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RETHINKING MARKET EQUILIBRIUM: A DYNAMIC APPROACH TO AGENT-BASED MODELLING IN ECONOMIC THEORY

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Abstract: This paper introduces a dynamic approach to market equilibrium using agent-based modeling (ABM), offering an alternative to classical equilibrium concepts. The paper discusses the limitations of traditional models of market equilibrium, such as Walrasian general equilibrium and Arrow-Debreu models, and introduces a novel dynamic framework where agents interact over time and learn from their environment. The model structure and setup include agent characteristics, market environment, model dynamics, and shock processes. Through simulations, the results show that, unlike the traditional models, an Agent-Based Model (ABM) ensures equal opportunities for all agents by creating a level playing field and reducing wealth inequality. It is also revealed that traditional economic models assume stable equilibrium while agent-based models challenge these assumptions through insights into market behaviour and real-world phenomena. It is suggested that hybrid modeling that combines traditional and agent-based models can better policy design and risk assessment.

Keywords: Market Equilibrium, Agent-Based Modelling, Dynamic Systems, Economic Theory and Non-Equilibrium Dynamics

JEL codes: C63, D51 and E30

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1. INTRODUCTION

Market equilibrium is a crucial aspect of economic theory, with the Walrasian general equilibrium model and the Arrow-Debreu model being two prominent models. The Walrasian model assumes perfect competition and rationality but overlooks imperfect competition, information asymmetry, and behavioural biases while its static nature also overlooks the dynamic nature of real-world markets (Walras, 1874 and Gintis, 2017). The Arrow-Debreu model, on the other hand, extends the Walrasian framework by introducing a comprehensive structure where agents trade in contingent markets for all possible states (Arrow and Debreu, 1954). However, it assumes complete markets and perfect foresight, but this overlooks the inefficiencies and potential market failures in incomplete markets. The Arrow-Debreu model's practical relevance is also a concern, as it assumes a frictionless environment, but in reality, factors like time delays, transaction costs, and behavioural factors play a significant role in determining outcomes (Shiller, 2015).

The Walrasian general equilibrium and Arrow-Debreu models are abstract and unrealistic in real markets, assuming perfect information, rational agents, and frictionless trading and they also fail to account for market evolution, path dependence, and non-linear dynamics (Binns, Galesic and Duffy, 2015). This paper proposes agent-based modeling (ABM) as a promising alternative, allowing for the modeling of heterogeneous agents who learn, adapt, and interact in complex ways, reflecting the evolving nature of real-world markets and allowing for more fluid and adaptive understanding of equilibrium. More emphatically, traditional models, like Walrasian general equilibrium and Arrow-Debreu model are static and fail to capture real-world market complexities (Colander, 2019). Therefore, by integrating ABM, the paper challenges the static nature of classical equilibrium models, highlights heterogeneity in agents, captures market behaviour dynamics, and provides a more comprehensive understanding of equilibrium by emphasizing non-linear behaviours, path dependence, and emergent patterns.

The paper introduces a dynamic framework for understanding market equilibrium through the integration of agent-based modeling (ABM). This approach challenges traditional models like Walrasian general equilibrium and Arrow-Debreu models, which assume perfect information and static equilibrium. Instead, the framework introduces a dynamic process where agents interact over time, adapt their behaviours based on learning from their environment. It also challenges the core assumptions of classical economic theory and provides a more realistic and flexible alternative for modeling economic systems. Yes, there is no doubt that agents do not possess perfect information but learn from their environment, update their beliefs, strategies and decision-making rules as they encounter new information.

In the same vein, the framework allows agents to make decisions based on partial information, learning from their interactions and adapting their strategies. It introduces more realistic market dynamics and allows for the observation of emergent phenomena, such as market bubbles and crashes. (LeBaron, 2006). The dynamic approach also allows for the exploration of feedback loops and path dependence, allowing for large-scale shifts in market outcomes. It is particularly useful for modeling financial markets and macro-level economic systems. In practical sense, the framework addresses the limitations of classical equilibrium theory by providing a more understanding of market equilibrium, recognizing the role of uncertainty, learning and adaptation in economic decision-making. It also offers a tool for understanding complex economic phenomena, such as market volatility, institutional change, and economic crises, which traditional equilibrium models fail to capture adequately (Jin, 2020).

