulombe et al. 2022.



Cross Validation Strategy

But finding $\mathbf{x}^*$ can be computationally expensive. If d is large, the unbounded search complexity scales to $\mathcal{O}(n^d)$, -where n is the average range size of each hyperparameter. The Tree-structured

Parzen Estimator (Bergstra et al. 2011) avoids this drawback by searching $\mathbf{x}^*$ in an "intelligent" way, unlike grid search.

Tree-structured Parzen estimator (TPE) is a Bayesian Optimization method that reduces the amount of evaluations needed to find the best set of hyperparameters, by proposing new promising candidates each time the objective function is evaluated.

1. Given a number of initial evaluations to the objective function (say N^{init}), we define $\mathcal{D} := \{(\mathbf{x}_n, y_n)\}_{n=1}^{N^{init}}$ as the pairs of hyperparameter configuration, objective function.
2. TPE splits $\mathcal{D}$ in a better and worse group of evaluations $\mathcal{D}^l, \mathcal{D}^g$, by ranking the objective function with a quantile $y^\gamma, \gamma \in [0, 1)$.
3. Probabilty density functions (PDFs) $p(\mathbf{x}|\mathcal{D}^l), p(\mathbf{x}|\mathcal{D}^g)$ are construded by using a prior distribution for the hypeparameters, $p_0(\mathbf{x})$, and kernel density estimators (Parzen estimators).

4. With the PDF from the best group of evaluations, it samples $\mathcal{S} := \{\mathbf{x}_s\}_{s=1}^{N_s} \in p(\mathbf{x}|\mathcal{D}^l)$.
5. Optimize a so-called *surrogate function*, to get an optimal candidate:

$$\mathbf{x}^*_{\mathbf{N+1}} = \underset{\mathbf{x} \in \mathcal{S}}{\operatorname{argmax}}\, r(\mathbf{x}|\mathcal{D})$$
$$r(\mathbf{x}|\mathcal{D}) = p(\mathbf{x}|\mathcal{D}^l)/p(\mathbf{x}|\mathcal{D}^g)$$

6. Evaluate the objective function with the optimal candidate: $y_{N+1} = f(\mathbf{x}^*_{N+1})$
7. Update the set of observations $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{x}_{N+1}, y_{N+1})\}$.
8. Go through 1-7 until maximum number of evaluations to the objective function $f(x)$ is reached.

Hyperparameter Search Space

Hyperparameter calibration

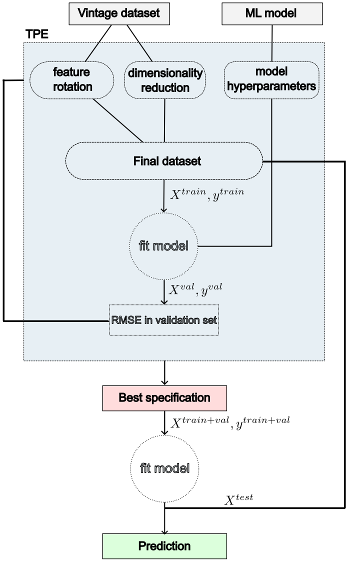
Model	Hyperparameter	Search space
Lasso	Alpha	Uniform$(10^{-3}, 3 * 10^{-1})$
Ridge	Alpha	Uniform$(10^{-1}, 10^{2})$
Elastic Net	Alpha	Uniform$(10^{-3}, 3 * 10^{-1})$
	Ratio L1	Uniform$(10^{-4}, 1)$
SVR	Gamma	Uniform$(10^{-7}, 0.5)$
	C	Uniform$(1,10^{5})$
Decision Tree	Max. Depth	DiscreteUniform(3,100)
	Min. samples for leaf	DiscreteUniform(4,10)
	Min. samples for split	DiscreteUniform(4,10)
	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)

Hyperparameter Search Space

Hyperparameter calibration

Model	Hyperparameter	Search space
XGBoost	Columns per tree	Uniform(10^{-2}, 0.99)
	Gamma	Uniform(10^{-2}, 0.99)
	Learning Rate	Uniform(10^{-4}, 1)
	Subsample	Uniform(0.5,0.99)
	Maximum Depth	Discrete uniform(3,100)
	N. Estimators	Discrete uniform(30,200)
Bagging	Nř 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)
	Beta 1	Uniform(10^{-2}, 1)
	Beta 2	Uniform(10^{-2}, 1)

Overview



Vintage dataset
ML model
TPE
feature rotation
dimensionality reduction
model hyperparameters
Final dataset
X^{train}, y^{train}
fit model
X^{val}, y^{val}
RMSE in validation set
Best specification
$X^{train+val}, y^{train+val}$
fit model
X^{test}
Prediction

