

## Nowcasting Türkiye's GDP with over 10 million Bridge-Equation Models

Sercan Pişkin

May 21, 2026

**Abstract:** Assessing the current state of economic activity in real time is a central challenge for policymakers and market participants, particularly in environments where official GDP statistics are released with considerable delay. The growing availability of high-frequency indicators has therefore increased the demand for empirical frameworks capable of synthesizing large and heterogeneous data flows into timely signals of aggregate activity. This study develops a nowcasting and backcasting system for Türkiye using 126 high-frequency indicators covering real sector production, services activity, external demand, retail trade, construction, labor markets and financial conditions. From this dataset, we construct over ten million bridge-equation models and evaluate all specifications through a recursive pseudo-out-of-sample procedure, allowing the data, rather than restrictive priors, to determine the combinations of indicators providing stable real-time signals for quarterly GDP. The results show that the top-performing models draw on a broad and balanced set of indicators, with meaningful contributions from multiple segments of economic activity rather than from any single data block. Ensemble forecasts based on the best models closely track realized GDP and offer an informative benchmark relative to survey expectations. Overall, the findings underscore the value of large-scale model evaluation in extracting robust and timely signals from Türkiye's diverse and evolving high-frequency dataset.

**Özet:** GSYH verilerinin gecikmeli yayımlanması, iktisadi faaliyetin mevcut seyrinin politika yapıcılar ve piyasa katılımcıları açısından gerçek zamanlı olarak izlenmesini önemli hale getirmektedir. Türkiye'de yüksek frekanslı göstergelerin kapsamının ve çeşitliliğinin zaman içinde artmasıyla bu verilerle kısa dönemli büyüme görünümüne ilişkin daha tutarlı sinyaller üretmeye yönelik ihtiyaç da artmaktadır. Bu çalışmada, sektörel üretim ve faaliyet göstergeleri ile dış talep, işgücü piyasası ve finansal koşullara ait farklı frekanstaki 126 gösterge kullanılarak oluşturulan 10 milyonun üzerinde köprü modeli ile Türkiye'de ekonomik büyüme için angörü (nowcasting) ve geriye dönük tahmin (backcasting) sistemi oluşturulmaktadır. Bulgular, en başarılı modellerin iktisadi faaliyetin farklı alanlarını temsil eden dengeli ve geniş kapsamlı gösterge kombinasyonlarına dayandığını; tahmin performansının belirli bir veri grubundan ziyade farklı sektör ve faaliyet alanlarından gelen ortak bilgi içeriğiyle güçlendiğini göstermektedir. En başarılı modellerden elde edilen bileşik tahminlerin, anket yoluyla derlenen piyasa beklentilerine kıyasla daha düşük tahmin hatası yaptığı görülmektedir. Sonuçlar, Türkiye'de giderek genişleyen yüksek frekanslı veri setinin gerçek zamanlı ekonomik analiz açısından önemli bir bilgi değeri taşıdığını ve geniş ölçekli model yaklaşımının kısa dönemli büyümenin izlenmesinde etkili bir çerçeveyi sunduğunu göstermektedir.

## 1. Introduction

Timely and reliable assessments of current economic conditions are essential for monitoring the business cycle, guiding fiscal and monetary policy decisions, and anchoring private-sector expectations. While quarterly GDP remains the most widely used summary measure of a country's economic performance, it is released with a substantial delay, is subject to non-trivial revisions, and often reflects information that lags turning points in real activity. As a result, policymakers and market participants rely heavily on high-frequency indicators to form timely assessments of current economic conditions. This has elevated the role of nowcasting and backcasting frameworks that synthesize scattered, asynchronous and heterogeneous monthly data into coherent real-time estimates of quarterly GDP, an approach that has become widely used in the real-time monitoring and short-term forecasting literature.

The challenge, however, lies in translating a large and heterogeneous flow of monthly information into reliable real-time estimates of quarterly GDP. Models relying on a narrow set of predictors may perform well during stable periods but often lose predictive power when the composition of economic activity shifts or when sector-specific shocks disrupt the co-movement among indicators. These episodes, commonly observed around turning points and periods of heightened volatility, tend to amplify aggregation biases and reduce the stability of simple indicator-GDP relationships (Stock & Watson, 2002; Giannone, Reichlin & Small, 2008). In contrast, models that incorporate a large number of predictors into a single regression face high-dimensional estimation issues, including multicollinearity, parameter proliferation, and limited degrees of freedom, which collectively undermine out-of-sample performance (Boivin & Ng, 2006; Inoue & Kilian, 2008).