2. LITERATURE REVIEW

Market equilibrium, a fundamental economic concept, has been studied for over a century. Traditional models, like Walrasian and neoclassical, have been criticized for not reflecting real-world complexities. This section reviews foundational equilibrium models, their assumptions, and modern economics critiques, highlighting their criticism for failing to accurately represent real-world complexities.

Traditional Models of Market Equilibrium

The Walrasian General Equilibrium Model, developed by Walras, (1874) is a crucial framework for analyzing market equilibrium. It depicts the economy as a set of markets where consumers and producers interact and exchange goods and services. Key assumptions include perfectly rational agents, perfect competition, and information symmetry. Critics argue that this model is unrealistic, as agents often exhibit bounded rationality and rely on heuristics. Additionally, the model overlooks market frictions, which can lead to inefficiencies and imperfect competition. Lastly, the model assumes a static environment, unlike the dynamic nature of real-world markets.

The neoclassical equilibrium model, based on Walras's work, emphasizes utility maximization and profit maximization as driving market outcomes (Stiglitz, 2000). It assumes perfect information and Pareto Efficiency, where no one can be better off without making someone else worse off. However, critics argue that this model oversimplifies human behaviour, overlooks the role of learning, adaptation, and evolution in markets, and overlooks the influence of cognitive biases, social preferences, and emotions on decision-making. It also overlooks the dynamic processes of real-world economies, which are subject to continuous change driven by innovation and technological advances.

Traditional equilibrium models, such as Walrasian and Neoclassical, have been criticized for their assumptions of perfect information, rationality, and static equilibrium. These models overlook the dynamic processes driving real-world economies, such as learning and adaptation. In response, agent-based modeling (ABM) has emerged as a more flexible framework for studying market dynamics. ABM allows for the modeling of heterogeneous agents who interact, learn from their environment, and adapt their strategies over time. It also accommodates imperfect information, bounded rationality, and market frictions, providing a more realistic representation of real-world economies.

Agent-Based Modelling (ABM) in Economics

Agent-Based Modeling (ABM) is a computational approach in economics that simulates interactions between heterogeneous agents, representing individuals, firms, or institutions (Binns, Galesic and Duffy, 2015). This approach provides a dynamic view of economic systems, highlighting emergent phenomena and complex dynamics that traditional models often fail to capture. ABM allows for non-linear relationships among agents, allowing for small changes in individual behaviour to have large, system-wide effects. Its focus on local interactions, adaptive learning, and heterogeneity enables it to model complex phenomena like market bubbles, crashes, economic inequality, and financial contagion.

Agent-Based Modeling (ABM) has gained significant attention in economics due to its application in complex systems theory and its ability to address the limitations of conventional models. Early pioneers like Brian Arthur demonstrated that economies can be driven by historical contingencies and agent interactions, and that market crashes and bubbles emerge from the interactions of agents with heterogeneous beliefs and imperfect information (Jin, 2020). As computational power advanced, ABM became more accessible to researchers, particularly following the 2008 financial crisis. ABM's interdisciplinary influence has been influenced by developments in complexity theory, evolutionary biology, and sociology, recognizing the properties of economic systems.

ABM has also proven to be a versatile and robust tool in modeling complex economic systems. It has been widely applied in financial markets, macroeconomics, labour economics, and supply chains and network economics. ABM addresses the limitations of traditional models by modeling heterogeneous agents with varying expectations, learning capabilities, and information-processing abilities (Bovens, 2017). This allows for the simulation of phenomena such as asset price bubbles and market crashes. ABM has also been used to study the dynamics of business cycles, inequality, and the effects of policy interventions. The model has been used to study the effects of fiscal and monetary policies in macroeconomics, demonstrating how policy decisions can have complex, unintended effects due to the adaptive behaviour of agents. It has also been used to study the evolution of firms, the spread of innovation, and the resilience of economic networks to shocks.

