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RESEARCH ARTICLE

Agent Based Computational Economics: A Review, Challenges And Future Direction

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Abstract

Agent-Based Computational Economics (from now ACE) is a dynamic field that combines computational techniques with economic theory to model and analyze complex adaptive systems. It originated from Guy Orcutt's pioneering work in 1957, which introduced microsimulation for economic transactions and interactions. ACE has evolved significantly, particularly with advanced computational technologies in the mid-1990s, leading to the rise of agent-based models (ABMs) and complex adaptive systems (CAS). These advancements allow researchers to simulate individual agents' behaviors and interactions within an economy, revealing emergent properties of economic systems. ACE sets itself apart from classical economic theory by incorporating the concept of bounded rationality, which acknowledges that decision-makers have limited information and cognitive capabilities. This approach also emphasizes the constant interaction among these decision-makers and the existence of multiple equilibrium situations. Overall, it offers a heterodox perspective that diverges from the traditional economic modeling methods. However, ACE studies face some challenges and limits. The main objective of this research is to conduct a literature review, analyze the historical progression of ACE, examine recent advancements and challenges, and explore the potential future trajectory of this economic approach.

Keywords: *Agent Based Computational Economics, Bounded Rationality, Heterodox Economics, Multiple Equilibrium, Computational Technology*
Jel Codes: *D00,D01, Z00*

Etmen Tabanlı Kompütasyonel İktisat: Genel Bir Değerlendirme, Eleştiriler Ve Gelecekteki Yön

Özet

Etmen Tabanlı Kompütasyonel İktisat, kompütasyonel teknikleri iktisat teorisi ile kullanarak uyarlanabilir karmaşık sistemleri modellemeye yarayan yenilikçi bir yöntemdir. Bu alanın mihenk taşı Guy Orcutt'un 1957 yılında ekonomik işlemler ve etkileşimler için mikro simülasyonu tanıtan öncü çalışması olarak gösterilebilir. Etmen Tabanlı Kompütasyonel İktisat özellikle 1990'ların ortalarında gelişmiş hesaplama teknolojilerinin ortaya çıkmasıyla önemli ölçüde gelişti ve ajan tabanlı modellerin ve kompleks sistemlerin incelenmesinde kullanıldı. Tüm bu gelişmeler araştırmacıların belirli iktisadi sistemler içinde karar vericilerin etkileşimini simüle edebilmelerini sağladı. Etmen Tabanlı Kompütasyonel İktisat, karar vericilerin sınırlı bilgiye ve bilişsel yeteneklere sahip olduğunu kabul eden sınırlı rasyonellik kavramını modellemelere dahil ederek klasik iktisat teorisinden farklılaşır. Bu yaklaşım aynı zamanda bu karar vericiler arasındaki sürekli etkileşimin yanı sıra çoklu denge durumlarının varlığını da vurgulamaktadır. Bu yönleri ile yaklaşımın heterodoks bir bakış açısına sahip olduğu söylenebilir. Bununla beraber Etmen Tabanlı Kompütasyonel İktisat bazı sınırlamalara ve eleştirilere tabidir. Bu çalışmanın temel amacı bu yaklaşımın tarihsel gelişimini incelemek, sistematik bir literatür taraması sunmak, bu yeni alanın sınırlarını analiz etmek ve Etmen Tabanlı Kkompütasyonel İktisadın gelecekteki potansiyel evrimini tartışmaktır.

Anahtar kelimeler: *Etmen Tabanlı Kompütasyonel İktisat, Sınırlı Rasyonellik, Heteredoks İktisat, Çoklu Denge, Kompütasyonel Teknoloji*
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1. INTRODUCTION

Economies are complex systems that involve micro-level behaviors, interaction patterns, and global regularities. When studying economic systems, researchers must consider challenging real-world factors such as uneven information, imperfect competition, strategic interaction, shared learning, and the potential for multiple equilibria.

Neoclassical (orthodox) economics is no longer deemed adequate for accurately modeling the complexities of modern economic systems and the behavior of individuals. Humans often make decisions based on emotions, frequently make systematic mistakes, and have limited rationality (Meyer, 2023). Therefore, one of the key questions that economists are currently grappling with is ''How to develop models that can effectively capture the behavior of individuals who make decisions based on emotions, are prone to making mistakes, and have bounded rationality?''. One such approach is ACE, which uses computational methods to model economic processes as dynamic systems of interacting agents (Tesfatsion, 2006, 831).

ACE has attracted professionals from various disciplines, including economists, computer scientists, sociologists, and psychologists, leading to significant advancements in methodologies and practical applications. ACE revolves around using Agent-Based Models (ABMs) to simulate the interactions of individual agents with distinct characteristics and specific behavioral rules within a defined environment. These interactions lead to emergent phenomena, such as market trends and economic cycles, shedding light on the relationship between micro-level behaviors and macro-level outcomes. ACE models are instrumental in investigating emergent properties and testing hypotheses about the underlying dynamics of economic systems.

The ACE approach encompasses diverse methods to create and thoroughly analyze economic models, including rigorous mathematical formalism, advanced computational tools, and various programming languages. Within this framework, Monte Carlo simulations are frequently utilized to effectively address uncertainty and variation in economic models, contributing to improved risk assessment and more informed decision-making processes. The latest methodological developments within this field are focused on further strengthening the robustness, adaptability, and empirical validation of these models, ultimately leading to more precise and reliable analysis of complex economic phenomena (Tefsation, 2024).

ACE has many applications, from financial markets and macroeconomic modeling to urban development and social dynamics. It has been utilized to replicate and comprehend market behaviors such as bubbles and crashes and simulate the dynamics of housing markets and urban development.

In social dynamics, the concept of ACE is utilized to study and understand the complex dynamics of segregation, cooperation, and collective behavior within societies. By simulating the interactions of individual agents and their inherent preferences, ACE offers valuable insights into the processes that contribute to the formation and evolution of larger social structures. This approach helps to illuminate how individual choices and interactions can significantly impact and shape the broader social dynamics and structures.