These considerations have prompted both academic and institutional forecasting frameworks to emphasize approaches that combine information across many low-dimensional specifications rather than relying on any single preferred model. Forecast-combination methods, dating back to Bates and Granger (1969) and further developed in Stock and Watson (2004) and Timmermann (2006), offer a structured way to address model uncertainty while drawing on the informational breadth of diverse high-frequency indicators. This logic also underlies the influential model-uncertainty perspective of Sala-i-Martin (1997), who shows that evaluating a very large universe of small-scale specifications can reveal stable predictors that remain obscured in individual models. By evaluating multiple small-scale specifications in parallel, such frameworks balance econometric tractability with robustness, allowing heterogeneous data signals to be incorporated systematically into short-term assessments of GDP.

In line with these broad developments in the literature, institutional forecasting practices have increasingly relied on mixed-frequency and indicator-based models for real-time assessment. Research published by major central banks provides extensive documentation on the use of mixed-frequency and indicator-based models for monitoring high-frequency developments in real time. For the United States, Bok et al. (2018) describe the Federal Reserve Bank of New York's large-scale mixed frequency nowcasting architecture, which integrates dozens of monthly indicators under real-time publication constraints. The European Central Bank has similarly developed mixed-frequency dynamic factor models for real-time monitoring of Euro Area activity (Bańbura and Rünstler, 2011), while Modugno (2013) shows how mixed-frequency factor models are employed to synthesize large information sets. Comparable "suite-of-models" frameworks are documented for the Bank of England (Bell et al., 2014) and the Bank of Canada (Chernis and Sekkel, 2017). For Türkiye, Günay (2015) implements a large-scale bridge-equation exercise, in which model selection is based on in-sample RMSE and on a data structure dominated at the time by industrial indicators; subsequent services and construction series that now broaden the real-time information set were not yet available. Although institutional implementations differ, these studies collectively underscore the practical value of allowing diverse model structures to contribute predictive information in real time.

Building on these developments, the present study adopts an empirical strategy that accommodates Türkiye's increasingly diverse high-frequency information set. The expansion of services, construction and demand-side indicators in recent years, together with shifts in the structure of economic activity, makes it important to employ a framework that can systematically evaluate heterogeneous signals without relying on strong prior model restrictions. A large model universe, assessed through recursive pseudo-out-of-sample (OOS) evaluation, provides a transparent way to manage model uncertainty and to identify predictor combinations that retain explanatory value across different periods. By structuring the analysis in this manner, the study aims to offer a balanced and data-driven approach for interpreting the broadened and evolving flow of monthly indicators.

The remainder of the paper is structured as follows. Section 2 outlines the empirical methodology, describing the bridge-equation framework, the construction of quarterly indicators from heterogeneous monthly series, and the large model universe evaluated through recursive pseudo-OOS procedures. Section 3 introduces the data, summarizing the composition, frequency and publication characteristics of the 126 high-frequency indicators. Section 4 presents the main results, including forecast performance across more than ten million specifications and a comparison of model-based backcasts with survey expectations. Section 5 concludes by summarizing the main empirical findings and their implications for real-time monitoring of economic activity.

## 2. Methodology

Our forecasting strategy combines a linear bridge-equation framework with an extensive model-combination exercise, allowing a large number of mixed-frequency indicator sets to inform quarterly GDP nowcasts and backcasts. The motivation for this approach is twofold. On the one hand, relying on a narrow group of indicators risks missing important shifts in the composition of economic activity; on the other hand, heavily parameterized models tend to perform poorly in short samples, a recurring empirical finding in the macroeconomic literature. In the presence of model uncertainty and heterogeneous predictors, combining forecasts across multiple specifications has been shown to deliver stable performance relative to selecting a single model, an insight supported by a large empirical literature (Bates and Granger, 1969; Stock and Watson, 2004; Timmermann, 2006). Within this framework, our approach aims to exploit the informational richness of a broad monthly dataset while maintaining the parsimony needed to avoid instability in limited samples.

Building on this motivation, we implement contemporaneous bridge equations that map quarterly GDP growth to quarterly aggregations of monthly indicators, constructing all possible combinations of two to four predictors from a set of 126 monthly and quarterly variables, yielding 10,342,500 candidate specifications (2-variable: 7,875 + 3-variable: 325,500 + 4-variable: 10,009,125 = 10,342,500 regression models). The restriction to a maximum of four regressors reflects degrees-of-freedom considerations and the finding that small models offer a favorable balance between flexibility and stability in samples of limited length. This design allows the data, rather than a strong prior structure, to determine which combinations have meaningful real-time explanatory content.

