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The role of Artificial Intelligence in Economic Forecasting and Policy Development

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Abstract

This paper examines the influence of Artificial Intelligence on economic forecasting and policy making, highlighting how advanced data sets and techniques enable economists and policymakers to develop more comprehensive and informed analyses of economic trends and predictions. The research findings indicate that integrating AI significantly enhances the accuracy, precision, and efficiency of economic predictions. By leveraging sophisticated data techniques, AI facilitates the extraction of critical insights from large, complex datasets, simplifying financial market analysis and deepening the understanding of market dynamics.

Keywords: Artificial Intelligence, Economic Forecasting, Economic Policy.

The history of AI technology spans over many years with a constant change and active evolution (Bello, 2022). Big data: a revolutionary phenomenon is one of the most persistent discussed topics in the modern age and is expected to prevail in the foreseeable future (Bello, 2022). The emergence of big data has transformed multiple disciplines, including economic forecasting and policy making, by providing unparalleled access to diverse information sources and advanced analytical tools (Bello, 2022). This transformation is reshaping the way economists predict economic trends and how policymakers design and implement strategies with greater precision and efficiency (Bello, 2022).

Economic forecasting traditionally depended on historical data analysis and econometric models which in spite of their utility became reconciled to notable limitations (Channe, 2024). For instance, the economic "nowcasting" and "forecasting" consists of using the AI technologies in order to detect the early signs of the economic turmoil, thus allowing the policymakers to course-correct quicker and direct the economy through the multiple economic cycles (Channe, 2024). For example, the OECD nowcasts weekly GDP growth by using the data from 46 countries across the numerous economic sectors (Channe, 2024). Additionally, the model makes use of machine learning in order to identify the correlations between the frequency of the searches for the terms such as "unemployment", "investment", "crisis", and "recession", as well as the changes in the varying GDP constituents (Channe, 2024). Thus, by providing the real-time measures with regards to the economic activity, the OECD Weekly Tracker can readily quickly evaluate the changing data, as in the event of an economic crisis (Channe, 2024).

The integration of big data into the field of economic forecasting makes use of multiple advanced techniques along with tools (Bello, 2022). Data mining techniques facilitate the extraction of valuable insights from large, complex datasets, while real-time analytics enable prompt decision-making based on current information (Bello, 2022). For example, the predictive analysis that is conducted for the stock market can forecast the price movements with substantial accuracy, while the analysis of the consumer spending patterns extends valuable insights into the retail trends (Bello, 2022). Further, the economic policy making benefits deeply from the incorporation of big data (Bello, 2022). The decision making that is derived from data permits for the design of the policies that are more responsive to the real-time economic conditions that are customized to the particular factors (Bello, 2022). Through continuous monitoring and evaluation of policy impacts via real-time data, policymakers can adapt strategies effectively and promptly, ensuring improved outcomes (Bello, 2022). This effective approach contrasts sharply with the traditional methods that are many times relied on the delayed and less comprehensive data (Bello, 2022).

Challenges such as time lags, data scarcity, and accuracy issues often impeded precise forecasting in the past (Bello, 2022). Nevertheless, the upsurge of big data, fuelled by the advancements in technology and the expansion of digital information, has brought about new dimensions to economic analysis (Bello, 2022). Furthermore, Applying AI models for demand forecasting enhances the accuracy of the forecasts thus enabling the reduction of margins or the errors exponentially (Guerrero, 2024).

In this fast-changing world of financial markets, Artificial Intelligence (AI) and Data Science have changed the ways by which we invest, trade and manage risks (Soudaei, 2024). It thus assists the companies to avoid the overstocking and optimizes the supply chain. Additionally, AI permits companies to foresee market changes and accordingly adjust their pricing strategies presciently and in real-time (Guerrero, 2024). Furthermore, with the predictions being more accurate, the retailers can manage their inventory in a more efficient manner thus reducing the likelihood of excess stock or running out of stock (Guerrero, 2024). Additionally, with the use of AI, companies could also adjust the prices of the products with the inelastic demand in order to improve the profit margin or lower those with more elastic demand in order to boost the sales (Guerrero, 2024).

The stock market often faces volatility, having varying trends and complexity thus making it challenging for the traders, hedge fund managers and portfolio management services (PMS) to face persistent challenges (Bansal, 2024). The use of AI in the financial market has brought a paradigm shift in the way stock investing and trading is conducted (Bansal, 2024). The use of data can be seen as constructive for market data analysis by computing an early warning indicator called the volume-synchronized probability of informed trading (VPIN) on a massive set of futures trading records (Wu et al, 2013). Deep learning holds an opportunity and potential to provide solutions to address the learning and data analysis issues that are present in a large amount of data (Big Data), these are also better at learning the complex data patterns (Sohangir et al, 2018).

