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A NOVEL HYBRID FORECASTING MODEL FOR GEORGIAN GDP

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INTRODUCTION

Following the collapse of the Soviet Union, Georgia faced significant economic challenges, including political instability and conflicts. This resulted in a severe economic recession in the 1990s, with GDP contracting sharply. In the early 2000s, Georgia began implementing economic reforms aimed at liberalizing the economy, improving governance, and attracting foreign investment. These reforms laid the foundation for future growth. During this period, Georgia experienced robust economic growth, with GDP expanding at relatively high rates (averaging 9.7% annual growth between 2003 and 2007), driven by reforms, foreign investment, and improvements in infrastructure and governance.

However, the global financial crisis of 2008-2009 significantly affected Georgia's economy, leading to a slowdown in growth (average growth dropped to -0.6%). However, the country quickly recovered, and GDP growth resumed, though at a more moderate pace (4.8% average yearly growth) compared to the mid-2000s. Throughout the 2010s, Georgia continued to implement reforms to enhance its business environment, attract foreign investment, and diversify its economy beyond traditional sectors like agriculture.

Georgia's GDP growth in the late 2010s and early 2020s was characterized by some fluctuations (averaging 4.9% during 2018-2021), influenced by both domestic and external factors. These included geopolitical tensions in the region, global economic conditions, and internal political developments. Despite these challenges, Georgia maintained positive GDP growth (9.8% and 8% annual growth in 2022 and 2023, respectively), although at varying rates, reflecting the resilience of its economy and ongoing efforts to diversify and modernize key sectors.

In an ever-evolving economic landscape, understanding and predicting Gross Domestic Product (GDP) fluctuations is crucial for policymakers, businesses, and investors. As we navigate through dynamic global markets, the need for accurate GDP forecasting models increases. In recent years, economic indicators have exhibited countless of trends, influenced by factors ranging from geopolitical shifts to technological advancements. These trends underscore the complexity of modern economies, where interconnections between various sectors and regions shape overall growth trajectories.

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In a world characterized by constant change, forecasting GDP efficiently enables stakeholders to anticipate economic conditions, thereby facilitating informed decision-making. For policymakers, accurate forecasts serve as invaluable tools for planning effective monetary and fiscal policies aimed at stabilizing economies, promoting growth, and mitigating risks. Similarly, businesses rely on GDP forecasts to measure consumer demand, plan investments, and navigate market volatility. Moreover, investors utilize these forecasts to assess potential returns and allocate resources strategically. This policy brief describes and analyzes the performance of a novel hybrid forecasting approach for Georgian GDP. This model aims to update and enhance the previous model used by the ISET (for details on the previous ISET model, see the Annex.).

THE FORECAST STRATEGY USED TO BUILD THE HYBRID ENSEMBLE MODEL

This section explains the hybrid ensemble forecasting methodology. The new model, in particular, employs and combines the distinct characteristics and features of five common time series forecasting approaches, averaging the output of each to obtain the final forecast. The chosen forecasting single techniques are as follows:

- The Seasonal Autoregressive Integrated Moving-Average with Exogenous Regressors (SARIMAX);
- The exponential smoothing model (ETS);
- The neural network autoregression model (NNAR);
- The Seasonal-Trend decomposition using LOESS (STLM);
- And the exponential smoothing state space model with Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS).

The SARIMAX model is one of the most often used linear methods for forecasting non-stationary time series. It predicts future values of a time series based on its own previous values, which are represented by lags and residuals. Specifically, lags and residuals refer to seasonal and non-seasonal autoregressive (AR) and moving-average (MA) processes, which are adjusted for seasonal and non-seasonal fluctuations to make the time series stationary. Finally, external data (exogenous variables) are employed to represent real-world events that can be related to Georgian GDP. SARIMAX's benefits and characteristics are listed below:

- This tool can detect both seasonal and nonseasonal patterns in time series data, as well as trends;
- It is capable of forecasting complicated data with cycles that are common in GDP time series;
- And finally, incorporating external inputs allows SARIMAX models to deliver more accurate and comprehensive forecasts (Hyndman and Athanasopoulos, 2021; Perone, 2022).