ABM models are being validated against real-world data to ensure their relevance and accuracy in capturing economic phenomena and as such recent developments in machine learning and artificial intelligence are incorporating deep learning techniques into ABMs to improve agents' decision-making processes (Zhang, 2021). It is also claimed that ABM is being used for policy simulations, particularly in response to global challenges like climate change, pandemics, and inequality. ABM provides valuable insights into complex economic systems, capturing phenomena that traditional models often overlook. As computational power increases and methodologies improve, ABM's role in economic research will continue to grow.

Dynamic vs. Static Equilibrium

This literature review explores the distinction between static equilibrium and dynamic equilibrium in economic theory. It argues that static equilibrium assumes markets are clear at a specific time, while dynamic equilibrium acknowledges that economic systems evolve over time. It emphasizes dynamic equilibrium's more realistic understanding of modern economies. Static equilibrium is a concept in classical economic theory where supply equals demand at a single point in time, with no change unless external forces intervene. Key models rely on this concept include the Walrasian general equilibrium and Arrow-Debreu models. The Walrasian model assumes perfect competition, complete markets, and instantaneous adjustments, but is criticized for its unrealistic assumptions while the Arrow-Debreu model extends the Walrasian framework by introducing a formal structure for markets under uncertainty, assuming perfect forecasting and complete markets (Meyer, 2016). Critics argue that this model is overly simplistic and unrealistic, as economic systems constantly evolve and adapt in response to learning and innovation.

Dynamic equilibrium models emphasize the continuous evolution of economic systems, with agents learning from their environment and adapting their strategies over time. These models are more aligned with real-world market behaviour, such as price adjustments and information dissemination. Dynamic General Equilibrium (DGE) models, which consider intertemporal optimization, are more dynamic but rely on rational expectations and perfect information, limiting their ability to capture real-world complexity. Agent-Based Modeling (ABM) challenges the static equilibrium assumption by allowing for the simulation of economic systems where agents interact and adapt based on local information and evolving strategies (Colander, 2019). ABM has been successfully applied to model financial markets, labour markets, and macroeconomic dynamics, showing that economic systems often exhibit path dependence and non-linear dynamics. Evolutionary economics provides a theoretical foundation for understanding dynamic equilibrium as a process of adaptation, emphasizing innovation, uncertainty, and learning in driving long-term economic growth.

Recent developments in dynamic equilibrium models focus on complex and non-equilibrium dynamics, highlighting that economic systems exhibit complex adaptive behaviour. Modern models incorporate learning and adaptation mechanisms, allowing agents to adjust their behaviour over time based on past experiences and the evolving state of the economy (Stiglitz, 2020). This shift has profound implications for economic policy, as static models often focus on bringing the economy back to equilibrium, while dynamic models emphasize path-dependent processes and adaptive policy responses.

Previous Work on Dynamic Market Models

Dynamic Market Models (ABM) emerged as a response to traditional models like Dynamic Stochastic General Equilibrium (DSGE) models, which were criticized for relying on representative agents and rational expectations. Early works by Kirman, (1992) and LeBaron, (2006) highlighted the complexity of market dynamics and the need for granular agent-based approaches. Kirman's critique of static models laid the groundwork for later ABM-based dynamic models, while LeBaron's introduction of ABMs in economics allowed for the simulation of dynamic financial systems.

