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Modeling decentralized markets under complexity: A behavioral and computational approach

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Abstract

Decentralized markets characterized by heterogeneous agents, bounded rationality, and interaction-driven dynamics pose significant challenges to conventional analytical approaches. Models based on representative agents, equilibrium assumptions, and historical data often fail to capture adaptation, feedback mechanisms, and the endogenous emergence of market organization. This paper addresses this methodological gap by proposing a framework for analyzing such markets using agent-based modeling. The study adopts a theoretical and methodological approach grounded in complexity economics and computational modeling. It systematizes the core elements required to model decentralized markets, including agent heterogeneity, behavioral rules, local interactions, and dynamic processes, and organizes them into a structured framework for model construction, simulation, and validation. The results show that agent-based modeling provides a more suitable analytical architecture for representing economic systems in which coordination emerges from decentralized interactions. By explicitly incorporating behavioral adaptation, informational constraints, and interaction mechanisms, the framework enables the analysis of emergent outcomes such as price formation, coordination patterns, and market structure. The application to agricultural biomass markets illustrates how the framework can be operationalized in environments characterized by uncertainty, spatial heterogeneity, and evolving institutional conditions. The findings have important implications for economic research. They suggest that understanding market organization in complex environments requires methodological approaches that move beyond equilibrium-based representations and integrate behavioral realism with computational analysis. The proposed framework contributes to bridging the gap between complexity economics and applied research, offering a structured tool for analyzing economic behavior and organization in decentralized systems.

1. Introduction

Economic markets are increasingly recognized as systems in which aggregate outcomes emerge from decentralized interactions among heterogeneous agents operating under conditions of limited information and bounded rationality (Axtell; Farmer, 2025; Amendola; Pereira, 2025). In such environments, market organization cannot be fully understood through approaches that rely on representative agents, equilibrium assumptions, or purely historical data. Instead, the dynamics of these systems are shaped by adaptive behaviors, local interactions, and feedback mechanisms that generate non-linear and often unpredictable outcomes.

This perspective is consistent with the view of economic systems as complex adaptive systems, in which heterogeneity, interaction, and adaptation are central features (Bar-Yam, 2019; Gatti, 2018; Russo et al., 2018). In these systems, agents differ in their characteristics and decision rules, learn from past experiences, and continuously adjust their behavior in response to changes in the environment. As a result, macroeconomic patterns arise endogenously from micro-level interactions, rather than being imposed by equilibrium conditions. Such properties challenge traditional analytical frameworks and

require methodological approaches capable of capturing emergent dynamics and non-linear interactions (Dosi et al., 2020; Dosi; Roventini, 2019).

Despite these advances, a significant portion of the economic literature continues to rely on analytical and econometric approaches that are better suited to environments characterized by stability, linearity, and well-defined data structures (Amendola; Pereira, 2023; 2025). These models are powerful tools for identifying causal relationships and testing hypotheses based on historical data. However, they face important limitations when applied to systems in which agents interact strategically, information is imperfect, and structural change is endogenous. In particular, they struggle to capture processes such as learning, adaptation, and the emergence of collective patterns from decentralized decision-making.

These limitations become especially relevant in markets that lack consolidated empirical regularities or are subject to high levels of uncertainty and heterogeneity. In such contexts, the reliance on past data and equilibrium-based reasoning may lead to incomplete representations of market dynamics. This is particularly evident in emerging and decentralized markets, such as those associated with agricultural biomass supply for advanced biofuels, where coordination occurs through dispersed interactions among heterogeneous agents and where institutional structures are still evolving.

Agent-based modeling (ABM) has been increasingly adopted as a methodological approach capable of addressing these challenges (Pyka; Fagiolo, 2007; Tesfatsion, 2017; 2023; Axtell; Farmer, 2025). By explicitly representing heterogeneous agents, bounded rationality, and decentralized interactions, ABM enables the analysis of economic systems as evolving processes rather than static equilibria. Unlike conventional analytical models, ABM does not require strong assumptions about optimization or equilibrium conditions. Instead, it allows for the simulation of adaptive behavior, the exploration of counterfactual scenarios, and the identification of emergent patterns resulting from the interaction of agents over time (Amendola; Pereira, 2023; 2025).

This paper argues that decentralized markets characterized by heterogeneity, informational frictions, and local interactions require a methodological shift from equilibrium-based analytical models to interaction-based computational approaches. In particular, it advances the view that agent-based modeling provides a more suitable analytical framework for understanding how economic organization emerges in complex systems. Rather than treating market outcomes as the result of exogenously imposed structures, this approach emphasizes the endogenous formation of coordination patterns, prices, and allocation mechanisms.

To develop this argument, the paper proposes a methodological framework for analyzing decentralized markets under complexity, drawing on insights from the theory of complex adaptive systems and computational economics. The framework identifies the conditions under which agent-based modeling becomes particularly relevant, clarifies its advantages and limitations relative to conventional approaches, and provides guidance for its application in economic research.

As an illustrative application, the paper considers agricultural biomass markets associated with advanced biofuels. These markets exhibit many of the features that characterize complex systems, including heterogeneous agents, decentralized coordination, uncertainty, and strong dependence on local interactions. However, the objective is not to provide a sector-specific analysis, but rather to use this context to illustrate how the proposed methodological framework can be applied to real-world economic systems.

