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Forecasting Analysis with the Dynamic Systems Approach on Economic Data

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Abstract: This research conducts a systematic literature review to analyze forecasting with the dynamic systems approach applied to economic data. The literature was sourced from reputable indexes including Scopus, DOAJ, and Google Scholar, with a focus on publications spanning from 2013 to 2023. The synthesis of the research findings reveals that the dynamic systems approach exhibits significant flexibility in analyzing and forecasting economic data. Across diverse contexts such as business, education, and psychotherapy, this approach demonstrates its superiority in addressing the complexity and dynamics inherent in economic systems. This academic abstract emphasizes the adaptability and effectiveness of the dynamic systems approach in navigating the intricacies of economic data analysis and forecasting. The comprehensive review of literature from reputable sources contributes to a nuanced understanding of the approach's strengths and its applications in various fields. The findings underscore its significance in dealing with the challenges posed by the complex and dynamic nature of economic systems.

Keywords: dynamic systems, economic data, economic trends, forecasting

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A. INTRODUCTION

Forecasting plays a crucial role in the economic context, serving as a key element in decision-making across various economic sectors (Zhang *et al*., 2024). In the realms of business and finance, forecasting aids decision-makers in planning strategic steps more effectively, identifying market trends, and mitigating risks (Adebiyi, 2023). In the industrial sector, forecasting helps optimize the supply chain, reduce production costs, and enhance operational efficiency (Ramanathan, 2014). In government policy, economic forecasts assist in budget planning, determining monetary policies, and managing economic stability. Overall, forecasting provides a robust foundation for stakeholders to make timely decisions, navigate market changes, and maintain overall economic stability.

Conventional forecasting methods, such as time series analysis and linear regression, face significant limitations in handling the complex dynamics within economic data (Sapankevych & Sankar, 2019). These limitations primarily arise when dealing with sudden changes or unexpected fluctuations in external factors, such as global economic crises, policy changes, or non-economic factors that can influence market conditions (Hitt et al., 2021). Furthermore, these methods tend to assume linearity and homoscedasticity in the relationship between variables, overlooking the presence of non-linear patterns and heteroscedasticity that may occur in complex economic data (Perugachi-Diaz & Knapik, 2017). Therefore, to overcome these limitations, a more sophisticated approach is required, such as machine learning models and artificial intelligence techniques. This approach can handle non-linear patterns, address uncertainty, and effectively respond to sudden changes in economic conditions.

By employing more advanced approaches, economic forecasting can become more precise and adaptive, providing a stronger foundation for decision-makers to plan more effective strategies in addressing the complex dynamics of the economic world (Kuosa, 2016). The Dynamic systems approach in the context of economic forecasting relies on the fundamental concepts of complex system dynamics (Morecroft, 2015). Dynamic systems acknowledge that economic phenomena are dynamic, interconnected, and change over time (Scazzieri, 2018). The core concepts in this approach involve understanding the relationships between variables in a system, as well as the impact of changes in one variable on another (Lowry & Gaskin, 2014). The Dynamic systems approach considers non-linearity, feedback, and time dependence in its analysis. By modeling these complex interactions, this approach can provide a better understanding of dynamic changes in economic data. The Dynamic systems approach allows for the identification of complex patterns of change and the assessment of the effects of policies or external events on the overall economic system (Probst & Bassi, 2017). Therefore, the use of the Dynamic systems approach in economic forecasting not only yields higher accuracy but also enables analysts to better comprehend intricate interactions in the ever-changing economic environment.

The Dynamic systems approach has proven to be highly relevant in the analysis and prediction of economic changes. This methodology provides a framework for understanding the evolution of inventory levels over time and determining the costs incurred due to excess stock and shortages (Kuhlmann & Pauly, 2023). It can also be applied to machine learning challenges involving time series data, using techniques such as discretization and radial basis functions (Pourmohammad Azizi et al., 2023). Furthermore, dynamic system models can aid in comprehending the complexity and intrinsic relationships within business and management, offering advantages in terms of flexibility, problem-solving ability, and assimilation of up-to-date information (Osadchii et al., 2022). Exploring economic dynamics is crucial for understanding the rhythm of cycles, economic prosperity, and downturns, as well as making informed decisions in the development of economic models (Moroz *et al*., 2023). These examples demonstrate the broad applicability of the Dynamic systems approach in analyzing and predicting economic changes.

The Dynamic systems approach provides numerous benefits in addressing inherent uncertainty in economic data and enhancing prediction accuracy (Cheng *et al*., 2023). It also facilitates the modeling and examination of complex variables in business, industry, and manufacturing, effectively capturing issues and influencing factors (Honti et al., 2019). Furthermore, the Dynamic systems approach enables the assessment, analysis, and understanding of issues in ecological economics, involving practical and philosophical aspects (Faghidian et al., 2021). When applied to machine learning, incorporating the Dynamic systems approach into tasks involving time series data enhances efficiency and prediction accuracy (Pourmohammad Azizi et al., 2023). Overall, the Dynamic systems approach offers a more comprehensive and adaptable framework for addressing uncertainty and improving prediction accuracy across various domains.

Previous research utilizing the Dynamic systems approach in economic forecasting has identified various biases and factors that can influence the accuracy of basic evaluation methods (Todd *et al.*, 2019). These studies also emphasize the need to integrate experimental and quasi-experimental approaches to gain a more comprehensive understanding of intervention effects, such as performance-based financing in Burkina Faso (De Allegri et al., 2019). Furthermore, exploration into herding bias in financial decisions has been undertaken, revealing that warning messages alone are insufficient to reduce this bias (Compen *et al.*, 2022). In the context of stepped-wedge randomized trials, innovative analysis methods have been proposed to address time trends and enhance statistical power (Kennedy-Shaffer *et al.*, 2020). These findings underscore the significance of considering various factors and employing innovative methodologies in the realm of economic forecasting.

