Abstract

This dissertation aimed to investigate the swarm-like behaviour emergent in the financial market using an agent-based approach. It utilised agent-based modelling (ABM) to simulate such emergent phenomena within a continuous call auction market. This dissertation aimed to address the following challenges: 1. to understand how the swarm-like behaviour could form using opinion dynamics. 2. to derive insights into how such swarm-like behaviour could affect the stock price. 3. to derive insights of how influencers and hedge funds could alter the pattern of such swam-like behaviour 4. to derive insights how hedge funds could potentially gain and lose in the event of swarm-like behaviour exists. 5. to provide a peek of one of the potential causes for the collapse of the swarm-like behaviour by limiting the wealth of the traders. This dissertation also attempted to derive further insights into swarm-like behaviour by comparing the simulation result with the GameStop 'short squeeze' affair in January 2021.

The ABM applied the mechanism of opinion dynamics, which allowed the exchange of opinions between individual heterogeneous agents, and introduced coordinated traders to initiate the swarm-like behaviour. On top of the swarm formation, influencers and hedge funds were introduced to the model to reflect more realities of the real-world financial trading market.

Analysis showed that the degree of the swarm-like effect could be controlled by parameters such as the initial wealth given to the agents and the number of trader agents. Nevertheless, the result showed that the swarm could cause the price to rise more than ten times its original price. Besides, the influencer's action could give a one-off boost to the overall value of the opinions by 37%. Besides, it also showed the possibilities for hedge funds to lose money by trading against the swarm (short selling at a low price) and earning profit by trading with the swarm (going long the shares) or short selling when the swarm was about to collapse. Finally, It was believed that the comparison between the simulation result and the GameStop 'short squeeze' fair led to some of the critical characteristics of the swarm-like behaviour that happened in the actual financial market were captured. Overall, the findings gave a better understanding of the swarm-like behaviour in the financial market and how it could interrupt the financial market.

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Contents

Chapter 1

Introduction

In today's world, a common phenomenon can be seen that many autonomous agents behave the same as each other without an explicit leader. Such phenomena happen in various fields, including robotic and finance. For example, during January and February 2021, the price of GameStop shares in the US financial market has had large fluctuations due to the individual retail investors attempting to move the price up, whereas market professionals attempted to move the price against it.

Such exciting phenomena can be analogised to the swarming-like behaviour where it is usually defined by a large group of flying insects, such as bees, interacting with each other and acting like those around it without a leader. Such emergent swarm-like behaviour has raised the public's curiosity about how the swarm has been built up. However, challenges have been raised regarding understanding the underlying cause of swarm-like behaviour systemically. Especially such affairs happened in a complex and fast-pacing financial market which involved the actions of many investors. Some augments suggest that such behaviour indicates irrational exuberance, which is hard to explain by typical economic or financial theory.

This dissertation aimed to investigate the underlying causing of such arising phenomena by building agent-based models (ABM) that simulated heterogeneous agents' swarm-like behaviour within a continuous call auction market. It aimed to address the following challenges: 1. to understand how the swarm-like behaviour could form using opinion dynamics. 2. to derive insights of how such swarm-like behaviour could affect the stock price. 3. to derive insights of how influencers and hedge funds could alter the pattern of such swam-like behaviour. 4. to derive insights how hedge funds could potentially gain and loss in the event of swarm-like behaviour exists. swarm-collapse5. to deliver a peek of one of the potential causes for the collapse of the swarm-like behaviour by limiting the wealth of the traders. This dissertation attempted to evaluate the model by comparing the simulation result with the GameStop 'short squeeze' affair in January 2021.

Since it could be seen that the swarm-like behaviour could cause significant interruptions in the financial market in an unusual manner, it would be essential to address these challenges. Doing such would better understand the cause of the swarm-like behaviours and how it could impact the market. Uncertainties could also be reduced when formulating trade strategies. Awareness for such behaviour to occur in the future could also be raised.

