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NAVIGATING THE STOCK MARKET: MODELING WEALTH EXCHANGE AND NETWORK INTERACTION WITH LOSS AVERSION, DISPOSITION EFFECT AND ANCHORING AND ADJUSTMENT BIAS

Hisse Senedi Piyasasında Yön Bulma: Kayıptan Kaçınma, Eğilim Etkisi ve Çapa ve Ayarlama Yanlılığı ile Zenginlik Değişimi ve Ağ Etkileşimi Modellemesi

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Keywords: Loss Aversion, Disposition Effect, Anchoring and Adjustment Bias, Agent Based Modelling.

JEL Kodları: C6, H3, D01, G41

Abstract

This study aims to integrate meta-analysis into agent-based models and provide foundational insights into biased agent interactions. It delves deeply into the effects of various behavioral biases such as anchoring, disposition effect, loss aversion, and others on market dynamics and investor decisions. Using agent-based models, it presents simulations of market scenarios and investor behaviors, emphasizing the impact of individual decisions on market dynamics. The innovative approach of this study lies in integrating behavioral finance theories with real market data, offering a nuanced analysis of market behaviors. This work contributes a new perspective to behavioral finance and encourages the use of agent-based models to deepen our understanding of market dynamics and investor behaviors, which can be helpful in financial market analysis and policy-making. This study aims to provide a foundational framework for those looking to integrate meta-analysis into agent-based models and explore biased agent behaviors. The findings demonstrate the ability to model the interactions of loss aversion, disposition effect, and anchoring and adjustment bias taking into account agents' socio-demographic and psychological factors, as close to the real world as possible. The results offer highly favorable forecasts for modeling human behaviors more accurately in portfolio optimizations and for expanding the applications of Generalized Artificial Intelligence in financial market implementations.

Anahtar Kelimeler: Kayıptan Kaçınma, Eğilim Etkisi, Çapa ve Ayarlama Yanlılığı, Ajan Temelli Modelleme.

JEL Codes: C6, H3, D01, G41

Öz

Bu çalışma, ajan tabanlı modellere meta-analizi entegre etmeyi ve yanlı ajan etkileşimlerine dair temel içgörüler sunmayı amaçlamaktadır. Çapa, mülkiyet etkisi, kayıptan kaçınma ve diğer çeşitli davranışsal yanlılıkların piyasa dinamikleri ve yatırımcı kararları üzerindeki etkisini derinlemesine incelenmektedir. Ajan tabanlı modeller kullanarak, piyasa senaryoları ve yatırımcı davranışlarının simülasyonlarını sunmakta ve bireysel kararların piyasa dinamikleri üzerindeki etkisini vurgulanmaktadır. Çalışmanın yenilikçi yaklaşımı, davranışsal finans teorilerini gerçek piyasa verileriyle bütünleştirmesinde yatmakta ve piyasa davranışlarının nüanslı bir analizini sunmaktadır. Bu çalışma, davranışsal finansa yeni bir perspektif katmakta ve piyasa dinamikleri ile yatırımcı davranışlarının daha iyi anlaşılması için ajan tabanlı modellerin kullanımını teşvik etmektedir, bu da finansal piyasa analizi ve politika oluşturmada yardımcı olabilir. Çalışma, meta-analizi ajan tabanlı modellere entegre etmek isteyen ve yanlı ajan davranışlarını incelemeyi sağlayacak temel bir altyapı sunmayı hedeflemektedir. Çalışmanın bulguları, ajanların sosyo-demografik ve psikolojik faktörlerini dikkate alarak, kayıp kaçınımı, mülkiyet etkisi ve çapa ve ayarlama yanlılığının etkileşimlerini gerçek dünyaya en yakın şekilde modellenebildiğini göstermektedir. Sonuçlar, insan davranışlarının portföy optimizasyonlarında daha doğru modellenebilmesine ve Genelleştirilmiş Yapay Zeka'nın finansal piyasalara yönelik uygulamalarının genişletilmesine yönelik uygulamalarda oldukça elverişli öngörüler sunmaktadır.

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1. Introduction

The analysis of investor behaviors in financial markets constitutes a significant area of behavioral finance. The aim of this study is to understand individual investor behaviors in financial markets and analyze the effects of these behaviors on market dynamics through models. The comprehensive literature review conducted in this study encompasses 50 different works, which have revealed various behavioral biases affecting investor decisions and their widespread effects in financial markets. These studies have thoroughly examined biases such as anchoring heuristics, disposition effect, overconfidence, loss aversion, representativeness bias, mental accounting, confirmation bias, gambler's fallacy, regret aversion, and familiarity bias.

The objective of this study is to better understand the effects of these behavioral biases on individual investors and to demonstrate how these biases are reflected in market behaviors. As a result, it will be possible to further develop studies aimed at incorporating human behaviors into portfolio optimization techniques. For this purpose, agent-based models will be used to simulate the interactions between market scenarios and investor behaviors. Agent-based models will allow us to visualize how each investor's decisions and interactions create an impact on the overall market dynamics, thereby enabling a more realistic modeling of the complexity and diversity of investor behaviors. The ABM (Agent-Based Modeling) methodology, which forms the basis of this study, will continue to maintain its importance in the coming period. This is because the point reached in the learning and response speeds of large language models heralds the onset of Artificial General Intelligence (AGI), representing generalized human cognitive abilities in software, beginning to interact with humans in various fields, especially in financial markets. Consequently, modeling transactions in the markets and outlining interactions between AGIs will again constitute the fundamental subjects of ABM.

The innovative approach of this study is to provide a general framework for researchers to conduct a more comprehensive analysis of market behaviors by integrating behavioral finance theories with real market data. Agent-based models are a highly effective tool in demonstrating how behavioral biases affect market prices and volatility, how these biases interact with each other, and how they can lead to cyclical movements in financial markets.

The contribution of this study to the literature is that it presents a new perspective in the field of behavioral finance and encourages the use of agent-based models. These models will help understand the effects of investor decisions and behaviors on markets more deeply and will provide significant tools for better understanding and managing financial markets. Furthermore, this study will also contribute to the development of policy recommendations aimed at preventing instability in financial markets.

In the ongoing second part of the study, it presents a literature review on the interaction between loss aversion, disposition effect, anchoring and adjustment bias, and socio-demographic and psychological factors, as well as on ABM and behavioral biases in financial markets. The third section delves into the foundation of the simulation related to the ABM, explaining the basic classes, methods, assumptions, and models to shed light on the methodological and analytical depth of the research. The fourth section examines the findings and analysis results related to the agents obtained. The fifth and final part contains the general conclusions and evaluations of the study. This structure illuminates the methodological and analytical depth of the research by formally conveying the relevant theoretical and practical findings.

2. Theoretical Framework and Literature Review

The section delves into pivotal behavioral economics concepts, chiefly loss aversion, and the disposition effect, elucidating their profound influence on financial decision-making. It embarks on a comprehensive journey through the intricate ways in which loss aversion—people's tendency to prefer avoiding losses over acquiring equivalent gains—shapes individual and collective economic behaviors, guided by seminal theories like Prospect Theory. Furthermore, it explores the disposition effect, highlighting investors' bias towards selling winners too early and holding losers for too long. This narrative is enriched with empirical evidence spanning various demographics, showcasing the multifaceted impact of these biases on economic decisions and investor behavior across different socio-economic backgrounds. Through an in-depth analysis of existing literature, this section not only underscores the complexity of financial decision-making processes but also sets the stage for understanding how these biases interact within the broader financial ecosystem, contributing significantly to the fields of ABM and behavioral economics.

2.1. Loss Aversion

The studies discussed in this section illuminate the role of loss aversion in financial decision-making processes and how this concept interacts with various socio-demographic and psychological factors.

Loss aversion can be defined as the tendency of individuals to be more affected by losses than by gains, and it is one of the most significant concepts in behavioral economics. This phenomenon was thoroughly examined within the Prospect Theory developed by Tversky and Kahneman (1991, 1992) and has played a crucial role in studies concerning financial decision-making processes, investor behaviors, and economic models. Loss aversion manifests not only on an individual level but also within societal and economic structures in various forms. In this context, understanding how loss aversion interacts with demographic, socio-economic, and psychological factors is critical for comprehensively understanding the financial decisions of individuals and communities.

Fisher (2013) questioned the presence of loss aversion in household saving behaviors in Spain, while Malloy (2015) assessed the effects of parental income on children's education and income levels from the perspective of loss aversion. On the other hand, the study by Boyce et al. (2013) addressed the effects of income changes on individuals' living conditions and their responses to these changes from the perspective of loss aversion. It was noted that factors such as employment status, household structure, and health condition play a significant role in the responses to income changes.

Johnson et al. (2015) investigated how loss aversion affects the decision-making processes of car buyers. He found that the importance car buyers place on attributes such as fuel consumption, comfort, safety, and information systems is determinative of loss aversion. Arora and Kumari’s (2015) study examines the effects of age and gender on loss aversion and regret among 450 investors, while Vendrik and Woltjer (2007) evaluates the impact of income changes relative to social reference groups on individuals' life satisfaction within the framework of prospect theory.

Boyce et al. (2016) associated the impacts of income changes on individuals' life satisfaction with levels of conscientiousness, while Gächter et al. (2022) examined levels of loss aversion in risk-free and risky choices. These studies have shown that loss aversion not only affects financial decision-making processes but also influences individuals' life satisfaction and perceptions of risk.

Blake et al. (2021) conducted a survey study with over 4.000 participants in the United Kingdom to reveal how loss aversion is related to demographic characteristics. The study found significant correlations between loss aversion and factors such as gender, age, education, and financial knowledge, demonstrating how this aversion to loss reflects individual differences. Dawson (2023) explored the role of psychological factors in risk preferences by associating gender differences with optimism and loss aversion, examining how these psychological factors influence risk preferences.

Specifically, these studies have investigated how loss aversion interacts with demographic factors such as age, gender, education level, income, and social class, and how this interaction shapes individuals' economic decisions. Additionally, the relationship between loss aversion and individuals' psychological states, personality traits, and future expectations has also been a focal point of these studies. This overview provides a rich foundation for understanding loss aversion and assessing its role in economic decision-making processes. It contributes significantly to ABM and behavioral economics theories, establishing a basis for comprehending the multifaceted nature of loss aversion and its complex role in financial decision-making processes (see Table 1).

