Peculiarities of forecasting the behaviour of economic agents in non-stationary conditions

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Forecasting the behavior of economic agents in non-stationary conditions is a critically important research area in economics, especially considering the dynamic and constantly changing nature of modern economic systems. In environments characterized by non-stationarity, the behavior of economic agents undergoes temporal fluctuations, posing significant challenges for accurate forecasting and informed decision-making. This underscores the necessity of developing specialized tools and models capable of adeptly predicting the behavior of economic agents, thereby enhancing the competitive advantage of enterprises. Before delving into the main research findings, it is pertinent to consider the distinctions between stationary econometric models and forecasting methods, adapted to the specific characteristics of the time series data (see Table 1).

These differences highlight the importance of the process of identifying non-stationarity, as failure to recognise non-stationarity can create a huge source of error, undermining the reliability of forecasts and increasing their complexity. The inherent volatility and uncertainty inherent in non-stationary conditions create significant obstacles to the accuracy of conventional forecasting models based on stationary assumptions. Thus, when forecasting the behaviour of economic agents in non-stationary conditions, experts face a significant number of challenges - ranging from reconciling the dynamic interaction of changing models and taking into account systemic trends to structural uncertainty introduced by interruptions and reactions of adaptive agents - which requires the development of a complex and adaptive methodological paradigm and appropriate tools.

Table 1 – Differences between steady-state and non-steady-state conditions

Steady-state conditions	Non-stationary conditions
Statistical properties such as mean and variance remain constant over time	Statistical properties change over time
Time series data are predictable and suitable for forecasting	Time series data are unpredictable, making them difficult to model or accurately predict
Allows for reliable economic analysis and decision making due to stable statistical properties	Introduces uncertainty that makes it difficult to generalise the impact of variables over time
This applies to reinforcement learning as it affects the behaviour of agents in a dynamic environment	Can lead to problems with adaptation to non-stationary conditions, affecting the ability of agents to behave optimally
Provides a basis for developing robust models and strategies for economic analysis	Requires appropriate handling to avoid unreliable and spurious results with significant financial implications
Variance is constant over time	Variance may change over time or exhibit volatility
No systematic trend in the trend	The trend may show an upward or downward trend
No unit root in time series tests	The presence of a unit root in time series tests

Non-stationary conditions significantly impact the selection of a forecasting model, prompting the consideration of models capable of handling non-stationary data, transforming data to attain stationarity, and delivering precise and dependable forecasts. Simultaneously, the violation of assumptions inherent in many time series models due to non-stationary data renders traditional forecasting methods unreliable and prone to errors (2). This violation influences the model selection process, as models designed for stationary data may exhibit suboptimal performance in non-stationary conditions. Common forecasting models employed for non-stationary time series data encompass ARIMA, fuzzy time series, random walk, and VAR models. The choice of a specific model relies on the distinct characteristics of the data and the nature of non-stationarity inherent in the context. However, despite their widespread utilization, these models exhibit several notable drawbacks that complicate their application and may lead to erroneous conclusions. The most significant drawbacks encompass various issues (3).

- Qualitative nature: many forecasting models rely on qualitative data and expert judgement, which can cause subjectivity and bias in interpretation;

- Resource intensive: forecasting can be time-consuming and resource-intensive, especially when dealing with non-stationary data;

- fundamental unknowability of the future: The biggest limitation of forecasting is that it deals with the future, which is fundamentally unknowable today. As a result, forecasts can only be best guesses. Although there are several methods to improve the reliability of forecasts, the assumptions used in the models or the data input to them must be correct.

Among the available innovative approaches that allow taking into account non-stationarity conditions, solving a significant number of forecasting tasks and obtaining more reliable results, in our opinion, we can single out non-stationary fuzzy sets (NSFS) and P-MARL/Multi-Agent Reinforcement Learning (3; 4). Both approaches are oriented to work in non-stationary conditions and have their own peculiarities in application.

Non-stationary fuzzy sets (NSFS) are employed within the realm of forecasting in non-stationary environments, specifically addressing heteroscedastic time series characterized by unconditional variance. This methodology leverages NSFS to predict time series data where variance displays temporal non-constancy, a challenge encountered by conventional forecasting methods. The utilization of NSFS in forecasting mitigates inherent unpredictability and complexities linked to non-stationary time series data, notably in financial modeling and economic forecasting. Through the incorporation of NSFS, researchers and practitioners can enhance their capacity to model and forecast time series data exhibiting non-stationary behavior, ultimately yielding more precise and dependable predictions within dynamic economic contexts (3).

P-MARL signifies a noteworthy advancement in handling non-stationary environments within the domain of multi-agent reinforcement learning, holding the potential to augment agent adaptability and decision-making proficiency in dynamic and evolving economic systems. Employing a prediction mechanism to acquire prior insights into the non-stationary dynamics of the environment, P-MARL subsequently enhances agents' learning and decision-making processes (4).

In summation, this study contributes to the ongoing discourse on predicting the behavior of economic agents by unraveling the characteristics associated with non-stationary conditions.

References

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