Asian Journal of Scientific Research and Innovations
ISSN: 2715-xxxx (online) | IF: 10.23 | Vol: 1, issue 1
Available: http://asiansciencejournal.org

TIMELINE ANALYSIS: IDENTIFYING TRENDS AND SEASONAL CHANGES

G'afforov Azizbek Zayniddinovich
Student of the Samarkand Institute of Economics and Service
gafforovazizbek57@gmail.com
Raximova Umida Ziyadullayevna
Senior Lecturer at the Department of "Higher Mathematics" of the Samarkand Institute of Economics and Service
raximovaumida2018@gmail.com

Abstract: This article highlights the theoretical and practical aspects of the time series analysis approach in analyzing innovation and investment processes. The study examined methods for determining trends and seasonal changes, and analyzed the capabilities of the STL decomposition, ARIMA, and LSTM models. The results obtained demonstrate the effectiveness of these methods in economic forecasting and substantiate their importance in investment decision-making.

Keywords: time series analysis, trend, seasonality, innovation, investment, STL, ARIMA, LSTM.

Introduction

In the modern economy, innovation and investment processes manifest as a dynamic, multi-factor, and time-dependent system. In the context of intensifying global competition, capital flows, technological innovations, and market conditions are constantly changing. For this reason, time series analysis is considered an important methodological tool for the in-depth analysis of economic processes. Through this approach, it is possible to determine how economic indicators change over time, reveal their internal structure, and forecast future trends. In particular, identifying the main components of time series trends and seasonality is of particular importance in innovation and investment activities. While the trend component represents a long-term direction of growth or decline, seasonality reflects changes that recur with a specific frequency. For example, an increase in investment volumes near the end of the year or the intensification of startup activity in certain quarters may be associated with seasonal factors. In this regard, the separate analysis of these components increases the accuracy and reliability of economic decision-making.

In recent years, the development of the digital economy, the emergence of large volumes of data, and the improvement of analytical technologies have made time series analysis methods increasingly relevant. In particular, machine learning and artificial intelligence-based approaches provide high accuracy in identifying trends and seasonality. This serves to evaluate the effectiveness of innovative projects, reduce investment risks, and improve strategic planning.

Literature Review

Scientific literature on time series analysis shows that this method is of great theoretical and practical importance in studying economic processes, especially innovation and investment activities. Within the framework of classical approaches, the Box-Jenkins methodology holds a special place. This methodology analyzes time series using autoregressive and integrated models, allowing for the identification of trend and random components[83]. Numerous studies have emphasized that ARIMA models possess a high level

[83] Box G.E.P., Jenkins G.M., Reinsel G.C., Ljung G.M. Time Series Analysis: Forecasting and Control. 5th ed. Hoboken: Wiley, 2015. 712 p.

of reliability in forecasting investment flows and macroeconomic indicators. In addition, exponential smoothing methods, in particular the Holt-Winters model, allow for the joint identification of trend and seasonal components in time series[84]. This approach is effective in short-term forecasting of demand for innovative products and services and is characterized by its accurate reflection of seasonal fluctuations.

In recent years, modern approaches have been widely developed in scientific literature. In particular, deep learning-based neural networks such as LSTM are demonstrating high efficiency in identifying long-term relationships in time series[85]. Such models play an important role in the analysis of economic processes based on complex, nonlinear, and large-scale data, including the assessment of investment risks. In addition, methods for dividing time series into components are also widely covered in the scientific literature. In particular, using the STL decomposition method, it is possible to analyze trend, seasonal, and random parts separately[86]. This method is effectively used to identify hidden trends in innovative development indicators, as well as for in-depth analysis of economic cycles.

Methodology

In this study, time series analysis was applied to analyze innovation and investment indicators. To determine the data structure, the STL decomposition method is used, which divides the time series into trend, seasonal, and random parts. The results were compared and evaluated using the traditional ARIMA model (a statistical model based on historical values) and the modern LSTM (long-distance neural network) for forecasting.

Results And Discussion

In the in-depth study of innovation and investment processes, time series analysis serves as a primary tool for determining the dynamics of economic indicators over time. Under this approach, the time series is typically divided into three main components: trend, seasonality, and random fluctuations. The trend component represents a long-term upward or downward trend. For example, the growth of foreign direct investment (FDI) in many developing countries over the last decade shows a steady positive trend. At the same time, factors such as global financial crises or the pandemic create temporary declines and short-term fluctuations that disrupt the trend[87].