By repositioning the analysis of market dynamics within a complexity-based perspective, this paper contributes to the literature on economic behavior and organization by highlighting the importance of methodological choices in shaping our understanding of decentralized economic systems. More broadly, it seeks to bridge the gap between advances in complexity economics and their application to the study of market organization, offering a structured approach for analyzing systems in which behavior, interaction, and emergence are central.

2. Market organization under complexity

Economic markets that involve decentralized coordination, heterogeneous agents, and imperfect information can be understood as complex adaptive systems. In such systems, aggregate outcomes emerge from the interaction of multiple agents whose behaviors are interdependent, adaptive, and often non-linear. This perspective departs from conventional representations of markets as systems that converge toward equilibrium and instead emphasizes processes of continuous adjustment, feedback, and emergence (Bar-Yam, 2019; Gatti, 2018; Russo et al., 2018).

A key distinction in this context is between complicated and complex systems. While complicated systems may involve multiple components and layers, their behavior remains predictable and decomposable into smaller parts, allowing for control and precise forecasting. In contrast, complex systems are characterized by non-linear interactions, feedback loops, and emergent properties that cannot be reduced to the sum of individual components. As a result, understanding such systems requires analytical approaches that account for interdependence, adaptation, and endogenous dynamics.

From an economic perspective, markets exhibit features of complexity when at least four conditions are present. First, agents are heterogeneous, differing in their characteristics, resources, and decision-making rules. Under such conditions, the use of representative agents becomes insufficient, as aggregate outcomes depend on the distribution of individual behaviors rather than on average characteristics (Pyka; Fagiolo, 2007; Tesfatsion, 2017; 2023). Second, agents operate under bounded rationality, facing cognitive limitations and imperfect information, which leads them to rely on heuristics, learning processes, and adaptive strategies rather than full optimization.

Third, interactions among agents play a central role in shaping market dynamics. Decisions are not made in isolation but are influenced by the actions of other agents, either directly through transactions and negotiations or indirectly through market signals such as prices and observed behaviors. These

interactions generate feedback mechanisms that can amplify or dampen individual decisions, producing non-linear and path-dependent outcomes. Fourth, markets are inherently dynamic, evolving over time through processes of adaptation, innovation, and selection, without necessarily converging to a stable equilibrium (Dosi et al., 2020; Dosi; Roventini, 2019).

These four elements—heterogeneity, bounded rationality, decentralized interactions, and emergence—are jointly responsible for shaping market organization in complex systems. Rather than being imposed exogenously, coordination mechanisms such as pricing, contracting, and exchange emerge endogenously from the interaction of agents operating under uncertainty and informational frictions.

To synthesize these relationships, Fig. 1 presents a conceptual framework of the main features that characterize complex economic markets and their interactions. The figure highlights how micro-level characteristics—heterogeneity and bounded rationality—interact through decentralized exchanges, generating feedback loops that lead to the emergence of macro-level patterns and economic organization.

Source: Elaborated by the author.

Following this perspective, market outcomes are not the result of a centralized coordination mechanism or a pre-defined equilibrium structure. Instead, they emerge from adaptive and interdependent processes in which agents continuously adjust their behavior in response to local information and past interactions. This implies that similar initial conditions may lead to different aggregate outcomes, reinforcing the importance of analyzing economic systems as evolutionary and path-dependent processes.

These characteristics are particularly relevant in markets where empirical regularities are weak or still forming, and where historical data provide limited guidance for predicting future dynamics. In such contexts, the structure of the market cannot be assumed a priori, but must be understood as the outcome of decentralized coordination processes shaped by behavioral, informational, and institutional factors.

Within the broader set of tools used to analyze complex systems, different methodological approaches emphasize distinct aspects of market dynamics. Network analysis focuses on the structure of connections among agents and the flow of information within the system. Machine learning methods are designed to identify patterns and optimize predictions based on large datasets. However, in environments characterized by structural uncertainty and limited data availability, these approaches may be insufficient to uncover the mechanisms that generate observed patterns.

Therefore, viewing markets through the lens of complexity shifts the analytical focus from equilibrium states to dynamic processes, from representative agents to heterogeneous populations, and from exogenous structures to endogenous organization. This shift has important implications for how economic systems are modeled and understood, particularly in contexts characterized by uncertainty, decentralized coordination, and adaptive behavior.

3. Limitations of conventional analytical approaches

Conventional analytical approaches have played a central role in economic research by enabling the identification of causal relationships and the formal testing of hypotheses based on historical data. Econometric models and optimization-based frameworks, such as linear programming and its extensions, are widely used to analyze market behavior, forecast trends, and support decision-making processes. These approaches are particularly effective in contexts where relationships between variables are stable, data are abundant, and system dynamics can be approximated through linear or equilibrium-based structures.

In the context of biomass and bioenergy systems, for example, optimization models such as Mixed-Integer Linear Programming (MILP) and multi-objective programming have been extensively applied to determine optimal decisions related to production, logistics, and infrastructure allocation. Studies have used these approaches to optimize feedstock collection, processing, transportation, and storage, as well as to design supply chain configurations under cost-minimization or efficiency criteria (Zhang et al., 2012; Lin et al., 2014; León-Olivares et al., 2020; Yildiz et al., 2024). These models rely on well-defined objective functions and constraints, allowing for precise and tractable solutions under controlled assumptions.