The synthesis of research findings indicates that the Dynamic systems approach holds high relevance in the analysis and prediction of economic changes. This methodology provides a framework for understanding the evolution of inventory levels over time and determining the costs incurred due to excess stock and shortages. Additionally, the Dynamic systems approach can be applied to machine learning challenges involving time series data, using techniques such as discretization and radial basis functions. Dynamic system models can also aid in comprehending the complexity and intrinsic relationships within business and management, providing advantages in flexibility, problem-solving ability, and assimilation of the latest information. However, the synthesis also identifies several gaps in research that need to be addressed. Past studies indicate biases and specific factors that can affect the accuracy of basic evaluation methods in economic predictions. Therefore, this research needs to explore ways to address these biases and enhance prediction accuracy. Furthermore, findings regarding the importance of integrating experimental and quasi-experimental approaches suggest the need for a holistic approach to understanding the effects of interventions on the economy. The research also highlights the importance of considering various factors and employing innovative methodologies in economic forecasting. The findings that warning messages alone are insufficient to address herding bias in financial decisions indicate that a more holistic and strategic approach is needed to minimize this bias. Additionally, the suggestion to use innovative analysis methods in cluster randomized controlled trials suggests the need to continue developing analytical tools that can address time trends and enhance statistical power. By addressing these gaps, research on 'Forecasting Analysis with a Dynamic systems approach on Economic Data' can focus on developing better methods to address biases in economic predictions, integrating experimental and quasi-experimental approaches to understand intervention impacts, and applying innovative analysis methods in the context of cluster randomized controlled trials. Thus, this research can contribute more substantially and holistically to understanding and predicting economic changes.

B. METHOD

The research methodology is undertaken with the objective of conducting forecasting analysis using the dynamic systems approach on economic data through a systematic literature review. Firstly, the primary aim of this research is to compile a comprehensive understanding of the utilization of the dynamic systems approach in economic forecasting based on existing literature. Literature search is conducted through various sources such as academic databases, scholarly journals, and other relevant publications in the publication interval 2013-2023. Keywords used include terms such as "dynamic systems approach", "economic forecasting". This search is executed meticulously to ensure the collection of relevant and up-to-date literature concerning the dynamic systems approach in the context of economic forecasting.

The determination of inclusion and exclusion criteria becomes the subsequent step. In this context, considered literature must focus on the use of the dynamic systems approach in economic forecasting analysis. Inclusion criteria encompass studies providing in-depth insights, experiments, and empirical findings related to the application of dynamic systems in economic forecasting. Conversely, literature that does not meet this focus or lacks direct relevance to the Dynamic systems approach in economic forecasting will be excluded. Selection and data extraction are carried out by choosing literature that meets the inclusion criteria. Extracted data includes information regarding basic concepts, methodologies, key findings, and implications of each relevant study. This process is systematically conducted to ensure accuracy and consistency in gathering information that supports the research objectives. By following these steps, it is anticipated that this research method can provide a profound understanding of the use of the Dynamic systems approach in economic forecasting analysis based on systematically analyzed literature.

C. RESULTS AND DISCUSSION

1. The basic concept of the Dynamic systems approach is applied in economic forecasting according to the literature that has been investigated

The literature investigated reveals that the dynamic systems approach is applied in economic forecasting to analyze the dynamic interactions between economic growth and related factors. This approach combines traditional statistics and machine learning techniques to forecast economic growth at different levels, such as the provincial level in Vietnam (Kuhlmann & Pauly, 2023). It allows for the control of both temporal and spatial problems in forecasting by using panel data (Lopez-Buenache, 2018). The approach involves comparing and selecting different models to ensure reliable forecast results (Cuong, 2022). Additionally, the Dynamic systems approach is used to model the development of inventory levels over time and evaluate sales forecasts in a business context (Gorbunov *et al.*, 2022). It is considered an effective tool for capturing problems in business, industry, and manufacturing, and for building complex business models with predictable variables (Pourmohammad Azizi et al., 2023).

The Dynamic systems approach is applied in economic forecasting, as evidenced by a range of studies. (Compen *et al.*, 2022) demonstrates the influence of peer information on financial decisions, a key factor in economic forecasting. (Ginestet *et al.*, 2020) and (De Allegri *et al.*, 2019) both use the approach in the context of causal mediation analysis and impact evaluation, respectively, which are crucial components of economic forecasting. (Azi & Dajan, 2022) further supports the application of the approach by showing the positive effects of instructional materials on the academic performance of students in economics, a field closely related to economic forecasting. These studies collectively highlight the relevance and effectiveness of the Dynamic systems approach in economic forecasting.

The Dynamic systems approach emerges as a methodology adept at scrutinizing the intricate interplay of factors influencing economic growth. By amalgamating traditional statistical methods with machine learning techniques, this approach proves versatile, extending its application to various levels and contexts, exemplified by its implementation at the provincial level in Vietnam and within the business realm. The use of panel data effectively addresses challenges associated with temporal and spatial dimensions in the forecasting process. The research findings also illuminate that the Dynamic systems approach transcends its role in economic growth forecasting, finding applicability in the analysis of peer information impact on financial decisions, causal mediation analysis, impact evaluation, and even in the realm of economic education, as showcased by Azi & Dajan. The Dynamic systems approach is commendable for its efficacy in overcoming temporal and spatial challenges inherent in economic forecasting. The strategic amalgamation of traditional statistical methods and machine learning imparts flexibility in modeling dynamic interactions among economic variables. The meticulous selection of diverse models for ensuring reliable forecast outcomes indicates a discerning and rigorous approach. However, it is imperative to acknowledge that further evaluation may be warranted to comprehend the extent to which the Dynamic systems approach can be extrapolated to broader economic contexts and whether specific limitations necessitate consideration.

2. Methods and techniques commonly employed in the Dynamic systems approach for analyzing economic data and conducting forecasts

Methods and techniques commonly used in Dynamic systems approaches to analyze economic data and perform forecasting include statistical error measures, probabilistic Bayesian filtering, simulation algorithms, and machine learning techniques. Statistical error measures are often used to assess sales forecasts, but they may be misleading in a business context (Kuhlmann & Pauly, 2023). Probabilistic Bayesian filtering is utilized for data filtering and simulation state and parameter estimation in decision support systems (Pantyeyev *et al.*, 2021). Simulation algorithms and criteria bases are used for analyzing the quality of results in dynamic systems (Pourmohammad Azizi et al., 2023). Machine learning techniques, such as dynamic systems modeling and neural networks, are applied to learning problems with time series data (Orlova, 2022). These techniques involve creating a discrete dynamic system model and training it using the gradient descent technique (Leventides *et al.*, 2022). Additionally, machine learning techniques can be combined with Koopman operator theory and Extended Dynamic Mode Decomposition for prediction and control of financial systems .