The ETS model utilized in this hybrid approach has four main equations: a single forecast equation and three smoothing equations. Specifically, the first smoothing equation represents the level, the second the trend, and the third the seasonal component. Thus, the forecast equation represents observed data, whereas the other three smoothing equations explain the behavior of unobserved states. The key benefits and features of the ETS strategy are:

- It considers trends in time series;
- It can model complex seasonality;
- It prioritizes current observations over historical ones when forecasting future values (Hyndman and Athanasopoulos, 2021)

NNAR is a machine learning model that may be represented as a network of neurons or nodes displaying complex nonlinear relationships and functional forms. As a result, it attempts to imitate the functioning of brain neurons. In this architecture, neurons are grouped into three layers: (i) the bottom layers identify the original time series (inputs), (ii) the top layers identify the predictions (outputs), and (iii) the intermediate levels identify the hidden neurons. The inputs contain the time series' lagged values. The primary benefits of NNAR are as follows:

- It can simulate complicated seasonality;
- It can detect asymmetry in cycles in time series, whereas SARIMAX cannot;
- And it is resilient to the existence of outliers in the time series (Hyndman and Athanasopoulos, 2021).

STLM employs an STL decomposition to describe seasonally adjusted data. It is especially effective for breaking down time series into three different components: the trend cycle, the seasonality component, and the residuals. It provides the following significant advantages:

- It is capable of handling any type of seasonality, including monthly and quarterly data;
- The seasonal component may alter over time;
- It is resilient against time series outliers, which do not affect the trend-cycle and seasonal component estimations (Hyndman and Athanasopoulos, 2021).

TBATS models are a type of model that combines many approaches: trigonometric terms for modeling seasonality, the Box-Cox transformation for addressing heterogeneity, ARMA errors for addressing short-term dynamics, damping (if any) trends, and seasonal components. Thus, the TBATS approach has the following major advantages:

- It handles effectively highly complex seasonal patterns, which may display daily, weekly, monthly, and yearly patterns simultaneously;
- It could tackle nonlinear patterns in time series.
- And it can handle any form of autocorrelation in the residuals Hyndman and Athanasopoulos, 2021).

The combination of several time series forecast methods with different properties is intended to maximize the chance of capturing seasonal, linear, and nonlinear patterns, and is particularly useful for predicting real-world problems and data with complex dynamics, such as GDP, while also achieving superior forecasting accuracy (Zhang, 2003; Panigrahi and Behera, 2017; Perone, 2021). The hybrid model with and without exogenous variables is provided here. The external regressors utilized in the model include a wide range of economic factors that might influence GDP, including trade statistics, money market data, inflation, commodity prices, and exchange rates.

PERFORMANCE EVALUATION OF THE HYBRID ENSEMBLE MODEL

The hybrid model given in this policy brief is created by integrating four previously mentioned models: SARIMAX, ETS, NNAR, and STLM.[1] To assess the hybrid model's performance, it is trained using historical Georgian GDP data (expressed in US dollars at constant prices). The data are first separated into two sets: training data (first 50 quarters of Georgian GDP from 2010-q1 to 2022-q2) and testing data (last four quarters of GDP from 2022-q3 to 2023-q2).

Table 1 includes a comprehensive set of metrics for assessing hybrid model accuracy with and without exogenous variables. The metrics used include mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), and root mean square error (RMSE). These metrics are commonly used to assess forecasting performance (Kırbaş, et al., 2020; Perone, 2021). The results show that the hybrid model with exogenous regressors significantly outperforms the model without exogenous variables, showing lower values in all accuracy metrics (Table 1). Notably, the MAPE, which evaluates how much predicted values depart from real data, is much less than 10%. This is significant because, according to Lewis's (1982) interpretation, models with MAPE less than 10% can be regarded as very accurate predictions. Notably, MAPE is close to zero in this instance, indicating that models almost produce error-free estimates. Specifically, MAPE is 1.67% for the model with exogenous regressors and 1.99% for the model without exogenous regressors, indicating that the models are consistent with the data. The model without regressors has a smaller MASE than the naïve technique, indicating superior forecast ability (Hyndman and Koehler, 2006). This justifies the employment of more complex models, such as hybrid ones (Perone, 2021).

This is also supported by a graphic depiction of the actual and fitted values of each component model on the Georgian GDP (original) dataset. Figure 1 shows that, for the hybrid model with exogenous variables, the fitted values for the individual models closely match the actual data.

