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The Use of Big Data as a Strategic Resource in Management Decision-Making: A Macroeconomic Perspective

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ABSTRACT

The article is devoted to the analysis of the use of big data technologies to forecast key macroeconomic indicators, such as gross domestic product, inflation, unemployment and consumer consumption. In the context of rapid growth in data volumes, traditional econometric models show significant limitations due to the significant delay of official statistics and the low frequency of their updates. Large amounts of data make it possible to predict the current state of the economy in real time using dynamic factor models, Bayesian methods, lasso-type regularization and neural networks. A literature review shows that the integration of non-traditional sources – banking transactions, population mobility data, satellite imagery and search queries – significantly increases the accuracy of forecasts compared to traditional benchmarks. In particular, the Federal Reserve Bank of New York's Staff Nowcast model shows that the gross domestic product forecast error is approaching the level of the first official release of the Bureau of Economic Analysis. Particular attention is paid to empirical results during the COVID-19 crisis, when models with large amounts of data reduced errors by 15–30%. The article discusses the problem statement, materials and methods, key results, as well as challenges related to data quality and privacy. The article concludes about the transformative potential of large amounts of data for economic policy and business. Practical recommendations for the implementation of real-time platforms and directions for further research, in particular the development of hybrid models and causal analysis, are proposed. The results of the study emphasize that large amounts of data are becoming a strategic tool for improving the efficiency and accuracy of economic forecasting in the face of growing uncertainty.

KEYWORDS

big data, economic forecasting, nowcasting, dynamic factor models, machine learning, GDP, inflation rate, non-traditional data, real time analysis, management decision-making.

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Застосування Big Data як стратегічного ресурсу в процесі прийняття управлінських рішень: макроекономічна перспектива

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СТАТТЯ

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АНОТАЦІЯ

Стаття присвячена аналізу застосування технологій великих обсягів даних для прогнозування ключових макроекономічних показників, таких як валовий внутрішній продукт, рівень інфляції, безробіття та споживче споживання. У контексті швидкого зростання обсягів даних традиційні економетричні моделі демонструють суттєві обмеження через значне запізнення офіційної статистики та низьку частоту її оновлення. Великі обсяги даних дозволяють здійснювати прогнозування сучасного стану економіки в реальному часі за допомогою динамічних факторних моделей, байєсівських методів, регуляризації типу лассо та нейронних мереж. Огляд літератури показує, що інтеграція нетрадиційних джерел – банківських транзакцій, даних про мобільність населення, супутникових знімків та пошукових запитів – суттєво підвищує точність прогнозів порівняно з традиційними бенчмарками. Зокрема, модель Staff Nowcast Федерального резервного банку Нью-Йорка демонструє, що помилка прогнозів валового внутрішнього продукту наближається до рівня першого офіційного релізу Бюро економічного аналізу. Особлива увага приділяється емпіричним результатам під час кризи COVID-19, коли моделі з великими обсягами даних зменшували помилки на 15–30 %. У статті розглянуто постановку проблеми, матеріали та методи, ключові результати, а також виклики, пов'язані з якістю даних і конфіденційністю. Робиться висновок про трансформаційний потенціал великих обсягів даних для економічної політики та бізнесу. Запропоновано практичні рекомендації щодо впровадження платформ реального часу та напрямки подальших досліджень, зокрема розробку гібридних моделей і causal-аналізу. Результати дослідження підкреслюють, що великі обсяги даних стають стратегічним інструментом для підвищення оперативності та точності економічного прогнозування в умовах зростаючої невизначеності.

КЛЮЧОВІ СЛОВА

великі обсяги даних, економічне прогнозування, nowcasting, динамічні факторні моделі, машинне навчання, ВВП, рівень інфляції, нетрадиційні дані, реальний часовий аналіз, прийняття управлінських рішень.