Table 1. Combined Effects Table of Socio-Demographic and Psychological Components on Loss Aversion

Feature Category	Features	Effect on Loss Aversion
Demographic	Gender	Women tend to exhibit a higher tendency towards loss aversion compared to men.
	Age	Young adults and older individuals have higher loss aversion; there's a tendency to decrease in middle age.
Education and Financial Knowledge	Education Level	The tendency towards loss aversion generally decreases as the level of education increases.
	Financial Knowledge	A low financial understanding indicates a higher tendency towards loss aversion.
Socio-Economic	Social Class	Higher social classes tend to exhibit less loss aversion.
	Income	As income increases, the tendency towards loss aversion decreases.
	Savings and Homeownership	Homeowners and individuals with high savings tend to have lower levels of loss aversion.
Personal Situation	Marital Status	Individuals who are single or have a partner exhibit less loss aversion compared to those who are divorced, separated, or widowed.
	Number of Children	Individuals without children exhibit higher levels of loss aversion.
Other	Personality Type	Competitive and optimistic individuals tend to exhibit less loss aversion.
	Emotional State	Emotional state can significantly affect loss aversion.
	Political Leanings	Individuals with conservative leanings tend to exhibit less loss aversion.

Note: The table above presents the combined effects of components identified as a result of a literature study, prepared for use in an ABM model. It is based on the findings from the studies of Blake et al. (2021), Boyce et al. (2013), Arora and Kumari (2015), Vendrik and Woltjer (2007), and Johnson et al. (2015). This integration of socio-demographic and psychological components into the ABM model aims to provide a more nuanced understanding of how various factors influence loss aversion among individuals, thereby enabling a more accurate simulation of economic and financial decision-making processes.

2.2. Disposition Effect

The disposition effect is a significant behavioral bias frequently observed in financial decision-making processes. This bias describes the tendency of investors to sell their winning investments prematurely and hold onto their losing investments for too long. Recent research in this field has highlighted the impact of the disposition effect on investor behaviors and how this effect is related to various factors (Weber and Camerer, 1998; Frazzini, 2006).

Orenga et al. (2021) used data from Brazilian individual investors to examine the relationship between demographic characteristics, market conditions, and risk-taking tendency with the disposition effect. Their findings suggest that risk-averse and male investors are more prone to the disposition effect, while age does not seem to be related to this tendency. Similarly, Dhar and Zhu (2002) analyzed investors' tendencies towards the endowment effect using trading records from a large discount brokerage firm, observing that individuals in wealthier and professional occupations exhibited less of an endowment effect. Zahera et al. (2019) reviewed research in the field of behavioral finance to highlight how investors' sophistication and trading experience, along with gender and other demographic variables, influence the endowment effect.

Cheng et al. (2013) analyzed how internal and external factors such as gender, age, and market conditions are related to the endowment effect among retail futures traders on the Taiwan Futures Exchange. They observed that women and older traders have a stronger endowment effect. Talpsepp (2013) focused on the trading characteristics and endowment effect tendencies of individual investors on the Estonian stock market, concluding that older age groups and female investors tend to perform better.

Cecchini et al. (2019) investigated the relationship between individuals' behaviors related to the endowment effect and their personality traits, observing that individuals with extroversion and high levels of conscientiousness tend to exhibit less of an endowment effect. Goo et al. (2010) examined the endowment effect and its potential characteristics among Taiwanese investors, finding that the investors' level of education and their experiences of gains or losses over the past three years have a significant impact on the endowment effect.

Trejos et al. (2019) analyzed the behaviors of individual investors related to overconfidence and the endowment effect, finding that investors' overconfidence can be explained by gender, career, and education level, but factors such as age and nationality were not significant. Richards et al. (2011) studied individual investors in the United Kingdom, showing that the endowment effect and the use of stop-loss orders decrease with age and sophistication.

Finally, Dharma and Koesrindartoto (2018) examined the behaviors related to the endowment effect among Indonesian investors, finding that demographic factors play a significant role in the decision to sell winning or losing stocks. All these studies collectively underscore the complex impact of the disposition effect on investor behaviors and demonstrate that this effect can be associated with a variety of demographic and psychological factors (see Table 2).

Table 2. Combined Effects of Socio-Demographic and Psychological Components on Disposition Effect

Feature Category	Features	Effect on Disposition Effect
Demographic	Gender (Male/Female)	Males are generally less prone to the disposition effect; females and older investors might have a higher endowment effect.
	Age	No clear relationship; however, older investors may have a higher endowment effect due to decreased investment abilities.
	Education Level	Individuals with higher education levels are generally less prone to the endowment effect.
	Ethnic Origin	Disposition effect tendencies vary according to ethnic origin.
Socio-Economic	Professional Status	Individuals in professional jobs generally have a lower endowment effect.
	Asset Size	Investors with larger investments may be less affected by the endowment effect.
	Sophisticated Investor Status	Sophisticated investors tend to sell profitable assets and hold onto losing ones.
Personal	Risk Taking Propensity	Risk-averse investors are more prone to the endowment effect.
	Trading Frequency	Investors who trade more frequently are more prone to this cognitive bias.
Market Conditions	Market Type (Bull/Bear Market)	Endowment effect decreases in bull markets, while it is higher in bear markets.
	Market Size and Liquidity	Smaller and less liquid markets are more prone to the endowment effect.

Note: This table shows the combined effects identified as a result of literature studies prepared for use in an ABM model, based on the findings from the studies of Orenga et al. (2021), Dhar and Zhu (2002), Zahera et al. (2013), Cheng et al. (2013), Talpsepp (2010), Cecchini et al. (2019), Goo et al. (2010), Cristian Trejos et al. (2019), Rutterford et al. (2011), and Dharma and Koesrindartoto (2018).

2.3. Anchoring and Adjustment Bias

Anchoring and adjustment bias play a significant role in the financial decision-making process. This psychological tendency manifests as individuals' excessive reliance on a specific starting point (anchor) and their insufficient adjustment to new information. Below are the findings and impacts from some key research studies on this concept.

Habbe (2017) revealed in his study that investors overreact to current earnings information by overly relying on past earnings levels and patterns, suggesting that investors use previous earnings as an anchor. This indicates the significant influence of anchoring on financial decision-making, where historical performance excessively shapes expectations for current and future performance. Simmons et al. (2010) investigated the accuracy of adjustments made from given anchor values and the effect of motivation on these adjustments. Their findings demonstrate that motivation and the credibility of anchor values can influence the magnitude of adjustments, highlighting the role of personal incentives and belief in the reliability of information in the adjustment process. Hien et al. (2014) conducted research on the susceptibility of analysts in the Vietnamese financial market to anchoring and adjustment bias in future earnings forecasts. The study found that analysts, regardless of gender, were affected by this bias, emphasizing the universal impact of anchoring across different demographics within professional financial analysis. Davis et al. (1986) explored how married couples predict each other's preferences, finding that participants tended to make predictions based on their own preferences. This shows that anchoring and adjustment bias play a significant role in everyday decision-making, not just in financial contexts. People use their personal preferences as anchors, which then biases their predictions about others' preferences. Together, these studies highlight the pervasive influence of anchoring and adjustment bias across various domains, from financial markets to personal relationships. They underscore the importance of being aware of how initial information or personal experiences can serve as anchors, potentially leading to biased adjustments and decisions.

Champonnois et al. (2018) tested the potential of different survey formats to mitigate the anchoring effect, revealing how various formats can influence participants' decision-making processes. This study emphasizes the impact of presentation and context on reducing cognitive biases. Hurwitz et al. (2018) examined the impact of anchoring bias on decisions regarding the allocation of retirement savings. They found that individuals used the mandatory minimum annuity amount as an anchor, leading to choices of higher annuities, which highlights the influence of initial reference points on financial planning decisions. Khan et al. (2017) analyzed the extent to which investors in the Malaysian and Pakistani stock markets are prone to various heuristic approaches and the effects of these approaches on investment decisions. Their study underlines the significance of heuristic biases in investment decisions, especially in emerging market contexts, pointing out the importance of intuitive thinking patterns on the financial behavior of investors. Arora and Rajendran (2023) explored the susceptibility of individual investors in India to anchoring and endowment effects and how these tendencies change under market volatility. Their research assesses the impact of these behavioral tendencies on portfolio performance, highlighting the need for awareness and mitigation of such biases in volatile markets. Shin and Park (2018) investigated the influence of foreign investors on the anchoring effect in the South Korean stock market. This study suggests that the presence of foreign investors might reduce cognitive biases in equity markets, indicating that international diversification could be beneficial in mitigating behavioral biases. Lastly, King (2023) examined how the severity of tax fraud penalties and national social norms influence tax compliance. This study provides a focused examination of the effects of anchoring and adjustment bias on economic decisions, specifically in the context of tax behavior, emphasizing the role of contextual factors and initial anchors in shaping compliance behavior.

This extensive literature review demonstrates that anchoring and adjustment bias plays a significant role in decision-making processes in financial markets and everyday life. Being aware of such biases can help investors and individuals make more informed and effective decisions (see Table 3).

Table 3. Combined Effects of Socio-Demographic and Psychological Components on Anchoring and Adjustment Bias Effect

Feature Category	Features	Effect of Anchoring and Adjustment Bias
Demographic	Gender	Men have shown a tendency to choose higher annuities and are more prone to anchoring and adjustment bias.
	Age	Young adults and retirement-age groups are more susceptible to anchoring and adjustment bias.
Socio-Economic	Income	Higher income levels may reduce the impact of anchoring and adjustment bias; individuals with higher income are less likely to be influenced by this bias when choosing higher annuities.
	Job Experience	Greater experience reduces the effect of anchoring and adjustment bias.
	Financial Knowledge	Those educated in finance and accounting are less susceptible to anchoring and adjustment bias.
	Regulation	The potential of penalties to increase compliance and the effect of social norms as anchor information exist.
Personal	Decision-Making Processes	Participants' unique decision-making processes tend to reduce susceptibility to anchoring and adjustment bias.
Market Conditions	Market Experience	Foreign investors with more market experience exhibit less anchoring and adjustment bias.
	Investor Origin	Foreign investors are less prone to anchoring and adjustment bias compared to local investors.
	Price Fluctuations	There is a high susceptibility to anchoring and endowment effects under market volatility.

