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An Agent-Based Approach to Artificial Stock Market Modeling

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Abstract

Consumer stock markets have long been a target of modeling efforts for the economic gains anticipatorily enabled by well-performing models. Aimed at identifying strategies capable of achieving desired returns, many modeling approaches have attempted to capture the innumerable and intricate complexities present within these adaptive socio-technical systems. Decreasingly constrained by available computation power, contemporary models have grown in sophistication to include several of the features present in de facto market systems. However, these models require extensive effort to dictate the variety of states, behaviors, and adaptations that entities of the system may exhibit. Mandating the development of complex formulas and an incredible number of situational considerations, traditional approaches to stock market modeling are intensive to architect and applicable to a limited range of scenarios. Further, these models commonly fail to incorporate external influences on the actions of investing parties. Employing an agent-based approach, independent and externally influenced entities are modeled to simulate market activity. Under the jurisdiction of assigned simple rules, agents of the system interact in complex and emergent ways without requiring macroscopic guiding equations. Successive trails are conducted using varying initialization values, enabling the determination of robust investment strategies performing well across a range of market scenarios.

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Keywords: Stock Market Modeling; Agent-Based Modeling; Simple Rules Modeling; Complex Adaptive Systems; Market Sentiment Analysis

1. Introduction

Consumer stock markets have long been a target of modeling efforts for the economic gains anticipatorily enabled by well-performing models. Aimed at identifying sets of strategies capable of achieving desired returns, a variety of modeling approaches have attempted to capture the innumerable and intricate complexities present within these adaptive socio-technical systems. Varying in scope and size, prior models have adopted many approaches and abstraction levels attempting to both mimic and predict the

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proceedings of realistic stock market systems. Bolstered by the promise of financial utility, an incredible amount of time and resources have been spent in search of veracious models.

Statistical techniques present some of the earliest efforts at modeling stock market behavior [9]. Attempting to create macroscopic equations that describe market proceedings, these practices are limited by the utilized methods' abilities to incorporate the prevalent nonlinearities of market factors [9]. Further, the use of these approaches requires an understanding of, or efforts to discover, the relationships between the many factors contributing to market behavior [1]. These models thus require extensive effort to conceptualize and may fail to capture the true nonlinear relationships driving stock market emergence.

Decreasingly constrained by available computation power, focus has increasingly shifted to more involved methods of stock market modeling. A principal area of emphasis has been the use of artificial neural networks (ANNs) to learn and predict the behavior of stocks and indices under circumstances of interest [2, 4, 5]. These widely applied models have proven effective at classification and prediction whilst operating under the circumstances for which they were trained [4]. They are, however, very computationally expensive to train, require large amounts of data to achieve desired accuracy, and lose applicability in scenarios dissimilar to their training focus. Investigations have also been made into the use of agent-based methods to model stock market dynamics. These efforts have sought to use increased computational availability to model classes of independently acting agents, simulating market activity [6, 7, 8]. Typically selecting investors as the agents of the model, these simulations seek to mimic the independence of real-world stockholders that change positions as market progressions occur. Often these agents are guided by a set of index-focused equations, dictating the actions they are to take as the simulated market fluctuates [3]. This internal focus contributes to many models failing to consider the external influences that impact investor behavior.

While each of these exertions have shown some affinity to model consumer stock market behavior, desires for a more comprehensive and flexible model still exist. An idyllic model would be computationally affordable, exhibit an architecture that closely resembles realistic consumer markets and their external influences, not require the development of complex guiding equations, and facilitate the recognition of investment strategies that perform well across a variety of market scenarios. In contrast, the current literature is often comprised of computationally intensive models that fail to incorporate the diverse network of influences driving market emergence. Further, these models -and the equations guiding them- frequently require extensive effort to develop and apply only to specific circumstances or market conditions.

1.1. Model proposition

Herein a model is proposed that uses an agent-based mechanism to simulate market activity and discern robust investment strategies. Repeated trials utilizing varying market initializations and agent states are conducted, subjecting the randomly generated set of strategies to diverse scenarios and allowing for the recognition of those consistently well-performing. Integrating both market salience and environmental effects, agents of the model will act according to independent simple rules, alleviating the need to generate encompassing behavioral equations. Possessing diverse and trial-variable personal characteristics, the agents utilizing the generated strategies will further allow the model to identify investment strategies that are robust to personal market sentiment variances.