Monthly indicators are transformed into quarterly predictors using a standard bridge-equation aggregation scheme. Let  $x_{j,m}$  denote the monthly value of indicator  $j$  in month  $m$ . For quarter  $t$ , the quarterly indicator is constructed as the simple average of the available observations in that quarter,

$$X_{j,t} = \frac{1}{n_t} \sum_{m \in Q(t)} x_{j,m},$$

where  $n_t$  is the number of months available for quarter  $t$ . Both the dependent variable (quarterly GDP) and the explanatory variables are expressed in year-over-year terms. In periods in which only the first

one or two months of a quarter are available, the aggregation uses matching-month partial averages: If, for example, October and November observations are available for quarter  $t$ , then the transformation compares the average of  $x_{j,\text{Oct}}, x_{j,\text{Nov}}$  with the average of the same months in the previous year. This procedure aligns with the ragged-edge treatments commonly used in mixed-frequency nowcasting frameworks (Schumacher and Breitung, 2008; Marcellino and Schumacher, 2010). The resulting contemporaneous bridge equation for each specification is

$$\Delta^{YoY} GDP_t = \alpha + \beta_1 \Delta^{YoY} X_{1,t} + \dots + \beta_k \Delta^{YoY} X_{k,t},$$

where  $k \in \{2,3,4\}$ . No autoregressive components or lagged predictors are included, reflecting the aim of isolating contemporaneous high-frequency signals.

Recursive pseudo-out of sample (OOS) evaluation is standard in the nowcasting literature (Giannone, Reichlin and Small, 2008) and is widely used in policy institutions to assess the stability of competing model structures. Building on this practice, we evaluate real-time performance using a recursive pseudo-OOS procedure. For each quarter  $t$ , the model is estimated using only the data available at that point, and one-step-ahead forecast for  $t + 1$  is produced. The evaluation window allocates roughly 80% of the sample to estimation and 20% to out-of-sample assessment, providing a balanced separation between training and validation periods. Repeating this process yields a sequence of real-time predictions for each specification, summarized using the root-mean-squared error across the evaluation window.

After estimating all candidate specifications, we rank the 10,342,500 models by their pseudo-OOS RMSE and retain the top 20, 50, 100 and 150 models for detailed analysis. For each subset, we examine both individual model forecasts and the simple average of their forecasts. The use of simple averages aligns with evidence documented in the forecast-combination literature—most notably Stock and Watson (2004) and Timmermann (2006)—showing that equal-weighting performs competitively when predictor relevance is uncertain. Because the selected specifications span a wide set of predictor combinations, even within the four-variable group, the resulting averages summarize information drawn from different segments of economic activity without imposing additional structure, consistent with large-model-universe approaches such as Sala-i-Martin (1997) and Günay (2015).

### 3. Data

Our study relies on a wide set of high-frequency indicators designed to capture multiple dimensions of Türkiye's short-term economic activity. The dataset encompasses 126 monthly and quarterly series grouped into several data blocks, including real-sector production, domestic demand, foreign trade, services activity, labor-market indicators, financial conditions and confidence surveys. The starting point of the series is generally the first quarter of 2012, although for certain indicators released at later dates, the beginning of the sample varies depending on the timing of their initial publication. The structure of these data blocks, the sources of series, and the typical publication lags, measured in weeks after the end of the reference month, are summarized in the table below.

A central component of the dataset is a detailed set of production indicators. Industrial production, including derived sub-indices calculated for capital-goods and core manufacturing components—such as those excluding sectors with recent high volatility (other transport equipment, computers and electronics, basic pharmaceuticals), provides granular information on sectoral output developments at a monthly frequency. In addition to official release, monthly composite industrial production indices were constructed for thematic categories such as exporters, non-exporters, construction-linked industries, and tourism-linked industries to better track heterogeneous sectoral dynamics. Additional real-activity measures include capacity utilization, manufacturing PMI, electricity consumption,

construction production, vehicle sales and production, white-goods production, and retail-trade indices, all of which offer timely signals on domestic supply and demand conditions. These indicators jointly reflect the behavior of both cyclically sensitive manufacturing industries and fast-adjusting consumption segments, which are known to carry meaningful short-term predictive content in real-time monitoring exercises.

External demand conditions are captured through several monthly and quarterly series, including OECD, G20 and European Union GDP growth, the Export Climate Index, foreign trade volume indices and the number of foreign visitors. These measures proxy global demand, trade momentum and tourism-related activity-dimensions that are particularly relevant given Türkiye's high degree of economic openness.

The dataset further includes a set of monthly fiscal indicators, such as the central government budget balance and its subcomponents (deflated by CPI), as well as labor market series (employment, unemployment, participation rate) and quarterly and monthly real wage measures. Financial conditions are represented through nominal and real effective exchange rates, interest rate indicators, and local and global risk and volatility indicators (CDS, currency volatility, MOVE, VIX, etc.). The frequency of the data ranges from monthly to quarterly, with monthly indicators entering the model as unbalanced panels in line with standard practice in mixed frequency nowcasting frameworks.