Note: The table above presents the combined effects of components identified as a result of a literature study, prepared for use in an ABM model. It is based on the findings from the studies of Orenga et al. (2021), Dhar and Zhu (2002), Zahera et al. (2013), Cheng et al. (2013), Talpsepp (2010), Cecchini et al. (2019), Goo et al. (2010), Cristian Trejos et al. (2019), Rutterford et al. (2011), Dharma and Koesrindartoto (2018), Habbe (2017), Simmons et al. (2010), Hien et al. (2014), Davis et al. (1986), Champonnois et al. (2018), Hurwitz et al. (2018), Khan et al. (2017), Arora and Rajendran (2023), Shin and Park (2018), King (2023).

2.4. All Biases Interactions

Parveen and Siddiqui (2018) explored the roles of anchoring and adjustment heuristic, disposition effect, and overconfidence biases in the decisions of investors at the Pakistan Stock Exchange. Their findings indicate that the anchoring and adjustment heuristic and disposition effect positively affect investment returns, whereas overconfidence bias has a detrimental effect. Moosa et al. (2017) highlighted the impacts of behavioral biases such as loss aversion, disposition effect, and representativeness bias on financial decision-making processes. They pointed out that these biases have widespread effects in financial markets and significantly shape investor decisions. Bokhari and Geltner (2011) demonstrated the importance of loss aversion and anchoring effects in the commercial real estate market. Their study analyzed the impact of these biases on the sale prices and listing prices of commercial real estate in the USA, showing that sellers' asking prices influence buyers' valuations and ultimately, the final sale prices. Asadi et al. (2020) conducted a study on the Tehran Stock Exchange to examine the roles of adjustment and anchoring bias and disposition effects in the formation of momentum returns. This research found that investors were more affected by adjustment and anchoring bias than by the disposition effect. Hascaryani and Maski (2021) investigated the relationships between investors' risk-taking behaviors and the intuitive herd behavior and disposition effect. Their study revealed that intuitive behaviors increase investors' herd behavior and disposition effect, leading to more aggressive risk-taking behaviors.

Leung and Tsang (2011) analyzed the predictability of home prices in the Hong Kong housing market in terms of loss aversion and anchoring effect. Their research highlighted the impacts of loss aversion and anchoring effect on home prices and transaction volumes, showing how these biases can significantly influence market dynamics. Cho and Chalid (2021) conducted a study on the Indonesian stock market to examine investors' behavioral biases and their effects on investment performance. The research identified overconfidence, loss aversion, anchoring and adjustment, mental accounting, and confirmation biases, finding that these biases have diverse impacts on the performance of certain investors. Madaan and Singh (2019) investigated the behavioral biases of individual investors at the Indian National Stock Exchange and their effects on investment decisions. The study revealed significant effects of overconfidence, anchoring, disposition effect, and herd behavior on investor decisions and market behaviors, emphasizing the importance of these biases in financial decision-making. Dervishaj (2021) conducted a literature review on the significance of the human factor in investor decisions and behavioral biases. This work distinguished between cognitive and emotional biases, addressing overconfidence, representativeness, anchoring, gambler's fallacy, regret aversion, confirmation bias, disposition bias, hindsight bias, familiarity, and home bias, showcasing the wide range of biases that affect investor decisions. Saivasan and Lokhande (2022) explored the relationship between investor risk perception and demographic and psychological factors. Their study analyzed the interactions between risk propensity, behavioral biases, and demographic factors, finding significant effects of overconfidence, disposition effect, herd behavior, anchoring effect, and familiarity bias on investors' risk perceptions.

Table 4. Behavioral Biases Interactions

Behavioral Bias	Interactions and Effects
Loss Aversion	Demonstrates that fear of losses significantly influences financial decisions and market prices, leading to a reduced inclination towards investing in risky assets. This aversion can cause market instability as investors react strongly to potential losses compared to equivalent gains.
Disposition Effect	Positively impacts investment returns by illustrating how investors are predisposed to sell assets that have gained value while holding onto assets that have lost value. This effect plays a crucial role in portfolio management and decision strategies.
Anchoring and Adjustment	Negatively affects investor decisions and investment returns by causing investors to overestimate their knowledge and decision-making abilities. This bias can lead to excessive risk-taking and disregard for potential market signals.
Overconfidence	Overconfidence bias negatively affects investor decisions and investment returns. Overconfidence causes investors to over-evaluate their own decision-making abilities.
Herd Behavior	Increases risk-taking behaviors among investors and reinforces the disposition effect. It highlights the tendency of investors to follow the majority, which can amplify market trends or contribute to the formation of bubbles.

Note: The table above presents the combined effects of components identified through a literature study, prepared for integration into an ABM model. It is based on the findings from the research of Moosa and Ramiah (2017), Leung and Tsang (2011), Parveen and Siddiqui (2018), Asadi et al. (2020), Bokhari and Geltner (2017), Cho and Chalid (2021), and Hascaryani and Maski (2021).

These studies reveal the presence of various behavioral biases that affect investor decisions in financial markets and the complex interactions among these biases. Understanding and managing these biases can contribute to the development of ABMs that can help investors make more rational decisions and policymakers make more effective decisions, thereby contributing to the stability of financial markets through more effective portfolio management (see Table 4).

3. Agent-Based Modeling (ABM)

ABM has indeed revolutionized the fields of finance and economics within the social sciences by transcending the limitations of existing theoretical frameworks and offering more comprehensive and realistic analyses. The unique representation that ABM provides for the social sciences forms a cornerstone of this discussion. It presents an ideal approach to modeling the complexities of financial markets through its ability to express the behaviors, motivations, and interactions of social agents, such as individuals and institutions, in a more natural and holistic manner. This allows researchers not only to understand interactions at the micro level but also to grasp how these interactions create new dynamics and structures at the macro level.

ABM's strength lies in its ability to simulate the individual actions of agents based on a set of rules, observing the emergent patterns and phenomena that result from the collective behavior of these agents. This methodological approach enables the exploration of complex adaptive systems where traditional models might fall short, providing insights into the emergent properties of financial markets such as bubbles, crashes, and market efficiency or inefficiency. The granularity and flexibility of ABM facilitate the examination of the specific conditions under which certain market phenomena occur, including the impact of regulatory changes, the introduction of new financial instruments, or shifts in investor sentiment.

Moreover, ABM's capacity to incorporate heterogeneity among agents—reflecting the diversity in investors' strategies, risk preferences, and reaction to new information—enhances its realism and applicability to real-world scenarios. This contrasts with more traditional models that often assume homogeneity and rationality among agents, potentially overlooking critical aspects of human behavior and market dynamics.

The most thrilling aspect of ABM is indeed its capacity to reveal emergent phenomena, a capability that traditional models often cannot match. Observing how market norms and institutions arise from the interactions of individuals allows us to explore areas previously inaccessible, shedding light on the complex dynamics that underpin financial and economic systems.

By focusing on how these emergent phenomena can be measured and evaluated, the study aims to quantitatively demonstrate how micro-level motivations translate into macro-level behaviors. This approach not only provides insights into the mechanisms driving market dynamics but also offers a framework for understanding the conditions under which certain phenomena emerge. For instance, ABM can elucidate how collective behaviors such as market trends, bubbles, and crashes develop from individual actions and decisions, offering a deeper understanding of market psychology and investor sentiment.

Consequently, ABM holds the potential to fundamentally transform our approach to comprehending and addressing complex issues in finance and economics. By materializing this revolutionary potential, the aim is to demonstrate ABM's transformative impact in the social sciences. This approach will not only expand the current body of knowledge but also provide a new roadmap for future research in these fields. The ability of ABM to incorporate a wide range of variables and simulate diverse scenarios makes it an invaluable tool for testing hypotheses, assessing policy impacts, and forecasting future trends. Through its application, researchers, policymakers, and practitioners can gain novel insights and develop more effective strategies for navigating the intricacies of financial markets and economic systems.

The roots of the ABM approach date back to the late 1940s, and it gained popularity in the 1990s alongside advancements in computer technology. One of the first conceptual models of ABM was the "segregation model" developed by Thomas Schelling (in 1971, 1974, and 1978), which was used to understand the dynamics of segregation between ethnic or economic groups. In the 1990s, ABM found a wide application in the social sciences, with significant models such as "Sugarscape" developed by J.M. Epstein and R. Axtell, examining social phenomena like migrations and the spread of diseases. Epstein and Axtell's model simulates complex social structures and phenomena that emerge from individuals acting on simple rules (Epstein and Axtell, 1996). ABM offers the ability to study the macro-level collective outcomes of micro-level individual decisions and interactions, aiding scientists in understanding the dynamics of complex systems and how these systems evolve (Gilbert, 2019).

Bankes (2002) emphasizes that ABM has created a revolutionary transformation in the social sciences, particularly in the fields of finance and economics. ABM has the potential to offer more comprehensive and realistic analysis by overcoming the limitations of existing theoretical frameworks. Bankes highlights that ABM allows for a deeper understanding of human behaviors and market dynamics by transcending traditional modeling limitations such as linearity, homogeneity, normality, and stationarity. He points out the advantages of ABM's unique representation in the social sciences, where behaviors, motivations, and interactions of social agents like humans and institutions can be expressed more naturally and holistically. This is especially ideal for modeling the complexity of financial markets. He underscores ABM's capability to guide the understanding not only of micro-level interactions but also of how these interactions create new dynamics and structures at the macro level. One of the most exciting aspects of ABM, as Bankes notes, is its capacity to uncover emergent phenomena—a realm beyond the reach of traditional models. This offers the opportunity to observe how market norms and institutions emerge from the interactions of individuals. The focus on how to measure and evaluate emergent phenomena and quantitatively examine how micro motivations transform into macro behaviors is a key area of study within ABM's application in social sciences.

Macal and North (2009) highlight the advantages of ABM as an approach capable of encompassing complex interactions and individual behaviors, especially against the limitations of traditional modeling methods in contexts such as economic markets. They note that agents in models are defined as independent components with heterogeneous, dynamic characteristics and behavior rules, which can range from simple "if-then" rules to complex behavior models. The autonomy, social interaction, and decision-making capabilities of agents are emphasized. For developing effective agent models, accurately defining the types and behaviors of agents is crucial, as agents are often considered as decision-makers of a system, and behavior models are designed to reflect the real-world behaviors of agents. ABM offers several advantages over traditional approaches in modeling economic systems, including reflecting agents' natural behaviors, adaptation and learning abilities, participation in dynamic strategic interactions, modeling organizational formation processes, and incorporating spatial components. The study also elaborates on different ABM applications such as the "Soup" model, Cellular Automata, Euclidean Space, GIS (Geographic Information System), and Network Topology, discussing their advantages. These models are used in various fields including social network analysis, the spread of contagious diseases, biological systems, traffic flow, urban planning, ecology, physical geography, environmental planning, disaster management, urban development, communication networks, and information dissemination (Macal and North, 2009).