Through the use of big data technologies for the purpose of providing and presenting financial and non-financial information regarding the companies whose shares are traded in the financial markets helps the investors in making investment decisions based on that information as well as its analysis (Alshehadeh et al, 2023). Additionally, in order to make various investment decisions, information is considered as an essential pillar in the market and trading on its basis by which the time period that is required to employ each alternative is determined (Alshehadeh et al, 2023). Big data analyses are of high value to the investor within the financial market, therefore the outputs of these analyses, whether good or bad, the market will comply with in a way compatible with the quality and nature of this information (Alshehadeh et al, 2023). The utilisation of various techniques and algorithms for analysing and forecasting stock prices represents a highly promising area of research (Shah et al, 2019).

Furthermore, (Menike et al, 2014) explains that big data analyses plays an important role in the stability of the financial markets by giving appropriate information of the securities to the main dealers who are the market makers and who play an important role in regulating and revitalizing the stock market, which therefore brings about a constant rise in the liquidity within the market which is the demand and supply and pricing efficiency and facilitation of the buying and selling with practicable competitive margins (Alshehadeh et al, 2023).

For instance, a multivariate factor-augmentation Bayesian shrinkage model on big data was used by (Miller et al, 2011) consisting of 143 monthly time series in order to forecast employment in eight sectors of the US economy (Silva et al, 2015). For example, (Gerunov, 2016) claims that the implementation of automated analytics, particularly in the context of time series forecasting, offers the advantage of efficiently generating forecasts for thousands of variables with a relatively high degree of accuracy over short timeframes while utilizing minimal resources.

Additionally, the application of the maximum likelihood estimates of the factor models for Big Data forecasting have been evaluated by (Doz et al, 2012) via a simulation study where the authors find this approach to be effective as well as efficient (Hassani et al, 2015). The prediction of foreign exchange rate is seen as an important and necessary issue in finance, and it attracts various researchers due to its complex nature and practical applications (Dadabada et al, 2018). Although this problem is studied well using the multiple statistical and machine learning techniques in stand-alone mode, many soft computing hybrids were also proposed to solve this problem with the aim of obtaining more accurate predictions during 1998-2017 (Dadabada et al, 2018).

Overall, it can be seen that the integration of big data within the array of economic forecasting has revolutionized the way through which analysts predict and interpret the fluctuations in economic trends. By leveraging a wide range of data taken from multiple sources economists can produce forecasts that are more accurate. Big data is revolutionising economic forecasting and policymaking by offering enhanced insights, greater accuracy, and enabling the development of more responsive and effective strategies (Bello, 2022).

The use of machine learning and AI tools magnifies and strengthens the predictive power that these tools hold. Additionally, by identifying patterns and correlations through the enormous datasets, these tools and technologies can predict potential economic disruptions, forecast unemployment rates, track the trends in inflation, etc. with larger accuracy.

For instance, large factor models use a few latent factors in order to characterize the co-movement of economic variables in a high-dimensional data set (Bai et al, 2016). High dimensionality leads to challenges along with new discernments into the advancement of econometric theory and due to their ability to constructively summarize information within the large datasets, the factor models have been used growingly in economics and finance (Bai et al, 2016). Furthermore, the factor estimates from the high-dimensional data, for instance could, aid in helping improve the forecasting, furnish enough adequate instruments, control for the non-linear unobserved heterogeneity as well as gather cross-sectional dependence (Bai et al, 2016).

At its core, forecasting is enhanced deeply by the use of big data with larger accuracy and preciseness, adaptability and real-time insights. By leveraging advanced pattern recognition and in-depth analysis of sudden market changes, Artificial Intelligence (AI) can effectively evaluate and interpret fluctuations in economic indicators. This capability enhances global trend monitoring and assessment while highlighting the interconnected dynamics that influence local economies. Models developed using big data not only adapt dynamically to new information, thereby increasing their relevance over time, but also facilitate the efficient tracking and management of key economic metrics such as unemployment rates, consumer spending, production activities, and more. By minimising delays inherent in traditional data collection methods, big data significantly transforms economic forecasting, offering quicker, richer, and more precise insights. This enables economists, business leaders, and policymakers to make informed, data driven decisions. These advancements in big data and AI highlight the potential to revolutionise decision making in an increasingly complex and rapidly evolving global landscape, marking a critical turning point in the field of economic forecasting.

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