**Table 1. Series Used in the Models**

<b>Data Block</b>	<b>Number of Series Used</b>	<b>Frequency</b>	<b>Source</b>	<b>Calendar Lag (number of weeks)</b>
Regional GDP Growth	3	Quarterly	Eurostat, OECD	4 weeks
Export Climate Index	1	Monthly	Istanbul Chamber of Industry	2 weeks
Industrial Production	25	Monthly	TURKSTAT, Author's own calculations	7 weeks
Capacity Utilization Rate	9	Monthly	CBRT	4 weeks
Manufacturing PMI	1	Monthly	Istanbul Chamber of Industry, S&P Global	1 week
Foreign Trade Volume Indices	2	Monthly	TURKSTAT, Author's own calculations	6 weeks
Electricity Consumption and Production	2	Monthly	Turkish Electricity Transmission Corporation	1 week
Number of Foreign Visitors	1	Monthly	Ministry of Culture and Tourism	4 weeks
Housing Sales	1	Monthly	TURKSTAT	3 weeks
Vehicle Sales and Production	10	Monthly	Automotive Manufacturers Association (AMA)	3 weeks
White Goods Sales and Production	5	Monthly	TURKBESD	4 weeks
Retail Trade	8	Monthly	TURKSTAT	6 weeks
Service Production Index	12	Monthly	TURKSTAT	7 weeks
Construction Production Index	3	Monthly	TURKSTAT	7 weeks
Budget Balance	11	Monthly	Ministry of Treasury and Finance, Author's own calculations	3 weeks
Confidence Indices	6	Monthly	TURKSTAT, CBRT	-
Labor Market Indicators	4	Monthly	TURKSTAT	4 weeks
Real Wages	2	Monthly and Quarterly	TURKSTAT, Author's own calculations	-
Nominal and Real Effective Exchange Rates	3	Monthly	Bloomberg, CBRT, Author's own calculations	1 week
Local, Regional and Global Risk and Volatility Indicators	8	Monthly	Bloomberg, Author's own calculations	-
Nominal and Real Interest Rate Statistics	6	Monthly	Bloomberg, CBRT, Author's own calculations	1 week

#### 4. Results

We begin by computing single-step pseudo-OOS RMSE values for over 10 million regression combinations involving 2, 3, and 4 variables, and subsequently focus on the top 20, 50, 100 and 150 models with the lowest OOS errors. As noted in previous work by Giannone, Reichlin and Small (2008), Bańbura et al. (2011), and Timmermann (2006), short-term macroeconomic forecasting often benefits from assessing a broad array of model specifications rather than relying on a single “best” model, and from selecting models on the basis of their OOS performance. In line with this, our study evaluates both the individual forecasts and the collective (ensemble) behavior of these selected models over time, thereby assessing the informational value that emerges from model diversity within the forecasting framework.

The composition of variables appearing in the top-performing models indicates a balanced reliance on indicators that capture multiple dimensions of economic activity - including demand conditions, production dynamics, services activity and trade-related flows. Out of the 126 variables available in the dataset, 95 appear at least once among the top 150 models, suggesting that the forecasting framework draws on a broad informational base rather than depending on a narrow set of predictors. Despite this broad coverage, the selected variables do not appear randomly; rather, they cluster around activity categories that typically exhibit strong co-movement with short-term GDP dynamics. Moreover, 18 variables are included in 10 or more of the top 150 models, and 5 variables appear in 20 or more models - notably the land transport services (34 models), the industrial production index excl. other transport equipment and computer, electronic and basic pharmaceutical products (32 models), the capacity utilization rate of small-scale enterprises (31 models) and the rental and leasing activities (21 models) - signaling stronger and more systematic signal content. These frequently selected indicators primarily represent transportation activities, capacity utilization in manufacturing, capital- and durable-goods production, external demand conditions and services, all of which tend to adjust rapidly to shifts in economic momentum. Overall, the distribution of variable usage underscores that the most successful models integrate information from diverse segments of the economy, with high-frequency services, trade and goods-production indicators providing particularly consistent contributions to short-term growth nowcasting.

**Table 2. Variables Used in the Top 150 Models**

Variable	Number of Models Used
Services Production Index - Land Transport Services	34
Industrial Production Index - excl. Other Transport Equipment, Computer and Electronic, Basic Pharmaceutical Products	32
Capacity Utilization Rate - Small-Scale Enterprises	31
Services Production Index - Rental and Leasing Activities	21
Export Climate Index	20
Industrial Production Index - Capital Goods	19
Services Production Index - Air Transport Services	18
Services Production Index - Total	18
Services Production Index - Accommodation and Food Service Activities	18
Industrial Production Index - Durable Consumer Goods	17
Industrial Production Index - excl. Other Transport Equipment	17
EUR/USD Exchange Rate	13
G20 GDP Growth	13
OVX (Crude Oil Volatility Index)	13
Industrial Production Index - Intermediate Goods	12
Services Production Index - Security and Investigation Activities	11
Retail Trade Volume Index - Automotive Fuel	11
Industrial Production Index - Non-Exporting Firms	10