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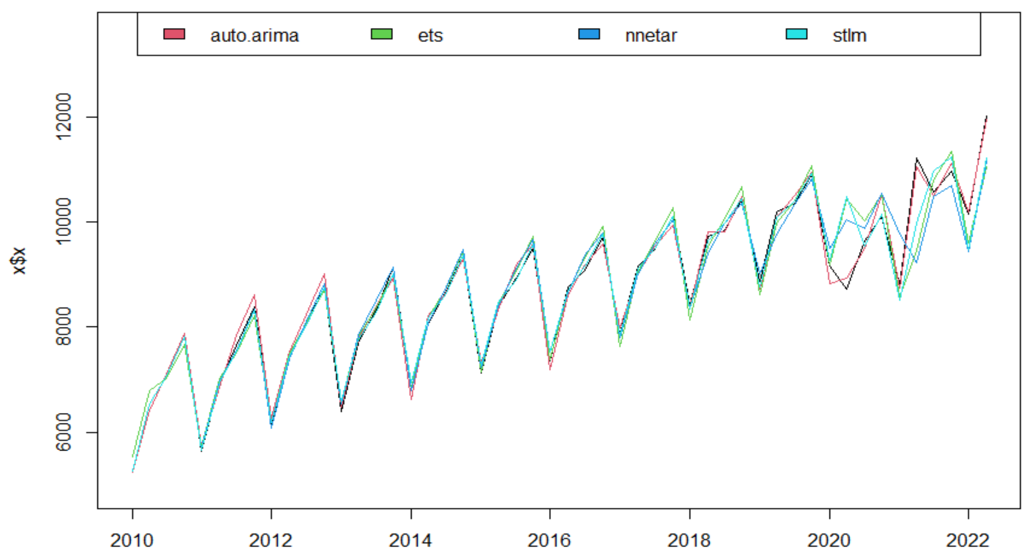
[1] Since the data utilized in this research are quarterly, TBATS is removed; nonetheless, it is more appropriate when monthly GDP Georgian data are used.

They closely follow the original time series from 2010 until the beginning of 2020. The only significant variation from the original statistics happened precisely in the second quarter of 2020 when the COVID-19 outbreak expanded rapidly over the world. As is well known, the following lockdown had a significant impact on economic activity, resulting in a severe and unprecedented recession. However, following this peculiar shock, the individual forecasting models become consistent and trustworthy, only deviating marginally from the original data. While Fig. 2 reveals that, for the hybrid model without exogenous variables, the fitted values for individual models diverge a bit more from the actual data after the second quarter of 2020.

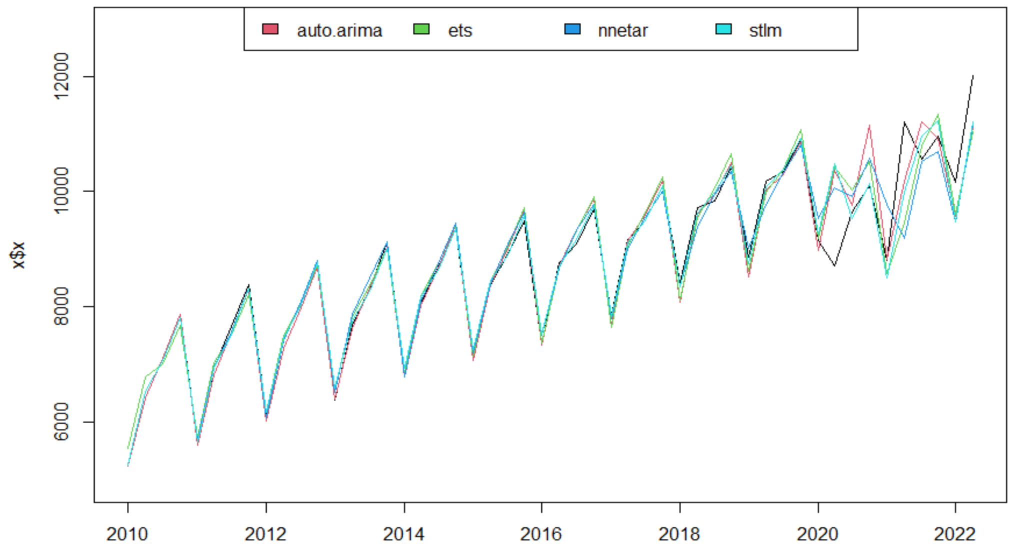
Finally, the Ljung-Box (1978) autocorrelation test accepts the null hypothesis that data are uncorrelated (i.e., independently distributed) at each lag (Table 2). As a result, the model is unaffected by autocorrelation issues.

