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Developing an International Macroeconomic Forecasting Model Based on Big Data

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I. Introduction

With the emergence of big data, the expansion of new data sources for forecasting has raised expectations for predicting economic conditions. In the face of economic uncertainty caused by global inflation, the COVID-19 pandemic, and oil price shocks, it is necessary to utilize all important information to improve the predictive power of forecasting models. As big data provides new information about economic and financial conditions, and machine learning has attracted attention as a methodology for analyzing it, numerous studies are underway. For example, economic sentiment indices are being constructed and utilized from text data such as social media postings, online search results, news contents, and newspaper articles. The Social Media Index (SMI) constructed by Statistics Netherlands has shown a significant relationship with the consumer confidence index. The Bank of Korea has also developed a News Sentiment Index (NSI) that quantifies economic sentiment appearing in economic news articles, and this index has been shown to lead major economic sentiment indicators and real economic indicators. Machine learning is a technique that automatically recognizes patterns within data, and it is possible to improve predictive power by utilizing a large number of variables and models.

Accordingly, this study aimed to comprehensively analyze big data-based forecasting and traditional macroeconomic forecasting to discuss future directions for economic forecasting research. More specifically, we utilized big data to forecast Korea's GDP growth rate and compared the results with those of traditional statistical models and structural macroeconomic models, thus analyzing whether predictive power is improved.

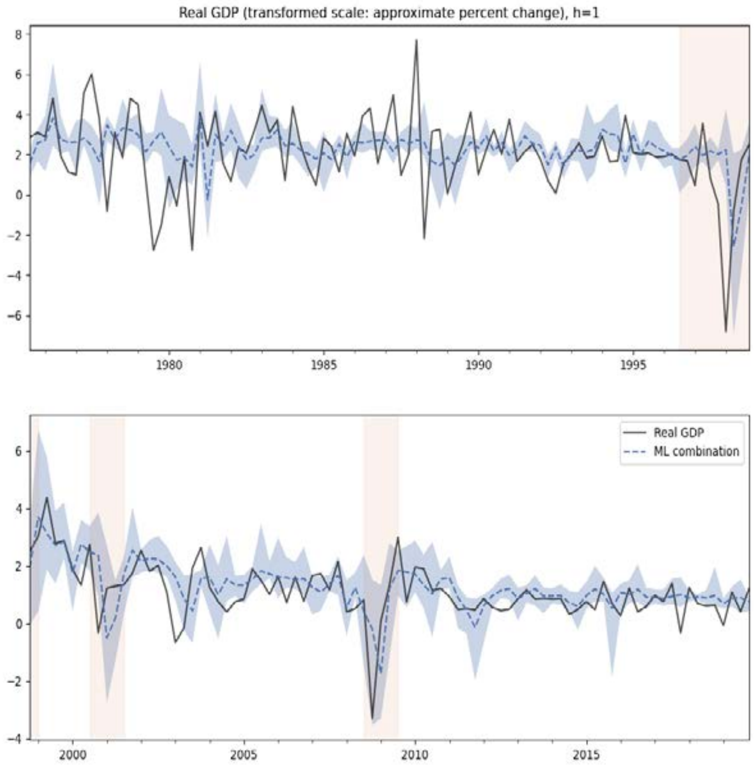
II. Analysis Results

1. Economic growth rate forecasting using big data and machine learning

Based on a large amount of structured data, forecasting the real GDP growth rates of Korea and the United States revealed that utilizing big data improved predictive power, and this was achieved through machine learning rather than traditional econometric models. Using around 200 macroeconomic and financial indicators for each country, we estimated three machine learning techniques, five ensemble models, machine learning forecast combinations, and traditional econometric forecasting models to forecast GDP growth rates. For the United States, a total of 230 macro and financial indicators from the first quarter of 1959 to the first quarter of 2023 were used, and for Korea, a total of 210 macro and financial indicators from the first quarter of 1960 to the first quarter of 2023 were utilized. The machine learning techniques used were Random Forest, XGBoost, and Long Short-Term Memory (LSTM), which have shown good predictive performance in previous studies. The ensemble models were methodologies that used two machine learning techniques for feature selection and forecasting, respectively, and in this study we used LASSO/OLS, LASSO/RF, LASSO/XGBoost, RF/OLS, and RF/LASSO. Finally, the traditional econometric forecasting models used were the Autoregressive Model (AR), the Dynamic Factor Model (DFM) that can handle a large number of predictive variables, and the Diffusion Index model by Stock and Watson (2002). As a result, machine learning generally outperformed econometric models that can handle a large number of predictive variables using common factors.