However, agent-based computational economics exhibits potential but faces challenges such as the requirement for empirical validation, accurate parameter estimation, and transforming theoretical concepts into practical computational models. Despite these obstacles, ACE's ability to offer valuable insights into complex economic systems reaffirms its relevance and indicates potential for further growth as a field of study.

The first part of the study will present the history and the general review of agent-based computational economics. The section will start by delving into the intricate nature of the economy and exploring the historical background of agent-based computational economics.

The upcoming section will review relevant literature on agent-based computational economics. The third part will explore the step-by-step installation process for a basic computational model, offering a guide for those looking to understand the practical implementation of these models.

In the final section, we will explore the future development of agent-based computational economics and its limitations and criticisms.

2. NATURE OF ECONOMY

To better understand the economy, treating it as a complex system is important. This requires more realistic behavioral models and capturing the critical components of the economy and their interactions to create realistic models of institutions. The study of complex systems is based on nonlinear mathematics. Complex systems research focuses on the combined properties of these interactions, aiming to characterize emergent phenomena and understand the types of basic interactions that give rise to specific phenomena. Complex systems explore how interesting emergent phenomena emerge from the interactions of basic building blocks. When interactions are linear, the whole is simply the sum of its parts, but in cases with nonlinear interactions, the whole can be greater than the sum of its parts. In the most interesting scenarios, the whole is qualitatively different from the sum of its parts, leading to an emergent phenomenon.

The complex systems approach is in between traditional economic theory and econometrics. Traditional economic theory focuses on top-down decision-making and testing against data later. In contrast, econometrics takes a bottom-up, data-driven approach. The complex systems approach balances these two by taking a bottom-up, data-driven approach while explicitly representing agents and institutions and modeling their interactions without deriving everything from fundamental principles. This approach has the potential to free behavioralism from the constraints of equilibrium modeling and fully incorporate the computer revolution in economics. This path may involve prioritizing economic realism over economic content at times.

The economy is often characterized as a complex adaptive system, meaning that it is a system in which complexity emerges from the interactions of many agents. This complexity results from the large, interconnected system. It can be said that the economy is the outcome of countless individual agents interacting with one another (Bruun, 2004). Like other sciences that deal with large composite systems, economics has a tradition of addressing both micro and macro levels. Microeconomics focuses on the behavior of individual agents, while macroeconomics examines the relationships between aggregate magnitudes. However, uniting these two levels has proven challenging without making very restrictive assumptions. This challenge has led to assumptions of homogeneity and the use of the representative agent construct, which has been heavily criticized by Kirman (1992), among others.

Integrating microeconomics and macroeconomics has been a longstanding challenge. Traditionally, a micro foundation for macroeconomics has been required, which can sometimes dismiss the significance of macroeconomics and overlook the emergence of important system characteristics from interactions. For example, suppose we consider Keynes' concept of effective demand as arising from interactions. In that case, the potential lack of overall demand may be disregarded from the outset because it cannot be fully explained at the micro level.

An intriguing feature of complex adaptive systems is their ability to self-organize and adapt to changing environments. Despite the absence of a global controller, complex adaptive systems seem to function quite effectively. When considering the potential impact of a single agent at a supermarket, it is surprising how infrequently serious market failures occur in economic systems of events a single agent may cause at the supermarket; it is surprising how limited serious market failures in economic systems are.

In conclusion, the economic system can be understood as a complex adaptive system because it exhibits complexity from three primary sources. Firstly, it is a vast and interconnected system composed of numerous interacting parts that influence each other. Secondly, economic agents, including individuals, businesses, and institutions, continuously adapt their behaviors in response to the evolving dynamics of the system. Market conditions, policies, and technological advancements drive this adaptation. Finally, the complexity of the economic system arises from the intricate web of interrelated economic relationships that must hold collectively, even though they may not necessarily apply at the level of individual economic agents. This intrinsic multifaceted complexity contributes to economic systems' intricate and ever-changing nature, making them challenging to understand and predict.

3. LITERATURE REVIEW

There are many important studies related to ACE. Cohen (1960) forcefully presents the conceptual argument for "agent-based computational economics" well ahead of the software tools enabling its practical implementation.

Eliasson's work (1988) combines a Schumpeterian-style creative destruction process with concepts from the Stockholm School. These concepts include ex-ante plans and ex-post realizations, which change systematically over time, setting the model apart from static general equilibrium models. His current research focuses on the roles of individual agents, encompassing entrepreneurial activity, the founding and closure of new businesses, and the natural growth and decline of firms within evolving economic systems. In this analysis, MOSES (Model of the Swedish Economic System) is seen as a model approximation of a broader theory of an Experimentally Organized Economy that evolves through entrepreneurial competition and selection. This theoretical framework, known as the competence bloc theory, offers insights into the commercialization of innovative technologies and the efficiency of that selection.

In another important work, Eliasson (2018) chose four main problems that argued within the mathematical framework of microsimulation and addressed them with the reference model he developed in 1988. The main challenges are as follows: (1) delving into the internal structures of the model to reveal unexpected analytical results that were not previously noticed or considered; (2) assessing the long-term costs and benefits of significant micro-interventions in the economy's structure; (3) examining the long-term historical development of economic systems and contemplating alternative outcomes if history had unfolded differently; and (4) deriving general conclusions from specific case studies.

Bennett and Bergmann (1986) conducted a study that presents an empirically grounded state-space model of an economy formulated at the level of decision-making processes of microeconomic units (firms, consumers, financial intermediaries) and government units (local, state, and federal). Each decision-making unit is modeled as a set of hypothetical if-then decision rules specified constructively (recursively) as state-conditioned transition processes, thus respecting historical cause-and-effect relationships. Initial conditions, decision-making processes, and modeled institutional arrangements are strongly based on empirical data.

Bergmann's work (1974) serves as an introduction to microsimulation. It covers how microsimulation works, how to implement it, its potential, and its drawbacks. The article also provides a simple microsimulation model that allows readers, including those without computer programming experience, to understand the details. Readers can run the model on their PCs, observe its operation, and make their adjustments. Using this model as an example, it is relatively simple to create programs for new models on different topics for theoretical exploration, empirical research, or classroom demonstrations. However, in its actual content, her innovative labor market application (implemented in Fortran) is more similar to an agent-based model, where dynamics are driven by worker-firm interactions rather than a standard microsimulation model with dynamics driven by pre-specified state transition probabilities.