Klügl and Bazzan (2012) emphasize the capability of ABM to generate a variety of complex phenomena, highlighting its potential to capture the core features of problems where the traditional modeling and simulation paradigm struggles. They note that ABM stands out by applying multi-agent systems to the foundational structure of simulation models and conceptualizing active components or decision-makers as agents, thereby showcasing the ability to generate a global phenomenon from the actions and interactions of individual agents. They identify three fundamental elements that must be considered when creating an ABM model: agents, interactions among agents, and the simulated environment. They stress that these interactions are responsible for producing the overall outcome of the model, and their design is of critical importance. They also detail the advantages ABM offers over traditional techniques, describing ABM as a modeling and simulation paradigm that allows for complex agent designs with high explanatory power. This approach provides the opportunity to observe and analyze model dynamics at both the local agent level and the macroscopic level, taking into account factors such as the heterogeneity of the agent population or variations in the environment. Furthermore, they list situations where ABM is particularly suitable. These include systems where dynamics emerge from flexible and local interactions, systems that need to represent heterogeneity in terms of behavioral rules, multi-layered systems containing emergent phenomena, systems where decision-making occurs at different aggregation levels, systems involving learning or evolutionary processes, and socio-technical systems that include intelligent human behaviors. This highlights ABM's versatility and its applicability to a wide range of complex systems across various domains.

Klein et al. (2018) thoroughly examine how ABM has transformed the study of social, economic, historical, and political phenomena. The research highlights the history and development of ABM's use in social sciences, drawing attention to how classical theoretical approaches like Adam Smith's "invisible hand" theory and Schelling's segregation model have been incorporated into ABM. It notes the rise in popularity of ABM with the spread of personal computers in the 1980s and how the terms "agent-based model" and "agent-based computational model" have become synonymous. The study also touches upon ABM's target systems and modeling objectives. It mentions that ABM can cover a wide range of target systems from singular events to general phenomenon classes, concretizing theoretical assumptions within these systems to test their ability to generate relevant phenomena. The modeling objectives are said to vary from explaining phenomena to predicting the future, with some models aiming to explain specific social phenomena while others illuminate policy decisions or future scenarios. Finally, the discussion turns to model validation and validity. ABMs can be considered "toy models," meaning they are highly simplified and abstract representations of target systems. The study emphasizes that such models are often not intended for making quantitative predictions but are used to test the consistency of existing theoretical frameworks or understand specific mechanisms (Klein et al. 2018).

Udehn (2001) and Hedström (2005) emphasize ABM's ability to analyze the dynamics of social systems by representing the repeated and coherent interactions of agents. These models demonstrate social-level dynamics as the aggregate result of interactions among agents within the system, where agents can range from individuals to states. Equipped with the capacity to perceive their environment and make autonomous decisions, these agents play significant roles in social systems. ABM employs elements such as agents, behavior rules, and interaction mechanisms to model social systems. This approach is utilized within Coleman's Social Theory framework to explain how macro-level structures influence micro-level behavior and vice versa. The design process of ABM compels modelers to explicitly state their assumptions and articulate all parameters and mechanisms precisely, offering a clearer understanding of the assumptions and scope underlying scientific arguments. This process enhances transparency and facilitates a deeper insight into the complex interplay between individual actions and collective outcomes, contributing significantly to our understanding of social phenomena.

ABMs vary depending on the target systems and modeling objectives. While some models aim to explain a specific event or a general class of phenomena, others are used to test existing theoretical accounts or to understand how specific mechanisms work and their effects. Grüne-Yanoff (2009) points out that ABMs differ in terms of model validation and validity, and in some cases, these models can be described as "toy models." These models are often used not for making quantitative predictions but rather for testing the consistency of existing theoretical frameworks or understanding specific mechanisms. These studies thoroughly explore the role and significance of ABM in social sciences, emphasizing its capability to understand and explain complex social dynamics. They provide a crucial guide for researchers working in this field, detailing the unique contributions of ABM to the understanding of social phenomena (Udehn, 2001; Hedström, 2005; Grüne-Yanoff, 2009).

J. Coleman's Social Theory is a framework used particularly in sociology to understand the interactions between individual behaviors and social structures. Coleman's theory focuses on the actions of individuals within social structures and the effects of these structures on individual behaviors. It aims to establish a connection between micro-level individual behaviors and macro-level social systems, visualizing this connection through a diagram known as "Coleman's Boat." Coleman's Boat explains the interactions between individuals' personal preferences, beliefs, behaviors, and social structures such as societal rules, norms, and institutions through three main components. Firstly, at the individual level, individuals' decisions are influenced by their inner worlds and social environments. Secondly, at the social system level, societal factors that affect individuals are considered. Thirdly, the micro-macro interaction examines how individuals' behaviors can impact broad social systems and how social structures can shape individuals' behaviors. This interaction demonstrates how the collective outcomes of individual behaviors can affect social structures and how social structures can guide individuals' behaviors. Coleman's Social Theory provides deep insights into social change, societal interaction, and the roles of individuals within social structures. It is widely used in social sciences to understand the complex interactions between individual and societal phenomena. The study by Türk (2015) compares Coleman's theory with Bourdieu's (1986) work on social capital, examining different approaches in sociological thought and discussions on social capital. Türk thoroughly discusses the contributions of these two thinkers to the concept of social capital and the similarities and differences between their theories (Türk, 2015, Bourdieu, 1986; Coleman, 1990;).

In social sciences, apart from Coleman's Social Theory, there are many significant theories that help understand the functioning of society, social structures, and behaviors. These theories offer various approaches to comprehend the complex interactions between society and individuals:

É. Durkheim introduced the concept of social facts to highlight the impact of society on individuals. According to Durkheim, social facts are societal norms, values, and institutions that are outside individuals' control and shape their behaviors. This theory examines the effects of society on individuals and how social norms and values are internalized (Gisbert, 1959; Varenne, 1995). K. Marx developed the conflict theory, arguing that society is founded on class struggles. This theory examines how economic forces affect the relationships between social classes and societal change. Marx's approach emphasizes the economic foundations of social structures and relationships and how class struggles lead to social change (Turner, 1975; Sedek, 2018). M. Weber analyzes the meanings and motivations behind individuals' social actions. Weber identifies four basic types of social actions and examines their effects on social organizations and institutions. Weber's approach focuses on understanding the individual meanings and motivations behind social actions and institutions (Munch, 1975). T. Parsons' Theory of Structural Functionalism argues that society functions like an organism where different parts work together as a system. He suggests that every social structure or institution has a function for the operation of society. Parsons' theory explores how social structures and functions interact with each other and maintain social stability (Parsons, 1951; Parsons and Shills, 1951). Symbolic Interactionism, developed by thinkers like George Herbert Mead and Herbert Blumer, concentrates on the interpretive processes that individuals employ to make sense of the social world. This perspective examines how individuals construct meaning through their interactions, thereby shaping social reality itself. It asserts that social meanings are not inherent but are created and modified through social engagement (Carter and Fuller, 2016; Blumer, 1986). M. Foucault developed the Power/Knowledge theory exploring how power and knowledge are interconnected in society and shape social relations. Foucault analyzes how power is not only repressive but also productive, forming social norms, identities, and knowledge. Foucault's theory reveals the interaction of power and knowledge in society, how social norms and identities are formed, and the productive role of power beyond its repressive functions (Townley, 2005; Willcocks, 2004).

These diverse social theories serve as foundational building blocks in the social sciences for understanding the functioning of society and the roles of individuals within social structures. Each theory addresses different aspects of society and various factors influencing human behavior, aiding in a better understanding of complex social phenomena. From Durkheim's Theory of Social Facts to Foucault's Power/Knowledge Theory, these approaches strive to explain how society and individuals influence each other and the outcomes of this interaction at the societal level. These theories and concepts provide a set of assumptions that are essential for accurately modeling real life in all stages of ABM, from the characteristics of agents, their interactions, to the impact they create on the market. Developing models without considering all these theories and concepts is not feasible, as they are crucial for reflecting the complexity and dynamics of real-world phenomena in ABM simulations.

3.1. Loss Aversion and Agent-Based Modelling

The integration of loss aversion with ABM offers significant progress in understanding financial markets and investor behaviors. The examination of this concept through various studies reveals the depth and complexity of financial decision-making processes.

Pruna et al. (2020) explore how ABM can be integrated with behavioral finance theories to deeply examine the effects of loss aversion in financial markets. The study focuses on expanding an existing asset pricing model to include the modeling of loss aversion effects. This model is designed to simulate market behaviors and asset prices, taking into account agents' varying levels of loss aversion. The interactions among these agents influence market dynamics and price movements. The methodology of the study involves simulations that analyze the behavior of the model under different parameters, and these simulations are used to test how well the model aligns with real market data. Findings indicate that loss aversion plays a significant role in asset prices and market volatility. Notably, agents with high levels of loss aversion can increase price fluctuations and contribute to market instabilities. Finally, the study highlights the importance of loss aversion in financial markets, demonstrating the value of using ABM as an effective tool to test and understand behavioral finance theories.

Ezzat (2020) addresses an agent-based model that examines the interactions in financial markets, particularly focusing on the impact of loss aversion on these interactions. Within the scope of the study, the decision-making processes and behaviors of agents in financial markets are simulated with respect to loss aversion, aiming to better understand agents' tendencies to overreact to potential losses, and how this behavior contributes to price fluctuations and the underlying causes of volatility in financial markets. The model investigates how agents respond to market conditions and the behaviors of other agents by employing both technical and fundamental analysis methods. Findings reveal that loss aversion significantly affects price fluctuations and volatility in markets, and the model successfully simulates some stylized facts observed in financial markets, especially market bubbles and crashes (Ezzat, 2020).

Lovric et al. (2010) have examined behaviors such as loss aversion and biased self-attribution that affect investor decisions in financial markets. Their study showcases the use of fuzzy aggregation operators to model the complexity of financial markets and investor behaviors. The model characterizes investor agents by their sensitivity to losses and their tendency to attribute successes to themselves and failures to external factors. These characteristics are identified as significant factors influencing the agents' market behaviors and decision-making processes. The findings of the study reveal that loss aversion and biased self-attribution have substantial effects on investors' risk-taking behaviors and market dynamics (Lovric et al., 2010).