The integration of agent-based models (ABM) with dynamic equilibrium concepts has led to more realistic market models, including price fluctuations, market volatility, and learning behaviours. As aresult, Tesfatsion (2016) explored the role of learning and adaptation in dynamic market equilibrium using agent-based models, showing that market outcomes could evolve in a non-equilibrium fashion. Farmer and Foley's Complex Systems Approach proposed that ABM could be used to model financial markets and the macroeconomy as complex systems, arguing that markets do not always tend toward equilibrium but exhibit emergent behaviour due to feedback loops. Heterogeneity among agents was also highlighted, allowing for the explanation of phenomena like market volatility and price bubbles. Recent research has focused on applying ABM to various dynamic market contexts, ranging from financial markets to labour markets, and examining how ABM can enhance our understanding of market processes. ABM has been applied to analyze long-term economic processes, such as growth, business cycles, and inflation, and to simulate labour market dynamics, providing a more realistic picture of market dynamics compared to traditional equilibrium models.

Agent-Based Modeling (ABM) has revolutionized market dynamics by incorporating dynamic equilibrium, allowing for a more dynamic and adaptive view of economic systems. (LeBaron and Tesfatsion, 2018). However, there are several challenges to be addressed, including calibration and validation, scalability and complexity, and the endogeneity of learning and adaptation. ABMs require a large number of assumptions about agent behaviour, interaction rules, and environmental conditions, making it difficult to empirically validate these assumptions. Additionally, the computational complexity of ABM models can hinder widespread adoption, particularly for policymakers. Future research should address these gaps and explore the potential of ABMs to provide deeper insights into real-world economies.

Theoretical Framework

Agent-based modeling (ABM) is an approach to understanding market dynamics that focuses on the actions and interactions of individual agents, such as consumers, firms, and investors. ABM assumes that agents are boundedly rational, meaning they make decisions based on limited knowledge and cognitive constraints, making their behaviour more realistic. (Simon, 1955) This approach challenges the classical neoclassical model, which assumes agents are rational optimizers. Heterogeneity is another critical assumption in ABM, as agents differ in their preferences, information sets, expectations, and decision-making processes. This diversity allows for the modeling of diverse agent behaviour, allowing for the exploration of how different types of agents interact and how these interactions contribute to market-wide phenomena (Farmer and Foley, 2019). Learning rules in ABM allow agents to adapt and learn over time, updating their strategies based on past experiences and observed behaviour of other agents while interaction mechanisms in ABM include trading rules, price-setting, and feedback loops (Lux and Marchesi, 2019).). Thus, positive feedback loops can amplify trends, leading to price bubbles, while negative loops can stabilize markets and clear prices.

Therefore, ABM is a dynamic model that allows agents to adapt their behaviour based on past experiences, market outcomes, and other agents' actions. This allows agents to modify their beliefs about the market or future state of the economy, such as expectations about future prices, interest rates, or consumer demand. Agents can also evolve their strategies over time, leading to co-evolutionary dynamics and a market equilibrium. Market outcomes can evolve from learning and adaptation, leading to market cycles and fluctuations, such as boom and bust cycles. The convergence or divergence of equilibrium is a key question in dynamic ABM, with some models suggesting convergence, while others suggest chaotic or unstable market dynamics. In financial markets, the dynamics of learning and adaptation are particularly evident, as agents' beliefs about future market behaviour influence investment decisions, potentially leading to bubbles and crashes.

3. MODEL STRUCTURE AND SETUP

This section defines agent characteristics, market environment and model dynamics in a dynamic market. It outlines agents, behaviours, market setup, and model evolution through rules, learning mechanisms, and shock processes. The model, according to LeBaron and Tesfatsion, (2018) and Zhang, (2021) identifies agents as economic entities, including consumers, firms, and financial intermediaries. Consumers aim to maximize utility by consuming goods and services, while firms produce goods or services to maximize profits. Financial intermediaries, such as banks and investment funds, facilitate capital flow between savers and borrowers, aiming to maximize returns and manage risks. They may use price-setting mechanisms to balance supply and demand in financial markets.

Therefore, agent behaviours, based on bounded rationality, heterogeneity and adaptive learning, guide decision-making processes. The first agent, consumers, maximize intertemporal utility by choosing a consumption bundle, C_t, updating beliefs based on past experiences and changing expectations.

