A comparison of mixed frequency approaches for nowcasting Mongolia’s GDP growth

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Introduction

Motivation

- **High volatility**: Since 2020, GDP growth volatility increased twice compared to the previous five years
- **Delay**: The official statistics were released with a substantial delay
- **Uneven growth**: Various shocks to different economic sectors

Objective

Timely and accurate analysis: Nowcasting GDP

- **Data coverage**: Sectoral monthly statistics; Internet-based daily information
- **Efficiency:** Mixed-Frequency estimation, Factor analysis, Machine Learning, Forecast combination
- **Automation**: Automatic data selection; Frequent model evaluation

Variable selection

Dataset:

- We have included a total of 110 indicators comprising main macro statistics, sectoral monthly series, and non-traditional daily information.

Variable selection process:

- Selecting optimal regressors in every forecasting round
  - Used AS-ARIMAX method (Xie, 2023) to find indicators with theoretically correct sign (coefficient) and statistically significant

Main publication lags

Indicators	Frequency	Publishing lag
Real Gross Domestic Product	Quarterly	45 days
Consumer price index	monthly	6 days
Industrial production	monthly	15 days
Money supply	monthly	20 days
Loan statistics	monthly	20 days
Interest rates	monthly	20 days
Exchange rates	monthly	20 days
Securities market statistics	monthly	20 days
Budget	monthly	15 days
Terms of trade	monthly	20 days
Balance of payment	monthly	7 days
Commodity export volume	monthly	7 days
China industrial production indices	monthly	7 days
Temperature	monthly	15 days
Food price index (world)	monthly	7 days
Rail transportation index	monthly	15 days
Agricultural statistics	monthly	15 days
Google trends	monthly	0 days

Nowcasting models

Models	Description
AR(p)	Used as a benchmark forecast model. The lag length (p) is specified according to the BIC.
BRIDGE	Linking high-frequency variables to low-frequency ones (GDP) using flow/stock aggregation
MIDAS / U-MIDAS	Converting high-frequency variables by split-sampling approach and Almon Distributed Lag
Factor U-MIDAS	Employing principal component analysis to extract factors from all indicators
MF – 3PRF	Generating targeted factors to forecast a specific variable of interest
LASSO / Ridge / Elastic Net	Penalized regression: functional to mitigate the problem of multicollinearity in linear regression, which commonly occurs in models with many parameters
Weighted average	$= w_{bridge} * BRIDGE + w_{midas} * MIDAS + \cdots + w_{Lasso} * Lasso$

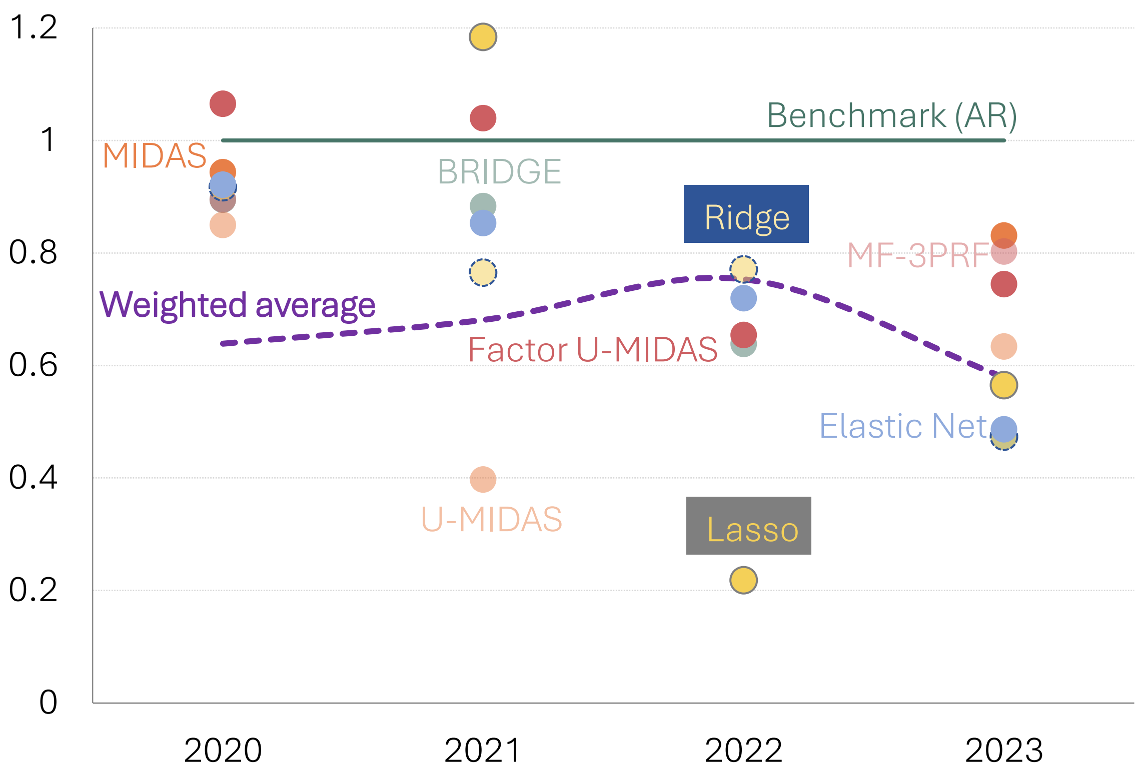
Nowcasting results for GDP: relative RMSE against AR benchmark