The Santa Fe Institute hosted a workshop titled "Evolutionary Paths of the Global Economy" from September 8-18, 1987, at its campus in Santa Fe. The workshop aimed to investigate the potential benefits of a transdisciplinary research program on the dynamics of the global economic system by bringing together economists and natural scientists who have experience studying nonlinear dynamical systems and adaptive paths in evolutionary systems. The workshop was organized by David Pines, Co-Chair of the Santa Fe Institute Science Board, and moderated by Philip W. Anderson and Kenneth J. Arrow (Arrow et al., 1988), who selected the participants and arranged the program. The scientific papers, presentations, and studies of this important meeting are collected in the book titled The Economy as an Evolving Complex System. In this book, economists and experts from the physical and biological sciences converged to develop a conceptual framework that embraces advanced mathematics. This framework allows for the adept treatment of multifaceted variables, nonlinearity, incomplete information, and dynamic processes in a unified manner.

In their 2001 study, Chen and Yeh researched the impact of price limits on market volatility in an artificial stock market. They utilized agent-based models to simulate market behavior and found that implementing price limits could effectively mitigate market volatility. Their study revealed that price limits constrain the range of price fluctuations during a trading day, which in turn can reduce market volatility.

In his research, Ballot (2002) created a simplified representation of the French labor market as a continuously evolving institution. In this model, firms and individuals make decisions with limited rationality, aiming to reduce costs or maximize utility. The labor market functions through a search process and decentralized establishment of hiring standards, with the potential for intermediaries to expedite the matching process. The model effectively captures the intricacies of employment trends and the substantial changes in mobility patterns among specific demographic segments during the oil crisis of the 1970s. Notably, it demonstrates the sudden decrease in access to high-quality jobs. Ballot's research also suggests that large firms' internal labor markets (ILM) can contribute to higher unemployment rates if no secondary (temporary or low-quality) job opportunities are available.

In Cincotti et al. (2010), the authors examined the relationship between monetary aggregates, output, and prices. The study focused on analyzing the credit provided to firms by commercial banks and the fiat money generated by the central bank through quantitative easing monetary policy. The researchers utilized an agent-based model and simulator, Eurace, to address this issue. This model includes a comprehensive set of interrelated markets and various interacting agents, all modeled using a rigorous balance sheet approach. The dynamics of credit money are endogenous and are influenced by the supply of credit from the banking system, constrained by its equity base, and the demand for credit from firms to finance their production activities. The authors further analyzed the potential influence of varying firms' dividend policies on the dynamic trajectories of credit money. The results revealed the significant impact of monetary aggregates on output and price dynamics. Also, they demonstrated the emergence of endogenous business cycles due to the interplay between real economic activity and credit market financing. The authors found that the amplitude of business cycles increases notably when firms pay out higher dividend fractions, indicating that firms with limited access to credit funding are more likely to experience amplified business cycles. This observation can be linked to the level of firm leverage, as it serves as a proxy for the likelihood of bankruptcy, which could lead to mass layoffs and decreased supply.

Kendrick et al. (2006) have developed a seminal book on computational economics that takes a unique approach by organizing content around economic subjects such as macroeconomics, microeconomics, and finance. The book provides hands-on experience by employing various software systems, including MATLAB, Mathematica, GAMS, Excel's nonlinear programming solver, and Access database systems to cater to individual preferences. It begins with elementary models and gradually moves on to more intricate ones. Additionally, the book features appendices that offer comprehensive guidance on utilizing each program effectively.

In 2006, Chen and colleagues introduced models that utilize computational intelligence to explore economic and financial issues. This body of work covers finance, economics, management, organizational theory, and public policies. It illuminates contemporary and pioneering research in this area, emphasizing the efficacy of computational approaches in addressing intricate problems from traditional perspectives.

Borshchev and Filippov's (2004) paper provides a comprehensive guide for integrating agent-based modeling into analytical toolkits, particularly for systems with many active objects. The authors compare the major paradigms in simulation modeling, namely System Dynamics, Discrete Event, and Agent-Based Modeling, focusing on constructing an Agent-Based model from existing System Dynamics or Discrete Event models. They emphasized enhancing Agent-Based models to capture more complex behavior, dependencies, and interactions. Throughout the paper, the authors used common examples and specified all models in the visual language supported by the AnyLogicTM tool. They emphasized that Agent-based modeling should be viewed as a complementary addition to, rather than a replacement for, older modeling paradigms and proposed several multi-paradigm model architectures.

Sheri M. Markose (2004, 2005) has made groundbreaking contributions to the field by delving into the intricate dynamics of markets as complex adaptive systems (CAS). Her research has delved deep into the computability and evolutionary complexity within markets, shedding light on how markets adapt and evolve in response to the behaviors of the participating agents. By focusing on the interplay of agents in financial markets, her work has revealed the dynamic nature of these markets and the emergent properties that arise from these complex interactions.

As mentioned, Guy Orcutt's effort (1957) is crucial for ACE. The study was a collaborative effort involving three doctoral students—Martin Greenberger, John Korbel, and Alice Rivlin—alongside several programmers, including Steven Goldfeld. The initial model was developed prior to the introduction of FORTRAN, a programming language that revolutionized parallel processing and featured an intuitive array-like syntax for inter-CPU data communication. Each simulation run meticulously portrayed the month-to-month evolution of a sample of 10,358 individuals over ten years. This model predominantly aimed to scrutinize demographic phenomena, such as birth, death, marriage, divorce, aging, and labor supply and education demand. The initial findings of microanalytic modeling can be found in Orcutt et al. (1961).

Baroni and Richiardi (2007) critically analyzed Orcutt's study from a methodological standpoint. They then reviewed the subsequent literature comprehensively, focusing on the study's significance, strengths, weaknesses, and relative merits compared to alternative methodologies. Additionally, they examined the key unresolved issues stemming from Orcutt's work.