Despite their strengths, these approaches present important limitations when applied to markets characterized by heterogeneity, decentralized interactions, and structural uncertainty. A central limitation lies in their reliance on representative agents or aggregated structures, which restricts the ability to capture the diversity of behaviors and strategies observed in real-world economic systems. By construction, these models tend to abstract from micro-level heterogeneity and interaction, focusing instead on average effects or optimal solutions under given constraints.

Another limitation concerns the treatment of time and dynamics. Conventional econometric and optimization models typically rely on static or comparative statics frameworks, or on time series that extrapolate past behavior into the future. While these approaches are suitable for identifying regularities and forecasting under stable conditions, they are less effective in capturing adaptive processes, feedback loops, and non-linear dynamics that characterize complex markets.

A further constraint is related to data requirements. Analytical models generally depend on the availability of consistent and reliable historical data to estimate parameters and validate results. In emerging or weakly structured markets, where empirical regularities are not yet well established, this requirement becomes a significant limitation. The absence of detailed micro-level data often leads to the use of aggregated proxies, which may obscure important mechanisms driving market behavior.

In addition, conventional models face difficulties in incorporating behavioral elements such as bounded rationality, learning, and heuristic-based decision-making. These models are typically grounded in assumptions of full rationality and optimization, which may not adequately reflect the cognitive and informational constraints faced by real-world agents.

These limitations are particularly relevant in markets where coordination is not centrally organized but emerges from interactions among agents. In the case of biomass supply chains, upstream decisions related to production, collection, storage, and logistics are shaped by local conditions, heterogeneous capabilities, and uncertainty regarding prices and demand. While optimization models can identify efficient configurations under given assumptions, they often overlook the processes through which coordination is achieved, as well as the role of contracts, incentives, and governance structures in shaping market outcomes (Yue; You, 2016).

More broadly, the analytical structure of these models constrains their ability to represent endogenous structural change. Institutional transformations, policy interventions, technological adoption, and shifts in market organization are often treated as exogenous shocks rather than as outcomes of agent interactions. This limits the capacity of conventional approaches to explore how economic systems evolve over time and how new patterns of coordination and organization emerge.

These limitations can be grouped into four core analytical constraints that restrict the applicability of conventional models in complex economic environments.

First, a representational limitation arises from the reliance on representative agents and aggregated structures, which prevents the adequate representation of heterogeneity across agents and the distributional effects of their interactions (Pyka; Fagiolo, 2007; Tesfatsion, 2017; 2023). Second, a behavioral limitation stems from the assumption of full rationality and optimization, neglecting bounded rationality, learning processes, and heuristic-based decision-making. Third, a dynamic limitation is associated with the predominance of equilibrium-based or static frameworks, which are not well suited to capture adaptive processes, feedback loops, and path-dependent dynamics (Dosi et al., 2020; Dosi; Roventini, 2019). Finally, a data-related limitation reflects the dependence on historical and structured datasets, which constrains model applicability in emerging or decentralized markets.

Table 1
Analytical limitations of conventional models in complex markets.

Dimension	**Conventional analytical approaches**	**Limitation in complex markets**
Representation of agents	Representative agent or aggregated structures	Inability to capture heterogeneity and distributional effects
Behavioral assumptions	Full rationality and optimization	Ignores bounded rationality, learning, and heuristics
Treatment of dynamics	Static or equilibrium-based frameworks	Fails to capture adaptation, feedback loops, and path dependence
Data requirements	Dependence on historical and structured datasets	Limited applicability in emerging or weakly structured markets

Source: Elaborated by the author.

Following this perspective, while conventional analytical and econometric approaches remain essential for empirical analysis and hypothesis testing, their applicability is limited in contexts characterized by complexity, uncertainty, and decentralized coordination. These limitations do not imply that such models should be discarded, but rather that they should be complemented by alternative approaches capable of capturing the micro-foundations of behavior, interaction, and emergence.

In this sense, the challenge is not to replace analytical models, but to integrate them within a broader methodological framework that allows for the analysis of economic systems as dynamic and adaptive processes. The next section addresses this challenge by examining how agent-based modeling can provide such a framework, offering a complementary approach that explicitly incorporates heterogeneity, bounded rationality, and decentralized interactions.

4. Agent-based modeling and economic behavior

Agent-based modeling (ABM) has emerged as a central methodological approach for analyzing economic systems characterized by heterogeneity, bounded rationality, and decentralized interactions. By explicitly representing agents as autonomous decision-making entities, ABM enables the study of how individual behaviors and local interactions generate aggregate patterns of economic organization. This approach departs from traditional analytical frameworks by focusing on processes rather than equilibrium outcomes, and on interaction-driven dynamics rather than optimization under fixed constraints (Pyka; Fagiolo, 2007; Tesfatsion, 2017; 2023; Axtell; Farmer, 2025).

In contrast to models based on representative agents and full rationality, ABM allows for the incorporation of behavioral rules that more closely reflect observed economic behavior. Agents can operate under bounded rationality, relying on heuristics, incomplete information, and adaptive expectations. Decision-making processes may be influenced by past experiences, local information, and interactions with other agents, rather than by global optimization. This flexibility enables the explicit modeling of learning processes, expectation formation, and behavioral adaptation, which are central to the analysis of economic behavior in decentralized environments.

A defining feature of ABM is its bottom-up structure, in which macroeconomic outcomes emerge endogenously from micro-level interactions. Rather than imposing equilibrium conditions, the model allows coordination, prices, and market structures to arise from the decentralized behavior of agents over time. This perspective is particularly relevant for understanding economic organization in contexts where coordination is not centrally imposed but emerges from interaction processes (Dosi; Roventini, 2019; Tesfatsion, 2017; 2023).