		BRIDGE	MIDAS	UMIDAS	Factor - UMIDAS	MF - 3PRF	LASSO	RIDGE	ENET	Weighted average
GDP by production	Agriculture	0.95	1.00*	0.95	0.98	1.21	0.95	0.97	0.96	**0.88**
	Total industry	1.12	1.69	1.00*	0.93*	1.10	1.12	1.10	1.12	**0.87**
	Services	1.04	1.10	1.28	1.08	1.21	0.92*	0.92*	0.92*	**0.82**
	Net Taxes on products	0.91*	1.12	0.91*	0.85*	0.97*	0.92	1.14	0.92*	**0.77**
GDP by expenditure	Household consumption	0.88*	1.08	1.08	0.98*	1.24	0.91*	**0.84**	0.90*	0.88
	Government cons.	0.91*	1.32	1.21	1.06	1.04	**0.86***	1.55	0.90*	0.96
	Gross capital formation	1.00*	0.92*	**0.79***	0.98*	0.94*	0.95*	1.06	1.00*	0.84
	Exports of G&S	0.97*	**0.86***	1.05	1.05	1.07	0.99*	0.97	0.98*	0.87
	Imports of G&S	1.13	1.43	1.40	1.22	1.61	1.13	1.11	1.13	**1.02**
Aggregation from production		0.95	1.29	0.98	0.93	1.11	0.93	0.96	0.92	**0.85**
Aggregation from expenditure		0.70	1.28	1.11	0.85	1.22	0.74	0.84	0.74	**0.67**
Direct approach		1.00	1.26	1.05	0.97	1.47	0.95	0.95	0.94	**0.89**

The numbers in bold show the best relative MSE performance for each horizon and each component. Asterisks indicate the individual models which appear to be statistically superior to the benchmark at a confidence level of 10% according to the modified Diebold–Mariano test. Weighted average and aggregation estimates are excluded from the testing procedures of the Diebold-Mariano test.

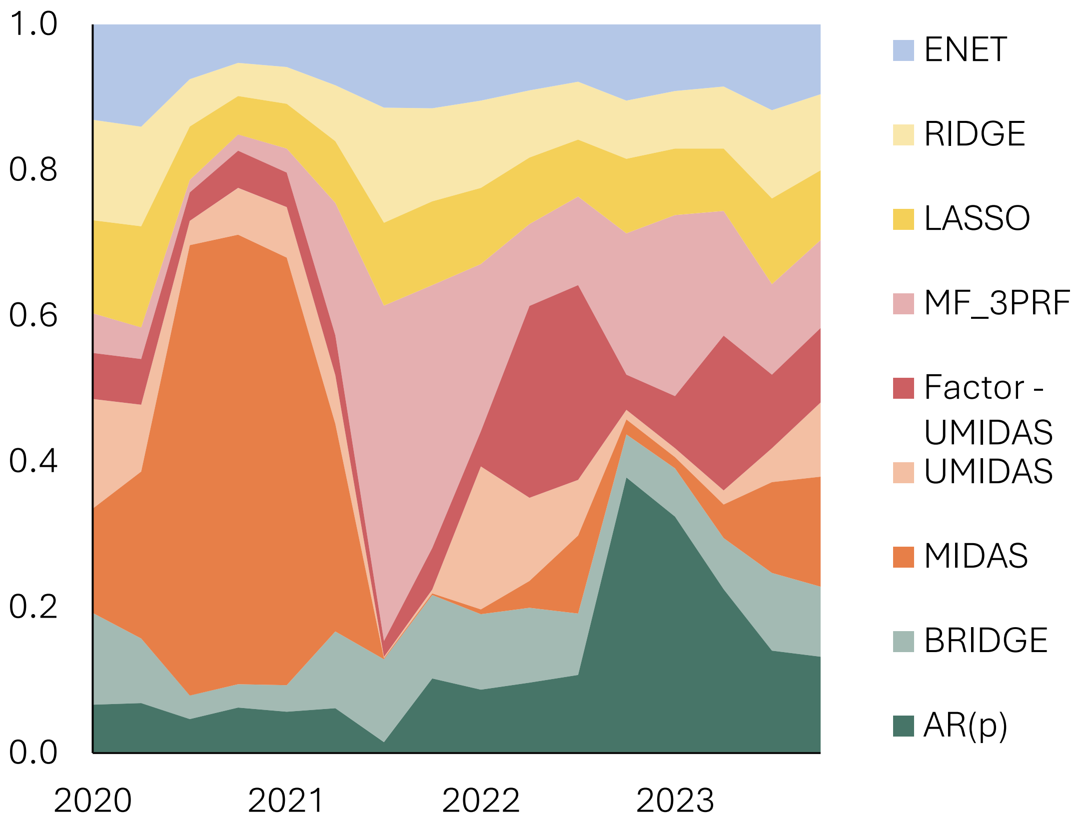
Forecast combination

Relative RMSE, by year



The relative RMSE results refer to nowcasts obtained by aggregating the results from the different components of GDP, disaggregated from the expenditure side.

Weight matrix



Example: The visual representation illustrates the fluctuations in the weights of individual models over time in the computation of the weighted average nowcast for service sector growth.

Summary

Major findings

- ✓ Mixed frequency models and Machine Learning techniques outperforms AR models in nowcasting Mongolian GDP during periods of crisis such as pandemic and geopolitical tension.
- ✓ The best-performing models and selected variables for nowcasting GDP components vary.
- ✓ Using an approach of aggregation has shown to be more impactful than a direct approach.
- ✓ Utilizing a weighted average estimate based on model performances leads to a 20-40% improvement in nowcasting economic growth between 2020 and 2023. The weighted average estimate performed consistently better than the benchmark, whereas individual models' performance regularly changes over time.
- ✓ Using the previous two quarters' forecasting performance as a weight for an individual model is the most effective method for nowcasting GDP components.

Challenges

- ✓ It is challenging to find the optimal (forecast) combination and to interpret the result.

Thank you for your time!

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