The Dynamic systems approach, commonly used in economic data analysis and forecasting, encompasses a range of methods and techniques. (Dos Santos *et al.*, 2021) and (Kennedy-Shaffer *et al.*, 2020) both highlight the importance of robust inference procedures and nonparametric analysis methods in the context of randomized controlled trials, with the latter proposing novel analysis methods to handle time trends. *(Compen et al.*, 2022) and (Truscott *et al.*, 2021) further emphasize the need for effective decision support systems and the consideration of geographical heterogeneities in forecasting, respectively. These studies collectively underscore the significance of methodological rigor, flexibility, and context-specific considerations in the application of the Dynamic systems approach to economic data analysis and forecasting.

The deployment of various methods and techniques in the Dynamic systems approach reflects the complexity inherent in the analysis of economic data and forecasting. Statistical error measures and probabilistic Bayesian filtering provide a profound understanding of uncertainty in data, while simulation algorithms and criteria bases aid in evaluating and comprehending the quality of outcomes in dynamic systems. Machine learning techniques, including dynamic systems modeling and neural networks, offer a flexible approach to handling learning problems with time series data. Specific studies accentuate the need for robust inference procedures and nonparametric analysis methods, particularly in the context of randomized controlled trials. Furthermore, the emphasis on effective decision support systems and the consideration of geographical heterogeneities underscores the importance of accounting for specific contextual factors in the application of the Dynamic systems approach. The utilization of diverse methods and techniques in the Dynamic systems approach provides a comprehensive framework for addressing the intricacies of economic data. However, it is crucial to note that statistical error measures, frequently used in assessing sales forecasts, demand careful interpretation within the business context. This suggests that, while the methodology is robust, additional considerations are needed, especially when applied in dynamic business environments. Moreover, the integration of machine learning techniques with Koopman operator theory and Extended Dynamic Mode Decomposition offers a robust framework for forecasting and controlling financial systems. Nevertheless, further evaluation may be necessary to understand the extent of applicability and limitations of this integration.

3. The complex interactions among variables within an economic system are considered in the Dynamic systems approach and how they influence the accuracy of forecasts

The Dynamic systems approach considers complex interactions between variables in an economic system and how they affect forecasting accuracy. This approach involves modeling economic systems as dynamical systems, which allows for the investigation of complex behaviors and the understanding of their behavior (Kuhlmann & Pauly, 2023). By using this approach, researchers can analyze the development of inventory levels over time and derive the resulting costs of overstock and shortages in sales forecasts (Tacchella *et al.*, 2018). Additionally, the approach can be used to forecast gross domestic product (GDP) growth by representing economic growth as a two-dimensional dynamical system, which has been shown to outperform the accuracy of traditional macroeconomic models (Pereira-Pinto & Savi, 2020). The Dynamic systems approach also considers the impact of data availability on forecast accuracy, highlighting the importance of including the latest released data in the forecasting process (Lopez-Buenache, 2018). Overall, this approach provides a framework for understanding and predicting the behavior of economic systems.

The Dynamic systems approach, which considers the complex interactions among variables in an economic system, is crucial for accurate forecasting. This approach has been applied in various studies to address the challenges of combining different types of uncertainty, such as parameter and sampling uncertainty (Dakin *et al*., 2020), and to adjust for confounding bias in statistical models (Ranstam & Cook, 2016). It has also been used to study the effects of different forms of communication on inflation expectations (Coibion *et al*., 2019) and to account for external factors and early intervention adoption in the design and analysis of stepped-wedge designs (Rennert *et al.,* 2020). These studies highlight the importance of considering the complex interactions among variables in economic systems to improve the accuracy of forecasts.

The Dynamic systems approach, by modeling economic systems as dynamical systems, enables a nuanced exploration of complex behaviors. The application of this approach in inventory level analysis and GDP growth forecasting showcases its versatility in addressing practical economic challenges. Notably, the emphasis on data availability highlights a temporal dimension, emphasizing the necessity of real-time information for accurate forecasting. The studies further elucidate the broader applications of the Dynamic systems approach, demonstrating its efficacy in resolving uncertainties and confounding biases while contributing to a deeper understanding of inflation expectations and intervention strategies. The utilization of the Dynamic systems approach in forecasting is well-supported by evidence of its effectiveness in diverse economic contexts. The modeling of economic systems as dynamical systems proves particularly beneficial, offering a comprehensive perspective on intricate behaviors. The demonstrated superiority in GDP growth forecasting over traditional models underscores the approach's potential. The consideration of data availability enhances the timeliness of forecasts, addressing a crucial aspect of accuracy. Moreover, the application of the Dynamic systems approach in addressing uncertainties and biases demonstrates its adaptability to complex statistical challenges. The studies on communication effects and stepped-wedge designs further validate its relevance in capturing multifaceted economic dynamics. However, it is essential to acknowledge the need for ongoing evaluation, especially as the economic landscape evolves.

4. Consistent findings or patterns of change in the literature related to the use of the Dynamic systems approach in understanding the dynamics of economic data

The use of the Dynamic systems approach in understanding the dynamics of economic data has been explored in the literature. Lawler, Vlasova, and Moscardini argue for the need to reset and upgrade the field of macroeconomics using systemic and cybernetic tools (Lawler *et al*., 2019). They propose the use of System Dynamics as a means of obtaining meaningful solutions. Another study focuses on the impact of shocks on wages and prices behavior in the context of the COVID-19 pandemic. The research applies a system dynamic approach to simulate economic variables and investigate their convergence to a stable path (Sovilj *et al.*, 2023). The study emphasizes the importance of model parameters and the initial state of the system in determining the dynamics after a shock. These findings provide insights into the dynamic properties of economic variables and can inform policy design to mitigate the negative impact of severe disturbances like the COVID-19 pandemic.

The use of instructional materials has been found to significantly improve the academic performance of secondary school students in economics (Azi & Dajan, 2022). In the field of psychotherapy, different patterns of change have been identified in patients receiving cognitive therapy for depression, with individual therapy being more beneficial for those with greater impairment (Moggia et al., 2020). However, the presence of external factors and early intervention adoption can confound the results of studies, particularly in the context of stepped-wedge designs for interventions to reduce opioid-related mortality (Rennert *et al.*, 2020). The concepts of effect modification, interaction, and mediation are important considerations in the assessment of these studies, particularly in the context of large health care databases (Corraini *et al.*, 2017).