To illustrate this mechanism, Fig. 2 presents a stylized representation of how agent-based models capture the emergence of economic organization from decentralized interactions. The figure highlights the sequential and interdependent processes linking heterogeneous agents, behavioral rules, local interactions, and feedback mechanisms to aggregate market outcomes.

Source: Elaborated by the author.

From a computational standpoint, ABM represents economic systems as dynamic processes evolving in discrete time. Agents are characterized by attributes, decision rules, and interaction mechanisms, and they operate within an environment that may include both endogenous and exogenous variables. The evolution of the system results from repeated interactions among agents and between agents and their environment, often incorporating stochastic elements and path-dependent dynamics (Arthur, 2014; Tesfatsion; Judd, 2006; Epstein, 2006; 2012).

This modeling approach provides a framework for analyzing economic behavior in settings where traditional methods face important limitations. In particular, ABM enables the representation of four key dimensions that are central to complex economic systems.

First, heterogeneity is explicitly modeled at the agent level, allowing for differences in preferences, technologies, resources, and decision rules. These differences can be specified exogenously or generated endogenously through the interaction process, enabling the analysis of distributional dynamics and structural diversity within the system (Axtell; Farmer, 2025).

Second, bounded rationality and information constraints are directly incorporated into decision-making processes. Agents may operate with limited information, rely on local signals, and adjust their behavior through learning mechanisms. This allows the model to capture more realistic behavioral dynamics compared to optimization-based frameworks.

Third, interactions among agents are modeled explicitly and locally, reflecting the decentralized nature of economic exchanges. Agents interact through transactions, negotiations, or indirect signals such as prices, generating feedback loops that shape system dynamics. These interaction patterns are central to the emergence of coordination, cooperation, and competition within markets.

Fourth, economic dynamics are modeled as out-of-equilibrium processes, in which the system evolves continuously without necessarily converging to a steady state. This allows the analysis of transitions, structural changes, and the emergence of new patterns of organization over time (Dosi; Roventini, 2019).

As illustrated in Fig. 2, these features position ABM as a particularly suitable framework for studying economic systems in which behavior, interaction, and adaptation are central. Importantly, ABM does not aim to replace conventional analytical or econometric approaches, but rather to complement them. While econometric models provide tools for empirical validation and hypothesis testing, ABM offers a platform for exploring mechanisms, generating stylized facts, and analyzing counterfactual scenarios in environments where data are limited or where system dynamics are not well understood (Fagiolo et al., 2019).

In this sense, ABM contributes to bridging the gap between theoretical and empirical analysis in economics. By generating synthetic data through simulation, ABM enables the application of statistical and econometric techniques to model outputs, facilitating validation and comparison with observed

patterns (Moneta; Windrum; Fagiolo, 2007; Gatti, 2018). This integration allows for a more comprehensive understanding of economic systems, combining the strengths of computational modeling and empirical analysis.

Beyond its methodological advantages, ABM provides important insights into economic organization. By modeling how coordination emerges from decentralized interactions, it allows the analysis of market structures, institutional arrangements, and governance mechanisms as endogenous outcomes. This is particularly relevant in markets characterized by uncertainty, heterogeneity, and evolving institutional frameworks.

In the context of agricultural biomass markets, for instance, ABM enables the representation of heterogeneous suppliers, spatially distributed production systems, and decentralized decision-making processes related to collection, storage, and commercialization. These markets are influenced by factors such as distance, quality attributes, and price variability, which affect agents' decisions and interactions. By incorporating these elements, ABM allows for the analysis of how coordination mechanisms, supply patterns, and price dynamics emerge over time.

However, the application of ABM also involves important challenges. Model construction requires the specification of behavioral rules, calibration of parameters, and careful validation procedures. The high dimensionality and stochastic nature of these models may complicate interpretation and require extensive computational resources. In addition, the balance between realism and tractability remains a central issue in model design (Epstein, 2012; Railsback; Grimm, 2019).

Despite these challenges, ABM provides a flexible and powerful framework for analyzing economic systems in which traditional approaches face limitations. By explicitly incorporating heterogeneity, bounded rationality, and decentralized interactions, it enables the study of economic behavior and organization in complex environments, offering insights into how market outcomes emerge from the interplay of individual decisions and interaction processes.

5. A methodological framework for modeling decentralized markets

Building on the limitations of conventional analytical approaches and the advantages of agent-based modeling discussed in the previous sections, this paper proposes a methodological framework for analyzing decentralized markets under complexity. The framework is designed to guide the construction, implementation, and validation of models that explicitly account for heterogeneity, bounded rationality, and interaction-driven dynamics.

Rather than providing a rigid modeling protocol, the framework organizes the key components and stages required to develop agent-based models consistent with the behavioral and organizational features of complex economic systems. In this sense, it contributes to bridging the gap between theoretical advances in complexity economics and their operationalization in empirical and computational research.

5.1. Structural foundations of the modeling framework

The first stage of the framework concerns the structural definition of the model, which is grounded in the identification of the phenomenon of interest, the formulation of research questions, and the specification of stylized facts. In complex economic systems, stylized facts play a central role in guiding model construction, as they provide empirical and theoretical benchmarks for evaluating model behavior (Fagiolo et al., 2019).