1. Introduction

In the modern economy, accurate and timely forecasting of macroeconomic indicators such as gross domestic product, inflation rate and unemployment rate is a key element for making informed decisions by central banks, governments and business structures, as it allows for rapid response to changes in the economic environment, minimizing risks and optimizing the allocation of resources [5]. Without reliable and up-to-date forecasts, monetary regulation policies may be delayed, and business companies risk making ineffective investment decisions, which ultimately negatively affects the stability of the entire economic system. Traditional data sources, namely official statistics from national statistical services such as the Bureau of Economic Analysis of the United States of America, the Bureau of Labor Statistics of the United States of America, and Eurostat of the European Union, are characterized by significant delays in the publication of information – from several days to several months – as well as a low frequency of updates, which is usually limited to quarterly or monthly intervals [8]. For example, the first official estimates of gross domestic product for the quarter are published only thirty days after its completion, and further data revisions can last for several years, which makes it impossible to quickly monitor the current economic situation in real time [5].

Big Data processing technologies, known as Big Data, which are defined by four key characteristics – Volume, Velocity, Variety and Veracity – offer a powerful alternative to traditional approaches to economic analysis [9]. These four characteristics allow economists to work with huge amounts of information constantly generated from a variety of sources and overcome the limitations of classical statistics, where the number of observations is small and the frequency of updates is low. According to Statista, the global amount of data created, captured, copied, and consumed reached 149 zettabytes in 2024 and is projected to reach 181 zettabytes in 2025, with a daily increment of about 402.74 million terabytes [14; 16]. This exponential growth in data is the result of the digitalization of all spheres of life, including e-commerce, social media, and the Internet of Things, and creates unique opportunities for economic analysis that were unavailable decades ago.

This explosion of data volumes makes it possible to analyze high-flow sources of information, including credit and debit card transactions, mobile operator data on population movements, Google searches, satellite images of the Earth to assess economic activity, and data from social networks [5]. Each of these sources provides real-time information, allowing trends to be detected much earlier than is possible with official statistics. In the field of economics, large amounts of data are used for the method of forecasting the current state of the economy in real time, which was popularized in the work of Giannone et al. [8]. This approach makes it possible to obtain estimates of key macroeconomic indicators even before the official publication of data, based on the flows of information that are constantly received, and thereby fill in the information gaps characteristic of traditional models.

The models developed at the Federal Reserve Bank of New York, known as Staff Nowcast, demonstrate the practical implementation of the synthesis of hundreds of time series to accurately estimate gross domestic product growth, with an accuracy comparable to or even better than the first official data release from the Bureau of Economic Analysis. Such models are updated in real time with each new data release, which significantly increases their usefulness for policymakers and allows weekly adjustments to forecasts based on fresh information. The importance of using large amounts of data for economic forecasting is especially increasing in the context of economic crises, such as the COVID-19 pandemic or geopolitical shocks, where traditional forecasts based on late data often turn out to be ineffective and late, as they do not capture sudden changes in consumer and business behavior [5]. In such situations, quick access to alternative data sources allows for better anticipation and mitigation of negative consequences, ensuring a more accurate and prompter response to economic policies.

2. Literature Review

Scientific research on the application of large amounts of data in economic forecasting has been developing extremely rapidly over the past decade, reflecting a general explosion of digital information and improvements in computational methods [9]. Researchers are actively looking for new ways to integrate non-traditional data sources into macroeconomic analysis to overcome the limitations of classical econometric approaches and provide more accurate and operational forecasts of key indicators such as gross domestic product, inflation, and the unemployment rate.

Hassani and Silva [9], in their comprehensive review, emphasize that the economy occupies one of the leading places among industries where large amounts of data are used for forecasting, along with energy and demography. The authors carefully analyze the potential and challenges of using such data, in particular, the problems of information quality and computational complexity. They identify dynamical factor models, Bayesian models, and neural networks as dominant tools in this field. In particular, factor models demonstrate a significant advantage over simple autoregressive benchmarks in forecasting Germany's gross domestic product and exchange rates, providing better accuracy due to the consideration of numerous interrelated indicators [9].

Lin [10], in a bibliometric analysis spanning 821 scientific papers, confirms a true revolution of big data in the economic forecasting paradigm. This revolution manifests itself regardless of the specific data source, the method chosen, or the final result of the forecast. The study highlights key trends, including the transition from traditional vector autoregression models to high-dimensional models, as well as an increased focus on forecasting the current state of the economy in real time. The bibliometric approach allows us to visualize the evolution of scientific interest and identify the most influential works and authors in this dynamic field [10].