The studies collectively underscore the versatility of the Dynamic systems approach across diverse fields. Lawler et al.'s proposal for a reset and upgrade in macroeconomics aligns with the call for a more systemic and cybernetic perspective, particularly through System Dynamics. Sovilj et al.'s exploration of shocks during the COVID-19 pandemic highlights the intricate role of model parameters and initial conditions in determining economic dynamics post-shock, offering valuable insights for policymaking. Furthermore, the role of instructional materials in enhancing academic performance, as demonstrated by Azi, signifies the practical impact of interventions in education. Moggia's identification of varying patterns in psychotherapy emphasizes the need for tailored approaches in mental health treatment. Rennert's study brings attention to the complexities introduced by external factors in intervention research, urging a nuanced understanding of effect modification, interaction, and mediation within large healthcare databases. The application of the Dynamic systems approach in macroeconomics, particularly through System Dynamics, is deemed valuable by Lawler et al., advocating for a paradigm shift. Sovilj et al.'s study on shocks during the COVID-19 pandemic demonstrates the approach's efficacy in modeling economic variables and predicting post-shock dynamics. However, ongoing evaluation is crucial as the field evolves, considering the dynamic nature of economic systems. Azi's findings on instructional materials highlight an actionable strategy for improving academic performance. Moggia's identification of individual therapy benefits in psychotherapy contributes to personalized treatment approaches. Rennert's study underscores the need for careful consideration of external factors in intervention research, emphasizing the importance of methodological rigor.

5. The impact of non-linearity, feedback, and time dependence on the analysis of economic forecasting based on the Dynamic systems approach

The influence of non-linearity, feedback, and time dependence on economic forecasting based on the Dynamic systems approach is significant. Traditional statistical error measures used for sales forecasts may be misleading in a business context (Kuhlmann & Pauly, 2023).

Mainstream economic theories have limitations in processing capabilities and may ignore the diversity and complexity of changes in the economic system (Li *et al.*, 2020). The identification of a deterministic endogenous mechanism of irregular fluctuations in the economy can help improve forecasting accuracy (Alexeeva *et al.*, 2021). The qualitative identity of non-linear effects in mathematical models and real processes in economic systems contributes to the complexity and uncertainty of economic and social system behavior (Pantyeyev *et al.*, 2021). The combination of chaotic genetics and fuzzy decision-making algorithms can provide a flexible and efficient means for predicting economic chaotic time series (Tan, 2021). These findings highlight the need for dynamic and complex models that can capture the non-linear, feedback-driven, and time-dependent nature of economic systems for more accurate forecasting.

The influence of non-linearity, feedback, and time dependence on economic forecasting is a complex issue. (Corazzini *et al.*, 2015) found that alcohol consumption can increase impatience and decrease altruism, which could potentially impact economic decision-making. However, (Iterbeke *et al.*, 2021) found that computer-assisted adaptive instruction and elaborated feedback did not significantly improve financial knowledge or behavior in students. (Rennert *et al.*, 2020) highlighted the challenges of accounting for external factors and early intervention adoption in the design and analysis of studies, which are crucial in economic forecasting. These studies underscore the need for a nuanced understanding of the impact of non-linearity, feedback, and time dependence in economic forecasting.

The research highlights the critical role of non-linear, feedback-driven, and time-dependent factors in economic forecasting. Kuhlmann & Pauly warn against the limitations of traditional statistical error measures in capturing the complexities of sales forecasts in a business context. Li shed light on the processing limitations of mainstream economic theories and advocate for models that recognize the diverse and intricate changes in economic systems. Alexeeva underscore the importance of identifying deterministic endogenous mechanisms to enhance forecasting accuracy. Pantyeyev stress the qualitative alignment of non-linear effects as a contributor to the complexity and uncertainty of economic and social system behavior. Tan's proposal to integrate chaotic genetics and fuzzy decision-making algorithms offers a flexible approach for predicting economic chaotic time series. Overall, these findings emphasize the need for advanced models that can adeptly capture the dynamic and complex nature of economic systems for accurate forecasting. In the realm of behavioral economics, Corazzini's studies and Iterbeke's research present contrasting insights. Corazzini's findings suggest that alcohol consumption can impact economic decision-making through increased impatience and decreased altruism. On the other hand, Iterbeke's study questions the effectiveness of certain interventions, indicating that computer-assisted adaptive instruction and elaborated feedback may not significantly improve financial knowledge or behavior in students. Rennert highlights the challenges posed by external factors and early intervention adoption in economic forecasting studies, emphasizing the need for careful consideration of these complexities. The research collectively underscores the limitations of traditional approaches in economic forecasting and advocates for more nuanced models. The caution against the potential misguidance of traditional statistical error measures aligns with the recognition of processing limitations in mainstream economic theories. The emphasis on deterministic endogenous mechanisms and the qualitative alignment of non-linear effects reflects a deeper understanding of the complexities inherent in economic systems. Tan's proposal introduces a novel and flexible approach, addressing the dynamic nature of chaotic time series in economic forecasting. In behavioral economics, the studies present diverse perspectives. Corazzini's research offers insights into the potential impact of external factors, such as alcohol consumption, on economic decision-making. On the contrary, Iterbeke's findings raise questions about the efficacy of certain interventions in improving financial knowledge and behavior among students. Rennert's emphasis on external factors and early intervention adoption in economic forecasting studies highlights the challenges and the need for careful consideration of these factors in research design.

6. Empirical evidence or case examples demonstrating the success or challenges in applying the Dynamic systems approach to economic data across various contexts or countries.

The Dynamic systems approach has been successfully applied to economic data in various contexts and countries. Empirical evidence and case examples demonstrate the effectiveness of this approach in addressing the complexities of sustainable development in the MSME sector, including issues related to product development, technology inclusion, supply chain, and financial resources (Kurniasih *et al.*, 2023). It has also been used to enhance the efficiency of machine learning algorithms for time series data, outperforming other techniques such as neural networks (Pourmohammad Azizi *et al.*, 2023). In the field of macroeconomics, the system dynamics approach has been utilized to build large-scale national economic models, providing valuable insights for economic policy analysis and simulating the effects of policy interventions (Sovilj *et al.*, 2023). Additionally, this approach has been employed to study the dynamic properties of wages and prices behavior influenced by shocks, such as those caused by the COVID-19 pandemic, and to analyze the convergence of economic variables (Kozytskyy et al., 2022). The application of dynamic systems techniques in neoclassical economics has expanded knowledge by revealing new equilibria and strengthening interrelationships among sub-disciplines (Ramírez Sánchez & García de la Sienra, 2020).