2. Model Description

2.1. Model agents

To establish bearings about the model, its composing agents will first be briefly described. These agents collectively represent the actors that directly drive the processions of consumer stock markets and the major forces that affect the market sentiment the driving actors possess. Agents that have a direct impact on the model market include *investors* and *mutual funds*. Modeled external forces that influence the behavior of these impacting agents include *media networks* and *social media*. These agent classes communicate through an intricate, yet simply assigned connection network, creating a system architecture capable of exhibiting complex and emergent behavior.

The investors agent class is composed of a large group of independently acting agents that have a direct impact on the modeled market index. Conducting themselves according to individually assigned simple rules, these agents are impacted by each other, mutual funds, media networks, social media, and the market. Simultaneously, they effect members of each of these agent classes, as well. The most numerous agent class, these actors exhibit diverse characteristics and have a large communal effect on the states of the remaining agents of the model. Investors maintain the ability to buy and sell securities, having a direct impact on the status of the market and thus other agents.

The mutual funds agent class resembles the investors class in that this assembly may also buy and sell stock, impacting the state of the market. A key differentiator is that mutual funds exist in far fewer numbers and possess increased individual buying power over agents of the investors class. Mutual funds are influenced by each other, media networks, social media, and the market. Concurrently, mutual funds directly impact the state of select investors and media networks, the market, and other mutual funds.

Members of the media networks class do not have a direct impact on the market; they do, however, circuitously impact market state by influencing the status of agents that drive market changes. Specifically, media network agents affect the state of select investors and mutual funds; while themselves being impressed by the market, social media, mutual funds, and intraclass influences. Providing an informative facility, these agents look to disseminate information throughout the system, relaying their perception of market conditions.

The social media class of pseudo-agents is described as such because of the source and temporality of its constituents. Created by investors, social media agents represent the avenues through which investor states may influence the other agents of the system. Mimicking the real-world socio-technical system, investors do not have a proportionate role in social media creation; instead some investors are responsible for the creation of many social media agents while others create far fewer. These pseudo-agents relay the market sentiments of creating investors to the mutual funds and media networks that view their content. The state of these entities is updated with each timestep in the model, directly reflecting the latest sentiment of the contributing investor.

The final and central agent of the model is the alluded market index, describing the condition of the stock market as driven by the market-affecting agent class actions. This agent is updated at each period of the simulation based on the supply-demand scenario precipitated by the investor and mutual fund classes. The namesake component of the model, the stock market agent is a source of influence for all other agents of system, providing effect through the states, trends, and other metrics it may exhibit.

Figure 1 provides the number of each type of agent included in the discussed model. Note that the number of social media members is dependent on the independent and randomly assigned post sharing characteristics of each member of the investor class.

Agent Class	Members
Investors	2500
Mutual Funds	25
Media Networks	25
Social Media	{0, 1, 2, or 3} Posts per Iteration per Investor

Figure 1 - Agent Class Membership Size

2.2. Model connectivity and agent learning

As described, the model agents are connected in a variety of ways to form the complex network of market-centric actors. The network architecture is described by the schematic in Figure 2, defining the nature of connections between agent classes. Referencing the *Key* in the figure, agent classes linked by a *Full Connection* relationship are defined by agents at the head of the arrow that receive information from all agents at the tail of the arrow. Classes connected by an *Entity Specific Connection* are defined by agents at the head of the arrow that receive information from an independent subset of the agent class at the arrow's tail.

These connections, along with independently assigned learning parameters, allow for market sentiment information to be shared by the agents within the system. Market sentiment is a state exhibited by each agent, describing their expectations for market direction. Existing on a continuous scale between negative and positive five, negative values indicate increasingly negative sentiment with increased magnitude. Positive values describe a positive sentiment, stronger with increased positivity. This convention serves as the central information source that is dispersed by the agents of the system. Varying initial sentiments, along with the complex connectivity structure shown, allow for emergent sentiment and market index patterns to arise.

The connection schemes shown in Figure 2 and the behaviors they enable can be created by the assignment of simple rules to each agent in the system. Upon creation of the rule-structure for each class of agents, the allocated values that comprise the rules can be assigned randomly, enabling the examination of varying scenarios.