3.2. Disposition Effect and Agent-Based Modelling

Studies on the disposition effect and ABM offer significant contributions to understanding financial markets and investor behaviors. Research-based on ABM in this area deeply examines the role of the disposition effect in financial decision-making processes and its impacts on market dynamics.

Li (2014) has examined the effects of the disposition effect in financial markets on investor behaviors and market dynamics. The agent-based model used in the study accommodates agents with various investment strategies and observes how these agents react to market conditions, especially how they behave in response to price changes. This behavioral tendency has significant effects on volatility and price movements in financial markets. The findings of the research reveal that the impact of bad news on the market is greater than that of good news, leading to asymmetric volatility.

Lin and Huang (2007) focused on the disposition effect in financial markets, examining its impacts on investor decisions and market performance through ABM. This study deviates from the assumptions of traditional finance theories and investigates investor behaviors in an artificial futures market, analyzing the tendency of investors to close profitable positions early and hold onto losing positions for too long. The findings of the study indicate that the disposition effect has a significant impact on investor behaviors and market outcomes. It suggests that while the S-shaped value curve based on prospect theory could contribute to this effect, short-term mean reversion expectations might play a more decisive role.

Ezzat (2019) examined the asset pricing dynamics in a scenario where investors' trading across multiple asset markets exhibits a trend effect. The study utilized an artificial financial market filled with investors following two heterogeneous trading strategies to investigate the effects of this trend on asset prices and the transition behaviors between multiple asset markets. The results demonstrate the effectiveness of this approach in explaining significant stylized facts observed in financial time series, such as the random walk dynamics of prices, bubbles, and crashes, fat-tailed return distributions, lack of autocorrelation in raw returns, long-term volatility memory, excess volatility, volatility clustering, and power-law tails. Additionally, it was found that asset returns exhibit a fractal structure and self-similarity features, but transition behavior is only possible between asset markets.

4. Model and Simulation

The ABM structure of the study is designed to simulate the real world by addressing the behaviors of individuals (agents) in financial markets, interacting with considered biases, and socio-demographic, and psychological factors. Each agent possesses socio-demographic characteristics such as age, income, and gender, which are combined with psychological factors like risk tolerance, utility, and value functions to form the behavioral profiles of the agents. Agents have behavioral biases such as loss aversion, disposition effect, and anchoring and adjustment bias. These characteristics are psychological tendencies that affect agents' financial decisions and play a significant role in market dynamics.

The working mechanism of the model involves agents making decisions to buy, sell, or hold based on market conditions. These decisions are shaped by the interaction of agents' socio-demographic and psychological characteristics with market conditions. Each decision made by the agents contributes to the total buying and selling pressure, which influences the determination of market prices. Thus, the market price dynamically responds to the collective behaviors of the agents.

At the end of the simulation, the changes over time in the agents' balances and the market price are analyzed. This analysis is used to assess how well the model reflects the behavior of financial markets. Descriptive statistics of the market price calculated with the data obtained from the model serve as a general summary of market dynamics.

Our model offers a powerful tool for understanding the complex nature of financial markets and exploring the effects of individual investor behaviors on market dynamics. It is also suitable for development to examine how market behavior can change under different economic conditions with the addition of parameters. This modeling approach serves as a valuable resource for predicting future behaviors of financial markets and managing potential risks.

For ABM simulation and analyses, Python libraries such as pandas, numpy, matplotlib, prettytable, and mesa have been utilized. The model defines two significant classes: "Financial Agent" and "Financial Market." The first class illustrates the characteristics of agents and how these characteristics translate into buying and selling decisions in response to other agents' moves in the market. The second class encompasses functions that describe the changes in the price of the financial asset based on the decisions of the agents. The characteristics of agents within the "FinancialAgent" class have been established considering the meta-analyses related to the literature review mentioned above.

4.1. Financial Agent Class

In this simulation model, each agent is initialized with a comprehensive set of attributes that define their presence in the financial market. The “__init__ function” is critical as it not only sets the agent's initial balance, reflecting their financial strength, but also assigns socio-demographic characteristics such as age, income, and gender, which are selected randomly within specified ranges. Moreover, this function determines the agent's psychological orientation towards risk-taking, a defining trait that shapes their approach to investment decisions. These initial settings are fundamental, as they establish the framework within which agents operate, laying the groundwork for their interactions within the market.

The psychological factors of each agent, encompassing risk tolerance, loss aversion, and disposition effect, are pivotal as they directly influence market behavior. Risk tolerance, varying from risk-averse to risk-neutral, to risk-loving, dictates the type of financial assets an agent is likely to invest in, from stable, low-yield options to high-risk, high-return ones. The methods calculating loss aversion and disposition effect further refine the agent's decision-making profile, as these traits affect how they respond to profits and losses within the market. The anchor balance sets a reference point for financial evaluations, embodying the anchoring bias that can skew an agent's perception of market fluctuations.

Lastly, the data structure serves as a repository for the outcomes of the agents' decisions, capturing details such as balance changes, asset prices, and transaction volumes. This data is instrumental for analyzing the agents' performance and the overall market dynamics. It provides insights into the collective impact of individual decisions, contributing to a deeper understanding of complex market behaviors. Together, these elements form a robust simulation environment where the nuanced interplay of agents' characteristics and market forces can be observed and analyzed.

Incorporating insights from seminal works by Kahneman and Tversky, particularly their loss aversion theory and Value Function, the utility function in this agent-based model is a vital mechanism for predicting financial behaviors. According to Kahneman and Tversky's research (1979 and 1984; Kahneman et al., 1991; Tversky and Kahneman, 1991, 1992), individuals experience losses more intensely than gains, an asymmetry central to the model's design. This function assesses an agent's utility based on financial fluctuations, implementing a standard utility function for gains by taking the square root of any positive change in balance, reflecting diminishing marginal utility as proposed by classic economic theory.

Losses, on the other hand, are treated with amplified sensitivity. Here, the Loss Aversion Coefficient (k) embodies the agent's degree of aversion to losses. The model takes the square root of any negative balance change, scaling it by this coefficient, to indicate the disproportionately negative impact of losses on utility—a principle central to behavioral economics.

These modeling choices are foundational in ABM for simulating market behavior. The utility function's differentiation between the agents' responses to gains and losses draws from and extends the work of Kahneman and Tversky, capturing the nuanced human responses to risk and financial outcomes. It's a crucial method for exploring how individual risk tolerance and behavioral biases influence financial decisions, providing a microfoundation for market dynamics that align with behavioral finance principles.

The value function in the agent-based model is a sophisticated tool that measures the perceived value of an agent's current financial state, taking into account both the relative changes from a baseline and the psychological underpinnings of financial decision-making.

The model starts by establishing a Reference Point (usually the agent's initial balance), which serves as a psychological benchmark, known as the anchor balance. This benchmark is then used to measure changes in the agent's financial position, calculating the Balance Change as the difference between the current balance and the reference point. These changes are not merely numerical but are imbued with subjective significance through the utility function, which interprets these changes in terms of gains or losses, reflecting the agent's sensitivity to changes in wealth.

Further, the Disposition Effect is factored into this evaluation by weighting the utility value with the agent's predisposition effect coefficient. This coefficient encapsulates the agent's psychological inclination to prematurely sell winning investments and hold on to losing ones, an important behavioral bias in financial markets that often leads to suboptimal financial outcomes.

By applying this value function, the model effectively simulates the complex interplay between an agent's financial state and their psychological responses to that state. It's a method that showcases the agent's behavioral tendencies and their past financial experiences, providing an intricate depiction of how these psychological factors can steer financial decisions and, by extension, shape the dynamics of the market. The model, thus, provides a comprehensive framework for examining the roles of both objective financial metrics and subjective behavioral biases in the economic decision-making process.

In agent-based financial models, the calculate loss aversion method is a pivotal function designed to quantify an agent's aversion to financial losses, incorporating socio-demographic attributes such as age, income, and gender. This method leverages the sigmoid function to integrate these factors, providing a nuanced understanding of how loss aversion varies among individuals.

For the age factor, the model utilizes a sigmoid function, reflecting a shift in loss aversion around the age of 40. This suggests a nuanced relationship between age and loss aversion, where younger individuals might exhibit a lower aversion to losses, potentially due to a higher risk tolerance or lesser financial responsibilities. In contrast, as individuals age, particularly past the 40-year mark, an increased sense of financial caution and hence higher loss aversion might manifest. This change underscores the impact of life stage on financial behavior, highlighting the importance of age in shaping one's approach to financial risk.

Similarly, the income factor employs a sigmoid function to model changes in loss aversion relative to income levels, pinpointing $50,000 as a critical threshold. This function suggests that individuals with lower incomes exhibit higher loss aversion, possibly due to the more significant impact of financial losses on their overall financial stability. Conversely, those with higher incomes might demonstrate lower loss aversion, given their greater capacity to absorb financial setbacks without severely compromising their lifestyle or financial goals.

The gender factor introduces another layer of complexity by suggesting gender-specific differences in loss aversion, with women presumed to have higher loss aversion than men. This assumption could be linked to broader societal and psychological factors that influence financial decision-making processes differently across genders.

By integrating these factors, the calculated loss aversion method synthesizes a comprehensive measure of an agent's loss aversion, encapsulating the nuanced interplay between socio-demographic characteristics and individual financial behavior. This approach not only enriches the model's ability to simulate realistic market dynamics but also underscores the critical role of individual differences in financial decision-making processes.

The calculated disposition effect method in agent-based models provides a sophisticated approach to understanding the disposition effect, a well-documented behavioral bias in financial markets. This effect, illustrating investors' inclination to sell winning assets too early while clinging to losing assets for too long, is rooted in a complex interplay of socio-demographic and psychological factors. By employing sigmoid functions and multipliers similar to those used in calculating loss aversion, this method advances the conventional analysis of the disposition effect, offering a more nuanced understanding rooted in individual characteristics.

The method's reliance on sigmoid functions allows for the nuanced modeling of how different factors influence the intensity of the disposition effect. For instance, age, income, and psychological attributes such as risk tolerance can significantly impact an individual's propensity towards this bias. Younger investors might exhibit a different reaction to gains and losses compared to their older counterparts, potentially due to varying financial goals or risk appetites. Similarly, investors with different income levels may display distinct behaviors when faced with the decision to realize gains or bear losses, influenced by their financial stability or risk tolerance levels.