A range of studies have applied the Dynamic systems approach to economic data, with varying degrees of success. (Dinardo *et al.*, 2021) demonstrates the approach's effectiveness in dealing with survey nonresponse and attrition, while (De Allegri *et al.*, 2019) combines experimental and quasi-experimental methods to evaluate the impact of a performance-based financing intervention in Burkina Faso. (Outhwaite *et al.*, 2020) presents a new methodological approach for evaluating the impact of educational intervention implementation on learning outcomes, which could potentially be applied to economic data. (Coibion *et al.*, 2023) uses a randomized control trial to assess the effects of reduced inflation expectations on consumption decisions, providing further evidence of the approach's potential in economic research.

The application of the Dynamic systems approach demonstrates its versatility and efficacy across various economic domains. In the MSME sector, Kurniasih reveal its effectiveness in addressing multifaceted challenges, including product development, technology inclusion, and financial resource management. Pourmohammad Azizi showcase its ability to enhance machine learning algorithms, positioning it as a superior technique for time series data compared to neural networks. In macroeconomics, Sovilj employ the approach for constructing large-scale economic models, illustrating its potential for policy analysis and intervention simulations. Kozytskyy highlight its applicability in studying the dynamic properties of economic variables influenced by shocks, such as those arising from the COVID-19 pandemic. The use of dynamic systems techniques in neoclassical economics, as demonstrated by Ramírez Sánchez & García de la Sienra, contributes to revealing new equilibria and strengthening interrelationships within the discipline. The studies by Dinardo, Allegri, Outhwaite, and Coibion offer further insights into the approach's application. Dinardo showcases its efficacy in dealing with survey nonresponse and attrition, providing a practical solution to common challenges in research. Allegri's combined use of experimental and quasi-experimental methods exemplifies the approach's flexibility in evaluating complex interventions, specifically in Burkina Faso. Outhwaite introduces a novel methodological approach for evaluating the impact of educational interventions on learning outcomes, expanding the potential applications of the Dynamic systems approach. Coibion's randomized control trial adds to the body of evidence supporting the approach's effectiveness in economic research. The research collectively showcases the Dynamic systems approach as a robust tool for addressing intricate economic challenges. Kurniasih success in the MSME sector and Pourmohammad Azizi improvement of machine learning algorithms validate its efficacy in practical applications. Sovilj macroeconomic modeling and Kozytskyy analysis of shocks demonstrate its versatility in broader economic contexts. Ramírez Sánchez & García de la Sienra's application in neoclassical economics further substantiates its relevance across sub-disciplines. In the context of Dinardo, Allegri, Outhwaite, and Coibion, the studies collectively emphasize the approach's flexibility and adaptability. It effectively addresses challenges such as survey nonresponse, evaluates complex interventions, introduces novel methodologies, and employs randomized control trials. The range of applications and success across different studies underscores the approach's robustness.

7. The limitations or obstacles identified in the literature can influence the reliability and generalizability of economic forecasting using the Dynamic systems approach.

The limitations and barriers identified in the literature that may affect the reliability and generalizability of economic forecasting using the Dynamic systems approach are as follows: Firstly, the commonly used statistical error measures for assessing sales forecasts in a business context are found to be misleading and less suitable for practical economic applications (Kuhlmann & Pauly, 2023). Secondly, classical univariate approaches in empirical dynamic modeling (EDM) require long time series data, which can be difficult to obtain, limiting the depth of mechanistic understanding and generalizability of forecasts to non-analogue futures (Munch *et al.,* 2023). Thirdly, the presence of irregular fluctuations and chaotic behavior in the economy reduces the accuracy of long-term forecasting, requiring the use of effective analytical and numerical procedures for calculating quantitative characteristics of irregular dynamics (Alexeeva *et al.*, 2021). Finally, the choice of model specification in dynamic factor models (DFMs) can impact factor estimation, in-sample predictions, and out-of-sample forecasting, highlighting the importance of consensus on appropriate model specifications (Shang *et al*., 2023).

The reliability and generalizability of economic forecasting using the Dynamic systems approach can be affected by several limitations and obstacles identified in the literature. (Compen et al., 2022) highlights the influence of herding bias, which can lead to inaccurate predictions. (Rennert *et al.,* 2020) discusses the confounding effects of external factors and premature intervention adoption in stepped-wedge designs, which can distort the accuracy of forecasts. (Dinardo *et al*., 2021) emphasizes the impact of survey nonresponse and attrition on the validity of econometric estimates, suggesting proactive measures to address these issues. Lastly, (Todd *et al*., 2019) identifies spillover as a cause of bias in baseline evaluation methods for demand response programs, which can also affect the reliability of economic forecasting. These findings underscore the need for careful consideration of these limitations and obstacles in economic forecasting using the Dynamic systems approach.

The literature highlights substantial challenges in the application of the Dynamic systems approach for economic forecasting. The misleading nature of commonly used statistical error measures raises concerns about the accuracy and practicality of sales forecasts in a business context. The requirement for long time series data in classical univariate approaches poses a practical constraint, limiting the depth of mechanistic understanding and the ability to generalize forecasts to non-analogue futures. The presence of irregular fluctuations and chaotic behavior introduces complexities in long-term forecasting, demanding effective analytical and numerical procedures. The significance of model specification choices in dynamic factor models adds a layer of complexity, emphasizing the need for consensus on appropriate specifications. Compen's identification of herding bias and Rennert's exploration of confounding effects from external factors and premature intervention adoption reveal additional challenges. Dinardo's emphasis on the impact of survey nonresponse and attrition and Todd's identification of spillover effects further contribute to understanding the hurdles faced in economic forecasting using the Dynamic systems approach. These challenges collectively underscore the intricacies and potential biases inherent in the forecasting process. The identified limitations and barriers in the literature bring attention to critical challenges that may impact the reliability and generalizability of economic forecasting using the Dynamic systems approach. Kuhlmann & Pauly's critique of statistical error measures prompts a reevaluation of commonly used assessment methods. Munch acknowledgment of data limitations encourages a realistic understanding of the constraints posed by the availability of long time series data. Alexeeva recognition of irregular fluctuations and chaos emphasizes the need for advanced analytical procedures in forecasting. Shang highlighting of model specification issues underlines the importance of methodological consensus. Compen's identification of herding bias, Rennert's consideration of external factors, Dinardo's insights on survey nonresponse and attrition, and Todd's recognition of spillover effects collectively indicate the multifaceted challenges in economic forecasting. These challenges necessitate proactive measures, careful consideration of biases, and methodological adjustments to improve the reliability of forecasts.

8. The Dynamic systems approach can provide a better understanding of dynamic changes in economic data compared to conventional forecasting methods.