At this stage, the model is defined in terms of its fundamental components: agents, environment, variables, and parameters. Agents represent the decision-making entities—such as firms, consumers, or producers—and are characterized by heterogeneous attributes and behavioral rules. The environment includes both endogenous variables, resulting from agent interactions, and exogenous conditions, such as institutional settings or market signals.

A key feature of this framework is the explicit distinction between micro- and macro-level elements. Micro-level components include agent attributes and decision rules, while macro-level outcomes emerge from the aggregation of individual behaviors and interactions. This structure reflects the bottom-up logic of ABM, in which system-level properties are not imposed but arise from decentralized processes (Tesfatsion, 2017; 2023; Epstein, 2006; 2012).

In addition, time is modeled as a discrete and sequential process, allowing the system to evolve through iterative interactions. This temporal structure enables the incorporation of learning, adaptation, and path dependence, which are central to the analysis of economic dynamics in complex systems.

5.2. Behavioral and interactional design

The second stage of the framework focuses on the specification of behavioral rules and interaction mechanisms. In contrast to optimization-based approaches, agent behavior is defined through rules that reflect bounded rationality, limited information, and adaptive learning processes. These rules may include heuristic decision-making, expectation updating, and responses to local information or past outcomes.

Interactions among agents are modeled explicitly, typically occurring at the local level through transactions, negotiations, or indirect signals such as prices. These interactions generate feedback loops that influence both individual decisions and aggregate outcomes. As a result, the model captures how coordination mechanisms—such as pricing, contracting, and exchange—emerge from decentralized processes rather than being imposed exogenously.

This stage is particularly important for representing economic behavior in environments characterized by uncertainty and informational asymmetries. By allowing agents to adapt their behavior over time, the model captures dynamic processes such as learning, experimentation, and adjustment to changing market conditions (Arthur, 2014; Dosi; Roventini, 2019).

5.3. Computational implementation and simulation design

The third stage involves the computational implementation of the model and the design of simulation experiments. Once the structural and behavioral components are defined, the model is implemented in a computational environment, allowing for the simulation of interactions over time.

Given the stochastic and dynamic nature of ABM, simulation plays a central role in analyzing system behavior. Models are typically evaluated through multiple runs using Monte Carlo techniques, which allow for the exploration of variability and robustness across different initial conditions and parameter configurations (Fagiolo et al., 2019; Lamperti et al., 2018).

Simulation outputs generate synthetic datasets at both the micro and macro levels. Micro-level outputs consist of panel data on agent-specific variables, while macro-level outputs represent aggregate indicators such as prices, quantities, or market concentration. These outputs enable the analysis of emergent patterns and the comparison of simulated dynamics with observed economic behavior.

5.4. Validation and empirical alignment

The final stage of the framework concerns model validation and empirical alignment. Validation in ABM does not rely on a single criterion but involves multiple complementary approaches. These include:

I. Empirical validation, based on the comparison between simulated outputs and observed data;
II. Theoretical validation, which assesses the consistency of model mechanisms with established economic theories;
III. Statistical validation, using monte carlo simulations to evaluate the robustness and distributional properties of model outcomes;
IV. Econometric validation, in which simulated data are analyzed using econometric techniques to test whether the model reproduces expected relationships (Windrum; Fagiolo; Moneta, 2007; Gatti, 2018; Fagiolo et al., 2019).

This multi-dimensional validation strategy is particularly important in complex systems, where direct empirical calibration may be limited by data availability. In such cases, the ability of the model to reproduce stylized facts and generate plausible behavioral patterns becomes a key criterion for evaluation. The overall structure of the proposed methodological framework is summarized in Table 2.

Table 2
Methodological framework for agent-based modeling of decentralized markets.

Stage	Core components	Analytical objective
Structural definition	Agents, environment, variables, parameters, stylized facts	Represent the economic system and define model boundaries
Behavioral and interaction design	Decision rules, bounded rationality, local interactions	Capture micro-level behavior and interaction mechanisms
Computational implementation	Simulation design, Monte Carlo experiments	Analyze system dynamics and emergent patterns
Validation and alignment	Empirical, theoretical, statistical, econometric validation	Ensure robustness and consistency with economic evidence

Source: Elaborated by the author.

5.5. Implications for modeling decentralized markets

The proposed framework, summarized in Table 2, highlights that modeling decentralized markets requires a shift from equilibrium-based representations to process-oriented approaches that emphasize interaction and adaptation. By structuring model development around behavioral, interactional, and dynamic components, the framework enables a more realistic representation of economic systems in which coordination emerges endogenously.

This is particularly relevant for markets characterized by heterogeneity, uncertainty, and weak institutional structures, where traditional models face important limitations. In such contexts, the framework provides a structured approach for incorporating key features of complexity into economic modeling, facilitating the analysis of how market organization evolves over time.

Importantly, the framework does not aim to replace conventional analytical methods but to complement them. By integrating computational modeling with empirical and econometric analysis, it contributes to a more comprehensive understanding of economic systems, combining explanatory depth with analytical rigor.

6. Illustrative application: agricultural biomass markets

Agricultural biomass markets associated with advanced biofuels provide a suitable empirical context to illustrate the application of the proposed methodological framework. These markets are characterized by decentralized coordination, heterogeneous agents, and significant uncertainty regarding supply, demand, and price formation. As such, they exhibit key features of complex economic systems, making them an appropriate setting for the application of agent-based modeling.