The STL decomposition method is important for the accurate identification of trends. This method is used to smooth out the time series and reveal its internal structure. For example, studies conducted on the volume of investments in the startup ecosystem revealed through STL that although there is a general growth trend, sharp jumps are observed in some periods. These leaps are often attributed to investments made by large technology companies or government support programs[88]. At the same time, the seasonal component also plays an important role. For example, in many countries, investment activity increases in the last quarter of the year, which is explained by the utilization of budget funds and the end of the fiscal year.

In the forecasting process, the ARIMA model is widely used as a classical statistical model. This model predicts future values based on past values in a time series and their

[84] Hyndman R.J., Athanasopoulos G. Forecasting: Principles and Practice. 3rd ed. Melbourne: OTexts, 2021. 442 p.
[85] Goodfellow I., Bengio Y., Courville A. Deep Learning. Cambridge: MIT Press, 2016. 775 p.
[86] Cleveland R.B., Cleveland W.S., McRae J.E., Terpenning I. STL: A Seasonal-Trend Decomposition Procedure Based on Loess // Journal of Official Statistics. 1990. Vol. 6, No. 1. P. 3 73.3.
[87] Box G.E.P., Jenkins G.M., Reinsel G.C., Ljung G.M. Time Series Analysis: Forecasting and Control. 5th ed. Hoboken: Wiley, 2015. 712 p.
[88] Hyndman R.J., Athanasopoulos G. Forecasting: Principles and Practice. 3rd ed. Melbourne: OTexts, 2021. 442 p.

interrelationships. For example, the ARIMA model, built on the volume of investments directed to industry, provides forecast results with high accuracy over a certain period. However, the primary limitation of this model is its linear structure, which fails to fully reflect complex nonlinear economic processes. Therefore, drastic changes occurring in economic systems (such as political decisions or global shocks) can reduce the accuracy of ARIMA forecasts[89].

In modern scientific research, the LSTM model is widely used. This model is based on artificial neural networks, allowing for the identification of long-term correlations within time series. For example, when analyzing technology sector investments, the LSTM model provides more accurate forecasts than traditional models, taking into account factors such as global market trends, inflation rates, and even political stability. Applied research indicates that the LSTM model works particularly effectively on large-scale and complexly structured data[90].

Innovation indicators are also an important object of analysis as time series. For example, indicators such as the number of patents, research funding, and the number of startups reflect a long-term trend. Research indicates that there is a positive correlation between R&D expenditures and economic growth. However, although there is less seasonality in these indicators, short-term declines are observed under the influence of economic cycles. For example, during periods of economic crisis, innovative activity decreases, but in subsequent periods, a recovery is observed again[91].

Furthermore, the combined use of decomposition and forecasting methods in time series analysis yields the most effective results. For example, if components are first isolated using STL and then predicted using ARIMA or LSTM, the results will be more accurate and reliable. Such an integrated approach plays an important role in developing investment strategies, risk assessment, and the formation of innovation policy.

Conclusion

The results of this study indicate that time-series analysis serves as an important scientific basis for the effective analysis of innovation and investment processes. In particular, identifying trend and seasonal components allows for a deep understanding of the internal dynamics of economic indicators and the development of well-founded forecasts. It was established that the methods used in the study, such as STL decomposition, the ARIMA model, and LSTM, yield high-precision results when used in combination. As a result, it was substantiated that these approaches are an effective tool for forecasting investment flows, assessing risks, and developing innovative development strategies.

REFERENCES

1. Box G.E.P., Jenkins G.M., Reinsel G.C., Ljung G.M. Time Series Analysis: Forecasting and Control. 5th ed. Hoboken: Wiley, 2015. 712 p.
2. Cleveland R.B., Cleveland W.S., McRae J.E., Terpenning I. STL: A Seasonal-Trend Decomposition Procedure Based on Loess // Journal of Official Statistics. 1990. Vol. 6, No. 1. P. 373.3.
3. Goodfellow I., Bengio Y., Courville A. Deep Learning. Cambridge: MIT Press, 2016. 775 p.
4. Hamilton J.D. Time Series Analysis. Princeton: Princeton University Press, 1994. 799 p.

[89] Hamilton J.D. Time Series Analysis. Princeton: Princeton University Press, 1994. 799 p.
[90] Goodfellow I., Bengio Y., Courville A. Deep Learning. Cambridge: MIT Press, 2016. 775 p.
[91] OECD. Innovation Indicators and Economic Growth. Paris: OECD Publishing, 2018. 320 p.

5. Hyndman R.J., Athanasopoulos G. Forecasting: Principles and Practice. 3rd ed. Melbourne: OTexts, 2021. 442 p.
6. OECD. Innovation Indicators and Economic Growth. Paris: OECD Publishing, 2018. 320 p.