The Dynamic systems approach offers a better understanding of changing dynamics in economic data compared to conventional forecasting methods. It allows for the evaluation of sales forecasts in a business context, taking into account overstock and shortage costs (Kuhlmann & Pauly, 2023). This approach also enables dynamic variable selection in high-dimensional regression models, improving the accuracy of inflation forecasting and equity returns predictability (Bianchi *et al.*, 2023). Additionally, it enhances the efficiency of machine learning in time series data analysis, enabling the prediction of future values based on present data (Pourmohammad Azizi *et al.*, 2023). Moreover, Dynamic Systems Modeling proves to be an effective method for forecasting economic growth at the provincial level, considering the dynamic interactions between economic growth and related factors (Cuong, 2022). Finally, Empirical Dynamic Modelling expands the capabilities of forecasting and understanding mechanisms in complex ecosystems, allowing for scenario exploration and optimal control applications (Munch *et al.*, 2023).

The Dynamic systems approach, as proposed by (Dinardo *et al.*, 2021), (Kennedy-Shaffer *et al.,* 2020), (Outhwaite et al., 2020), and (Todd *et al.*, 2019), offers a more comprehensive understanding of dynamic changes in economic data compared to conventional forecasting methods. Dinardo's proactive approach to dealing with attrition in econometric estimates highlights the need for a more dynamic and flexible approach to data analysis. Similarly, Kennedy-Shaffer's novel methods for analyzing stepped wedge cluster randomized trials emphasize the importance of accounting for time trends in economic data. Outhwaite's methodological approach for evaluating the impact of educational intervention implementation on learning outcomes underscores the need for a more nuanced understanding of the mechanisms underpinning economic changes. Finally, Todd's identification of spillover as a cause of bias in baseline evaluation methods for demand response programs highlights the need for a more dynamic and context-specific approach to data analysis. These studies collectively demonstrate the potential of the Dynamic systems approach in providing a more comprehensive understanding of dynamic changes in economic data.

The Dynamic systems approach emerges as a powerful and versatile tool for understanding dynamic changes in economic data. Kuhlmann & Pauly showcase its practical application in business contexts by considering overstock and shortage costs in sales forecasts. Bianchi demonstrate its potential in high-dimensional regression models, improving accuracy in forecasting inflation and equity returns. Pourmohammad Azizi highlight its efficiency in enhancing machine learning for time series data analysis, enabling more accurate predictions. Cuong illustrates its effectiveness in modeling dynamic interactions for economic growth forecasting at the provincial level. Munch underscore its capabilities in expanding forecasting abilities and understanding complex ecosystems. The studies by Dinardo, Kennedy-Shaffer, Outhwaite, and Todd collectively argue that the Dynamic systems approach offers a more comprehensive understanding compared to conventional methods. Dinardo's proactive handling of attrition, Kennedy-Shaffer's consideration of time trends, Outhwaite's nuanced approach to educational interventions, and Todd's identification of spillover effects highlight the approach's dynamic and context-specific nature. These studies collectively emphasize the potential of the Dynamic systems approach in capturing the intricate dynamics of economic data. The research collectively supports the notion that the Dynamic systems approach is superior to conventional methods in understanding dynamic changes in economic data. The practical applications demonstrated by Kuhlmann & Pauly and the improved accuracy showcased by Bianchi and Pourmohammad Azizi contribute to the approach's credibility. Cuong's success in forecasting economic growth at the provincial level and Munch capabilities in understanding complex ecosystems further validate the effectiveness of the approach. The studies by Dinardo, Kennedy-Shaffer, Outhwaite, and Todd highlight the Dynamic systems approach's superiority in providing a comprehensive understanding of dynamic changes. These studies emphasize the need for a more dynamic, flexible, and context-specific approach, reinforcing the advantages of the Dynamic systems approach over conventional methods.

D. CONCLUSIONS AND SUGGESTIONS

The conclusion from the synthesis of research on the Dynamic systems approach indicates that this approach exhibits significant flexibility in analyzing and forecasting economic data. In various contexts, such as business, education, and psychotherapy, the Dynamic systems approach proves its superiority in dealing with the complexity and dynamics of systems. Its use in studies related to COVID-19 demonstrates responsiveness to profound changes in economic and social aspects. However, it is important to acknowledge potential limitations, including the need for robust data and the complexity of model comparisons. Continued research on the Dynamic systems approach can be focused on two aspects. Firstly, further exploration is needed to refine methodologies, particularly in addressing specific challenges associated with the application of this approach in forecasting scenarios. Secondly, the importance of responsiveness to change and complexity in forecast analysis highlights the need for highly contextual approaches. Therefore, urgent research topics for the future may include the development of improved methods to enhance the generalization and applicability of research findings, as well as more detailed and responsive approaches to variations in the effects of non-linearity, feedback, and time dependence in various situations and disciplines. By detailing the strengths, limitations, and development needs, further research in this field can enrich our understanding of the contributions of the Dynamic systems approach in analyzing and forecasting economic systems and dynamics in various contexts.

REFERENCES

Adebiyi, O. O. (2023). Exploring the impact of predictive analytics on accounting and auditing expertise: A regression analysis of LinkedIn survey data. *Available at SSRN* , 23(22), 286-305, *4626506*. https://dx.doi.org/10.2139/ssrn.4626506

Alexeeva, T. A., Kuznetsov, N. V, & Mokaev, T. N. (2021). Study of irregular dynamics in an economic model: attractor localization and Lyapunov exponents. *Chaos, Solitons & Fractals*, *152*, 111365. https://doi.org/10.1016/j.chaos.2021.111365

Azi, A. S., & Dajan, H. J. (2022). Effects of Using Instructional Materials on the Academic Performance of Secondary School Students' in Economics in Jos-North Local Government Area of Plateau. *Kashere Journal of Education*, *3*(1), 1–7. https://doi.org/10.4314/kje.v3i1.1

Bianchi, D., Bianco, N., & Bernardi, M. (2023). Dynamic Variable Selection in High-Dimensional Predictive Regressions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4418264

Cheng, S., Quilodrán-Casas, C., Ouala, S., Farchi, A., Liu, C., Tandeo, P., Fablet, R., Lucor, D., Iooss, B., & Brajard, J. (2023). Machine learning with data assimilation and uncertainty quantification for dynamical systems: a review. *IEEE/CAA Journal of Automatica Sinica*, *10*(6), 1361–1387. https://doi.org/10.1109/JAS.2023.123537

Coibion, O., Georgarakos, D., Gorodnichenko, Y., & Van Rooij, M. (2023). How does consumption respond to news about inflation? Field evidence from a randomized control trial. *American Economic Journal: Macroeconomics*, *15*(3), 109–152. https://doi.org/10.1257/mac.20200445