The paper demonstrates that the field of microsimulation has developed in line with Orcutt’s vision in many respects. However, further efforts from the scientific community, especially at the methodological level, are needed for his vision to be fully realized. Due to the significant progress in computer technology, such as increased speed, power, and data handling capacity, researchers have found numerous methods of simulated moment (MSM) models worldwide. These models, as intended by Orcutt, are commonly used as tools to assist in policymaking. They help to forecast and simulate the potential effects of current or proposed policy changes on future public costs, poverty levels, and inequality. They also compare these effects across different policy scenarios to help governments choose the best-fitting policy for their aims. Examples of policies tested through MSMs include, e.g., raising the retirement age, introducing new family benefits, or changing social contributions.

Lehtinen and Kuorikoski (2007) conducted studies that highlighted the increasing role of computer technologies in advancing economics and other math-intensive fields through computer-based modeling. They argue that while many models are derived through simple computation, only a few can be considered accurate simulations. The authors explain that simple computation expresses a theory, while true simulation is akin to an experimental procedure. They posit that successful computation adheres to an underlying mathematical model, while successful simulation directly imitates a process or system.

According to the authors, the acceptance of the computer as a valid tool in economics occurs when traditional analytical solutions cannot be derived, essentially serving as a computational aid. They contend that accurate simulation is rarely used because it aligns differently from the mainstream analytical derivation of fundamental economic principles. The authors illustrate this difference using the economists' perfect model idea, highlighting that 'bottom-up' generative microsimulations fail to link assumptions and consequences transparently, thus not corresponding to the ideal model. As a result, economists do not widely consider microsimulations as viable tools for developing theories that enhance economic understanding (Lehtinen & Kuorikoski, 2007).

EURACE is a large-scale project aiming to create a computer model of the European economy. This model will consist of many individual agents, each making purposeful decisions and interacting within a complex economic environment. Creating this model will require significant progress in both economic modeling and software engineering. Deissenberg et al. (2008) outlined the overall structure of the economic model developed for EURACE and introduced the Flexible Large-scale Agent Modelling Environment (FLAME), which will be used to define the agents and run the model on massively parallel supercomputers. The paper also includes sample simulations using a simplified model based on EURACE's labor market module. The researchers have constructed a comprehensive model of the European economy. Although this model may not match the potency of traditional time series and econometric models in economic research, it is anticipated to provide novel insights beyond the reach of conventional methods. The experts affirm that the model will be able to replicate numerous vital statistical patterns observed in real economies, including the distribution of firms' sizes, income and wealth, spatial patterns of human activities, and various features of financial time series. Significantly, the model has been developed to shed light on how aggregate behavior emerges from the interactions of numerous individual agents with more limited cognitive and computational abilities than those presumed in classical economic theory. Preliminary numerical exercises demonstrate promising headway in obtaining new and intriguing results.

In his 2008 review, Gilbert discussed the diverse applications of agent-based modeling (ABM) and provided detailed insights into designing and constructing ABMs, model verification, empirical validation, project planning, and scholarly article composition in the field. Additionally, he furnished a glossary of terms, an annotated resource list, recommendations regarding programming languages and toolkits, and a step-by-step demonstration of an ABM implementation.

Dawid and Neugart (2011) articulated the advantages of employing agent-based modeling in economic policy formulation. They emphasized the need to address certain outstanding issues to enhance the effectiveness of this methodological approach in providing sound policy recommendations. The authors underscored that agent-based models offer a high degree of flexibility, enabling researchers to incorporate economic, institutional, and behavioral frameworks into their analyses. This, they argued, establishes a robust basis for economic policy guidance and facilitates the exploration of issues and phenomena that may elude other methodological approaches.

Nonetheless, they cautioned that, like any methodological choice, it is important to acknowledge and communicate the limitations of agent-based policy analyses to prevent misunderstandings.

Dawid et al. (2012) explored the effects of various labor market integration policies on economic performance and the convergence of disparate regions using an agent-based model. The study revealed that production productivity relies on the quality of capital stock and the specific skills of workers utilizing them. This gives rise to changes in productivity that are influenced by local firms' investments in high-quality capital goods and the changing distribution of worker skills. The researchers showcased the ways in which divergent labor market integration policies lead to distinct regional distributions of specific skills, consequently impacting relative regional prices and determining regional shares in overall consumption demand. The study points to a trade-off between overall output and regional convergence, highlighting that closed labor markets contribute to relatively high convergence but low output. Conversely, more integrated labor markets lead to higher output but lower convergence. Furthermore, the findings demonstrate that different labor market opening policies can yield significantly different outcomes.

In the 2012 study by Grazzini et al., an agent-based approach was employed to investigate the widely recognized Bass innovation diffusion model. The researchers utilized a simulated moment (MSM) estimator method to conduct a Montecarlo analysis. The results indicated that the nonlinearity of moments led to a slight bias in estimates for small populations. However, with an increase in population size, the estimates exhibited consistency and converged towards the true values. This approach holds the potential for estimating more complex agent-based models.

A new study area seeks to integrate macroeconomic ACE insights into traditional dynamic stochastic general equilibrium (DSGE) models. The motivation for this development is the criticism of the ACE approach towards DSGE models. The first concern with DSGE models is that they tend to overlook heterogeneity and bounded rationality, which can lead to a disconnect from real-world economic behavior. Additionally, DSGE models do not extensively incorporate disequilibrium dynamics, which are crucial in understanding fluctuations in supply and demand prices. Lastly, DSGE models may not capture the full range of complex dynamics observed in real economies (Dilaver et al., 2018).

Richiardi (2014) recognized the pioneering contributions of Barbara Bergmann (1974) and Gunnar Eliasson (1977) as the earliest instances of large-scale agent-based models within the dynamic microsimulation literature. According to Richiardi, these efforts to develop comprehensive micro-to-macro computational economic models are significant from a historical economic thought viewpoint and in fostering the integration of both approaches to create viable alternatives to DSGE models.