Industrial Production Index - Non-Durable Consumer Goods	9
Industrial Production Index - Medium-Low Technology	9
Services Production Index - Postal and Courier Activities	9
Total White Goods Production	9
Construction Production Index - Total Construction	8
Services Production Index - Transportation and Storage	8
Export Volume Index	8
Construction Production Index - Building Construction	7
Total Light Commercial Vehicle Sales	7
Industrial Production Index - Tourism-Related Industries	7
Construction Sector Confidence Index	7
Industrial Production Index - Capital Goods excl. Other Transport Equipment	6
Industrial Production Index - Manufacture of Rubber and Plastic Products	6
OECD GDP Growth	6
Services Production Index - Water Transport Services	6
Total Heavy Commercial Vehicle Sales	6
Unemployment Rate	6
Industrial Production Index - Basic Metals	5
Capacity Utilization Rate - Medium-Scale Enterprises	5
Capacity Utilization Rate - Non-Durable Consumer Goods	4
Services Production Index - Warehousing and Support Activities for Transportation	4
Industrial Production Index - Low-Technology	4
Industrial Production Index - Machinery and Equipment	4
Industrial Production Index - Motor Vehicles	4
Retail Trade (excluding watches and jewellery)	4
Real Sector Confidence Index	4
Real Effective Exchange Rate - CPI-Based	4
Real Effective Exchange Rate - ITO-Based	4
Services Production Index - Employment Activities	4
US Treasury Yield (10-year)	3
Services Production Index - Intermediate Goods	3
Electricity Consumption	3
Electricity Generation	3
Services Production Index - Real Estate Activities	3
Central Government Budget - Customs Duties (CPI Adjusted)	3
Retail Trade Volume Index - Non-Food (except automotive fuel)	3
Retail Trade Volume Index - Food, Drinks and Tobacco	3
Retail Trade Confidence Index	3
Industrial Production Index - Textiles	3
White Goods Exports	3
Capacity Utilization Rate - Consumer Goods	3
Industrial Production Index - Manufacturing	3
Central Government Budget - VAT on Imports (CPI Adjusted)	3
Central Government Budget Balance (CPI Adjusted)	2
Central Government Budget Expenditures (CPI Adjusted)	2
Industrial Production Index - Other Non-Metallic Mineral Products	2
Central Government Budget - Primary Expenditures (CPI Adjusted)	2
Housing Sales	2
RVX (Russell 2000 Volatility Index)	2
Retail Trade Volume Index - Audio-Video Equipment, Hardware, Paint, Glass, Electrical Household Appliances, Furniture, etc.	2
Industrial Production Index - Total Industry	2
Tractor Sales	2
Tractor Production	2
Consumer Confidence Index	2
Industrial Production Index - Construction-Related Industries	2

Imported Passenger Car Sales	2
Import Volume Index	2
Construction Production Index - Civil Engineering	1
Capacity Utilization Rate - Large-Scale Enterprises	1
EU GDP Growth	1
Economic Confidence Index	1
12-Month Euribor Rate	1
Services Sector Confidence Index	1
MOVE (US Treasury Volatility Index)	1
Passenger Car Production	1
PMI (Purchasing Managers' Index)	1
Retail Trade Volume Index - Total	1
Services Production Index - Postal or Internet-Based Services	1
Real TL Commercial Loan Rate (%)	1
Retail Trade Volume Index - Textiles, Clothing and Footwear	1
Total White Goods Imports	1
Total Light Commercial Vehicle Production	1
Total Passenger Car Sales	1
Türkiye's CDS Spread	1
Domestic Passenger Car Sales	1
Industrial Production Index - High-Technology	1
Labor Force Participation Rate	1

An examination of in-sample and pseudo-OOS RMSE values across the top 150 models shows that forecasting performance is heavily concentrated among specifications with 4 variables. Of the 150 highest-ranked models, 143 include 4 variables, while 6 rely on 3 variables and a single model uses 2 variables. This distribution suggests that moderately richer specifications achieve superior OOS accuracy within our evaluation framework, without displaying evidence of excessive in-sample overfitting. The OOS RMSE values for 4 variable models lie within a narrow band (approximately 0.00163-0.00289), forming a tight performance cluster that resembles the 'forecasting plateau' frequently discussed in the model-combination literature, where multiple specifications achieve similar predictive accuracy despite substantial differences in their predictor sets. By contrast, in-sample RMSE displays greater dispersion and declines systematically with model dimensionality, consistent with improvements in within-sample fit when additional regressors are incorporated. However, the weak negative association between in-sample and OOS errors further indicates that better within-sample fit does not mechanically produce improved real-time performance, implying that the OOS ranking criterion effectively limits overfitting.