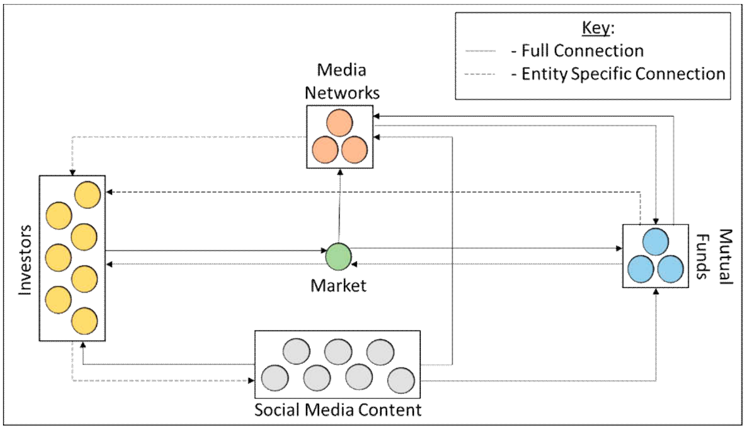

Figure 2 – Model Connectivity Schematic

The investors agent class is assigned a variety of independent rules, dictating their connectivity, learning, and sharing behaviors. As disclosed, investors learn sentiment information from other investors, mutual funds, media networks, social media content, and the market. Facilitating this, each investor is assigned a learning parameter relating to each of the previous information sources. In addition, they are allocated an inertia parameter, describing the contribution of their current sentiment to their next exhibited sentiment. Each of these values exist as a value between zero and one, inclusive. Owning these parameters, investor learning can be modeled by (1).

$$S_{p+1} = \frac{l_p S_p + l_i S_i + l_f S_f + l_m S_m + l_s S_s + l_c S_c}{l_p + l_i + l_f + l_m + l_s + l_c} \tag{1}$$

Where l_x is the agent's x learning parameter
Where S_x is the corresponding source x's sentiment value
Where x ∈ {p: own previous sentiment, i: investors, f: mutual funds, m: media networks, s: social media, c: market state}

This equation describes the next exhibited sentiment (S_{p+1}) of an investor as the weighted sum of each of its learning parameters multiplied by their corresponding source sentiment.

Having established the dynamics for the learning process, the mechanism for determining the contributors to each investor's learning must also be considered. Each investor is assigned a random number of mutual funds and media networks to which they subscribe. Respectively, the average sentiment of these assigned subscriptions constitutes the S_f and S_m parameters of (1). The investor additionally learns from the aggregate average sentiment of all social media pseudo-agents (S_s) and the market state parameter (S_c) to be described in section 2.4.

Investors also learn from a subset of the remaining investor population, known as the investor's Moore neighborhood [10]. To derive the contribution of these neighboring agents, a schema must be developed describing the investors composing the neighborhood at a given time. Accomplishing this, each agent is assigned six random positions to cycle through during each iteration-step of the simulation. This is included to mimic the natural migration of individuals as they regularly change locations (work, home, school, etc.) and encounter different members of their fellow population. With a location vector assigned to each member of the agent class, the class may be graphed in a cellular automaton that ascribes each agent a set of iteration-dependent neighbors. A demonstration of this is shown in Figure 3, exemplifying the diverse influences an agent may experience even in a small automaton.

For each cellular arrangement, each investor is subjected to a distinct set of neighbors that contribute equivalently to the focal agent's S_i value for the current iteration. This procedure allows sentiment information to travel in complex and intractable ways throughout the agent class. Investors are also assigned a social media sharing parameter, dictating the number of posts they contribute during each iteration of the simulation (see Figure 1).

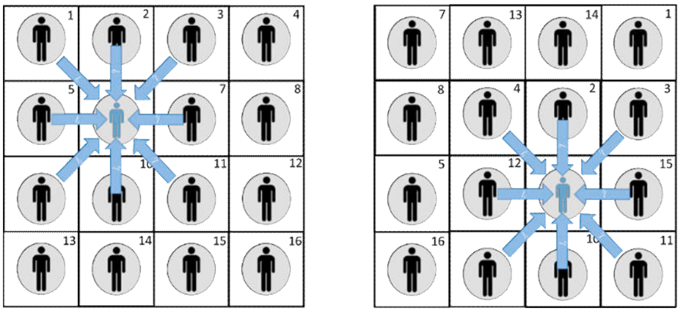

Figure 3 – Cellular Automata Neighborhood Example

Possessing greater information collection and attention resources than investors, mutual funds and media networks maintain full connection learning relationships between each of their contributors. Following the organization of (1), these two agent classes are assigned learning parameters l_p, l_f, l_m, l_s, and l_c relating to contributions from their previous state, aggregate average mutual fund, media network, and social media sentiments, and market state, respectively. These connections further sponsor the ability of the model to develop emergent sentiment sharing patterns.