For the United States, machine learning showed a predictive power for GDP growth generally superior to traditional econometric models. However, for Korea, machine learning failed to demonstrate superior predictive power before 2000. For both countries, machine learning forecasts of GDP growth one quarter ahead were significantly better than the benchmark models, but predictive power decreased as the forecast horizon lengthened. For the United States, excluding the financial crisis period, machine learning forecasts of GDP growth one quarter ahead were significantly better than AR(4), while for Korea, the predictive performance of Random Forest, LASSO/RF, and machine learning forecast combinations was superior. In the Korean situation, machine learning and DFM showed similar predictive power, but in the U.S., DFM lagged behind machine learning in forecasting. In summary, while the predictive performance of machine learning utilizing big data is generally good, it should be noted that the results were obtained using a rolling window and a sample size for the training and validation sets,

Figure 1. Machine Learning Forecast Combination for Korea's GDP Growth Rate



Note: The dotted line represents the average of seven forecasts from machine learning and ensemble models (Random Forest, XGBoost, LSTM, LASSO/OLS, LASSO/RF, LASSO/XGBoost, RF/LASSO), and the shaded area including the dotted line indicates the minimum and maximum values among the seven forecasts.

Source: Constructed by the author based on the estimation results using data from the Bank of Korea, Statistics Korea, Korea Energy Economics Institute, Ministry of Land, Infrastructure and Transport, BIS, IMF, OECD, Bloomberg, and CEIC (accessed on July 24, 2023).

and predictive power may vary depending on the forecast horizon, country, and period.

2. Economic growth rate forecasting using unstructured data

In a subsequent study, search data gained from Naver, a leading search provider in Korea, was defined as unstructured data, and Korea's GDP growth rate was forecasted using Dynamic Model Averaging and Selection (DMA and DMS) by Koop and Onorante (2019). Since the study by Choi and Varian (2012), using internet search data for nowcasting has attracted attention among policymakers seeking timely macroeconomic indicators. Koop and Onorante (2019) showed that using Google search data along with existing macroeconomic variables improves overall macroeconomic forecasting. In this study, it was assumed that Naver search volume provides collective knowledge about the state of the Korean economy, and a search index was constructed by standardizing the Naver search volume related to eight macroeconomic and financial indicators that are commonly used as

Table 1. Forecasting Results of DMA and DMS

		λ = α = 0.95		λ = α = 0.97		λ = α = 0.99	
		DMA	DMS	DMA	DMS	DMA	DMS
Not Using Search Index	AR(2)	32.84	-	-	-	-	-
	OLS	1.57**	-	-	-	-	-
	R.W.	0.91	-	-	-	-	-
Using Search Index	ω =1	0.79*	0.76**	0.73**	0.66**	0.69**	0.65**
	ω =0.75	0.84*	0.74**	0.78*	0.71**	0.73**	0.69**
	ω =0.5	0.80*	0.74**	0.75**	0.71*	0.71**	0.69**
	ω =0.25	0.77**	0.71**	0.73**	0.68**	0.69**	0.65**
Using Search Index Only	ω =0	0.75**	0.71**	0.72**	0.68**	0.68**	0.65**
	OLS	1.82*	-	-	-	-	-

Source: Constructed by the author based on the estimation results using data from the Bank of Korea (accessed on December 20, 2023), Statistics Korea (accessed on December 20, 2023), and Naver Data Lab (accessed on September 9, 2023).

predictive variables for GDP growth rate. Naver search data collected from January 1, 2016, to June 30, 2023, was matched to the eight macroeconomic variables through principal component analysis, resulting in a total of eight macroeconomic variables and eight Naver search indices as predictive variables.

It was confirmed that DMA and DMS using Naver search indices for forecasting Korea's GDP growth rate improved predictive power compared to OLS, AR(2), and random walk models that did not use search indices. Additionally, DMA and DMS that added Naver search indices as auxiliary variables to macroeconomic variables showed improved predictive power compared to using only macroeconomic variables, suggesting that online search data can provide useful information for economic forecasting. It was also shown that while existing forecasting models tended to exhibit mean-reverting behavior, DMA and DMS using Naver search indices performed well in predicting turning points, suggesting their usefulness during economic fluctuations. Among the eight Naver search indices, those for unemployment rate, interest rate spread, and industrial production consistently contributed to the DMA model with high probability.