Biomass supply chains involve multiple types of agents, including agricultural producers, intermediaries, and processing units, each with distinct characteristics in terms of scale, technology, resource

endowments, and access to information. These agents operate under heterogeneous conditions, including differences in productivity, land availability, logistics costs, and quality attributes of the biomass. As a result, supply decisions are not uniform but vary across agents and over time, depending on both individual conditions and market signals.

In addition to heterogeneity, these markets are shaped by bounded rationality and informational constraints. Producers often make decisions based on expectations regarding prices, demand, and operational costs, which are subject to uncertainty and may be updated over time as new information becomes available. Decision-making processes are influenced by local conditions—such as distance to processing facilities, storage capacity, and seasonal availability—rather than by complete information about the market as a whole.

Interactions among agents are decentralized and occur through bilateral transactions, negotiations, and market signals. Prices are not determined by a centralized mechanism but emerge from the interaction between supply and demand under conditions of uncertainty and asymmetric information. These interactions generate feedback loops, as past outcomes influence future expectations and decisions, contributing to the dynamic evolution of the market.

From a structural perspective, biomass markets are also influenced by logistical constraints, seasonality, and institutional factors. The availability of biomass is often concentrated in specific periods, while storage capabilities vary across agents, affecting intertemporal supply decisions. Transportation costs and infrastructure limitations further shape market participation and the spatial distribution of transactions. In addition, regulatory frameworks, environmental requirements, and policy incentives influence both supply and demand conditions, adding another layer of complexity to market dynamics (Zhang et al., 2012; Lin et al., 2014; León-Olivares et al., 2020; Yue; You, 2016).

These characteristics make biomass markets difficult to represent using conventional analytical approaches. Optimization models can identify efficient configurations under given assumptions, but they often abstract from decentralized interactions, adaptive behavior, and the endogenous formation of coordination mechanisms. As discussed in Section 3, such approaches are limited in their ability to capture the processes through which market organization emerges in complex environments.

Within the proposed methodological framework, biomass markets can be modeled by explicitly incorporating the structural, behavioral, and interactional elements that define their dynamics. At the structural level, agents are represented with heterogeneous attributes, including production capacity, costs, and spatial location. At the behavioral level, decision rules reflect bounded rationality, allowing agents to adapt their supply strategies based on past outcomes and expectations. At the interaction level, transactions occur through decentralized exchanges, generating price signals and feedback mechanisms that influence subsequent decisions.

To synthesize these elements, Table 3 presents a mapping between the main characteristics of agricultural biomass markets and the corresponding components of the proposed modeling framework.

Table 3
Mapping biomass market characteristics to ABM framework components.

Market characteristic	ABM component	Modeling implication
Heterogeneous producers	Agent attributes	Differences in productivity, costs, and resource endowments
Informational constraints	Behavioral rules	Expectation formation, adaptive decision-making
Decentralized transactions	Interaction mechanisms	Bilateral exchanges, price formation through interaction
Seasonality and storage	Temporal dynamics	Intertemporal decision-making and stock management
Logistics and spatial factors	Environment structure	Distance, transportation costs, spatial interactions
Policy and regulation	Exogenous variables	Institutional constraints and incentives

Source: Elaborated by the author.

As shown in Table 3, the complexity of biomass markets arises from the interaction of multiple dimensions that must be jointly represented to capture system dynamics. By structuring the model around these elements, the proposed framework enables the analysis of how coordination, pricing, and supply patterns emerge over time.

Importantly, the purpose of this illustrative application is not to provide a detailed sectoral model, but to demonstrate how the methodological framework can be operationalized in real-world contexts. The same approach can be applied to other decentralized markets characterized by heterogeneity, uncertainty, and interaction-driven dynamics.

7. Implications for economic research

The analysis developed in this paper has several implications for economic research, particularly for the study of market organization and behavior in environments characterized by heterogeneity, uncertainty, and decentralized coordination. By highlighting the limitations of conventional analytical approaches and proposing a structured methodological framework based on agent-based modeling, the paper contributes to a broader rethinking of how economic systems are conceptualized and analyzed.

These implications can be grouped into five interrelated dimensions concerning heterogeneity, behavior, interaction, dynamics, and methodological integration.

A first implication concerns the role of heterogeneity in economic modeling. Traditional approaches often rely on representative agents to simplify analysis, but this abstraction limits the ability to capture distributional effects, strategic diversity, and interaction-driven dynamics. The framework proposed in

this paper reinforces the importance of explicitly incorporating heterogeneous agents, allowing for a more realistic representation of economic systems in which outcomes depend on the interaction of diverse actors rather than on average behavior (Pyka; Fagiolo, 2007; Tesfatsion, 2017; 2023).

A second implication relates to the treatment of economic behavior under bounded rationality. The assumption of fully rational agents remains central in many economic models, yet it often fails to reflect how decisions are made in practice. By incorporating heuristic-based decision rules, learning processes, and adaptive expectations, agent-based modeling provides a more flexible and empirically grounded representation of behavior. This approach aligns with a growing body of literature that emphasizes the importance of cognitive and informational constraints in shaping economic decision-making.

A third implication concerns the analysis of interaction and coordination mechanisms. In decentralized markets, coordination does not arise from centralized control or equilibrium conditions but emerges from local interactions among agents. The framework developed in this paper highlights the need to model these interactions explicitly, as they play a central role in determining market outcomes. This perspective contributes to the literature on economic organization by emphasizing how structures such as prices, contracts, and exchange mechanisms are formed endogenously through interaction processes.