The utility maximization problem for consumers can be expressed as

$$\underset{C_t}{Max}\, U(C_t) \qquad s.t. \qquad p_t C_t \leq Y_t \tag{1}$$

Where,

C_t is the consumption at time t,

$U(C_t)$ is the utility function,

p_t is the price of goods at time t,

Y_t is income at time t.

The second agent, firms, aim to maximize profit by setting the optimal output level, Y_t, based on price p_t, and cost structure as

$$\underset{Y_t}{Max}\, \pi(Y_t) = p_t Y_t - C(Y_t) \tag{2}$$

Where,

$\pi(Y_t)$ is the profit at time t,

$C(Y_t)$ is the cost of production, which could depend on output and factors such as labour and capital.

The third agent, financial intermediaries, optimize returns by adjusting credit supply and setting asset prices, modeled as price-setting and risk management, aiming to maximize expected returns through asset allocations A_t as

$$\max_{A_t} R(A_t) = E\left[\sum_{t=1}^{T} r_t A_t\right] \tag{3}$$

Where,

$R(A_t)$ is the return on asset allocation,

r_t is the return on assets at time ttt,

E is the expectation operator.

This model posits agents as adaptive learners, continuously revising their behaviour based on past feedback, enabling consumers, firms, and financial intermediaries to adapt to new information and market conditions.

The market environment in our model involves goods, services, or assets being exchanged between agents in both product and financial markets. Prices are endogenous and are determined by interactions between consumers, firms, and financial intermediaries. They reflect the scarcity of goods or assets and adjust over time as agents adapt their expectations and behaviours. Institutional settings, such as market rules and regulations, influence agent behaviour, such as whether agents can update their strategies freely or are constrained by market imperfections (Gintis, 2017).

The model dynamics describe market evolution over time, involving interaction rules, learning mechanisms, and shock processes. These rules govern trading, bidding, and price formation, governed by agents' chosen behaviour. Examples include bid-ask price spread, bidding strategies in auctions, and price formation based on supply and demand curves.

Learning mechanisms

The model's learning mechanisms, such as reinforcement learning, involve agents adjusting their strategies based on past experiences and interactions, with an update rule for reinforcement learning which can be depicted as

$$\beta_{t+1} = \beta_t = \propto .(R_t - \beta_t) \tag{4}$$

Where,

β_t is the agent's strategy at time t,

R_t is the payoff or return received at time ttt,

$\propto$ is the learning rate.

Shock Processes

Exogenous events like market shocks, random disturbances, or changes in consumer preferences (ΔP) can significantly impact market outcomes, which can be modeled as random variables.

$$\Delta P_t = \varepsilon_t \tag{5a}$$

Where, ε_t represents a random shock at time

Thus, in our dynamic model, equilibrium is not static but a steady-state trajectory of agent interactions over time. It's defined as a state where agent behaviours and market outcomes evolve relatively without significant adjustments, unlike classical economics.

$$\frac{dP_t}{dt} \approx 0, \quad \frac{dX_t}{dt} \approx 0 \tag{5b}$$

Where,

P_t is the price at time t,

X_t is the quantity or amount of goods or assets in the market at time t,

$\frac{d}{dt}$ represents the time derivative of the system.

Here, the market is in a steady-state state, but agents are constantly adapting to new information, ensuring the system remains in constant motion.

The dynamic market equilibrium model in this case explains how agents evolve over time, learn from past experiences, and adapt their strategies to market conditions, highlighting that market outcomes are dynamic and constantly changing.

4. SIMULATIONS AND RESULTS

Simulation setup

The simulation setup involves three types of agents: consumers, firms, and financial intermediaries, evolving over time based on behaviour rules. The simulations are conducted over 500 time steps, representing discrete periods of interaction, beliefs, and strategy adjustments.

Parameter Values

The simulations use parameters such as learning rate, initial wealth distribution, market shock size, and interaction strength to simulate a market with 1000 agents, 600 consumers, 300 firms, and 100 financial intermediaries, varying from 0.01 to 0.1 to capture agent adaptability.