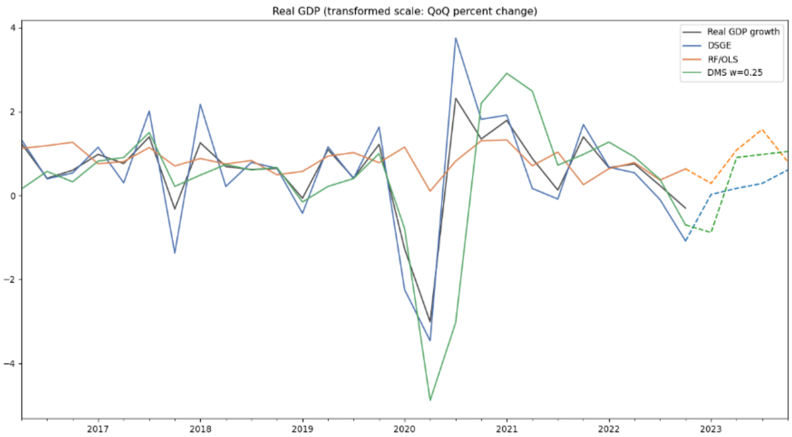
While online search results themselves may not accurately reflect economic information, they can reflect public sentiment or consumer economic sentiment that existing macroeconomic data fails to capture, so using them as auxiliary indicators in economic forecasting models could be expected to improve predictive power.

3. Comparison of the results

Finally, we used the Dynamic Stochastic General Equilibrium (DSGE) model, a structural macroeconomic model capable of not only forecasting but also analyzing the effects of economic policies, to predict Korea's GDP growth rate. Unlike the theoretically consistent DSGE model, machine learning, DMA, and DMS models have the limitation of being unable to conduct impulse response analysis for changes in economic policies. However, since the GDP growth rate forecasts from the DSGE model estimated in this study are in-sample forecasts, it is difficult to directly compare them with the out-of-sample forecasts based on big data.

Comparing the predictive power using RMSE from the second quarter of 2016 to the fourth quarter of 2022, machine learning using a large amount of structured data appears to be superior to DMA and DMS using Naver search indices, but the difference is not statistically significant. When plotting the actual economic growth rate and the forecasts of each forecasting model, the DMA and DMS forecasts show similar movements to the plunging GDP growth rate in 2020, but the machine learning forecasts lag behind. The DSGE model's forecasts are similar to the actual values, but since they are in-sample forecasts, it cannot be claimed that their predictive power is superior.

Figure 2. GDP Growth Rate (QoQ) Forecast for Korea, 2016Q2-2022Q4



Note: While the composition and starting point of the data used for the forecasting models may differ, they all conclude at the same endpoint, the 4th quarter of 2022. The solid line represents out-of-sample forecasts (RF/OLS, DMS) and in-sample forecasts (DSGE), while the dashed line indicates out-of-sample forecasts of quarterly Korean GDP growth rates from the 1st to the 4th quarter of 2023. It should be noted that in-sample forecasts may exhibit a good fit to the actual data due to overfitting issues.

Source: Bank of Korea, e-Nara Jipyo (e-National Indicator), Bureau of Economic Analysis (BEA), Federal Reserve Economic Data (FRED) (all data accessed on: August 30, 2023), Bank of Korea, Statistics Korea, Korea Energy Economics Institute, Ministry of Land, Infrastructure and Transport, Bank for International Settlements (BIS), International Monetary Fund (IMF), Organisation for Economic Co-operation and Development (OECD), Bloomberg, CEIC (all data accessed on: July 24, 2023), Bank of Korea, Statistics Korea (all data accessed on: December 20, 2023), and Naver Data Lab (accessed on: September 9, 2023). These results are based on the author's estimation.

III. Policy Implications

Based on the results of this study, the finding that utilizing big data improves the forecasting of economic growth rates suggests the need to discover data from various sources and construct a macroeconomic database. The fact that forecasts using Naver search indices better predicted the plunging and rebounding movements of economic growth compared to forecasting models using only macroeconomic variables implies that data from new sources are an important element in forecasting economic indicators. As online search data can reflect consumers' economic sentiment in real-time and is useful for forecasting rapidly changing economic situations, it is necessary to actively utilize data from various sources.

In addition to constructing a database for data to be used in economic forecasting, there is a need to develop and research new analysis techniques that can be utilized for forecasting. While traditional econometric methodologies (DFM, Diffusion Index, etc.) that can handle large amounts of data are already widely used, this study confirmed that machine learning using the same data relatively outperformed these in terms of predictive power. Although machine learning-derived economic forecasts cannot completely replace existing forecasting models or qualitative judgments by economic forecasting experts, they can be utilized to construct auxiliary indicators for final forecasts or economic situations.

Suggestions for future follow-up economic forecasting research related to this study are as follows. The first short-term task is to construct an indicator for forecasting or assessing economic situations based on the combined database of unstructured and structured data used in this study. The second short-term task could be to study a forecasting model that combines structural macroeconomic models and big data utilization methodologies. As a long-term task, constructing a database and platform necessary for macroeconomic forecasting by using text mining techniques on data from search engines as well as social media and online news would provide meaningful foundational data. KIEP