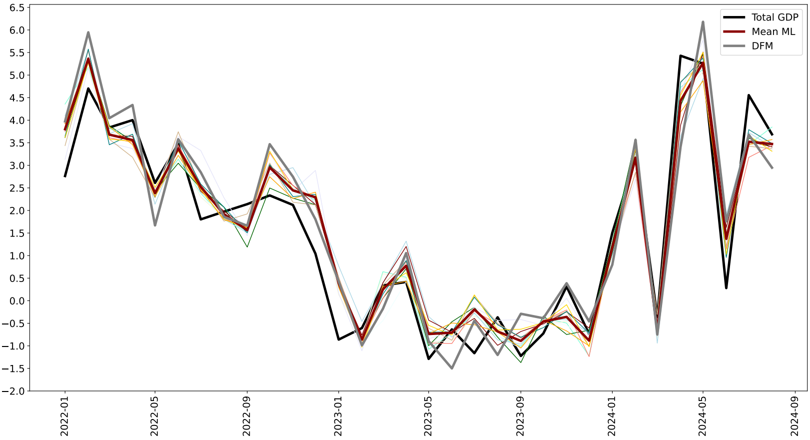
Model Evaluation

Model performance is assessed using Root Mean Squared Error (RMSE). For a given model m, the RMSE is computed by taking the square root of the mean of the squared differences between the actual values y_t and the predicted values $\hat{y}_t$. RMSE measures the average magnitude of projection errors, penalizing larger errors more heavily. The RMSE for each model is calculated as follows:

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

Results are benchmarked against the traditional Dynamic Factor Model (DFM).

GDP



Total GDP
Mean ML
DFM
6.5
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05
2024-09

GDP

Table 1: 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

Non-Primary GDP

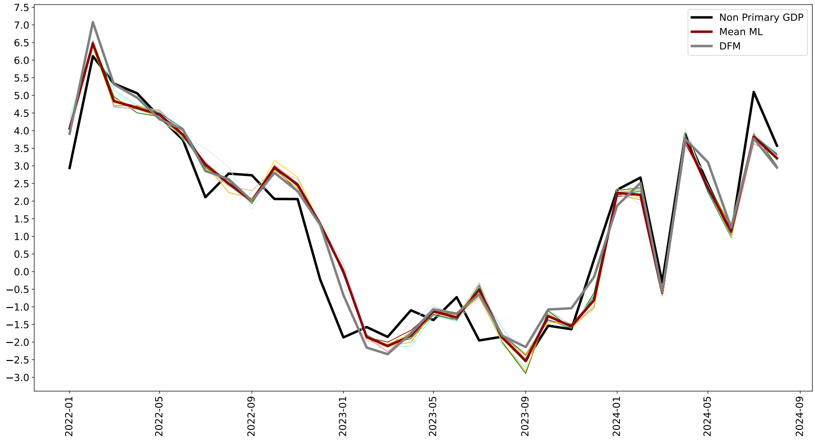


Table 2: Nowcast of YoY Non-Primary GDP (bottom-up)

	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

Regarding dimensionality reduction techniques, we observe that LARs was the preferred method among most of our out-of-sample exercises. On the other hand, adding rotations such as moving averages of features, latent factor that summarize the information from each feature and its lags, and features in levels can boost models' performance.

Table 3: Frequency of usage in Out-of-Sample exercises

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

* This table shows the frequency of use, in percentage points, of the contemplated methods for dimensionality reduction and feature matrix rotations. In total, we conduct 12(N. of models)*7(N. of objective variables)*32(N. of OOS exercises per objective variable) = 2688 OOS excercises.

Appendix: Dynamic Factor Model (DFM)

- The methodology follows Bańbura et al. 2013, Mariano and Murasawa 2010, and Fulton 2020.
- Used for dimensionality reduction, forecasting, and nowcasting.

$$
\begin{aligned}
z_t &= \Lambda f_t + \epsilon_t \\
f_t &= A_1 f_{t-1} + \ldots + A_p f_{t-p} + u_t
\end{aligned}
$$

- z_t: Observable stationary monthly series.
- f_t: Unobservable factors modeled as a VAR(p).
- Λ: Factor loadings matrix.
- ϵ_t: Idiosyncratic disturbances.
- $u_t \sim N(0, Q)$: Factor disturbances.

Table 4: 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

Appendix

Table 5: 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

Appendix

Table 6: 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

Appendix

Table 7: 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

Appendix

Table 8: 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