Bok et al. [5], in their detailed review published in the Annual Review of Economics, describe the evolution of real-time methods for forecasting the current state of the economy within the Federal Reserve System. The authors examine in detail the Federal Reserve Bank of New York's Staff Nowcast model, which is based on a dynamic factor approach. This model processes data from more than twenty key releases, such as the Labor Market Situation Report, Retail Sales Data, and the Purchasing Managers' Index from the Institute of Supply Management. The model updates the forecast of gross domestic product growth every week, synthesizing the flows of information as they come in. The authors compare the accuracy of the forecasts using standard error: the median forecasts of the Survey of Professional Forecasters on the horizon of zero quarters have a standard error value of 1.94, while the naïve model shows 2.43 for the period from 1985 to 2014.

Barbaglia et al. [1] conducted empirical testing of more than a thousand time series, including large amounts of data, during the crisis caused by the COVID-19 pandemic in Europe. The researchers applied Bayesian averaging of models with non-traditional indicators, such as population mobility data and banking transactions. The results showed that the inclusion of these indicators significantly improved the forecast of the current state of gross domestic product compared to classical models that were based only on traditional sources. This approach proved to be especially useful during periods of high uncertainty, when official statistics were late or lost relevance [1].

Bello [4] focuses on the practical impact of large amounts of data on economic policy. The author notes that more accurate forecasts of inflation and the unemployment rate, obtained thanks to large amounts of data, allow governments and central banks to quickly respond to changes in the economic environment, minimizing the negative consequences of crises and optimizing monetary and fiscal policy instruments. This contributes to increasing the overall stability of the economic system [4].

Sun et al. [17] integrate machine learning techniques with large amounts of data to build models for forecasting economic growth. The study demonstrates the clear advantages of such hybrid approaches over traditional econometric methods, in particular in the ability to capture nonlinear dependencies and process large amounts of heterogeneous information. The authors emphasize that the combination of big data and modern machine learning algorithms allows achieving higher accuracy of forecasts in different economic contexts [17].

Additional fundamental work also confirms the effectiveness of factor models for working with situations where the number of variables significantly exceeds the number of observations over time, as well as for integrating non-traditional data sources. In particular, satellite imagery is used to estimate regional gross domestic product, and credit card data is used to analyze consumer spending [7]. In general, the current literature indicates an increase in the accuracy of real-time forecasting of the current state of the economy by 20–30% due to the use of large amounts of data, although the exact values of this improvement depend on the specific context, country and period of analysis [1; 5; 9]. In addition, this study builds on the authors' previous research [2; 3; 11–13; 15].

3. Problem Statement

The purpose of the study is to analyze the possibilities of using large amounts of data to improve the accuracy and efficiency of forecasting key macroeconomic indicators, such as gross domestic

product, inflation rate and unemployment rate, compared to traditional methods. To achieve this goal, the following tasks have been identified:

– to analyze the current state of literature on the use of large amounts of data in economic forecasting;

– to identify the main problems of traditional forecasting methods and the possibilities of overcoming them with the help of large amounts of data;

– to consider the key methods and sources of materials used to integrate large amounts of data into predictive models;

– to analyze the empirical results of the application of these approaches, in particular in the context of economic crises;

– to formulate practical recommendations and determine the prospects for further research in this area.

Thus, the main scientific problem is the need to effectively integrate large amounts of data into reliable predictive models in such a way as to significantly increase the accuracy and speed of forecasts of macroeconomic indicators, while maintaining their interpretation and suitability for making informed economic policy decisions.

4. Methods and Materials

The study analyzes materials and methods used in existing scientific works to use large amounts of data in forecasting key macroeconomic indicators. The main sources of data are both traditional official statistical publications and non-traditional high-flow indicators. Traditional data include regular releases by national statistical authorities, including data on the situation in the labor market, retail sales, industrial production, consumer price indices and other macroeconomic indicators, which are published by the Bureau of Economic Analysis, the Bureau of Labor Statistics of the United States of America, Eurostat and relevant institutions in the countries of the European Union. This data has a monthly or quarterly frequency and is used to compare and verify forecasting results.