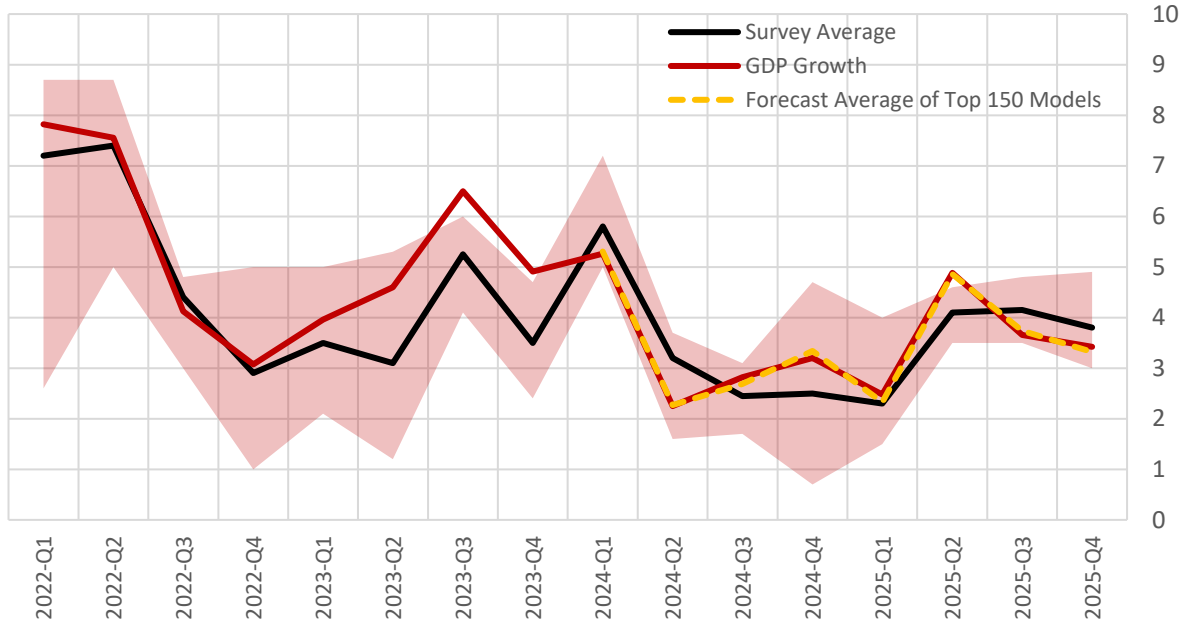
**Table 3. RMSE Averages by Number of Variables**

<b>Number of Variables</b>	<b>Number of Models</b>	<b>In-Sample RMSE (Average)</b>	<b>OOS RMSE (Average)</b>
2	1	0,0352	0,0021
3	6	0,0182	0,0026
4	143	0,0124	0,0025

To benchmark the model-based forecasts against market expectations, Chart 1 compares realized quarterly GDP growth with the Bloomberg survey mean, the survey range and, for the most recent periods, the average forecast across the top 150 models for the last 8 quarters (OOS RMSE period). The red area represents the dispersion of survey expectations, while the black line denotes the survey mean. Over the sample, the survey range is typically sizeable, often on the order of 1-2 percentage points, indicating a non-trivial degree of uncertainty surrounding economic growth. Chart 2 examines forecast errors more directly by plotting the deviations of both the survey mean and the top-150-