Chapter 2

Background Research

2.1 Collective Behaviour

It is essential to understand the underlying concept of swarm-like behaviour or swarm-trading. The concept of swarm trading comes from the theory of collective behaviour. Collective behaviour is when an individual unit's activity is influenced by the activities of its neighbours, and this applies to other individual units. Eventually, all units will change their behaviour from how they would behave on their own and instead act in the common behaviour. A common pattern is then formed. [1] The theory shows that detail of interactions between individuals are insensitive to the transitions, and individuals can eventually behave in a common pattern.
That explains the concept of swarm trading that individual investors are influenced by other investors, and through the interactions, investors are vied to move the price in their desired direction. The self-affine growth of bacterial colonies can demonstrate a similar concept to this. If the bacteria growth is dependent on the number of nutrients, the majority of the nutrient can be consumed by the bacteria in the most advanced parts of the surface, leaving little for the other bacteria. The result is that the bacteria growth of the entire colonies are showed to be similar, and again, the behaviour is independent of the detail of the dominating development of bacteria.[2]
Similar to the collective behaviour, swarming consists of many individuals grouped and moved in the direction as same as those around them. The individuals stay close to each other but prevent collisions. Grabbing the critical characteristics of collective behaviours and swarming could provide a foundation for building the swarm-like behaviour using agent-based models. An analogy would be to have a group of individual investors buying shares at the same time. Since the financial stock market is dimensionless, the other rules might not be appreciable.

2.2 Research that Investigated the Collective Behaviours

There were researches able to show that emergent behaviour could be achieved by the individual particles. Tamas, Andras, Eshel, Inon and Ofer introduced a model that aimed to investigate the emergence of self-driven behaviour of the biological particles with interaction.[3] In that model, it had the velocity of the particle to be the input parameters which its value was determined by the rule and irregularly fluctuation. The rule given to the particle was simple that at each time step, a particle moved with constant velocity. The research showed that at some time step, particles eventually tend to move in the same direction. Although there are other parameters such as density and noise specified, it was apparent that the result showed that despite this simple rule, this model resulted in realistic and dynamic transitions of the particles. In this research, the key points to take were that the emergent behaviour was achieved through the interaction of the individual particles with each of them given simple rules of what to do. Reading the research led to further thoughts of using an agent-based approach since ABM could bridge the linkage between the agents, as micro-level and the state of the environment, as macro-level. In the ABM of this dissertation, the trader agents would only be given simple rules. Through interactions, the agents could form a swarm.

2.3 Agent-Based Models

The main elements of the ABM should be well understood. An ABM consists of three main elements [4]. The first one is agents. Agents are a fundamental unit of agent-based modelling. Rules were given to each agent for them to access the situation during the simulation and make decisions. Each type of agent has its characteristics. The communication of these agents leads to causing to change in the status of other agents. Through the given instructions and the interaction of the agents, modellers could produce the scenario in their interest. The second element is the environment. The environment in the model can be static or dynamics. It can be just a static environment that provides a space for the agents to interact or change when they interact. The third element is time. During the model simulation, it would go through specific time steps, as known as the tick. At each tick, agents take action based on the given rules, update their status correspondingly.
There could be multiple autonomous and heterogeneous agents such as traders when modelling the stock market. Such agents might have different but simple decision marking strategies, such as when to buy or sell the price to buy within a set period. Such agents would follow the rules specified, and through the interaction of the agents, expected results could be achieved.

2.4 Why Agent-Based Models?

Whether ABM could effectively model the scenario to address the challenges would be worth discussing. An ABM guide [5] suggested Agent-based models allow the possibilities to explore the heterogeneity of the agents. In agent-based models, different agents have different behaviours. When such agents interact, some macro insights that emerge from those interactions can be derived. [5] ABMs also enables the creation of unseen scenarios, which could be helpful for the investigation of the result of such behaviours. This would allow the exploring of the possibilities of how the agents interact with each other. Such heterogeneity and interactions bring complexity, non-linearity and multiple equilibria to the model, resulting in stylized facts and more realistic behaviours that can be observed. An example of using ABMs could be to model the high-frequency trading, in which various trading strategies of market players are modelled and the microstructure of the exchanges, for instance, the behaviours based on some auction rules and execution policies.
Majewski, Ciliberti and Bouchaud [6] has shown the importance of the agent-based model in the financial industry. In some behavioural finance models they have researched, they expressed

one of the weaknesses of those models: the link between the biases of such individual investors in the market and the dynamics in the market as a whole was unclear. They suggested the biases of the investors and overall dynamics were at two different levels: micro and macro. Moreover, by using the agent-based model technique were able to connect such two levels. Since in the agent-based models, at the micro-level, agents given simple rules [7] and interactions of the agents would be able to build up the dynamics that could happen in the financial market at a macro-level In other words, such result of the price dynamics would be described more appropriately in ABM.