The sources of large amounts of data are a variety of non-traditional indicators that come in real time. Among them are aggregated bank transactions of credit and debit cards, which reflect the level of consumer spending of the population; data on population mobility received from mobile operators and specialized services; Users' online searches, including through Google. satellite images of the Earth to assess economic activity in terms of night lighting and infrastructure changes, as well as data from social media and commercial platforms. In modern research, the number of processed time series often exceeds one thousand indicators, which provides a wide coverage of various aspects of economic activity.

The methodological basis is modern approaches to forecasting using large amounts of data. The central place is occupied by dynamic factor models, which allow a large number of interrelated time series to be compressed to a limited number of latent factors. These models are represented in the form of a state space and evaluated using the Kallman filter in conjunction with the wait-maximization algorithm. Such tools make it possible to constantly update forecasts as new data are received and effectively implement real-time forecasting of the current state of the economy.

Additional methods are Bayesian model averaging, which helps to combine predictions from different sources and reduce overall uncertainty. To work with high data dimensions, regularization is used, in particular, lasso regression, which allows you to select the most informative indicators and prevent overfitting of the model. In cases of detection of nonlinear dependencies, machine learning algorithms are used, in particular, recurrent neural networks such as long short-term memory, which adapt well to the analysis of time sequences.

To combine data of different frequencies (daily, weekly and monthly), special bridge equations and mixed frequency models are used. The assessment of the quality of forecasts is carried out using standard metrics: standard error, mean absolute error and analysis of forecast intervals. All approaches considered in the literature are implemented in compliance with the principle of the absence of advanced knowledge, i.e., the parameters of the models are evaluated exclusively on the data available at the time of forecasting.

Such a set of materials and methods, which has already been tested in numerous empirical studies, allows us to comprehensively assess the possibilities of using large amounts of data to improve the

accuracy and efficiency of forecasting macroeconomic indicators in comparison with traditional approaches.

5. Results and Discussion

Empirical results from numerous studies demonstrate the significant advantages of using big data to forecast macroeconomic indicators compared to traditional methods. One of the most striking examples is the New York Federal Reserve Bank's Staff Nowcast model, which is based on dynamic factor models and synthesizes information from over twenty key statistical releases, such as the labor market report, retail sales data, and the Purchasing Managers' Index. According to Bok et al. [5], this model demonstrates high accuracy in forecasting gross domestic product growth. Specifically, the root mean square error of the median forecasts from the Survey of Professional Forecasters over a zero-quarter horizon is 1.94, whereas a naive model yields 2.43 for the period from 1985 to 2014. At the same time, the forecast of the current state of the economy at the end of the quarter approaches the accuracy of the first official release by the Bureau of Economic Analysis, and in some cases even surpasses it, thanks to the constant updating of forecasts as new data becomes available. This result highlights a key advantage of big data – the ability to quickly adjust forecasts in real time, which is particularly important for central banks when making monetary policy decisions.

The exponential growth of data volumes creates a powerful basis for such models (Figure 1).