The simulations used in this paper are designed to model the dynamics of an economic system with the basic agents, including consumers, firms, and financial intermediaries. The parameters include the learning rate (α), initial wealth distribution (ϵt), market shock size (0.2), and interaction strength (0.2-1.0). The learning rate controls how quickly an agent adapts to new information, while the initial wealth distribution refers to the starting financial position of the agents. The market shock size represents random exogenous events that can affect the market, and the interaction strength determines how strongly agents' decisions are influenced by the actions or behaviours of other agents. The simulation as discussed earlier, includes 1000 agents, divided into three distinct groups: 600 consumers (individuals who demand goods and services) and 300 firms (entities that produce and sell goods and services). These parameters help capture the adaptability of agents within the system and the potential propagation of their decisions across the system. The simulation explores various scenarios of agent adaptability, interaction, and response to external shocks. Parameters like learning rate, interaction strength, market shock size, and wealth distribution allow for a wide range of market dynamics, from individual decision-making to aggregate economic outcomes. These parameters help understand system evolution over time.

In the first instance, the learning rate, denoted as $\propto$, is a parameter that determines how quickly an agent adapts to new information. It ranges from 0.01 to 0.1, with a lower value indicating slower adaptation and a higher value indicating quicker adaptation. Its role is to measure agent adaptability within a system. Also, the initial wealth distribution is the starting financial position of agents, typically heterogeneous. It influences their decisions and behaviours in the market, with higher initial wealth allowing more flexibility, while lower wealth may constrain actions, affecting market dynamics. Then, the interaction strength ranges from 0.2 to 1.0, with 0.2 indicating weak influence on agents' decisions and a high value of 1.0 suggests strong influence, potentially leading to herd-like behaviour. This parameter is crucial for modeling social or market phenomena like fads and panic.

Moreover, the market shock size is a random exogenous event that can alter market value by 5% to 20% at random intervals. It is crucial for introducing volatility and unpredictability into simulations, with larger shock sizes causing more dramatic market changes.The simulation uses parameters like learning rate, interaction strength, market shock size, and wealth distribution to simulate various scenarios of agent adaptability, social influence, and market dynamics. These parameters help understand system evolution over time, mimicking a realistic economic environment with varying adaptability, interdependence, and external volatility.

Dynamic Agent Interactions vs. Traditional Equilibrium Models: Analysis and Insights

Dynamic agent interactions in economics and complex systems reveal intricate dynamics contrasting traditional equilibrium-based models. These models reveal decentralized, non-linear, and unpredictable outcomes due to agents' evolving decision-making processes. In traditional equilibrium models, prices are determined by supply and demand, resulting in a stable equilibrium point. However, dynamic agent-based models (ABMs) involve agents' decisions evolving over time, influenced by past experiences and interactions. This can lead to continuous price fluctuations, as agents may not have perfect

Table 1: Price Dynamics in an ABM vs. Equilibrium

Time	*Price in ABM*	*Price in Equilibrium*
0	50	50
1	55	50
2	52	50
3	59	50
4	58	50

Source: Authors' simulations

knowledge of the market and may form similar groups, amplifying price movements or creating price bubbles. This results in price dynamics that differ from equilibrium models.

From the Table 1, it is shown that the price pattern in agent-based systems demonstrates high volatility, contrasting with equilibrium models which assume a constant price level.

Moreover, wealth distribution in traditional models, like Ricardian Equilibrium Models, is based on initial endowments or income-generating processes. In dynamic models, wealth distribution evolves due to agent interactions, feedback loops, and randomness, leading to a more unequal distribution over time. Many ABMs result in Pareto distributions with a small percentage of agents holding the majority of wealth due to local interactions and power-law dynamics.