Because the financial market in nature is complex, millions of market participants in the market indirectly interact with each other. Majewski, Ciliberti and Bouchaud [6] has clearly shown the advantages and power of using ABM in finance due to the ability to connect the more individuals level and the macro-level by allowing the interactions to happen. Moreover, such interactions could yield non-linear outcomes. The models could take care of the behaviours of the agent, whereas the ABM could take care of the interactions between the agents.

2.5 Synthetic Reality of Financial Market

Extend from the previous paragraph, the complexity of ABMS could capture the complex dynamics of financial markets.[8] Having a large amount of individuals agents, which would make a different decision based on the agent type, such as a significant investor or casual investor. It would be essential to express that the result observed in the financial market would be not just the sum of the agents' decisions but, more importantly, the underlying interactions between agents. With different actions of the trading agents, different outcomes and different phenomena could be produced. Hence why ABMs are powerful as they could give complexity and non-linearity over the traditional model testing method.

In such complex and volatile financial markets, it would be no doubt that a small alternation of the input parameters could result in significant price fluctuation. [9] In other words, by modelling the behaviour of the investors' behaviour, the movement of price in the market at the macro level could be observed as a result. This section explained why the ABM would be best suited to model the complex financial market. Using ABM, the state of the financial market, such as the market price, could be well captured and used for analysis.

2.6 Types of Trader in Financial Market

When it comes to design the ABM, types of traders would be one of the main focuses. It would be reasonable to assume that there would be different types of traders in a continuous call auction market. However, it might not be possible to model every type of trader in the model since there could be millions of traders and modelling all of them could over-complicate the model and could cause the outcome very unpredictable and difficult to understand. Hence, it might well figure out the most common type of traders in the financial market. Kenneth and Dave described several types of traders.[10] First one is the Near-Zero- Intelligence (NZI) Traders. They were most likely to follow the other traders' trade behaviour in the event of the price rising and falls in a concise period. It would be similar to the momentum traders. The second type of trader is Zero-Intelligence-Constrained (ZIC) traders. Kenneth and Dave mentioned that ZIC traders randomly trade in the market, following the sole budget constraint that the ask or bid prices should not make a loss. Again, this would be similar to the fundamental traders.

The paper also mentioned that the population of ZIC traders, compared to the population of human traders, were statistically observable, which were influenced by the allocative efficiency scores of the continuous double auction (CDA) market. Gode and Sunder [11] also mentioned the ZIC trader traded which traded based on their intrinsic value. On the other hand, Duffy and Utku [12] proposed that ZIC traders had a loose budget constraint, that was, they brought when they had enough wealth or sell it when they had a tradable asset. Such indicated that budget or wealth called in the dissertation would be a factor that could affect the outcome.

The third type of trader described were Opinionated Traders or Opinionated-ZIC (OZIC) traders. The idea was very intuitive that OZIC would be similar to ZIC traders, but instead, OZIC traders had an opinion, and its opinion influenced their trade activities. In other words, OZIC submits quote prices as usual, and this submission took account of the opinion. If the opinion was positive, the bid was higher and vice versa. The fourth type of trader was Opinionated NZI (ONZI) Traders. Kenneth and Dave mentioned that if the prevailing opinions of the population would be unanimous, these ONZI traders could trigger price bubbles. The paper also showed that OZIC traders with extreme positive opinions could lead to high transaction history, i.e., transactions at higher prices. In opposite, with a highly negative opinion, low transaction history could be recorded. This further brought the idea of bringing the opinions into the trader agents.

In the paper published by Majewski, Ciliberti, and Bouchaud [6], some of the widespread types of traders were discussed and implemented in the ABM: trend-followers which they trade based on the price trend; fundamentalists who trade based on the fundamental value of the asset or stock; noise-traders which could have a different view from the point of the investment.