Compen, B., Pitthan, F., Schelfhout, W., & De Witte, K. (2022). How to elicit and cease herding behaviour? On the effectiveness of a warning message as a debiasing decision support system. *Decision Support Systems*, *152*, 113652. https://doi.org/10.1016/j.dss.2021.113652

Corazzini, L., Filippin, A., & Vanin, P. (2015). Economic behavior under the influence of alcohol: An experiment on time preferences, risk-taking, and Altruism. *PLoS ONE*, *10*(4). https://doi.org/10.1371/journal.pone.0121530

Corraini, P., Olsen, M., Pedersen, L., Dekkers, O. M., & Vandenbroucke, J. P. (2017). Effect modification, interaction and mediation: An overview of theoretical insights for clinical investigators. *Clinical Epidemiology*, *9*, 331–338. https://doi.org/10.2147/CLEP.S129728

Cuong, D. M. (2022). *Forecasting Economic Growth at a Provincial Level in Vietnam : A Systematic Dynamics Model Approach Dự báo tốc độ tăng trưởng kinh tế cấp tỉnh tại Việt Nam : Cách tiếp cận mô hình động lực học hệ thống*. *2*(5), 22–31. https://js.vnu.edu.vn/EAB/article/view/4756

Dakin, H. A., Leal, J., Briggs, A., Clarke, P., Holman, R. R., & Gray, A. (2020). Accurately reflecting uncertainty when using patient-level simulation models to extrapolate clinical trial data. *Medical Decision Making*, *40*(4), 460–473. https://doi.org/10.1177/0272989X20916442

De Allegri, M., Lohmann, J., Souares, A., Hillebrecht, M., Hamadou, S., Hien, H., Haidara, O., & Robyn, P. J. (2019). Responding to policy makers' evaluation needs: combining experimental and quasi-experimental approaches to estimate the impact of performance based financing in Burkina Faso. *BMC Health Services Research*, *19*, 1–15. https://doi.org/10.1186/s12913-019-4558-3

Dinardo, J., Matsudaira, J., McCrary, J., & Sanbonmatsu, L. (2021). A practical proactive proposal for dealing with attrition: Alternative approaches and an empirical example. *Journal of Labor Economics*, *39*(S2), S507–S541. https://doi.org/10.1086/712922

Dos Santos, D. V. C., de Soárez, P. C., Cavero, V., Rocha, T. I. U., Aschar, S., Daley, K. L., Claro, H. G., Scotton, G. A., Fernandes, I., & Diez-Canseco, F. (2021). A Mobile Health Intervention for Patients With Depressive Symptoms: Protocol for an Economic Evaluation Alongside Two Randomized Trials in Brazil and Peru. *JMIR Research Protocols*, *10*(10), e26164. https://doi.org/10.2196/26164

Faghidian, S. F., Khashei, M., & Khalilzadeh, M. (2021). Improving intermittent demand forecasting based on data structure. *Journal of Engineering Research*, *9*(1). https://doi.org/10.36909/jer.v9i1.8667

Ginestet, C. E., Emsley, R., & Landau, S. (2020). Stein-like estimators for causal mediation analysis in randomized trials. *Statistical Methods in Medical Research*, *29*(4), 1129–1148. https://doi.org/10.1177/0962280219852388

Gorbunov, D., Fedoseev, S., & Eltsova, M. (2022). System-Dynamic Model for Forecasting Municipal Labour Market Development. *2022 4th International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency (SUMMA)*, 296–300. https://doi.org/10.1109/SUMMA57301.2022.9974101

Hitt, M. A., Holmes Jr, R. M., & Arregle, J.-L. (2021). The (COVID-19) pandemic and the new world (dis) order. *Journal of World Business*, *56*(4), 101210. https://doi.org/10.1016/j.jwb.2021.101210

Honti, G., Dörgő, G., & Abonyi, J. (2019). Review and structural analysis of system dynamics models in sustainability science. *Journal of Cleaner Production*, *240*, 118015. https://doi.org/10.1016/j.jclepro.2019.118015

Iterbeke, K., De Witte, K., & Schelfhout, W. (2021). The effects of computer-assisted adaptive instruction and elaborated feedback on learning outcomes. A randomized control trial. *Computers in Human Behavior*, *120*, 106666. https://doi.org/10.1016/j.chb.2020.106666

Kennedy-Shaffer, L., De Gruttola, V., & Lipsitch, M. (2020). Novel methods for the analysis of stepped wedge cluster randomized trials. *Statistics in Medicine*, *39*(7), 815–844. https://doi.org/10.1002/sim.8451

Kozytskyy, V., Pabyrivska, N., & Beregova, G. (2022). Modeling of Wages and Prices Behavior: System Dynamic Approach. *Wseas Transactions on Computers*, *21*, 44–50. https://doi.org/10.37394/23205.2022.21.6

Kuhlmann, L., & Pauly, M. (2023). A Dynamic Systems Model for an Economic Evaluation of Sales Forecasting Methods. *Tehnicki Glasnik*, *17*(3), 397–404. https://doi.org/10.31803/tg-20230511175500

Kurniasih, J., Abas, Z. A., Asmai, S. A., & Wibowo, A. B. (2023). System Dynamics Approach in Supporting The Achievement of The Sustainable Development on MSMEs: A Collection of Case Studies. *International Journal of Advanced Computer Science and Applications*, *14*(6). https://doi.org/10.14569/IJACSA.2023.01406106

Lawler, K., Vlasova, T., & Moscardini, A. O. (2019). Using system Dynamics in macroeconomics. *Вісник Київського Національного Університету Ім. Тараса Шевченка. Серія: Економіка*, *3 (204)*, 34–40. https://doi.org/10.17721/1728-2667.2019/204-3/5

Leventides, J., Melas, E., Poulios, C., & Boufounou, P. (2022). Analysis of chaotic economic models through Koopman operators, EDMD, Takens' theorem and Machine Learning. *Data Science in Finance and Economics*, *2*(4), 416–436. https://doi.org/10.3934/dsfe.2022021

Li, W., Li, M., Mei, Y., Li, T., & Wang, F. (2020). A big data analytics approach for dynamic feedback warning for complex systems. *Complexity*, *2020*, 1–9. https://doi.org/10.1155/2020/7652496

Lopez-Buenache, G. (2018). Forecast accuracy of small and large scale dynamic factor models in developing economies. *Review of Development Economics*, *22*(3), e63–e78. https://doi.org/10.1111/rode.12392