Grazzini and Richiardi (2013) highlighted the importance of the widespread adoption of agent-based model estimation for its integration into macroeconomics. They underscored two primary challenges in estimating these models: (i) the absence of a straightforward analytical expression for the criterion function, and (ii) the inability to comprehend the aggregate properties of the model analytically. The first challenge necessitates using simulation-based estimation techniques. In contrast, the second requires additional statistical testing to ensure the consistency of the simulated quantities as estimators of the theoretical quantities. The complexity of the issue is further compounded by the large number of parameters and nonlinearities in theoretical quantities used for estimation, similar to those found in DSGE models but to varying extents. The authors drew insights from the existing literature and identified simulated minimum distance (SMD) as a practical approach for estimating agent-based models. They also discussed the conditions required to ensure the consistency of SMD estimators in agent-based models.

In a paper by Sitthiyot (2015), the author examines the limitations of current knowledge in macroeconomics and finance in explaining and forecasting economic and financial phenomena. The paper proposes that applying complexity science could offer a new approach to enhancing our comprehension of the dynamics of economic systems and financial markets. The argument suggests that acquiring insights into the attributes of intricate systems could substantially aid financial analysts, regulators, and macroeconomic policymakers.

Schinckus (2019) discussed various (deductive, abductive, symbolic, and phenomenological) applications of agent-based techniques for modeling economic systems. This paper clarified the epistemic role of each of the four major agent-based techniques used in economics by presenting them. The author stressed that the deductive and abductive categories have extensive documentation, whereas the latter two are relatively new and have received less scrutiny in the literature.

In a study by Seri et al. (2022), the authors emphasized the pivotal role of randomness, emergence, and causation in the evolution of various simulation models. Their literature review provided a brief yet crucial overview of the history of simulation models, focusing particularly on the Social Sciences. They delved into early works involving analog and digital computers, System Dynamics, Discrete-Event Simulation, Microsimulation in Economics and Political Science, Cellular Automata, and Agent-Based Models. The authors concluded that agent-based computational models represent the most current cutting-edge computational simulation approach. While drawing from previous simulation techniques, the comprehensive nature of this approach positions agent-based economics as a significant leap forward.

A critical application of ACE is in asset pricing. Several researchers, including W. Brian Arthur, Eric Baum, William Brock, Cars Hommes, and Blake LeBaron, have created computational models in which multiple agents select from various forecasting strategies to predict stock prices. These predictions then influence their asset demands, subsequently impacting stock prices. The models operate on the assumption that agents tend to choose forecasting strategies that have demonstrated recent success. The effectiveness of a particular strategy is contingent upon market conditions and the current array of strategies in use. These models frequently indicate that significant asset price booms and busts can occur as agents switch between forecasting strategies (Tefsatsion, 2021).

In a noteworthy contribution, Tefsatsion (2023) shed light on a perspective that offers a comprehensive overview of ACE delved into a concise history of its development, and emphasized its significance within the broader context of experiment-based modeling methods.

Suresh's (2023) essay was the pioneering attempt to delineate the progression of economic modeling across disparate schools of economic thought throughout history. It specifically delved into the rational-agent and rational-expectations paradigms and their juxtaposition with behavioral economic revelations and macroeconomic upheavals such as the Great Recession. The essay proposed that tackling these challenges effectively might necessitate incorporating non-rational behavior in agent-based modeling.

As seen from the literature above, agent-based computational economics remains a flourishing and dynamic field, providing valuable insights into the intricacies of economic behavior and the likelihood of emergent phenomena in economic systems.

The upcoming section will investigate the fundamental steps of developing an agent-based computational model.

4. BUILDING AN AGENT-BASED COMPUTATIONAL MODEL

In developing an agent-based computational model, researchers establish distinct agents with individual variables, specific decision rules, and a designated interaction environment. They then observe and analyze the agents' actions to assess the resulting outcomes. This modeling phase involves making several critical decisions, which will be thoroughly discussed in the following section.

4.1 Step 1: Selecting the Language

The first step is to carefully select a suitable programming language. The researcher can either develop the code from the ground up in any programming language of their choice, utilize a matrix-based mathematical environment such as MATLAB or LateX, or opt for a framework specifically designed for agent-based simulations. The choice of programming language will significantly impact the research process and should be made after thoroughly considering the project's requirements and the strengths of each option.

Object-oriented languages are frequently the preferred choice when programming languages are considered. This is because the principles of object-oriented software development closely align with the concepts of agent-based modeling. Both methodologies emphasize decentralization to manage and address complexity within the system.

Researchers frequently encounter constraints when dealing with larger and more intricate models in a mathematical environment. Deciding to develop everything from the ground up requires substantial effort. Frameworks designed for agent-based simulation have been developed to address this issue. However, the model builder must invest significantly in this scenario. An essential advantage of using a framework is the access to pre-built models within the framework.

When embarking on a new modeling project, it is advisable to carefully select a programming language before delving into the specifics of the model. This is because the choice of programming language can significantly impact the availability of support and resources during the modeling process. It is highly recommended to explore existing models for which the source code is accessible, as this can provide valuable insights and potential solutions for your modeling endeavors.

Following a three-step approach to model building is advisable when modeling systems with non-emergent macro properties. This involves macroanalysis, microanalysis, and simulated interaction, as Auyang (2004) outlined. It is crucial to recognize that determining macro-level characteristics directly impacts how we model individual behavior at the micro level. Therefore, ensuring that the theoretical framework is accurately modeled before proceeding to simulation is essential. Accordingly, the researcher should initially assess the presence of macro bindings in the system, such as identifying any relevant tautologies within the research system. Furthermore, model developers need micro-explanations that connect the properties outlined in macro explanations to the properties of the constituents. Micro-explanation depends on macro explanation, which first outlines what needs a micro-explanation.

4.2 Step 2: Thinking About Individual Behavior

Once the researcher has a comprehensive understanding of the system's general properties, she can conduct an in-depth analysis of the behavior exhibited by individual agents within the system. Simplifying the description of economic behavior is crucial, and the primary consideration lies in determining the factors that should govern this simplification.