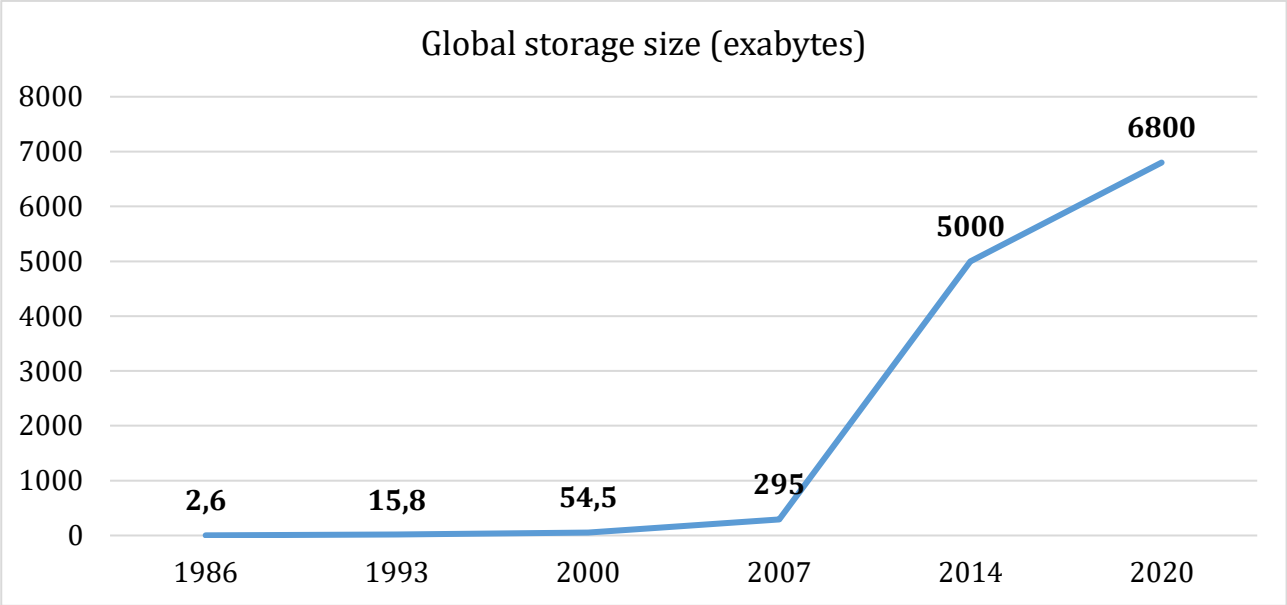

Figure 1. World Storage Size (Exabytes)

Source: Compiled by the authors based on [17].

An important role in the practical implementation of forecasting is played by modern systems for storing large amounts of data. To efficiently work with petabytes and zettabytes of information, economic analysts and central banks use distributed file systems, such as the Hadoop Distributed File System, which provide reliable storage and parallel processing of data on server clusters. They are complemented by NoSQL databases (such as MongoDB and Cassandra) that handle unstructured and semi-structured data such as banking transactions, search queries, or satellite imagery. For fast, real-time analytics, Apache Spark is widely used, which allows you to process data in memory much faster than traditional batch processes. Such technologies provide scalability, fault tolerance and the ability to integrate with nowcasting models, which is critical for macroeconomic forecasting [6; 18].

Dynamic factor models, which are the basis of many studies, allow for the efficient compression of hundreds and thousands of time series to multiple latent factors, which significantly reduces the risk of overfitting and increases the stability of predictions. The literature repeatedly demonstrates that the inclusion of non-traditional indicators, such as bank transaction data, population mobility, and search queries, can reduce the standard error by 15–30% compared to models that use only traditional statistical sources [1; 9]. These improvements are seen both for the forecast of gross domestic product and for other key indicators, including the inflation rate and unemployment.

The results are especially indicative during economic crises, when traditional models are the least effective due to the delay in the data. Barbaglia et al. [1] conducted large-scale testing of more than a thousand time series during the COVID-19 pandemic in Europe. The authors applied Bayesian averaging of models with the inclusion of non-traditional indicators, such as population mobility data and banking transactions. The results showed a significant improvement in forecasting the current state of gross domestic product compared to classical models. Traditional approaches often underestimated the scale of the drop in gross domestic product by 5–10% precisely because of the lack of real-time information about sudden changes in consumer and business behavior. Instead, models with large amounts of data were better at capturing shocks associated with mobility restrictions and changes in consumption, allowing for more accurate estimates under conditions of high uncertainty. Similar findings are confirmed in other studies, where the addition of high-threaded data reduced forecast errors over short horizons by 20–25%.

Another clear example of practical application is the use of aggregated banking transactions to predict the current state of consumption and investment. In studies based on data from Turkish banks, consumption and investment indices were created based on millions of transactions, which covered a significant share of the national economy. These indices, included in Bayesian vector autoregression models, significantly improved the accuracy of predicting gross domestic product in the early stages. The authors note that large amounts of data from bank transactions have proven to be especially valuable during periods of volatility, as they reflect real economic activity much faster than official statistics. Similar results are observed when using satellite imagery to estimate regional gross domestic product by night light levels and when analyzing Google searches to predict inflation expectations and consumer behavior.