2.3. Mechanisms of investment

In developing a model to mimic market behavior, it is important to recognize the mechanisms by which the actions of the imitated system transpire. Central to stock market proceedings, the action of investment must be understood to enable its dutiful modeling in the artificial system. While the literature of investment strategy presents innumerable methodologies and variations, all can be reckoned to have two focal mechanisms: *investment cues* and *movement strength*. Investment cues describe the prompts in a metric that stimulate an investing party to make an investment action. Simplistically, these actions take on the form of buy or sell, respectively telling the party to increase or decrease their position in a security. Movement strength describes the magnitude of the action the investing party takes once a position change is cued. The party may look to make a large change to their position or a smaller one, depending on a variety of factors that differ between entities and situations. Collectively, these mechanisms define the crux of all investment activity, dictating when actions occur and the degree to which cued actions take place.

Investment cues can be ascribed to the market influencing agents by simple rules assigned at the onset of the simulation. At this time, each investor and mutual fund is randomly dispensed a cue metric, in addition to a buy and sell cue from the range associated with the given metric. These values dictate that their corresponding action be taken when the cue metric value of the modeled market crosses their threshold. The cue metrics used in the current model are shown in Figure 4, along with their corresponding ranges. Randomly assigning these characteristics allows for a diverse pool of investment strategies to be simulated.

Cue	Minimum Value	Maximum Value
Market Index	50	200
Market Index Slope	-10	10
Market Level - Index Average	-50	50
Consecutive Periods Up/Down	5	15
Market Index Acceleration	-12	12
MACD Level	-7	7
Stochastic Oscillator Level	0	100
Moving Average (52-day)	75	175
Moving Average (26-day)	75	175
Relative Strength Index	0	100

Figure 4 - Investment Cues

As investment cues prompt investing parties to make a position move, a modified logistic function (2) is used to determine the magnitude of the action. This function uses investing party sentiment and available capital to ensure that the party does not attempt to buy or sell more than their current position allows. For a given investor, a housed market sentiment with a greater absolute value triggers a larger position change than a smaller value.

The application of this function requires that three more characteristics be assigned to each investing party upon their creation. Each is assigned a *Movement Confidence* factor; a value between zero and one that defines the confidence a party has in their sentiment and serves as the logistic growth rate of the function. Each is also assigned a current investment value (N) and a current liquid capital amount (contributing to K). In the current simulation, these values are randomly selected from a uniform distribution with maximum of $100,000 for investors and $1 million for mutual funds. These differentiators further diversify the investing agent pool to mimic real-market conditions.

$$N_{New} = \frac{N_{Old}(K)}{N_{Old} + (K - N_{Old})e^{-r*a}} \quad (2)$$

Where N_{New} is the invested capital after the action has been completed
Where N_{Old} is the invested capital prior to the action
Where K is the total investment capacity of the investor, a summation of N_{Old} and liquid capital
Where r is the logistic growth rate (Movement Confidence) of the agent
Where a is the market sentiment of the agent

2.4. Market que and market state

With established investment processes, a mechanism for handling investment orders and driving market index value is necessitated. Upon the completion of each iteration, the buy and sell orders are segregated and randomized within their segregations. Buy orders are then matched with sell orders until the less lucrative of the two categories is depleted. At this time, the market index is altered based on the excess supply (sell orders) or demand (buy orders) remaining in the market queue. Excess supply mandates a drop in the market index while excess demand sees the index's improvement. The magnitude of the index change is dynamically set as the ratio of excess trade volume to total market holdings. The mechanics of this alteration are shown in (3). The index fluctuations fostered by this queuing mechanism allow for emergent behavior to arise as investment cues are met, sponsoring further orders and continued market index change.

$$Index_{n+1} = Index_n * \left(1 + \frac{V_{demand} - V_{supply}}{V_{market}}\right) \quad (3)$$

Where $Index_i$ is the market index at iteration i
Where V_{demand} is the amount of stock buy orders occurring during the iteration
Where V_{supply} is the amount of stock sell orders occurring during the iteration
Where V_{market} is the total number of stock holdings in the market

A final convention, *market state*, is needed to complete the artificial stock market model. This metric serves as a status indicator of the market index and is regarded by the peripheral agents of the model as they adapt their market sentiments. Denoted as S_c in (1), this measure is the average value of the eleven market metrics shown in Figure 5, normalized between negative and positive five by the proceedings of (4). Serving as the market agent's sentiment surrogate, the fluctuations exhibited by this value have profound impact on the other agents of the model.