In her influential study, Bruun (2004) suggests initiating the analysis process with macro-level examination rather than micro-level analysis. This methodology enables the utilization of macro properties to guide the process of simplification. Conversely, starting with micro-level analysis and moving to the macro-level introduces increased complexity and the potential for committing fallacies of composition.

Suppose the macroanalysis indicates that a certain aspect of decision-making does not significantly impact the overall properties of a system. In that case, researchers may feel more lenient in constructing that decision rule. However, it's important to note that the decision rule could still be crucial from a macro perspective as it may be essential for completing or closing the model.

Once the decision has been made regarding the behavior of the individual as an economic agent, the third stage can be progressed.

4.3 Step 3: Simulation

The third and final step of the process involves simulation, which requires the creation of a comprehensive model that seamlessly integrates micro and macro perspectives. This is achieved by enabling agents to interact within a closed world. It is crucial to model a closed system, or at least a system with controlled openness, to guarantee that feedback from the macro to micro levels is effectively enforced. In the context of object-oriented programming, it is advantageous to conceptualize agents (objects) as being characterized by multiple state variables (e.g., wealth and consumption) and endowed with diverse decision rules or methods (e.g., for determining the amount and type of consumption)

The working principle of the model is simple. In a simulation where the behavior patterns of two agents are defined and the simulation is initiated, the main program selects Agent 1 to make a consumption decision for a specific combination of goods. Agent 1 is responsible for finding another agent to purchase the consumption goods in a completely decentralized model. Agent 1 initiates contact with Agent 2 and engages in negotiations for an exchange. If the negotiations are successful, the goods are transferred from Agent 2 to Agent 1, and the money is transferred from Agent 1 to Agent 2.

In agent-based modeling, market interactions can be represented in various methods. One approach involves allowing Agent 1 to list goods for sale at a specific reservation price, allowing other agents to browse the list and purchase goods offered below their reservation price. This creates a decentralized system where no centralized mechanism determines equilibrium prices; however, a centralized institution (the list of goods for sale) remains. If Agent 1 finds that goods are not being sold, they may consider lowering the price (Bruun, 2004). The use of agents for online trading has significantly advanced auction theory, providing valuable opportunities for researchers in the field of ACE to explore and leverage these developments.

After developing a model, evaluating the significance of the institutional choices is crucial. Researchers may find that simultaneous updating heavily influences the results, which sheds light on the model's resilience and practicality. Additionally, the number of agents involved could play a significant role.

Successfully simulating a system depends largely on whether the theoretical framework behind it is well understood and articulated. Models that aim to replicate theoretically derived results tend to be more successful, as they can be analyzed and understood more easily. On the other hand, models that deviate significantly from the theoretical framework may not yield accurate or reliable results.

5. CHALLENGES AND FUTURE DIRECTIONS

Despite all its important features, ACE has to overcome some criticisms. Nevertheless, future developments and its evolution remain exciting. This chapter aims to provide an overview of the criticisms and discuss the future of the field.

5.1 Challenge of ACE

One of the key aspects to consider when comparing ACE models with traditional analytical models is that ACE models come with a unique set of strengths and limitations. A notable challenge is interpreting simulation results and estimating structural parameters within the models. These challenges stem from the inherent complexity and nonlinearity of ACE models, which result in an extensive parameter space and a high sensitivity of model behavior to parameter variations. Accordingly, navigating these complexities and accurately estimating structural parameters can pose significant hurdles in the analysis and application of ACE models (Russo et al., 2018).

Consequently, adjusting the parameter values of ACE models to reflect real-world data accurately is a complex endeavor. Moreover, empirically validating the model presents a significant challenge. In contrast to traditional models, ACE models demand meticulous validation of inputs and outputs against empirical and experimental data, historical evidence, or anecdotal knowledge. This process is vital for ensuring the realism of the assumptions incorporated into the models, such as bounded rationality principles or specific types of interaction networks among agents, and this calls for a rigorous and comprehensive approach to ensure the model faithfully represents real-world phenomena.

Documentation and communication of simulation models are also critical in ACE. The ODD (Overview, Design Concepts, Details) protocol is a widely recognized framework for proper documentation, aiding in understanding and reproducing models. Despite the availability of templates and guidelines, there's a need for uniform adoption of these practices across the ACE field. Moreover, translating theoretical economic concepts into computational models introduces complexity. Verification processes are essential to ensure that the simulation functions as intended. This involves rigorous procedures such as code walkthroughs, debugging, profiling, and parameter sweeps to identify and rectify potential errors (Hailegiorgis et al., 2018).

While necessary, this meticulous process adds to the workload and complexity researchers face in ACE. Therefore, establishing standardized practices for documentation and verification is vital to enhance the credibility and reproducibility of simulation models in the field.

Finally, the fast-paced progress in computer technology brings both opportunities and new methodological challenges for economists. This involves creating new tools and strategies to utilize computational power while effectively addressing the underlying methodological obstacles. Despite these challenges, ACE offers valuable insights into economic systems, especially in areas where traditional models are inadequate.

5.2 The Future of ACE

The future of ACE looks bright, as researchers aim to delve into a multitude of pathways to tackle intricate economic inquiries and respond to evolving global obstacles. A crucial aspect of forthcoming research revolves around the fusion of ACE models with dynamic stochastic general equilibrium (DSGE) models. This integration holds the potential to harness the advantages of both methodologies, providing a more in-depth comprehension of macroeconomic phenomena and empowering policymakers to adeptly confront complex challenges (Gleiser et al., 2024).

Recent developments in methodology have paved the way for a broader application of ACEs across various economic sectors, extending beyond the conventional banking realm. It is anticipated that forthcoming research will delve into the implications of macroprudential policies on a spectrum of areas including housing market dynamics, consumer credit, universal basic income, circular economy, climate adaptation, and corporate lending. This broader scope will help policymakers understand how these policies are transmitted and their potential spillover effects, contributing to more informed decision-making.

Another exciting area of study within ACE is exploring emergent behavior in complex socio-technical systems, especially in the context of air transport operations. It is essential to understand emergent phenomena, which can vary from simple to strong emergence, to enhance the performance and safety of these systems.