A fourth implication relates to the understanding of economic dynamics as out-of-equilibrium processes. Conventional models often focus on equilibrium states or comparative statics, which may be insufficient to capture the evolving nature of economic systems. By modeling economies as dynamic and adaptive systems, the proposed framework allows for the analysis of transitions, structural change, and path-dependent processes (Dosi; Roventini, 2019). This is particularly relevant for studying emerging markets and technological transitions, where equilibrium conditions are rarely observed.

A fifth implication concerns the integration of computational and empirical approaches. While agent-based models are often viewed as primarily theoretical or simulation-based tools, this paper emphasizes their potential to complement empirical analysis. By generating synthetic data, ABM enables the application of econometric techniques to simulated outputs, facilitating validation and comparison with observed patterns (Windrum; Fagiolo; Moneta, 2007; Gatti, 2018; Fagiolo et al., 2019). This integration creates opportunities for a more comprehensive methodological approach that combines the strengths of both traditions.

Beyond these methodological contributions, the framework also has implications for the study of institutional and policy design. In markets characterized by complexity, policy interventions may produce unintended consequences due to feedback effects and adaptive behavior. By explicitly modeling these processes, agent-based approaches can provide insights into how policies influence market organization, coordination, and performance over time. This is particularly relevant for sectors such as bioenergy, where technological uncertainty, regulatory frameworks, and decentralized decision-making interact to shape market outcomes.

Finally, the framework contributes to advancing the dialogue between complexity economics and mainstream economic analysis. Rather than positioning these approaches as substitutes, the paper emphasizes their complementarity. Analytical and econometric models remain essential for hypothesis testing and empirical validation, while agent-based models provide tools for exploring mechanisms, generating stylized facts, and analyzing systems in which data are limited or dynamics are not well understood.

Taken together, these implications suggest that the study of economic behavior and organization in complex environments requires a broader methodological toolkit, capable of integrating behavioral realism, interaction-driven dynamics, and computational analysis. By providing a structured framework for modeling decentralized markets, this paper contributes to this methodological expansion and offers a foundation for future research on complex economic systems.

8. Conclusion

This paper examined the methodological challenges associated with analyzing decentralized markets characterized by heterogeneity, bounded rationality, and interaction-driven dynamics. It argued that conventional analytical approaches, while valuable for empirical analysis and hypothesis testing, face important limitations in capturing the adaptive, non-linear, and emergent properties of such systems.

To address these limitations, the paper proposed a methodological framework based on agent-based modeling, designed to represent economic systems as complex adaptive processes. By explicitly incorporating heterogeneous agents, behavioral rules, local interactions, and feedback mechanisms, the framework enables the analysis of how market organization emerges endogenously from decentralized decision-making.

The contribution of the paper lies in structuring a coherent approach to modeling markets under complexity, bridging theoretical insights from complexity economics with practical guidelines for model construction, simulation, and validation. Rather than replacing conventional methods, the framework emphasizes their complementarity with computational approaches, highlighting the importance of integrating empirical and simulation-based analysis.

The illustrative application to agricultural biomass markets demonstrated how the proposed framework can be operationalized in real-world contexts characterized by uncertainty, spatial heterogeneity, and decentralized coordination. More broadly, the framework is applicable to a wide range of economic settings in which market outcomes cannot be adequately explained by equilibrium-based models.

These findings have implications for both economic theory and applied research. They suggest that advancing the study of economic behavior and organization requires methodological approaches capable of capturing interaction, adaptation, and emergence. In this sense, agent-based modeling provides a valuable tool for exploring the mechanisms underlying market dynamics and for analyzing systems in which empirical regularities are still evolving.

Future research may extend this framework by integrating richer behavioral assumptions, incorporating institutional and policy dimensions more explicitly, and strengthening the empirical validation of simulation-based models. Such developments would contribute to a deeper understanding of economic systems as dynamic and adaptive processes, reinforcing the role of computational approaches within the broader field of economic analysis.

Declarations

Author Contribution

S.C.M.R. conceived the study, developed the methodology, performed the analysis, and wrote the manuscript. The author read and approved the final manuscript.