By integrating these socio-demographic and psychological variables, the calculate disposition effect method enriches the traditional models, which primarily focus on trading volumes and market data to analyze this phenomenon. It shifts the focus from a posterior examination of market behavior to a more detailed, agent-specific analysis, considering individual investor characteristics that predispose them to the disposition effect. This approach not only provides insights into the behavioral underpinnings of financial decision-making but also enhances the predictive power of agent-based models, offering a more comprehensive framework for analyzing and understanding market dynamics and investor behavior.

However, this model allows for a more anticipatory (prior) evaluation of the disposition effect at the individual level by directly using agents' socio-demographic and psychological characteristics as factors in calculating the disposition effect. This approach aims to better understand the impact of individual differences and characteristics on financial behaviors within the framework of ABM (Kaustia, 2010; Hens and Vlcek, 2011).

In the model, the inversion of the sigmoid function used in the loss aversion function represents a significant innovation in calculating the disposition effect. This method calculates the disposition effect as a combination of factors such as age, income, and gender, taking into account the characteristics of the agents. Thus, it allows for the analysis of this significant phenomenon in behavioral finance theories from a more individual and unique perspective.

This approach contributes to a deeper understanding of market behaviors and investor decisions. Moreover, the model highlights the role of behavioral factors in understanding financial markets and investor decisions in a more detailed and nuanced manner. This presents a new tool and perspective that can be used in both academic research and financial market analyses.

In the realm of financial decision-making, the disposition effect stands as a behavioral bias where investors are prone to sell assets that have gained in value too quickly while holding onto those that have incurred losses for too long. The calculate disposition effect method integrates several socio-demographic and psychological factors, such as age, income, and gender, to offer a nuanced perspective on how these factors influence an investor's susceptibility to this effect.

The age factor, defined by the formula

$$age\ factor = -1 + np.\exp(-0.1 * (age - 40))) + 1 \tag{1}$$

posits a pivotal change around the age of 40. This modeling suggests that younger individuals, below the age of 40, may exhibit a stronger disposition effect. Consequently, they might prematurely sell assets that have appreciated in value or excessively hold onto underperforming ones. This tendency, however, is indicated to diminish as individuals age, pointing to a maturation in financial decision-making or a shift in investment strategies over time.

Similarly, the income factor, expressed as

$$income\ factor = -1\big(1 + np.\exp\big(-0.0001 * (income - 50000)\big)\big) + 1 \tag{2}$$

implies that as an individual's income increases, their susceptibility to the disposition effect decreases. Wealthier individuals, therefore, might demonstrate a greater propensity to divest from losing investments more promptly or retain profitable ones for an extended duration, possibly due to a heightened ability to absorb losses or a more strategic approach to asset management.

Gender also plays a significant role in shaping the disposition effect, with the model setting a higher gender factor for men (gender factor = 1.2 for men, 1.0 for women). This indicates that men may be more likely than women to prematurely sell assets that have gained in value or to hold onto those that have declined, potentially highlighting gender differences in risk tolerance or investment behavior.

Through the application of these factors, the calculate disposition effect method provides a sophisticated tool for understanding the psychological and demographic dimensions underpinning the disposition effect. By acknowledging the complex interplay between age, income, gender, and investment behavior, this approach enhances the realism and depth of agent-based financial models, offering valuable insights into the mechanisms driving investor behavior in the market.

At the heart of ABM models is the step function, a dynamic mechanism that encapsulates the decision-making processes of agents—be it to buy, sell, or hold assets. This process is intricately shaped by the evolving market dynamics and the agent's own perception of value, which is influenced by a spectrum of psychological factors including loss aversion, the disposition effect, and the anchoring and adjustment bias.

The make decision function within the model embodies the essence of financial decision-making, replicating how agents navigate through the financial market's volatility. It operates on a foundation built upon the agent's balance and perceived value, meticulously factored in with psychological underpinnings. A notable feature of this function is the Random Decision Mechanism, introducing an element of unpredictability with a 50% chance for the agent to engage in buying or selling, or alternatively, to hold its current position, thus mirroring the partial rationality observed in real-world financial decisions.

Perceived value plays a pivotal role in steering the agent's actions, calculated through the value function. This valuation hinges on the contrast between the current balance and a predetermined reference point, directing the agent towards profit realization by selling if the outcome is positive, or asset acquisition by buying in the face of losses. However, this propensity is further nuanced by the agent's loss aversion and disposition effect, which are recalibrated at each step based on the agent's demographic and psychological profile.

The decision-making calculus unfolds as follows: in profit scenarios, the agent's selling tendency is activated if the current balance surpasses the anchor balance, with the disposition effect determining the likelihood of selling. Conversely, in loss situations, the decision to hold or buy is influenced by the agent's level of loss aversion. This dual mechanism of decision-making not only enhances the realism of the model but also provides profound insights into the behavioral dynamics governing financial markets. Through such ABM, the intricacies of investor behavior under varying market conditions are vividly brought to life, offering a rich tapestry of analysis for understanding market dynamics.

The agent-based models within financial market simulations embody the nuanced decision-making processes of buying and selling assets, reflecting the complex interplay between individual financial capabilities and market dynamics. In these models, the buy and sell functions serve as the cornerstone for simulating agents' financial transactions, with each function tailored to replicate the real-world scenarios of asset trading.

The buy function meticulously calculates the quantity of assets an agent can acquire, drawing from its current balance and income to mirror real-life financial constraints. This calculated quantity determines the total cost of purchase, which is then deducted from the agent's balance, exemplifying the immediate financial implications of asset acquisition. Moreover, the cumulative buying pressure, augmented by the quantity of assets bought by each agent, models the collective impact on market prices, showcasing the direct relationship between buying decisions and market dynamics.

Conversely, the sell function outlines the process of selling assets, where the quantity sold is influenced by the agent's current holdings and the prevailing market price. The resultant sales revenue enhances the agent's balance, mirroring the financial boon of asset liquidation. Additionally, the aggregate selling pressure, incremented by the sales of individual agents, depicts the market-wide repercussions of selling activities, highlighting the intricate balance between supply and demand.

The models extend further with the hold function, representing scenarios where agents opt for inaction, emphasizing the strategic choice to maintain the status quo in fluctuating markets. This decision reflects the cautious stance agents might take in response to uncertainty or unfavorable market conditions.

Furthermore, the decision-making prowess of agents is showcased through the decided quantity to buy and decide the quantity to sell functions. These functions model the deliberate allocation of a portion of the agent's income or balance for buying or selling, respectively. The calculated quantities, adjusted to feasible transaction sizes, underscore the pragmatism embedded in financial decision-making processes, where agents meticulously plan their market engagements based on current prices and personal financial health.

Together, these functions not only encapsulate the strategic financial decisions made by agents in a simulated market environment but also illuminate the broader market mechanics influenced by individual actions. By simulating these decision-making processes, agent-based models offer invaluable insights into the dynamics of financial markets, enabling a deeper understanding of how individual actions culminate in collective market behavior.

Income, price, and wealth effects have been considered for the functions created for buying and selling quantities. Income is one of the key factors determining individuals' purchasing power. In this function, a certain percentage of the agent's income is allocated for purchases. As income increases, the agent can buy more assets, affecting market demand and thus market dynamics. Agents respond to changes in asset prices based on their incomes. While low-income agents may be more sensitive to price increases, high-income agents may be more comfortable with price fluctuations. When examined from the perspective of the disposition effect, price increases generally lead to a decrease in buying quantity and an increase in selling quantity. Conversely, in the case of price decreases, buying quantity may increase while selling quantity decreases. In the model, market price serves as a fundamental parameter in agents' buying and selling decisions. Changes in market prices contribute to shaping overall market trends by influencing agents' behaviors. For the decided quantity to sell function, the quantity owned by the agent is considered as their wealth. Agents' current wealth (balances) affects their selling decisions, and agents with higher wealth tend to sell larger quantities, often to diversify their portfolios or mitigate risk. Agents' wealth levels play a significant role in market liquidity and price movements, as large-scale sales by high-wealth agents can have significant effects on the market, leading to fluctuations in prices.

4.2. Financial Market Class

The Financial Market class forms the backbone of simulating a dynamic financial market within agent-based models, providing a structured environment for the interaction of multiple agents. This class is meticulously designed to capture the intricacies of market dynamics and the consequential behaviors emerging from the collective actions of individual market participants.

The initialization method, __init__, sets up the foundational aspects of the market, including the incorporation of agents through the num agents parameter. This parameter is pivotal as it directly influences the complexity and the richness of the market simulation, enabling the representation of diverse investor behaviors and strategies. The Random Activation schedule, an essential feature, randomizes the order of agents' activations in each step, mirroring the unpredictable nature of investor decisions in real-world markets.

A crucial aspect of the market setup is establishing the initial price, which acts as the baseline from which all subsequent market fluctuations are measured. This price is dynamically altered by the agents' collective decisions to buy or sell assets, effectively capturing the essence of market dynamics.

The agent balances Data Frame plays a vital role in tracking the financial status of each agent, serving as a key determinant in their decision-making processes and their ability to influence market trends. This data structure provides insights into the financial health of the agents and their potential impact on market liquidity and price movements.

The step method is the engine room of the simulation, where agents are activated in sequence to engage in their respective decision-making processes, encompassing buying and selling activities. These actions are the catalysts for changes in the market price, directly affecting the market's supply and demand dynamics.

The update price function recalibrates the market price based on the aggregate buying and selling pressure exerted by the agents. This function is central to simulating the fluid nature of market prices, which are inherently influenced by the interplay between supply and demand forces. This mechanism allows for the visualization of market liquidity and price volatility, highlighting the responsiveness of market prices to the collective actions of market participants.

In summary, the Financial Market class encapsulates the core elements of market simulations in agent-based models, offering a comprehensive framework to explore and understand the multifaceted nature of financial markets. By simulating the interactions among agents and their impact on market dynamics, this class provides valuable insights into the complexities of financial markets, paving the way for further exploration of economic theories and market behaviors.

The dynamics of financial markets are intricately simulated in agent-based models, particularly through mechanisms like the step and update price functions within the Financial Market class. These functions collectively orchestrate the complex interplay between agent decisions and market outcomes, providing a nuanced understanding of market behaviors.