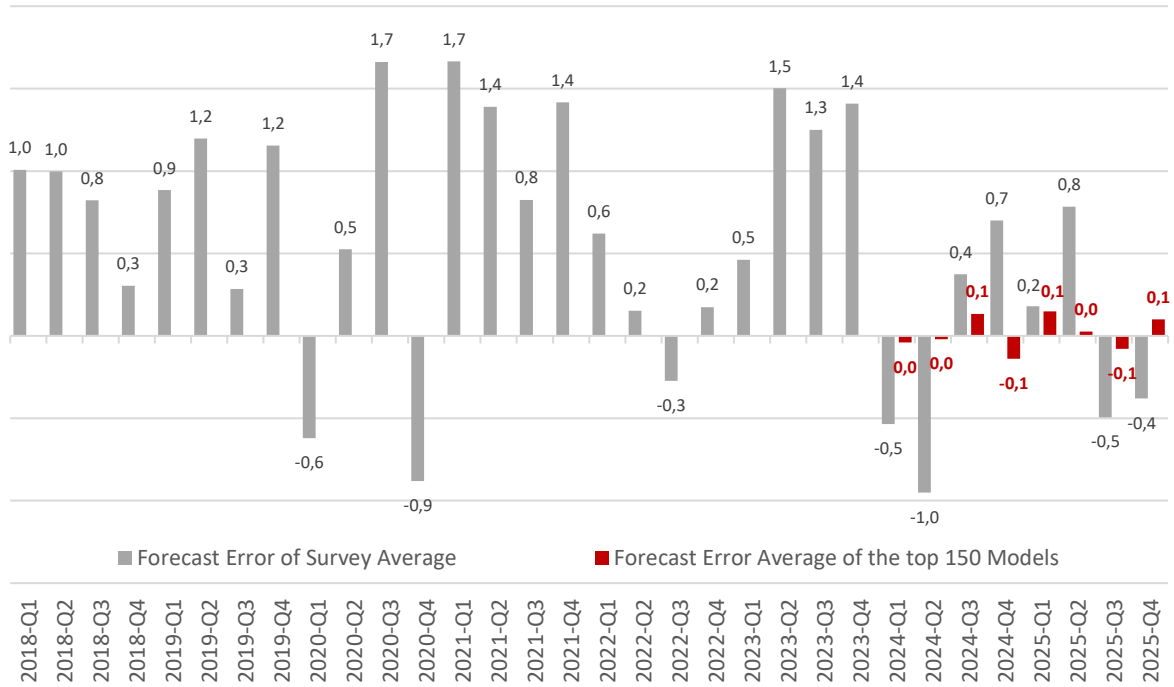
model average from realized GDP growth. For the recent period in which both measures are available, survey errors range between roughly 0.2 and 1 percentage point in absolute value, whereas the model-based nowcasts exhibit considerably smaller errors, with an average absolute forecast error of about 0.08 percentage points. Taken together, these comparisons show that the top-150-model average tracks realized GDP more closely than the Bloomberg survey mean in several recent quarters, while both measures broadly mirror the cyclical pattern of GDP.

**Chart 1. Model Performance**



Source TURKSTAT, Bloomberg, Author's own calculations

**Chart 2. Forecast Error Comparison: Bloomberg Survey Average vs Forecast Average of Top 150 Models**



Source TURKSTAT, Bloomberg, Author's own calculations

## 5. Concluding Remarks

This study develops a large-scale nowcasting and backcasting framework for Türkiye's GDP by systematically evaluating the real-time informational content of a broad set of high-frequency indicators. Using a dataset comprising 126 monthly and quarterly series covering production, services, external demand, retail trade, construction, labor markets and financial conditions, we estimate and assess 10,342,500 bridge-equation specifications constructed from different combinations of two to four predictors. By ranking these models according to their recursive pseudo-OOS RMSE, the analysis allows the data, rather than restrictive prior assumptions, to determine which combinations of indicators provide the most stable real-time signals for quarterly GDP.

Several findings emerge from this large model-universe exercise. First, the results highlight the informational value of a broad and heterogeneous dataset. Among the top-performing specifications, 95 of the 126 indicators appear at least once in the top 150 models, suggesting that short-term GDP dynamics are best captured through a combination of signals drawn from multiple segments of the economy rather than from a narrow subset of predictors. Indicators related to transportation services, industrial production, capacity utilization and selected demand-side variables appear most frequently, indicating that both goods-producing and services-related activities provide meaningful high-frequency signals for tracking economic momentum.

Second, forecasting performance is strongly concentrated among specifications with four predictors. Of the 150 best-performing models, 143 contain four variables, while only a small number rely on two or three indicators. The pseudo-OOS RMSE values of these models lie within a relatively narrow band, forming a performance cluster that resembles the "forecasting plateau" often documented in the forecast-combination literature. This pattern indicates that multiple model structures achieve similar predictive accuracy despite differences in their indicator composition. At the same time, the weak relationship between in-sample and out-of-sample fit underscores the importance of model selection based on real-time predictive performance rather than within-sample explanatory power.

Third, the comparison between model-based forecasts and survey expectations suggests that ensemble predictions derived from the best-performing models provide a useful empirical benchmark for assessing near-term growth. While survey expectations display considerable dispersion across forecasters, the average prediction of the top models tracks realized GDP relatively closely over the available period, with forecast errors remaining comparatively contained. These results illustrate how systematically combining signals from a wide set of high-frequency indicators can complement market expectations and improve the interpretation of incoming macroeconomic data.

Taken together, the findings underscore the practical value of large-scale model evaluation in environments characterized by abundant high-frequency information and evolving economic structures. For Türkiye, where the range of available indicators has expanded substantially in recent years, exploring a large universe of small bridge-equation models provides a transparent and flexible framework for real-time monitoring of economic activity.