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Figures

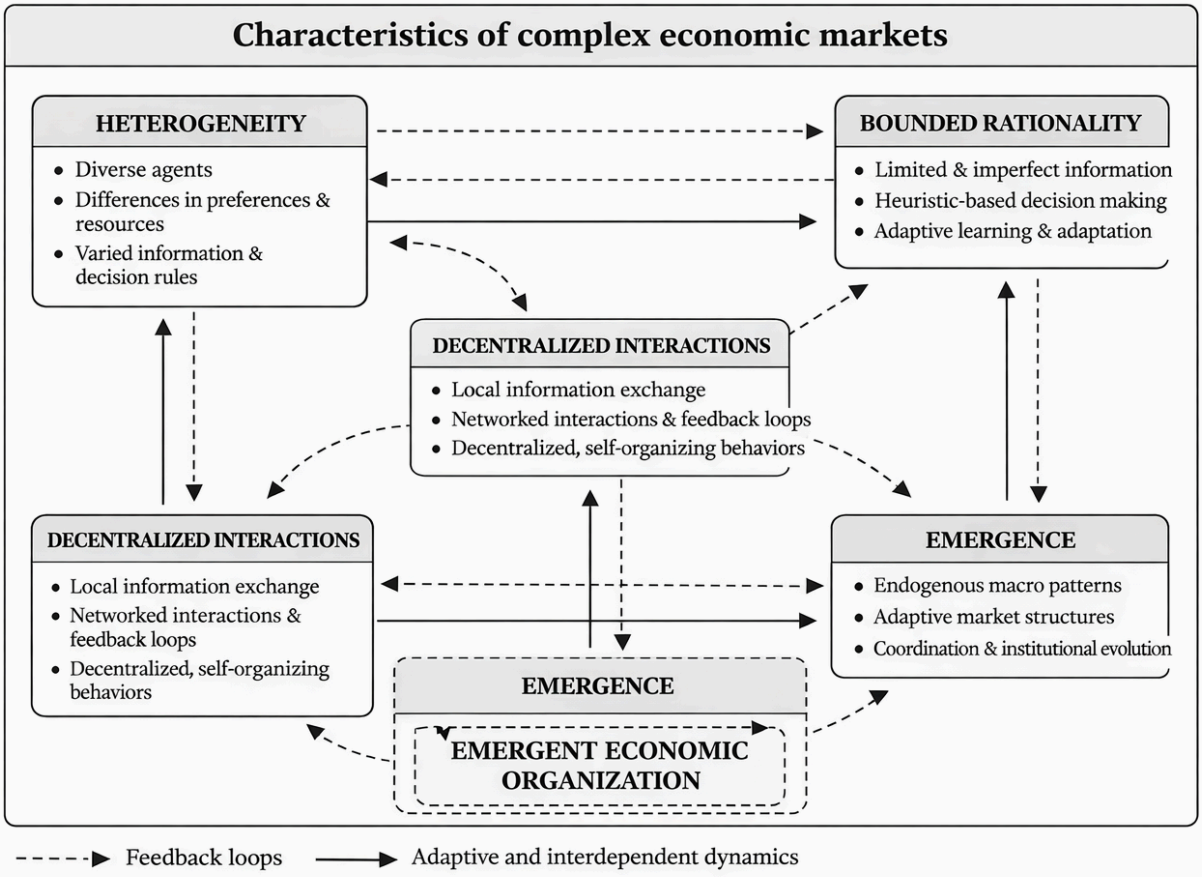


Figure 1: Characteristics of complex economic markets

Figure 1

Characteristics of complex economic markets.

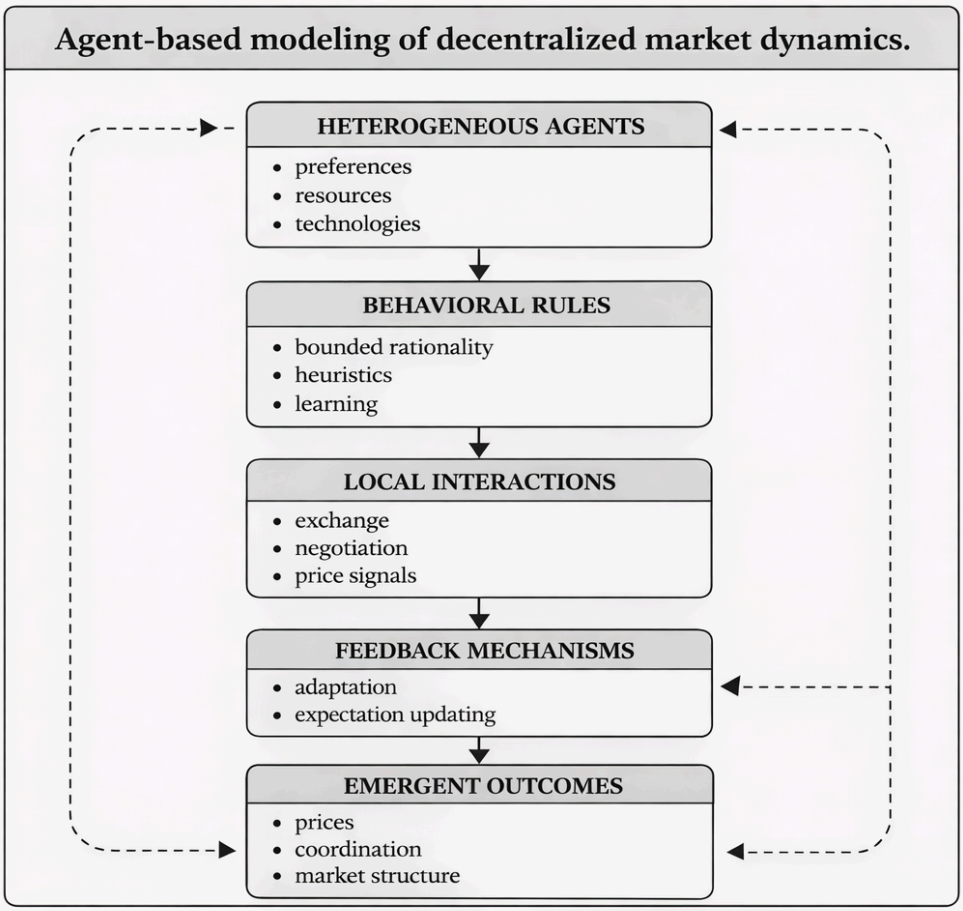


Figure 2. Agent-based modeling of decentralized market dynamics.

Figure 2

Agent-based modeling of decentralized market dynamics.