The step function is crucial for advancing the market simulation. At each step, the market price is adjusted to reflect the latest transactions, and the financial standings of all agents are updated accordingly. This ongoing process ensures that the model captures the fluid nature of market dynamics, where prices are continually influenced by the actions of market participants.

The update price function recalibrates the market price, taking into account the cumulative buying and selling pressures exerted by the agents. This is where the concepts of total buy pressure and total sell pressure come into play, representing the aggregate demand and supply forces within the market, respectively. Agents with balances above the market price exert buying pressure, indicating a willingness to purchase assets at the current price, potentially driving prices up. Conversely, agents with balances below the market price contribute to selling pressure, signaling an inclination to offload assets, which could lead to price decreases.

Agent activation is a key feature that facilitates the execution of decision-making processes by the agents in a sequential manner at each step. This process triggers transactions within the market, leading to fluctuations in the market price. The cumulative effect of buying and selling decisions by the agents updates the market price, reflecting the ongoing interplay between supply and demand forces. This not only influences market liquidity but also captures the market's responsiveness to the collective behaviors of its participants.

High buying pressure, signaled by a significant number of agents willing to act as buyers, suggests a market trend towards increasing demand. This scenario often precedes a rise in market prices. In contrast, high selling pressure, indicated by a plethora of agents ready to sell, denotes an abundance of supply, which may precipitate a fall in prices.

In essence, the Financial Market class, through its step and update price functions, adeptly models the core principles governing financial markets. It encapsulates the essence of market dynamics, offering insights into how collective agent behaviors shape market trends, liquidity, and price movements. This simulation approach provides a valuable framework for exploring economic theories and understanding the factors that drive market behaviors.

The price is updated by subtracting the total selling pressure from the total buying pressure and dividing by a certain constant (here, 100). This allows the market price to dynamically change based on buying and selling tendencies in the market.

This update illustrates how the market price evolves in response to the collective decisions of the agents. An increase in price reflects situations where demand exceeds supply, while a decrease in price reflects situations where supply exceeds demand. The economic significance of this method is to model how supply and demand forces in financial markets affect prices. In real markets, prices constantly change based on the actions of buyers and sellers. The update price method provides a simplified model of these changes and demonstrates how the market price can reach equilibrium.

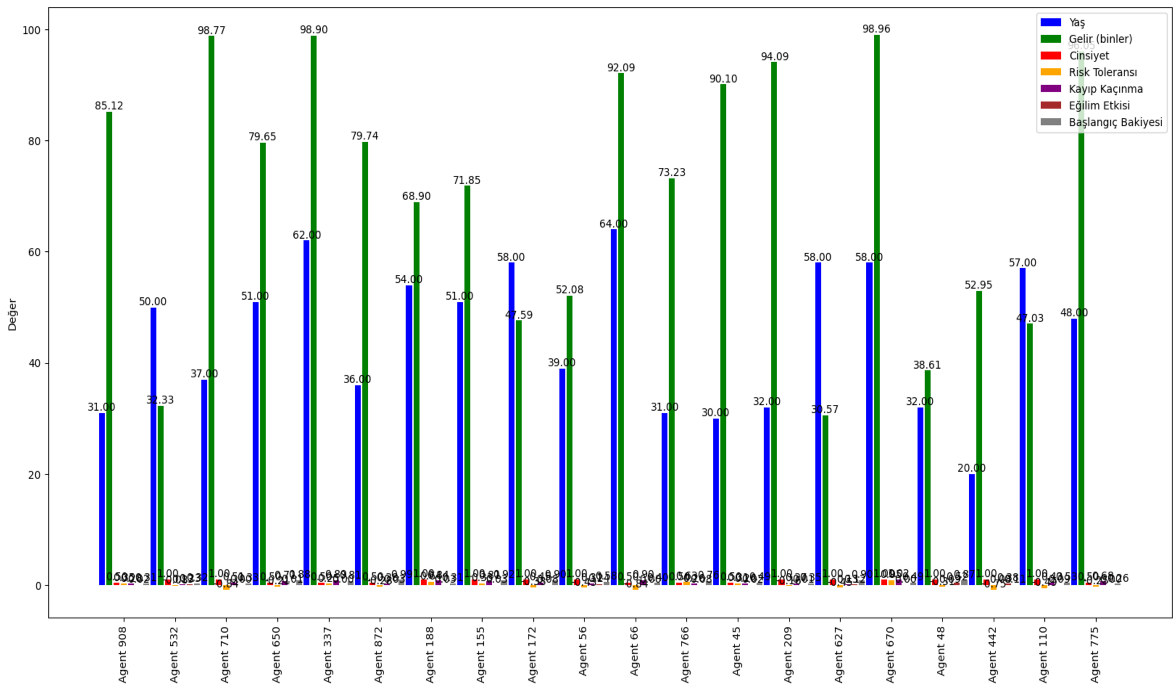
The record balances function plays a pivotal role in the ABM of financial markets, serving as a key tool for tracking and analyzing the evolving financial positions of individual agents over the course of a simulation. By meticulously documenting each agent's balance, this function provides a detailed ledger of financial activities and outcomes, enabling researchers to observe how agents' balances change in response to market dynamics, transaction decisions, and the interplay of various behavioral and psychological factors.

This continuous recording of balances is instrumental for several reasons. First, it allows for a comprehensive analysis of the financial health and decision-making processes of agents, offering insights into patterns of profit and loss, risk-taking behavior, and the impacts of different market conditions on agent strategies. Second, by comparing these balances over time, researchers can identify trends, anomalies, and emergent behaviors within the simulated market, shedding light on the underlying mechanisms that drive market movements.

Moreover, the record balances function facilitates a deeper understanding of the cumulative effects of individual decisions on the market as a whole. By examining the shifts in agents' financial standings, researchers can infer the broader economic implications of micro-level actions, including the formation of bubbles, market crashes, or periods of stability and growth. This analysis can also reveal the effectiveness of different trading strategies, the prevalence of certain biases and heuristics among market participants, and the potential for systemic risks or opportunities.

5. Findings

The overall tendencies and behavioral characteristics of all agents in the model are presented in the following graphs and tables. The average age of agents is 40.68, indicating that this age group might be more experienced in financial decision-making, thus potentially providing a certain level of maturity and stability in the market. The income category shows a wide range, indicating that the model represents a diverse population economically. Risk tolerance is close to zero on average, suggesting that agents generally neither strongly avoid nor seek excessive risk. The values for loss aversion and disposition effect indicate that agents exhibit moderate sensitivity to market movements. This suggests that agents might provide a relatively balanced response to market fluctuations. These tables serve as fundamental tools in understanding the impact of agents' behavioral characteristics on market dynamics in ABM. Characteristics such as income levels, risk tolerance, loss aversion, and disposition effects of agents could have significant effects on market prices and trading volume.



Graph 1. The Socio-Demographic and Psychological Levels of the First and Last 10 Agents Based on Balance

Note: age=>blue bars; income=>green bars; gender=>red bars; orange=>risk tolerance; loss aversion=> purple bars; disposition effect=> brown bars; initial income=>green bars

In Graph 1, the diversity of agents' socio-demographic and psychological characteristics is observed. For instance, it is evident that income is distributed across a wide range among the agents, with some having very high incomes while others have relatively low income levels. Gender distribution, risk tolerance, and initial balance factors also exhibit similar variability. The age factor stands out, especially among individuals with high incomes, where it appears to be higher. Psychological factors such as loss aversion tendency and disposition effect also show significant variability, which can be interpreted as a reflection of behavioral differences in individual investment decisions. In the literature, the impact of such characteristics on investment behavior has been supported by various studies; for example, the effects of gender and age on risk-taking tendencies have been extensively explored (Barber and Odean, 2001; Dohmen et al., 2011). Additionally, it is observed that risk tolerance and loss aversion tendencies play critical roles in individuals' financial decisions and market behaviors (Kahneman and Tversky, 1979).

Table 5 presents descriptive statistics on the socio-demographic and psychological characteristics of the 1.000 agents in the model. These statistics help us understand the behavioral tendencies, social, and economic statuses of the agents in depth. The average age of the agents is approximately 40.68, ranging from 18 to 64 years old, indicating that our model covers a wide age range. The distribution of age varies from young adults to middle-aged individuals. The average income of the agents is approximately 66.117,94 units, ranging from a minimum of 30.122,41 to a maximum of 99.993,87 units. The standard deviation of income (20.540,07) indicates the diversity in income and economic disparities. Gender is coded as 0 (female) and 1 (male). The average gender value is 0.51, indicating that approximately half of the agents are of each gender. The average risk tolerance of the agents is 0.01, indicating that agents in the model generally have a balanced distribution of risk tolerance. Risk tolerance ranges from -1 (risk-averse) to +1 (risk-seeking). The average loss aversion value is 0.39, indicating that agents exhibit moderate sensitivity to losses. The maximum value of loss aversion at 1.08 suggests that some agents have high levels of loss aversion. The average disposition effect is 0.15, indicating that agents have a moderate tendency to realize gains early and hold onto losses. The average anchor balance of the agents is 5.394,95 units, indicating that the initial balances of the agents vary widely and this value is used as a reference point in the decision-making process of the agents.

Table 5. Descriptive Statistics of All Agents

	Age	**Income**	**Gender**	**Risk Tolerance**	**Loss Aversion**	**Disposition Effect**	**Anchor Balance**
Count	1000	1000	1000	1000	1000	1000	1000
Mean	40,68	66.117,94	0,51	0,01	0,39	0,15	5.394,95
Std. Dev.	13,17	20.540,07	0,50	0,58	0,8	0,19	2.560,02
Min	18,00	30.122,41	0,00	-1,00	0,01	0,00	1.000,95
25%	30,00	48.433,65	0,00	-0,49	0,15	0,01	3.247,92
50%	41,00	65.977,41	1,00	-0,02	0,32	0,07	5.321,13
75%	52,00	8.4711,20	1,00	0,50	0,60	0,21	7.578,75
Max	64,00	9.9993,87	1,00	1,00	1,08	0,94	9.983,06

Table 6 provides descriptive statistics related to the socio-demographic and psychological characteristics of the top 10 agents with the highest balances in the model. These statistics help us understand the behavioral tendencies and economic profiles of agents with high balances. The average age of agents with the highest balances is approximately 46,9, indicating that this group generally consists of middle-aged individuals. The age range varies from 31 to 62, showing that age is a determinant factor for the balance. The average income of this group of agents is about 71.5 (billion) units, indicating that the agents are quite high-income. The maximum income reaches up to 98.9 billion units, while the minimum is 32.3 (billion) units, showing a direct correlation between high income and high balance. The average gender value is 0,6, indicating that the majority of this group is men (coded as 1), suggesting that gender has an effect on the size of the balance. The average risk tolerance is -0,06, this negative value indicates that agents tend to avoid risk generally. How risk tolerance is related to balance suggests that a tendency to avoid risk could be associated with high balances. The average loss aversion value is 0,53, indicating that agents are sensitive to losses, and this sensitivity could be associated with high balances. The average disposition effect is 0.06, indicating that agents have a moderate tendency to realize gains early and hold onto losses. The average anchor balance of agents is approximately 6.36 billion units, showing that agents' initial balances were quite high, and this value is used as an important reference point in their decision-making processes.