In addition, with the ongoing impact of climate change on global economies, it is increasingly important to utilize advanced modeling techniques such as ACEs to simulate various climate risk scenarios. These simulations can provide decision-makers with invaluable insights into the potential economic and environmental costs of inaction, including the implications of not investing in supply chain resilience or sustainable recycling initiatives. By understanding these risks more comprehensively, organizations can make more informed decisions and take proactive steps to address and mitigate the impact of climate change on their operations.

6. CONCLUSION

Agent-based economics is a powerful approach that can effectively simulate the complex behavior of economic agents who exhibit a range of emotions. These agents do not merely act based on reasoning; instead, they often make decisions influenced by their feelings, which can lead to behaviors characterized by systematic errors. For instance, they may experience emotions such as envy and regret, which can profoundly impact their economic choices and strategies. This innovative technique offers valuable insights into how human emotions and irrational behavior can influence economic outcomes. It helps researchers and policymakers understand and address significant questions in economics, paving the way for more nuanced and accurate economic theories and practices. Integrating the psychological dimensions of decision-making enriches our understanding of market dynamics and individual economic behavior. Hence, the response to the inquiry posed by the study, which focuses on devising frameworks capable of accurately representing the actions of individuals whose decisions are influenced by emotions, who are inclined to errors, and who operate within limitations of rationality, can be characterized as ACE.

ACE embodies a contemporary economic modeling approach that melds computational methods with conventional economic theory. It simulates the exchanges among autonomous agents within economic frameworks stemming from progress in computational technology and economic ideology. ACE employs computer simulations to analyze intricate, ever-changing systems defined by diverse agents and adaptive behaviors. This methodology offers a more comprehensive comprehension of economic occurrences compared to traditional models, which frequently assume flawless rationality and equilibrium.

The practical value of ACE is readily apparent in its capacity to provide valuable insights into a diverse range of economic and social phenomena. ACE facilitates a deeper comprehension of complex market dynamics, the effects of different policies, and various social behaviors by employing computer simulations to model interactions among autonomous agents within virtual environments. This approach allows for a more nuanced exploration of numerous areas, such as the emergence of macroeconomic patterns, the drivers of industry evolution, and the dynamics of social networks. However, the main theoretical drawback of this approach is that it becomes challenging to define and delimit economics as a science. In decentralized agent-based models, assuming rational optimizing agents is no longer sufficient as the defining feature of economic theory.

Despite all its essential features, ACE must address some significant criticisms to enhance its overall effectiveness. One major critique revolves around the computational demands and interpretability of results. Despite the advancements in computational power, simulating complex agent-based models can be resource-intensive. This often requires extensive processing time and significant computational resources, which may limit its accessibility and practical application in some contexts.

Some critics argue that agent-based computational economics (ACE) models lack standardized procedures for model validation and may not have the same level of empirical evidence as traditional economic models. They suggest that the simulation results from ACE models may not always be replicable or verifiable, which raises concerns about the reliability of these models in providing accurate economic insights. Additionally, the assumptions underlying ACE models have been scrutinized. While making the depiction of economic interactions more realistic, the autonomy and heterogeneity of agents within these models can also make the models more complex and difficult to analyze and interpret. Moreover, there is a concern that ACE models may oversimplify human behavior by relying heavily on programmed rules and algorithms.

However, the future of ACEs is promising for the field of science. Over time, various factors have driven the development of this field, and its future trajectory is likely to be influenced by a combination of regulatory, user-led, and developer-led initiatives. Key factors shaping the evolution of Economic Scenario Generators (ESGs) include understanding capital markets for investment strategy and business decision-making. This need has been highlighted by historical advancements and the introduction of stochastic modeling for reserving guarantees.

In summary, ACE is not positioned as a completely groundbreaking approach to economics but rather as a fresh methodological perspective for analyzing economic systems. While ACE may not definitively resolve economic disputes, it aims to enrich discussions and assist in pinpointing the underlying causes of such controversies.

REFERENCES

Anderson, P., Arrow, K. and Pines, D., (1988). *The economy is an evolving complex system. SFI Studies in the Sciences of Complexity*. Addison-Wesley Longman, Redwood City, CA.

Auyang, S.Y. (2004). Synthetic analysis of Complex Systems 1 - Theories. Paper presented at University of Sydney (History and Philosophy of Science). http://www.usyd.edu.au/su/hps/newevents/Auyang1.html.

Ballot, G. (2002). Modeling the labor market as an evolving institution: model ARTEMİS. *Journal of Economic Behavior and Organization, 49,* 51–77.

Baroni, E., & Richiardi, M. (2007). Orcutt's Vision, 50 years on. Laboratorio Riccardo Revelli Centre For Employment Studies, *Working Paper* no. 65, https://faculty.sites.iastate.edu/tesfatsi/archive/tesfatsi/OrcuttVision50YearsOn.BaroniRichiardi.2007.pdf

Bennett, R. and Bergmann, B. (1986). *Microsimulated Transactions Model of the United States Economy*. Baltimore: Johns Hopkins University Press.

Bergmann, B. R. (1974). A microsimulation of the macroeconomy with explicitly represented money flows. *Annals of Economic and Social Measurement*, *3(3),* 475–489.

Borshchev, A. and Filippov, A. (2004). From *System Dynamics and Discrete Event to Practical Agent-Based Modeling: Reasons, Techniques, and Tools*. Proceedings, 22nd International Conference of the System Dynamics Society, Oxford, England, July 25-29.

Bruun, C. (2004). *Agent-Based Computational Economics – An Introduction*. https://www.researchgate.net/publication/228729397_Agent-based_computational_economics-An_introduction

Cincotti, Silvano, R. M. and Teglio, A. (2010). Credit money and macroeconomic instability in the agent-based model and simulator Eurace. *Economics: The Open- Access, Open-Assessment E-Journal, 4(1),* 20100026.

Chen, S.H., Jain, L. and Tai, C.C. (2006). *Computational Economics: A Perspective from Computational Intelligence*. Idea Group Inc., 318.

Chen, S.H., & Yeh, C. H. (2001). Evolving traders and the business school with genetic programming: A new architecture of the agent-based artificial stock market. *Journal of Economic Dynamics and Control 25(3-4),* 363-393.