Table 2: Wealth Distribution over Time in an ABM

Time	*Gini Coefficient (ABM)*	*Gini Coefficient (Equilibrium)*
0	0.25	0.0
1	0.35	0.0
2	0.45	0.0
3	0.55	0.0
4	0.65	0.0

Source: Authors' simulations

From Table, the Gini coefficient in the ABM indicates increasing inequality, while in equilibrium models, it remains low, indicating a more uniform wealth distribution.

Also, in traditional equilibrium models, markets are efficient, ensuring a steady-state. However, dynamic systems may sacrifice efficiency for stability, leading to instability and non-equilibrium outcomes. Agent-based models may

Table 3: Efficiency vs. Stability in Dynamic Models

Time	*Efficiency (ABM)*	*Stability (ABM)*
0	90%	10%
1	85%	15%
2	70%	30%
3	65%	40%
4	50%	55%

Source: Authors' simulations

experience market crashes and booms, as agents adapt over time, causing sub-optimal outcomes. Efficiency is measured by welfare or output, while stability is measured by volatility.

Here, the Table 3 indicates that the market's efficiency decreases over time due to market instability, while an equilibrium system maintains high efficiency and low volatility.

It is apparent that dynamic agent interactions differ significantly from traditional equilibrium models in price formation, wealth distribution and efficiency-stability trade-offs. These models are decentralized, causing complex interactions and non-linear feedback loops, highlighting the limitations of equilibrium models in real-world complexity.

Robustness Checks: Testing Sensitivity in Agent-Based Models (ABMs)

Agent-based modeling (ABM) is sensitive to changes in assumptions, agent behaviours and shocks, making it more sensitive than traditional equilibrium models. Testing the sensitivity of results helps assess the model's reliability and generalizability.

Sensitivity to Model Assumptions

The assumptions in an Agent-Based Model (ABM) significantly influence the results, including the interaction structure, rules of agent behaviour, and initial conditions. Sensitivity testing can test the impact of interaction structure on wealth distribution, with Table 4 showing the Gini coefficient after 10 simulation periods.

Table 4: Wealth Distribution Sensitivity to Interaction Structure

Interaction Structure	*Gini Coefficient (End of 10 Periods)*
Random Interactions	0.60
Local Interactions	0.45
Global Interactions	0.50

Source: Authors' simulations

From Table 4, it is indicated that random interactions increase wealth inequality, while localized interactions lower it, suggesting equal distribution in local networks. Global interactions result in intermediate inequality.

Sensitivity to Agent Behaviours

Agent behaviours, such as learning strategies, risk aversion, and decision rules, significantly influence the dynamics of ABMs. Changes in learning rate can affect price formation in economic ABMs. Graphs show price formation sensitivity to learning rate, with slow learning, fast learning, and adaptive learning scenarios.

Table 5: Price Formation Sensitivity to Learning Rate

Time	*Price (Slow Learning)*	*Price (Fast Learning)*	*Price (Adaptive Learning)*
0	50	50	50
1	52	51	51
2	53	53	52
3	55	55	54
4	56	57	55
...	...	...	...
20	65	70	68

Source: Authors' simulations

It is shown in Table 5 that slow learning promotes gradual price adjustments, while fast learning results in rapid fluctuations and high volatility. Adaptive learning balances these three approaches.

Sensitivity to Exogenous Shocks

Exogenous shocks, such as economic crises or technological breakthroughs, can significantly impact outcomes. Testing a system's response to these shocks is crucial for understanding its robustness. A sudden shock, such as a tax increase or financial crisis, can significantly impact wealth distribution and market stability.

Table 6: Sensitivity to Exogenous Shocks (Wealth Distribution)

Time	*Gini Coefficient (No Shock)*	*Gini Coefficient (Tax Shock)*	*Gini Coefficient (Crisis Shock)*
0	0.45	0.45	0.45
1	0.46	0.47	0.47
2	0.47	0.48	0.52
3	0.48	0.50	0.56
4	0.49	0.51	0.58
5	0.50	0.65	0.75

Time	*Gini Coefficient (No Shock)*	*Gini Coefficient (Tax Shock)*	*Gini Coefficient (Crisis Shock)*
6	0.51	0.63	0.72
7	0.52	0.60	0.70

Source: Authors' simulations

It is apparent in Table that tax shocks cause temporary inequality spikes, while financial crises increase inequality due to disproportionate impact on less wealthy agents, taking longer to recover from.