Metric		
Change from Previous Period	Value/50-Period Moving Average	Average Acceleration (Last 5 Periods)
Value/Historic Average	Average Slope (Last 5 Periods)	Average Acceleration (Last 20 Periods)
Value/5-Period Moving Average	Average Slope (Last 20 Periods)	Average Acceleration (Last 50 Periods)
Value/20-Period Moving Average	Average Slope (Last 50 Periods)	

Figure 5 - Market State Metrics

$$-5 + 10\frac{(\sum_{i=1}^{11} M_i - P_{min})}{(P_{max} - P_{min})} \quad (4)$$

Where M_i is the value of metric i from Figure 5 at the iteration
Where P_{min} is the minimum exhibited M-value from the historic data
Where P_{max} is the maximum exhibited M-value from the historic data

3. Results and Validation

Applying the described model, 50 trials were conducted at a length of 50 iterations each. The set of investing cues assigned was maintained for each trial to determine the performance of each strategy across varying scenarios. All other rules and initial characteristics were randomly generated at the commencement of each trial. Initial *Market State* values were generated from a randomly selected 100-period consecutive sample of MATLAB's *SimulatedStock* MAT-file. By varying all parameters, apart from the investment cues, the repeated trials are able to test the aptitude of each cue strategy across a gamut of scenarios; enabling the identification of those that are robust to sentiment, movement strength, and market situation variances.

Demonstrating the emergent capabilities of the model, the market index procession arising from two initialization scenarios is shown in Figure 6. Note that while the two scenarios are driven by the same set of investment cues, the evolution of the market index is comparatively distinct. Indeed, for each of the 50 trials a unique pattern emerges, subjecting the model agents to unique market conditions.

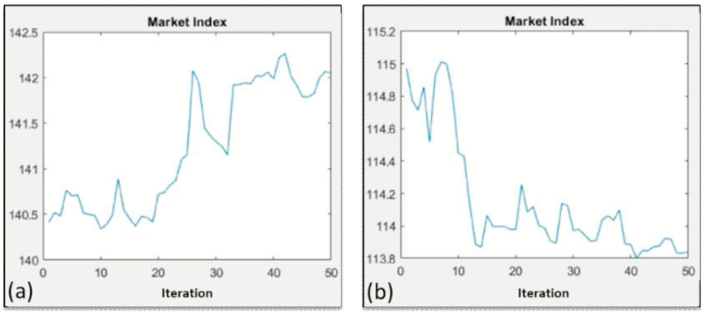

Figure 6 - Emergent Behavior of Market Index; (a) Trial 1, (b) Trial 2

Upon completion of the 50 trials, the generated returns of each strategy were averaged and ranked according to magnitude in descending order. Additionally, the number of times each strategy yielded a return in the top ten percent of all performers in a trial was also calculated. Figure 7 displays the marks received by the top five ranked performers, those that comprise the five rankings surrounding the first quartile mark, and those constituting the five median performers. It is evident from the figure that some strategies were able to consistently outperform their counterparts, despite dissimilar scenarios between trials. For reference, the mean return of all strategies across all trials was roughly 2.87 percent for the 50-day period.

Rank	Cue	Buy Mark	Sell Mark	Upper Decile Performance	Mean Return
1	Relative Strength Index	69.0479	92.2707	29	1.8553
2	Stochastic Oscillator	41.5641	2.2442	38	1.8061
3	Stochastic Oscillator	68.5133	99.7663	35	1.7982
4	Stochastic Oscillator	49.9581	95.0058	30	1.7806
5	Market Index Acceleration	0.2965	1.4923	36	1.7199
		...			
623	Market Index	96.0634	190.9276	2	1.0332
624	Market Index Slope	1.3091	7.9906	4	1.0330
625	Moving Average (26-Day)	129.3233	118.0028	4	1.0326
626	MACD Level	-1.8957	-4.1415	2	1.0321
627	MACD Level	2.7356	5.1378	4	1.0318
		...			
1248	Consecutive Periods Up/Down	8.8737	14.2091	2	1.0035
1249	Market Index - Average	-31.9029	47.2031	2	1.0035
1250	Market Index Slope	5.5564	8.5996	0	1.0035
1251	Market Index	182.5335	86.5370	1	1.0035
1252	Market Index Acceleration	-9.6203	8.7143	1	1.0035

Figure 7 – Investment Cue Performance Summary

Seeking to validate the superiority of the higher-ranked strategies in realistic-market scenarios, the performance of each cue strategy was tested, using homogeneous sentiment and movement confidence parameters, across twenty-five 50-day samples of the *SimulatedStock* MAT-file. In support, this analysis revealed the average of those strategies ranked in the first decile outperforming those of subsequent deciles, as shown in Figure 8. Further, the first decile's strategy average was shown to considerably outperform the overall market index average. Note that a depiction of the standard deviation of each decile is shown with each bin.