Agents with high balances are high-income, exhibit a moderate tendency to avoid risk, are generally male, and are of middle to upper-middle age. These characteristics are significant factors in their financial decision-making processes and play an important role in market dynamics.

Table 6. Descriptive Statistics of Socio-Demographic and Psychological Levels of the Top 10 Agents by Balance

	Age	Income	Gender	Risk Tolerance	Loss Aversion	Disposition Effect	Anchor Balance
Count	10	10	10	10	10	10	10
Mean	46,9	71.493,84	0,60	-0,06	0,53	0,06	6.359,17
Std.	10,41	21.869,67	0,51	0,45	0,26	0,08	2.934,77
Min	31	32.327,80	0,00	-0,84	0,12	0,00	3.119,72
25%	37,5	56.286,88	0,00	-0,35	0,33	0,01	3.225,84
50%	50,5	75.747,29	1,00	-0,14	0,48	0,02	6.958,75
75%	53,25	83.776,69	1,00	0,31	0,78	0,06	8.915,48
Max	62,00	98.904,24	1,00	0,64	0,89	0,23	9.936,90

Table 7 presents descriptive statistics regarding the socio-demographic and psychological characteristics of the last 10 agents with the lowest balance in our model. These statistics allow us to understand the behavioral tendencies and economic profile of agents with low balances. The average age of agents with the lowest balance is approximately 43, indicating that this group is generally in the middle age range. The age range varies from 20 to 64. The average income of this group is approximately 71.4 (billion) units, indicating that they have high incomes despite having low balances. Income distribution varies widely, ranging from a minimum of 30.57 (billion) units to a maximum of 98.96 billion units. The average gender value is 0.6, indicating that the majority of this group is male. The average risk tolerance is -0,13, indicating that agents generally have a slight tendency to avoid risk. The relationship between risk tolerance and balance size has a complex relationship with risk aversion and high or low balances. The average loss aversion value is 0,42, indicating that agents are sensitive to losses and this sensitivity may be associated with low balances. The average endowment effect is 0,12, indicating that agents have a higher tendency to realize gains early and hold onto losses. The average anchor balance of agents is approximately 5.15 billion units. This indicates that agents have low initial balances, and this value is used as an important reference point in their decision-making processes. Low-balance agents tend to exhibit risk aversion despite being high-income earners and are generally composed of males across a wide age range.

Tablo 7. Descriptive Statistics of Socio-Demographic and Psychological Levels of the Bottom 10 Agents by Balance

	Age	Income	Gender	Risk Tolerance	Loss Aversion	Disposition Effect	Anchor Balance
Count	10	10	10	10	10	10	10
Mean	43	71.367,94	0,60	-0,13	0,42	0,12	5.145,62
Std.	15,62	26.541,16	0,51	0,58	0,33	0,18	2.592,53
Min	20	30.566,06	0,00	-0,83	0,08	0,00	1.051,71
25%	31,25	48.509,65	0,00	-0,48	0,16	0,00	3.635,27
50%	40	81.666,70	1,00	-0,27	0,31	0,04	4.897,73
75%	57,75	93.587,61	1,00	0,19	0,62	0,11	6.997,79
Max	64	98.961,90	1,00	0,95	1,02	0,52	8.984,57

When looking at the characteristics of the top 10 agents in terms of balance, it generally focuses on the richest agents, indicating that these agents could have a significant impact on market dynamics.

The average age suggests that this group may be more experienced and perhaps more cautious investors, which is consistent with the higher values observed in loss aversion and endowment effect. High average income levels indicate that these agents could trigger major movements in the market. For example, the study by Hascaryani and Maski (2021) highlighted the significant role of investors' intuitive behavior in determining market prices. This suggests that the decisions of high-balance agents should be taken into account when analyzing their impact on the market.

When looking at the characteristics of the last 10 agents in terms of balance, it generally focuses on the agents with the lowest balances, despite their low anchor balances and income levels, these agents have high endowment effect values, indicating that they tend to realize their gains early and hold onto losses for longer periods. The results, as in the study by Bokhari and Geltner (2011), suggest that this behavior can impact selling prices and listing prices. This group also exhibits a negative average risk tolerance, indicating their tendency to avoid risk, and therefore, they may lean towards low-yield investments.

When examining the general characteristics of all agents in the model, factors such as average age, income, gender distribution, risk tolerance, loss aversion, endowment effect, and anchor balance averages constitute the overall profile of the model. High standard deviation values indicate that the agents exhibit a wide diversity. The overall population of the model shows a neutral tendency in risk tolerance, meaning the agents neither exhibit a profile of seeking too much risk nor of avoiding it excessively. The average values of loss aversion and endowment effect indicate that the agents exhibit moderate financial behavior. This overall distribution suggests that market dynamics will be complex and multidimensional, and individual agent behaviors will significantly influence these dynamics.

The top 10 agents tend to have high income and moderate risk tolerance levels. Their average age is higher compared to the overall population in the model, indicating a more mature group in terms of financial accumulation and experience. The gender distribution suggests that the majority of this group is male, supporting findings that gender can influence financial decisions and risk-taking behavior. Loss aversion and endowment effect indicate that these agents are more sensitive to losses and tend to preserve their gains. The high anchor balance suggests that these agents have a higher reference point in their financial decisions, which influences their investment strategies.

While the characteristics of the last 10 agents show some similarities with the top 10, the noticeably lower average anchor balance stands out. This suggests that this group of agents has weaker financial positions, which can influence their investment decisions. Despite having high average income levels, their risk tolerance and loss aversion values indicate that these agents may be more cautious in financial decisions. The endowment effect suggests a tendency to realize gains early and hold onto losses, which can exert pressure on market prices.

6. Results and Policy Implications

In this study, an original ABM was created by identifying characteristic features of behavioral biases obtained from over fifty studies through meta-analyses, regarding the interaction of investors' loss aversion, disposition effect, anchoring and adjustment bias with socio-demographic and psychological factors. Agents were equipped with the tendencies observed in these studies and subjected to information and wealth transfer within a social network. Outputs regarding the behavioral biases of agents classified socio-demographically and psychologically, especially with respect to age, gender, income (initial and investment income) levels shaping their risk tolerances, and consequently, their buy-sell-hold investment decisions under loss aversion, disposition effect, and anchoring and adjustment bias, were thoroughly examined, indicating an ABM that can model the real world quite well.

Older agents in the top ten might exhibit a more conservative approach to investing due to increased loss aversion, as suggested by the concept of loss aversion changing with age. This aligns with the findings of Madaan and Singh (2019), which highlighted the significant impact of behavioral biases on investment decisions. Younger agents in the bottom ten, displaying higher disposition effects, might be more prone to selling winning investments too early and holding onto the losing ones for too long, a tendency that aligns with the disposition effect discussed by Asadi et al. (2020).

Higher-income levels in the top ten could correlate with lower loss aversion, implying these agents might take on more risk, as high-income individuals can better absorb financial losses. This observation is in line with Moosa and Ramiah (2017), who examined the effects of various behavioral biases on financial decision-making and planning. Lower-income agents in the bottom ten might be more susceptible to loss aversion, potentially leading to a higher propensity for risk-averse behavior. This supports the analysis by Saivasan and Lokhande (2022) on the influence of demographic and psychological factors on investors' risk perception. If the model assumes higher loss aversion for female agents, this might lead to more cautious investment behavior among women, a concept that could be traced back to the gender-based differences in investment decisions studied by Cho and Chalid (2021). Agents with higher risk tolerance in the top ten are likely to engage in more aggressive investment strategies, possibly chasing higher returns at the cost of higher risks. This behavior is consistent with the heuristic-driven risk-taking behavior studied by Hascaryani and Maski (2021).

On the other hand, agents with lower risk tolerance scores in the bottom ten might exhibit a preference for safer, lower-yield investments, avoiding the high volatility that risk-seeking agents might pursue. Agents with higher loss aversion and disposition effect scores might demonstrate behavior that involves avoiding losses at the expense of higher gains, a tendency that can be detrimental to achieving optimal investment returns, as explored by Bokhari and Geltner (2017) in their study on commercial real estate pricing.

The varying levels of disposition effect across agents suggest differences in how quickly they might realize gains or hold onto losses, potentially affecting market liquidity and price dynamics, which is a core concept in the study by Leung and Tsang (2013) regarding predictability in the housing market. Agents' decisions, driven by their socio-demographic and psychological characteristics, collectively contribute to market dynamics. For instance: Agents with a high risk tolerance and low loss aversion may contribute to market volatility by engaging in high-risk trades, potentially leading to speculative bubbles or sharp market corrections. Agents with a high disposition effect may contribute to price momentum by being quick to sell winning positions and slow to realize losses, influencing the persistence of price trends. Agents with high income and balance levels may influence market liquidity. Their larger trades can move the market, affecting price discovery and volatility.

In conclusion, the ABM outputs, when contextualized within the broader framework of behavioral finance research, provide insightful simulations of market behavior. They reflect how individual biases and preferences could potentially impact market efficiency and investor welfare, echoing the real-world implications discussed in the referenced academic studies. These simulations underscore the importance of understanding the psychological and socio-demographic underpinnings of financial decision-making to better navigate market complexities and investment strategies.

The findings of the study contribute to the integration of optimization techniques with human behaviors and the development of more useful models in the use of AGI in real-world applications. Future research is open to discovering new biases and considering socio-demographic and psychological attributes in interactions with existing and new biases to present more comprehensive and real-world models.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher’s Conflict of Interest
There is no potential conflicts of interest in this study.

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