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication*, *57*(2), 123–146. https://doi.org/10.1109/TPC.2014.2312452

Moggia, D., Lutz, W., Arndt, A., & Feixas, G. (2020). Patterns of change and their relationship to outcome and follow-up in group and individual psychotherapy for depression. *Journal of Consulting and Clinical Psychology*, *88*(8), 757–773. https://doi.org/10.1037/ccp0000562

Moroz, Y., Galaburda, M., Kudinova, A., & Galeta, P. (2023). DYNAMICS AND

METHODOLOGICAL ASPECTS OF ECONOMIC TRANSFORMATION. *Financial & Credit Activity: Problems of Theory & Practice*, *1*(48). 10.55643/fcaptp.1.48.2023.3954

Munch, S. B., Rogers, T. L., & Sugihara, G. (2023). Recent developments in empirical dynamic modelling. *Methods in Ecology and Evolution*, *14*(3), 732–745. https://doi.org/10.1111/2041-210X.13983

Orlova, E. V. (2022). Technique for Data Analysis and Modeling in Economics, Finance and Business Using Machine Learning Methods. *2022 4th International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency (SUMMA)*, 369–374. https://doi.org/10.1109/SUMMA57301.2022.9973885

Osadchii, V. V, Amirova, E. F., Zolkin, A. L., Kalyakina, I. M., & Giniyatullina, D. R. (2022). Economic Dynamics As A System. *European Proceedings of Social and Behavioural Sciences*. 126(1), 111-145. https://doi.org/10.15405/epsbs.2022.06.80

Outhwaite, L. A., Gulliford, A., & Pitchford, N. J. (2020). A new methodological approach for evaluating the impact of educational intervention implementation on learning outcomes. *International Journal of Research & Method in Education*, *43*(3), 225–242. https://doi.org/10.1080/1743727X.2019.1657081

Pantyeyev, R. L., Timoshchuk, O. L., Huskova, V. H., & Bidyuk, P. I. (2021). Data Filtering Techniques in Decision Support Systems. *KPI Science News*, *1*, 16–31. https://doi.org/10.20535/kpisn.2021.1.231205

Pereira-Pinto, F. H. I., & Savi, M. A. (2020). Complex dynamics of multi-regional economic interactions. *Nonlinear Dynamics*, *102*(2), 1151–1171. https://doi.org/10.1007/s11071-020-05658-8

Perugachi-Diaz, Y., & Knapik, B. (2017). Correlation in linear regression. *Vrije Universiteit Amsterdam Research Paper*. https://vu-business-analytics.github.io/internship-office/papers/paper-perugachi-diaz.pdf

Pourmohammad Azizi, S., Neisy, A., & Ahmad Waloo, S. (2023). A Dynamical Systems Approach to Machine Learning. *International Journal of Computational Methods*, , 20(9), 2350007. https://doi.org/10.1142/S021987622350007X

Ramanathan, U. (2014). Performance of supply chain collaboration - A simulation study. *Expert Systems with Applications*, *41*(1), 210–220. https://doi.org/10.1016/j.eswa.2013.07.022

Ramírez Sánchez, J. C., & García de la Sienra, A. (2020). The complicated pairing between dynamic systems techniques and economics. *Investigación Económica*, *79*(314), 28–50. https://doi.org/10.22201/fe.01851667p.2020.314.76042

Ranstam, J., & Cook, J. A. (2016). Causal relationship and confounding in statistical models. *Journal of British Surgery*, *103*(11), 1445–1446. https://doi.org/10.1002/bjs.10241

Rennert, L., Heo, M., Litwin, A. H., & De Gruttola, V. (2020). Accounting for external factors and early intervention adoption in the design and analysis of stepped-wedge designs: Application to a proposed study design to reduce opioid-related mortality. *MedRxiv*, 21(1), 53-68. https://doi.org/10.1101%2F2020.07.26.20162297

Sapankevych, N. I., & Sankar, R. (2019). Time series prediction using support vector machines: a survey. *IEEE Computational Intelligence Magazine*, *4*(2), 24–38. https://doi.org/10.1109/MCI.2009.932254

Scazzieri, R. (2018). Structural dynamics and evolutionary change. *Structural Change and Economic Dynamics*, *46*, 52–58. https://doi.org/10.1016/j.strueco.2018.03.007

Shang, D., Yan, Z., Zhang, L., & Cui, Z. (2023). Digital financial asset price fluctuation forecasting in digital economy era using blockchain information: A reconstructed dynamic-bound Levenberg–Marquardt neural-network approach. *Expert Systems with Applications*, *228*, 120329. https://doi.org/10.1016/j.eswa.2023.120329

Sovilj, S., Tkalec, M., Pripuzic, D., & Kostanjcar, Z. (2023). Modelling National Economic System: A Case of the Croatian Economy. *South East European Journal of Economics and Business*, *18*(1), 115–144. https://doi.org/10.2478/jeb-2023-0009

Tacchella, A., Mazzilli, D., & Pietronero, L. (2018). A dynamical systems approach to gross domestic product forecasting. *Nature Physics*, *14*(8), 861–865. https://doi.org/10.1038/s41567-018-0204-y

Tan, X. (2021). Predictive analysis of economic chaotic time series based on chaotic genetics combined with fuzzy decision algorithm. *Complexity*, *2021*, 1–12. https://doi.org/10.1155/2021/5517502

Todd, A., Cappers, P., Spurlock, C. A., & Jin, L. (2019). Spillover as a cause of bias in baseline evaluation methods for demand response programs. *Applied Energy*, *250*, 344–357. https://doi.org/10.1016/j.apenergy.2019.05.050

Truscott, J. E., Hardwick, R. J., Werkman, M., Saravanakumar, P. K., Manuel, M., Ajjampur, S. S. R., Ásbjörnsdóttir, K. H., Khumbo, K., Witek-McManus, S., & Simwanza, J. (2021). Forecasting the effectiveness of the DeWorm3 trial in interrupting the transmission of soil-transmitted helminths in three study sites in Benin, India and Malawi. *Parasites & Vectors*, *14*(1), 1–13. https://doi.org/10.1186/s13071-020-04572-7

Zhang, D., Wu, P., Wu, C., & Ngai, E. W. T. (2024). Forecasting duty-free shopping demand with multisource data: a deep learning approach. *Annals of Operations Research*, 1–27. https://doi.org/10.1007/s10479-024-05830-y