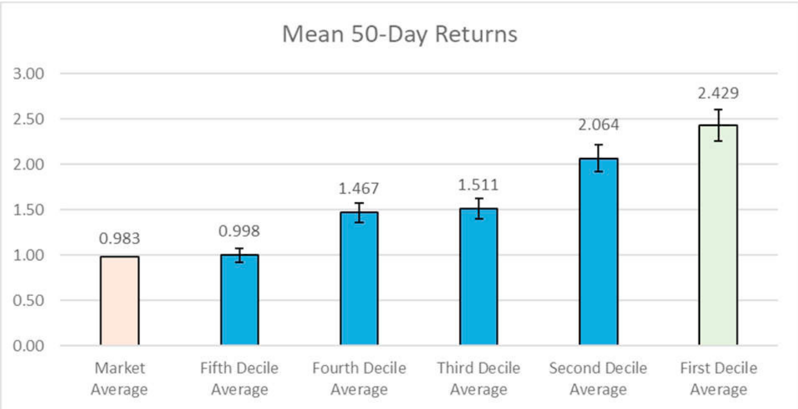

Figure 8 – Mean 50-Day Return by Decile

4. Conclusions and Future Work

Leveraging agent-based modeling and assigned simple rules, a model was constructed, capable of simulating the emergent behavior of investment-driven stock market indices. The model considered the effects of both investing and peripheral parties, mimicking the diverse and complex network of influences driving market change. A field of investment cues was examined across a range of initialization scenarios, enabling the determination of those appearing robust to market conditions and investor-dependent factors including market sentiment and movement confidence. These robust strategies were then validated using realistic market data to provide support of their claimed superiority. Further, the model was able to conduct repeated trials and holds the promise of new emergence within future trials due to the random assignment of governing agent rules. As an agent-based architecture, the model, additionally, did not require the development of complex behavior-guiding equations.

This work should be regarded as a preliminary effort to incorporate external and internal factors affecting investor behavior within an agent-based model. Recommendations for future work include increasing the pool of investment cues from which agent strategies are assigned and altering the number of iterations comprising each trial. Making use of agent-based modeling's ease of architecting, additional agent classes may also be added to the model to integrate other anticipated effects. Building upon the framework established, the addition of pertinent agent classes along with advancements to the mechanisms controlling agent behavior may improve the model. Finally, the model should be applied to real market data, determining its applicability beyond the scope of artificiality.

References

[1] Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: forecasting and control. Hoboken, NJ: John Wiley & Sons, Inc.

[2] Chen, A. S., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. *Computers & Operations Research*, 30(6), 901–923.

[3] Grazzini, J. (2013). Information dissemination in an experimentally based agent-based stock market. *Journal of Economic Interaction and Coordination*, 8(1), 179-209.

[4] Guresen, E., Kayakutlu, G., & Daim, T. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications*, 38(8), 10389-10397.

[5] Kimoto, T., Asakawa, K., Yoda, M., and Takeoka, M. (1990). Stock market prediction system with modular neural networks. 1990 IJCNN *International Joint Conference on Neural Networks*, 1-6.

[6] Llacay, B., & Peffer, G. (2018). Using realistic trading strategies in an agent-based stock market model. *Computational and Mathematical Organization Theory*, 24(3), 308-350.

[7] Palmer, R., Arthur, W. B., Holland, J. H., Lebaron, B., & Tayler, P. (1994). Artificial economic life: a simple model of a stockmarket. *Physica D: Nonlinear Phenomena*, 75(1-3), 264–274.

[8] Raberto, M., Cincotti, S., Focardi, S. M., & Marchesi, M. (2001). Agent-based simulation of a financial market. *Physica A: Statistical Mechanics and Its Applications*, 299(1-2), 319–327.

[9] Rather, A., Sastry, V., & Agarwal, A. (2017, 9 7). Stock market prediction and Portfolio selection models: a survey. *OPSEARCH*, 54(3), 558- 579.

[10] Tyler, T. (n.d.). The Moore Neighborhood. Retrieved from cell-auto.com: http://cell-auto.com/neighbourhood/moore/.