Figure 1. Performance of each time series forecasting method used in the hybrid approach (with exogenous regressors)



Notes: the original data are represented by a black dashed line.
The model was built before Geostat updated the methodology of calculating GDP.

Figure 2. Performance of each time series forecasting method used in the hybrid approach (without exogenous regressors).



Notes: the original data are represented by a black dashed line.

Table 1. Results of accuracy tests for the hybrid model with and without external regressors.

Model	Exogenous	RMSE	MAE	MAPE	MASE	ACF1
AENS	Yes	308.89	158.67	1.68%	N/a	0.046
AENS	No	380.85	189.8	1.99%	0.37	0.062

Notes: A, Arima; E, Ets; N, Nnar; S, Stlm. ACF1, autocorrelation function at lag 1; MAE, mean absolute error; MAPE, mean absolute percentage error; MASE, mean absolute scaled error; RMSE, root mean square error. N/a, not available.

Table 2. Results of the Ljung-Box autocorrelation test.

AENS	Exogenous	Chi-square	p-value
Lag = 2	Yes	0.4228	0.5155
Lag = 3	Yes	1.7171	0.4238
Lag = 4	Yes	3.8224	0.2813
Lag = 2	No	0.4086	0.5227
Lag = 3	No	1.5206	0.4675
Lag = 4	No	3.841	0.2792

Notes: the null hypothesis is that the residuals are independently distributed at the chosen lag.

PREDICTIVE ABILITY OF THE HYBRID ENSEMBLE MODEL

This presentation concludes with an evaluation of the new model's predictability capabilities compared to the previous ISET approach. Tables 3 and 4 provide estimates from the third quarter of 2022 to the second quarter of 2023 based on hybrid models with and without exogenous regressors. The projections for each table are calculated as follows. First, three hybrid models are fitted using the MAE, MASE, and RMSE minimization. Second, the output from the latter is averaged to determine the final forecasts.

In the model with exogenous variables, the average forecasts depart from the real data by 0.24% in the third quarter of 2022, 1.22% in the fourth quarter of 2022, 2.22% in the first quarter of 2023, and 4.44% in the second quarter of 2023. In the absence of exogenous factors, the average forecasts differ from the real data by 0.78% in the third quarter of 2022, 0.84% in the fourth quarter of 2022, 0.86% in the first quarter of 2023, and 4.24% in the second quarter of 2023. Errors, as would be expected, tend to progressively increase over time.

Table 5 takes a conservative approach by averaging the forecasts from Tables 3 and 4. Table 5 demonstrates that the estimates are practically flawless for the first forecasted quarter (i.e., the third quarter of 2022), with a relative error of only 0.05%. Then, it rises to 0.99% in the third quarter of 2022 and 1.77% in the first quarter of 2023. In this regard, Figure 3 also depicts a graphical comparison of the original time series and predicted values for Georgian quarterly GDP using the new hybrid model. The predictions are quite consistent with real data for the first three quarters and only begin to diverge somewhat from the observed data in the second quarter of 2023.

Then, Table 6 compares the forecasts derived by the new hybrid model given in this policy brief with those obtained by the old model adopted by the ISET. The results reveal that the new model significantly outperforms the previous one. The GDP growth rates estimated using the new hybrid model deviate from the real data by just 0.06% in the third quarter of 2022, 1.09% in the fourth quarter of 2022, and 1.91% in the first quarter of 2023.[2] The projections from the previous ISET model, on the other hand, indicate considerably greater deviations from real data, with absolute percentage errors of 6.13% in the third quarter of 2022, 2.03% in the fourth quarter of 2022, and 5.32% in the first quarter of 2023. Specifically, the old model overestimated the official GDP growth rate by 6.13% in the third quarter of 2022, 2.03% in the fourth quarter of 2022, and underestimated it by 5.32% in the first quarter of 2023. The new hybrid model overestimated it by just 0.06%, 1.09%, and 1.91%, respectively. Furthermore, during the first three predicted quarters (2022-2q to 2023-1q), the average percentage error (in absolute terms) for the old ISET model is 4.87%, compared to only 1.02% for the new model. Thus, the previous model has an inaccuracy about five times bigger than the new model.