## 6. References

- Bańbura, M., & Rünstler, G. (2011). A look into the factor model black box: Publication lags and the role of hard and soft data in forecasting GDP. *International Journal of Forecasting*, 27(2), 333-346.
- Bates, J. M., & Granger, C. W. J. (1969). The combination of forecasts. *Operational Research Quarterly*, 20(4), 451-468.
- Bell, V., Bowring, J., Corder, M., & Rowe, P. (2014). Forecasting UK GDP growth. *Bank of England Quarterly Bulletin*, Q1, 14-27.
- Boivin, J., & Ng, S. (2006). Are more data always better for factor analysis? *Journal of Econometrics*, 132(1), 169-194.
- Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., & Tambalotti, A. (2018). Macroeconomic nowcasting and forecasting with big data. *Annual Review of Economics*, 10, 615-643.
- Chernis, T., & Sekkel, R. (2017). A dynamic factor model for nowcasting Canadian GDP growth. *Bank of Canada Staff Working Paper*, 2017-27.
- Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4), 665-676.
- Günay, M. (2015). I just ran four million regressions: Uncovering the real drivers of growth. *Central Bank of the Republic of Turkey Working Paper*, No. 15/33.
- Inoue, A., & Kilian, L. (2008). How useful is bagging in forecasting economic time series? *Journal of the American Statistical Association*, 103(482), 511-522.
- Marcellino, M., & Schumacher, C. (2010). Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for German GDP. *Oxford Bulletin of Economics and Statistics*, 72(4), 518-550.
- Modugno, M. (2013). Now-casting inflation using high-frequency data. *International Journal of Forecasting*, 29(4), 664-675.
- Sala-i-Martin, X. (1997). I just ran two million regressions. *American Economic Review Papers and Proceedings*, 87(2), 178-183.
- Schumacher, C., & Breitung, J. (2008). Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data. *International Journal of Forecasting*, 24(3), 386-398.
- Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics*, 20(2), 147-162.
- Stock, J. H., & Watson, M. W. (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting*, 23(6), 405-430.
- Timmermann, A. (2006). Forecast combinations. In G. Elliott, C. W. J. Granger, & A. Timmermann (Eds.), *Handbook of Economic Forecasting* (Vol. 1, pp. 135-196). Elsevier.

This report is prepared by Akbank Economic Research

[Economic.research@akbank.com](mailto:Economic.research@akbank.com)

Çağlar Yüncüler, PhD – Vice President

[Caglar.Yunculer@akbank.com](mailto:Caglar.Yunculer@akbank.com)

M. Sibel Yapıcı

[Sibel.Yapici@akbank.com](mailto:Sibel.Yapici@akbank.com)

Sercan Pişkin

[Sercan.Piskin@akbank.com](mailto:Sercan.Piskin@akbank.com)

DISCLAIMER STATEMENT: The text, information and Charts in this report and comments has been prepared from the primary accessible systemic sources on a bona fide basis, and without consideration to establishing any guarantee and assurance for establishing a basis for any informed decision under any name or form, in terms of their accuracy, validity and effectiveness, and thus it has only been gathered for information purposes. Akbank TAŞ, Ak Yatırım AŞ and their employees will not be held responsible for any damages resulting from the comments included in this report such as lack of information and/or updates. Akbank TAŞ and Ak Yatırım AŞ may modify and/or remove the above information and recommendations at any time, without having to serve any prior notice and/or warning in any way, manner or form. Since this report and comments, the comprehensive information and recommendations which have been prepared in the form of general investment suggestions for the purpose of providing general information do not include any commitment by Akbank TAŞ and Ak Yatırım AŞ, the consequences of any decisions taken, conclusions reached, transactions made and any risks caused by any private and/or legal person based on such information will therefore rest with such persons. For this reason, Akbank T.A.Ş., Ak Yatırım A.Ş. and their employees shall not by any means or in any manner be liable for any material and moral damages, loss of profits, or any direct and/or indirect damages, whatsoever, incurred by the persons concerned or 3rd parties, as a result of the decisions taken, conclusions reached, or transactions performed by private and/or legal persons due to reliance on the information contained in this report, the comments and recommendations herein, and the persons concerned understand and accept that they are not entitled to claim any indemnity, whatsoever, from Akbank TAŞ, Ak Yatırım AŞ and their employees for any damages suffered/to be suffered. The information given in this report, and the comments and recommendations contained herein do not constitute an "investment consultancy" service and/or activity, but fall within the scope of a general investment consultancy activity, and individuals and entities willing to receive an investment consultancy service must contact entities and institutions that are authorized to provide such service and obtain such service under a service agreement pursuant to the legislations of CMB. Investment consultancy services are offered under an investment consultancy agreement to be signed between brokerage houses, portfolio management companies, banks that do not admit deposits and the clients. The comments and recommendations contained herein depend upon the personal opinions of the persons who make the comments and recommendations. Since such opinions have been arranged in the scope of a general investment consultancy activity they do not contain reports, comments and recommendations specific to a person, and may therefore not suit your financial status, risk and return preferences. Thus, making investment decisions solely based on the information contained herein might not bring an outcome that meets your expectations.