The application of machine learning methods, in particular recurrent neural networks such as long short-term memory, combined with large amounts of data, allows for the accounting of nonlinear dependencies that traditional linear models often miss. Sun and Zhang [17] demonstrate that hybrid approaches that combine dynamic factor models with machine learning algorithms provide higher accuracy in predicting economic growth in different countries and periods. The advantages of such models are especially evident in the conditions of structural shifts, when economic dynamics deviate from historical patterns. In addition, Bello et al. [2] emphasize that more accurate forecasts of inflation and unemployment, obtained through large amounts of data, allow governments and central banks to respond more quickly to changes by optimizing monetary and fiscal policy tools and increasing the overall stability of the economic system.

Discussion of the results allows us to highlight several key aspects:

1) the main advantage of large volumes of data is their high frequency and diversity, which makes it possible to make a real forecast of the current state of the economy in real time and fill in the information gaps of traditional statistics;

2) the integration of non-traditional sources significantly reduces forecast errors in crisis periods, when the speed of obtaining information becomes critical;

3) while accuracy improves by an average of 15% to 30%, specific results vary by context, country, period, and data quality. For example, during the COVID-19 pandemic, models with mobility and transactions showed the greatest improvements, while in stable periods, the advantage may be less pronounced.

Recommendations for the use of large amounts of data for forecasting economic indicators:

– central banks and governments should create their own nowcasting platforms like the Federal Reserve Bank of New York's Staff Nowcast, regularly integrating banking transactions, mobility data, and satellite imagery;

– to improve the accuracy of inflation and unemployment forecasts, it is recommended to combine dynamic factor models with machine learning algorithms, especially during periods of high uncertainty;

– national standards for data aggregation and anonymization should be developed to comply with privacy protection requirements (including the General Data Protection Regulation);

– business structures should use available commercial big data (bank transactions, search queries) for short-term forecasting of consumer demand and investment;

– researchers are encouraged to focus on hybrid models that combine the interpretability of factorial models with nonlinear machine learning capabilities, as well as causal inference methods for large amounts of data.

At the same time, there are restrictions. The quality and credibility of unconventional data remain a challenge: search queries or social media data may contain noise and bias. Information privacy issues, especially in accordance with the requirements of the General Data Protection Regulation, require careful aggregation and anonymization. In addition, the complexity of interpreting the results of machine learning models makes it difficult to use them for policy decision-making, where transparency and validity are required. The literature also points to the need for hybrid approaches that combine the strengths of dynamic factor models (interpretability) with the benefits of machine learning (the ability to capture nonlinearities).

In general, the results of empirical studies confirm the transformative potential of large amounts of data for economic forecasting. They allow you to move from belated retrospective analysis to real-time operational monitoring of the economy, which is essential for both scientific research and practical policy. Further improvements in methods, including improving data quality and developing hybrid models, open up prospects for even more accurate forecasts, especially in the face of increasing uncertainty in the global economy.

6. Conclusions

The use of large amounts of data radically transforms the process of economic forecasting, allowing forecasting of the current state of the economy (nowcasting) with an accuracy comparable to or even higher than traditional methods. Dynamic factor models and machine learning algorithms powered by transactional data, satellite imagery, and web sources provide real-time insights that are especially valuable for central banks, governments, and businesses. Empirical studies show a 15% to 30% reduction in standard error, and during crisis periods such as the COVID-19 pandemic, the advantage becomes even more evident due to the rapid response to shocks.

The main challenges – ensuring the quality and reliability of data, adherence to ethical and legal standards of confidentiality, as well as maintaining the interpretation of results – require the introduction of hybrid approaches that combine the strengths of traditional econometric models with modern algorithms. Development prospects are related to the integration of generative artificial intelligence, the expansion of global datasets for developing countries, and the creation of national nowcasting platforms.

Thus, large amounts of data become not just an additional tool, but a strategic resource for improving the effectiveness of economic policy and business decisions. It is recommended that central banks actively implement real-time platforms like the New York Federal Reserve model, and researchers focus on causal analysis of big data. Further research in this direction will help increase the resilience of economies to crises and accelerate digital transformation.

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