Finally, the outcome shows that the new hybrid ensemble model outperforms the old model used by the ISET in terms of predictive capacity, and it may be a trustworthy and accurate tool for forecasting Georgian GDP.

[2] It is obtained by subtracting the GDP growth rate estimated by the new hybrid models from the official GDP growth rate.

Table 3. Forecasts are calculated using the hybrid model with exogenous regressors.

AENS: Exogenous: Yes	Forecast 1 MASE	Forecast 2 MAE	Forecast 3 RMSE	Average Forecasts	Real data	Error (value)	Error in %
Q3 2022	11677	11677	11545	11633.03	11661.44	-28.41	-0.24%
Q4 2022	12269	12281	12076	12208.67	12061.81	+146.86	+1.22%
Q1 2023	11300	11250	11082	11210.67	10966.4	+244.27	+2.22%
Q2 2023	12559	12424	12169	12384	12958.98	-574.98	-4.44%

Notes: MAE, mean absolute error; MAPE, mean absolute percentage error; RMSE, root mean square error.

Table 4. Forecasts are calculated using the hybrid model without exogenous regressors.

AENS: Exogeno us: No	Forecast 1 MASE	Forecast 2 MAE	Forecast 3 RMSE	Average Forecasts	Real data	Error (value)	Error in %
Q3 2022	11771	11728	11759	11752.67	11661.44	+91.23	+0.78%
Q4 2022	12178	12127	12185	12163.33	12061.81	+101.52	+0.84%
Q1 2023	10889	10829	10887	10871.67	10966.4	-94.73	-0.86%
Q2 2023	12461	12542	12225	12409	12958.98	-549.98	-4.24%

Notes: MAE, mean absolute error; MAPE, mean absolute percentage error; RMSE, root mean square error.

Table 5. Forecasts are calculated by averaging the output given in Tables 3 and 4.

AENS: Average values	Forecast 1 MASE	Forecast 2 MAE	Forecast 3 RMSE	Average Forecasts	Real data	Error (value)	Error in %
Q3 2022	11724	11702.5	11652.05	11667.77	11661.44	+6.33	+0.05
Q4 2022	12223.5	12204	12130.5	12181.53	12061.81	+119.72	+0.99%
Q1 2023	11099.5	11039.5	10984.5	11160.29	10966.4	+193.89	+1.77%
Q2 2023	12510	12483	12197	12396.67	12958.98	-562.31	-4.34%

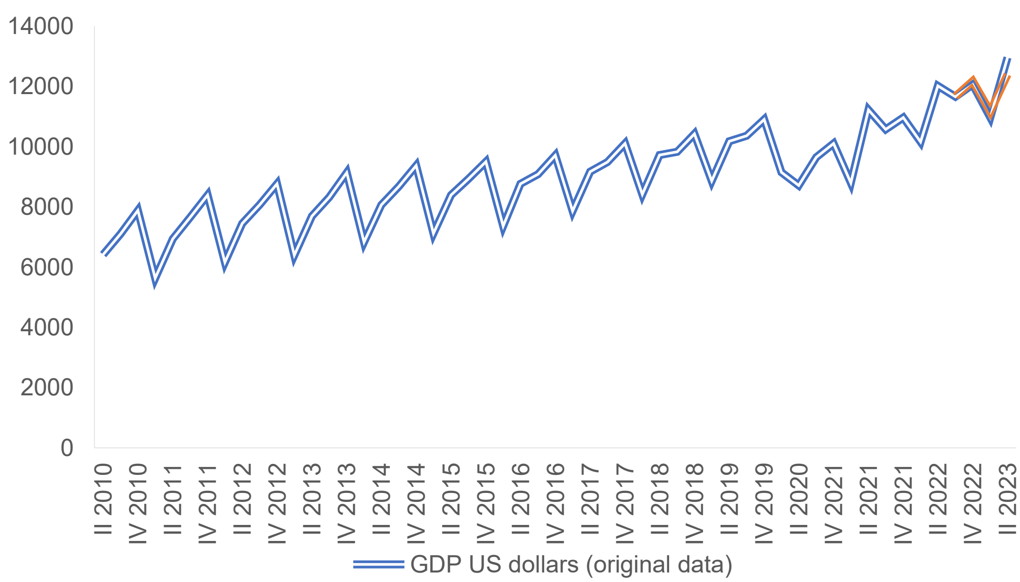
Notes: MAE, mean absolute error; MASE, mean absolute scaled error; RMSE, root mean square error.