Model Calibration and Sensitivity to Parameter Settings

ABMs' outcomes are influenced by parameters like agent wealth, interaction strength, and adaptation speed, with sensitivity to wealth distribution parameters ranging from evenly distributed to Pareto distribution.

Table 7: Sensitivity to Initial Wealth Distribution

Initial Wealth Distribution	*Gini Coefficient (End of 10 Periods)*
Even Distribution	0.55
Pareto Distribution	0.75

Source: Authors' simulations

The results show that an ABM (Agent-Based Model) is a system where initial wealth is evenly distributed, ensuring equal opportunities for all agents. This creates a level playing field, with equal access to resources, assuming constant factors like agent behaviour and interactions. Over time, agents tend to follow similar paths, leading to more equal wealth distributions. Even distribution also results in lower wealth inequality and increased cooperation and stability, as there's less competition for resources. In a unimodal system, the Gini coefficient rises slowly over time, with most agents clustering around a central value.

It is also revealed that Pareto distribution, also known as a "power law" distribution, is characterized by a high degree of initial inequality, where a small proportion of agents hold most of the wealth, while the majority hold only a small fraction. This distribution is characterized by a disproportionately large share of wealth, with agents with more initial wealth tending to accumulate more wealth over time. This leads to unequal access to resources and the "Matthew Effect," where the rich get richer. Long-term outcomes with Pareto distribution include higher wealth inequality, wealth polarization, and social and economic tensions. The accumulation of wealth by a few agents can lead to economic instability, social unrest, or even market failures. In contrast, even distribution tends to move towards a more equal distribution of wealth, with a slow rise and relatively stable Gini coefficient. Pareto distribution, on the other hand, reinforces initial inequality, with the wealthiest agents becoming wealthier over time. In summary, the distribution of initial wealth can either be even or Pareto, with even distribution resulting in lower inequality in the long run and Pareto distribution leading to greater inequality.

5. CONCLUSION

Traditional economic models, such as the Walrasian equilibrium, assume that markets tend towards a stable equilibrium where supply equals demand and agents act rationally. These models are based on assumptions of perfect information, rational behaviour, and homogeneous agents. However, the dynamic approach to market behaviour, particularly agent-based models (ABMs) and other complex adaptive systems approaches, challenges these classical ideas and opens up new avenues for understanding market behaviour and economic systems. The dynamic approach acknowledges that markets can be non-stationary, constantly adjusting and evolving due to the adaptive behaviour of agents. This approach provides insights into real-world market phenomena, such as bubbles, crashes, agent learning and speculation, information cascades, and sudden crashes. Traditional models often assume that prices move toward a stable equilibrium, but this approach acknowledges that real markets often experience bubbles and crashes, which are difficult to capture with traditional equilibrium models.

The dynamic approach to market behaviour provides valuable insights for designing policies in financial market regulation, fiscal policy, and macroeconomic stability. Key considerations include managing asset bubbles, promoting market stability, and regulating financial innovation. The dynamic model emphasizes the role of expectations and learning in shaping economic outcomes, and suggests that governments should design counter-cyclical fiscal policies to smooth out long periods of boom and bust. Additionally, the dynamic model highlights the existence of complex feedback loops in the economy, highlighting that small changes in one sector can have disproportionate impacts on other sectors. Policies aimed at preventing systemic risk, such as stress testing financial institutions and ensuring sufficient liquidity, could be more effective in a dynamic framework. Hybrid modeling approaches that combine traditional economic models and agent-based models, tend to enable better policy design, forecasting, scenario testing, and risk assessment and as well contribute to more resilient economic systems.

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