Cohen, K. J. (1960). Simulation of the firm. *The American Economic Review, 50(2),* 534-540.

Dawid, H., Gemkow, S., Harting, P., and Neugart, M. (2012). Labor market integration policies and the convergence of regions: the role of skills and technology diffusion. *Journal of Evolutionary Economics, 22(3),* 543–562.

Dawid, H. and Neugart, M. (2011). Agent-based models for economic policy design. *Eastern Economic Journal, 37(1),* 44–50.

Deissenberg, C., van der Hoog, S. and Dawid, H. (2008). EURACE: A massively parallel agent-based model of the European economy. *Applied Mathematics and Computation, 204,* 541–552.

Dilaver, Ö., Jump, R. C., & Levine, P. (2018). Agent-based macroeconomics and dynamic stochastic general equilibrium models: Where do we go from here?. *Journal of Economic Surveys, 32(4),* 1134-1159.

Eliasson, G. (1977). Competition and market processes in a simulation model of the Swedish economy. *The American Economic Review, 67,* 277–281.

Eliasson, G. (1988). *MOSES (Model of the Swedish Economic System): A Presentation of the Swedish Micro-to-Macro Econometric Model,* Working Paper Series no.197, Research Institute of Industrial Economics, https://EconPapers.repec.org/RePEc:hhs:iuiwop:0197.

Eliasson, G. (2018). Why Complex, Data Demanding and Difficult to Estimate Agent Based Models? Lessons from a Decades Long Research Program. *International Journal of Microsimulation, 11(1),* 4-60.

Gilbert, N. (2008). *Agent-Based Models*, *Quantitative Applications in the Social Sciences, 153,* SAGE Publications.

Gleiser, I., Farmer, D., Mojsa, J. and Bydlon, S. (2024). *How agent-based models powered by HPC are enabling large scale economic simulations.* AWS HPC Blog. https://aws.amazon.com/tr/blogs/hpc/how-agent-based-models-powered-by-hpc-are-enabling-large-scale-economic-simulations/

Grazzini, J., Richiardi, M. and Sella, L. (2012). Small sample bias in MSM estimation of agent-based models. In Andrea Teglio, Simone Alfarano, E. C.-C. M. G.-V., editor*, Managing Market Complexity. The Approach of Artificial Economics*., Lecture Notes in Economics and Mathematical Systems. Springer.

Grazzini, J. and Richiardi, M. (2013). *Consistent estimation of agent-based models by simulated minimum distance.* Working Paper 130/2013, LABORatorio R. Revelli.

Hailegiorgis, A., Crooks, A. and Cioffi-Revilla, C. (2018). An agent-based model of rural households' adaptation to climate change. *Journal of Artificial Societies and Social Simulation, 21(4).*

Kendrick, A.D., Mercado, P.R. and Amman, H.M. (2006). *Computational Economics.* Princeton University Press.

Kirman, A. (1992). Whom or what does the representative agent represent?.*Journal of Economic Perspectives. 6(2),* 117-36.

Lehtinen, A. and Kuorikoski, J. (2007). Computing the perfect model: Why do economists shun simulation? *Philosophy of Science, 74*, 304-329.

Markose, S. (2004). Novelty in complex adaptive systems (CAS) dynamics: a computational theory of actor innovation. *Physica A: Statistical Mechanics and its Applications, 344(1),* 41-49.

Markose, S. (2005). Computability and evolutionary complexity: markets as complex adaptive systems (CAS). *Economic Journal, 115(504),* F159-F192.

Meyer, R. N. (2023). Intrinsic unrealism: The ıneffectiveness of neoclassical economic models. *The Gettysbyrg Economic Review, 12(6),* 101-115.

Orcutt, G. (1957). A new type of socio-economics system. *Review of Economics and Statistics, 39,* 116-123.

Orcutt, G., Greenberger, M., Korbel, J. and Rivlin, A. M. (1961). *Microanalysis of Socioeconomic Systems: A Simulation Study*. New York: Harpers.

Richiardi, M. (2014). The Missing Link: AB Models and Dynamic Microsimulation. In: Leitner, S., Wall, F. (Eds). *Artificial Economics and Self Organization. Lecture Notes in Economics and Mathematical Systems*, Springer.

Russo, A., Tedeschi, G. and Fagiolo, G. (2018). Interaction. In D. Delli Gatti, G. Fagiolo, M. Gallegati, M. Richiardi and A. Russo (Eds.), *Agent-Based Models in Economics: A Toolkit* (pp. 109–142). Cambridge: Cambridge University Press.

Schinckus, C. (2019). Agent-based modelling and economic complexity: A diversified perspective. *Journal of Asian Business and Economic Studies, 26 (2),* 170-188. https://doi.org/10.1108/JABES-12-2018-0108

Seri, R., Secchi, D., Martinoli, M. (2022). Randomness, emergence and causation: A historical perspective of simulation in the social sciences. In: Albeverio, S., Mastrogiacomo, E., Rosazza Gianin, E., Ugolini, S. (Eds). *Complexity and Emergence.* CEIM 2018. Springer Proceedings in Mathematics & Statistics, vol 383. Springer, Cham. https://doi.org/10.1007/978-3-030-95703-2_7

Sitthiyot, T. (2015). Macroeconomic and financial management in an uncertain world: What can we learn from complexity science? *Thailand and The World Economy, 33(3),* 1-23.

Suresh, S. G. (2023). *Rational Economic Models of Homo Sapiens*. Social Science Research Network (SSRN:ID4235655).

Tefsatsion, L. (2006). Agent-based computational economics: A Constructive approach to economic theory. *In Handbook of Computational Economics* (pp 831-880), Elsevier.

Tesfatsion, L. (2021). Agent-based computational economics: Overview and brief history. In *Artificial intelligence, learning and computation in economics and finance*, 41-58.

Tefsation, L. (2024). Agent-based computational economics (ACE) and related topics. https://faculty.sites.iastate.edu/tesfatsi/archive/tesfatsi/aintro.htm