Table 6. Comparison of performance comparison between the new hybrid model and the previous model used by the ISET.

AENS: GDP growth rate (%)	Forecast New model	Forecast Old model	Real data	Absolute % error New model	Absolute % error Old model
Q3 2022	10.38%	16.45%	10.32%	+0.06%	+6.13%
Q4 2022	11.06%	12%	9.97%	+1.09%	+2.03%
Q1 2023	9.88%	2.65%	7.97%	+1.91%	-5.32%
Q2 2023	3.13%	1.8%	7.8%	-4.67%	-6%

Notes: the GDP growth rate is expressed as a percentage change from the same quarter of the previous year.

Figure 3. Comparison of the original time series and forecast values for Georgian quarterly GDP using the novel hybrid model.



CONCLUSION

This policy brief proposes a novel hybrid forecasting model for Georgian GDP that significantly improves upon the previous model used by the ISET. The new model integrates four individual models (SARIMAX, ETS, NNAR, and STLM) and leverages exogenous variables to achieve highly accurate predictions.

Here are the key findings:

- The hybrid model with exogenous variables exhibits superior performance, with MAPE values close to zero, indicating minimal error.
- Both models effectively capture the underlying trends in Georgian GDP data, even after the economic shock caused by the COVID-19 pandemic.
- The new model demonstrates exceptional accuracy in out-of-sample forecasting, with average errors below 0.5% for the first three quarters.
- Compared to the previous ISET model, the new hybrid model reduces the average prediction error by roughly five times.

Overall, this policy brief strongly recommends adopting the new hybrid model as a reliable and accurate tool for forecasting Georgian GDP.

REFERENCES

Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: principles and practice, 3rd edition. OTexts. https://otexts.com/fpp3/.

Kırbaş, İ., Sözen, A., Tuncer, A. D., & Kazancıoğlu, F. Ş. (2020). Comparative analysis and forecasting of COVID-19 cases in various European countries with ARIMA, NARNN and LSTM approaches. Chaos, Solitons & Fractals, 138, 110015.

Hyndman, R.J., & Koehler, A.B. (2006). Another look at measures of forecast accuracy. International Journal of Forecasting 22(4), 679–688.

Lewis, C.D. (1982). Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting. Butterworth Scientific: Boston, London.

Ljung, G. M. and G. E. P. Box (1978). On a measure of lack of fit in time series models, Biometrika 65, 297–303.

Panigrahi, S., & Behera, H. S. (2017). A hybrid ETS–ANN model for time series forecasting. Engineering applications of artificial intelligence, 66, 49-59.

Perone, G. (2021). Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy. The European Journal of Health Economics, 1-24.

Perone, G. (2022). Using the SARIMA model to forecast the fourth global wave of cumulative deaths from COVID-19: Evidence from 12 hard-hit big countries. Econometrics, 10(2), 18.

Zhang, G.P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing 50, 159–175.

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ANNEX – ISET'S PREVIOUS MODEL OF GDP FORECAST

The ISET's previous model for GDP forecasting relied on a massive dataset of economic indicators (120 indicators), updated monthly by the Statistics Office of Georgia, the National Bank of Georgia, the Ministry of Finance, and various sources. The model includes variables related to domestic and foreign currency deposits, exchange rates, monetary aggregates, remittances, external trade, crude oil prices, consumer credit, consumer and producer prices, value-added tax turnover, metal and agricultural raw material prices, tourism data, etc.

The model itself is a complex one, designed to be highly adaptable and data-driven. By applying a statistical technique called **Principal Component Analysis (PCA)**, the model identified a small number of underlying factors that explained most of the movement across all the individual economic indicators. These factors, combined with past GDP data, were then used to predict future GDP growth for the next few quarters. The specification of the forecasting model is the following:

$GDP_{t+h} = \mu + \sum_{j=1}^{r} factor_{j,t} + \sum_{i=1}^{q} GDP_{t-i}$, where

q is the number of GDP lags (GDP lags with i=0 is available for 2-5 vintages (updates);

r is a number of factors.

The model functioned like a constant learning system. With each new month's data release, the model would be updated, potentially revising its previous forecasts to reflect the latest economic information. This resulted in a series of forecasts throughout the quarter, with the final revision offering the most accurate prediction based on all available data.

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