Taking references from the papers above, the ABM in this dissertation would have fundamental traders, momentum traders, noise traders and coordinated traders as the significant type of individual retail investors in the market. It would be because fundamental traders, momentum traders, and noise traders were very commonly seen in the financial market, where the coordinated traders were referenced to the type of traders that took opinion into account. These would also be the critical agents that would trigger to start the swarm-like effect. Next, it would be to define how agents' interactions would change the model's state through price dynamics.

2.7 Price Dynamics

In the ABM of the dissertation, the price dynamics would be vital since it would describe the mechanism and the properties of the model, for instance, the market price. Such properties would simulate development or change within the system of the model during the simulation. Mathematical equations could likely derive the principle of price dynamics. The price dynamics in this dissertation would reference the extended Chiarella Model built by Majewski, Ciliberti and Bouchaud [6] and would further modify and extend on top of that. The model dynamics of their ABM consisted of three different types of investors being the agents in the model: trend-followers, fundamentalists and noise-traders. The model dynamics were given by:

$$D(t, t+\Delta) = \kappa \int_t^{t+\Delta} (V_s + P_s)\, ds + \beta \int_t^{t+\Delta} tanh(\gamma M_s)\, ds + \sigma_N \int_t^{t+\Delta} dW_s^{(N)} \tag{2.1}$$

where $D(t, t+\Delta)$ represented the total market demand for Δ amount of ticks. $\kappa \int_t^{t+\Delta} (V_s + P_s)\, ds$ represented the market demand by the fundamentalists. $\beta \int_t^{t+\Delta} tanh(\gamma M_s)\, ds$ indicated the market demand by the trend-followers. $\sigma_N \int_t^{t+\Delta} dW_s^{(N)}$ indicated the market demand by the noise-traders.
The paper suggested that when $\Delta \rightarrow 0$, the result of the price dynamics were described by a stochastic dynamics system given below:

$$dP_t = \kappa\ (V_t + P_t)\, dt + \beta\ tanh(\gamma M_t)\, dt + \sigma_N\ dW_t^{(N)} \tag{2.2}$$

where dP_t indicated the total market demand of one tick.

$$dM_t = -\alpha M_t dt + \alpha dP_t \tag{2.3}$$

where dM_t indicated the change of momentum.

$$dV_t = gdt + \sigma_V dW_t^{(V)} \tag{2.4}$$

The paper also took price volatility σ_V and average growth g into account. Since adopting g into the model would vastly increase the complexity of the model, to not over-complicate the model, the ABM in this paper only adopted σ_V whereas g became 0. The equation became:

$$dV_t = \sigma_V dW_t^{(V)} \tag{2.5}$$

The total link between the total market demand and price change was calculated with this equation:

$$P_{t+\Delta} - P_t = \lambda D(t, t + \Delta) \tag{2.6}$$

where λ here was the 'Kyle's lambda', which would be negatively related to the market liquidity. [13]
Moreover, Majewski, Ciliberti and Bouchaud [6] suggested the model could be implemented with linear demand functions and non-linear demand, which was driven by trend-followers. The two aspects have been investigated by Beja and Goldman [14] and Bouchaud and Cont [15] respectively.
The validity of the price dynamics in this dissertation could therefore be shown. Then, the link between the change in market price and the market demand of each type of trader would be clear. Understanding the price dynamics might not directly address the challenge. Instead, it would make the outcomes such as the market price or the trader agents' wealth predictable. This would be important because the fewer uncertainties the model would have, the higher control on the outcomes.

2.8 Particle Swarm Optimisation

In this dissertation, particle swarm optimisation was not used in the ABM, although it was in one of the considerations. However, relevant background research of particle swarm optimisation could be found in Appendix A.

2.9 Opinion Dynamics

Kenneth and Dave[10] believed that opinion dynamics play a significant role in impacting the price market in financial markets.
That is because most of the markets participants would hear, tell and believe the opinion of the other participants. These opinions are spread and interacting within the market and could significantly impact the market. In other words, they argued that most of the movement of market price could be due to some stories, called narratives. The spread of these narratives could influence the market heavily and ultimately lead to financial bubbles and crashes.
Some researches aimed to model the effect of opinion dynamics. The first one would be the Bounded Confidence, described by Krause.[16]. In the model, he suggested that a fixed number of agents hold an opinion. These agents exchanged their opinions and updated them when the distance between the opinion and the given threshold were close to a certain extent. He proposed the formula:

$$x_i(t+1) = a_{i1}x_1(t) + a_{i2}x_2(t) + ... + a_{in}x_n(t) \tag{2.7}$$

where x was the opinion of agent x, a_{ij} was the confidence factor between agent i and j. The closer the opinions between the agent i and agent j, the higher confidence factor a_{ij}, vice versa. The result is that when the model simulation reaches a steady state, all the opinions could reach a convergence.
Another model is Relative Agreement (RA), proposed by Deffuant[17] and . In RA, each of the agents held an opinion and uncertainty as well. When the overlap of the uncertainties of the agents was higher than the uncertainty of an individual agent, they updated the option with a weighting parameter and a Relative Agreement value. The equation to update the opinion and uncertainty were:

$$x_j := x_j + \mu RA_{ij}(x_i - x_j) \tag{2.8}$$

$$u_j := u_j + \mu RA_{ij}(u_i - u_j) \tag{2.9}$$

where x and u were the opinion and uncertainty of the agent, μ is the weight parameter, and RA is the relative degree value.
Relative Disagreement, proposed by Meadows Cliff[18], was a model that improves based on the RA model. It introduced the probability parameter λ to update the opinion and the concept of reactance. The achievement mentioned was that the same opinion convergences was reached without initialising the number of agents who holds extreme opinions. The formula for updating the opinion and uncertainties are almost the same as the RA's

$$x_j := x_j + \mu RD_{ij}(x_i - x_j) \tag{2.10}$$

$$u_j := u_j + \mu RD_{ij}(u_i - u_j) \tag{2.11}$$

where RD was the relative disagreement.
The advantages of opinion dynamics were that it gave an easily understandable intuition. Moreover, its mechanism would be similar to how the individual entities exchange their opinions with each other in real life. Furthermore, it was believed that this would be the key to derive the

swarm-like effect which could address the challenges. Besides, controlling the opinions in the financial market would have an enormous chance to move the price direction. In other words, the challenges regarding how swarm-like behaviour could affect the price could be addressed. Hence, opinion dynamics were chosen to implement in the ABM in this dissertation.

2.10 Jump Diffusion Process

The actual market value would like to follow a random walk fashion because the price would fluctuate up and down in real life. The jump-diffusion model would be a commonly used method to model such random walk movement of price.

The jump-diffusion model is often used to simulate the markets of riskless assets or risk assets. Examples of riskless assets include Bonds, and risk assets include stock or shares.[19]. Jump diffusion is a stochastic process consisted of jumps and diffusion. Using the jump-diffusion process would be able to model the unpredictable path of the stock price. It was used to simulated jumps in the stock prices from news and events. Hence, the update of the exogenous effect would be a consequence of the jump-diffusion process which would be the combination of Geometric Brownian motion (GBM) and compound Poisson process:

$$J_t = \sum_{i=1}^{N_t} Y_i \tag{2.12}$$

where J_t represented the jump-diffusion process, Y_i would be the jump size and would be an independent random variable, N_t would be the number of jumps generated from the Poisson process with jump intensity λ. Within jumps, the price would change based on the geometric Brownian motion. The jump could be exponential, increasing the randomness of the movement of an asset price. The effect of the jump-diffusion process would theoretically cause the movement of market price to look more realistic to what could be seen in real-life financial markets.

The involvement of the compound Poisson process in the price changing formula is since, in most financial applications, a single possible jump size usually does a negligible effect on the simulation[20]. Therefore, solely using a single jump size is not that useful when performing the model simulation. With the compound Poisson process, jump size can be drawn from an arbitrary distribution and, additionally, jump exponentially. That increases the randomness of the movement of an asset price.

The jump-diffusion process would be used to model the exogenous effect to update the market true value as part of the component. Implementation of the jump-diffusion process would allow the market price to move at a random walk fashion, without any significant interruption such as the swarm-like behaviour. In other words, the insights regarding the price increase by any interruption could be well captured and could further address the challenges.

Chapter 3

Software Implementation

3.1 Proposed Approach

This dissertation utilised the mechanism of opinion dynamics to achieve swarm-like behaviour in the financial market. It would allow the exchange of opinions between various trader agents. Agents would consider the value of the opinion when making a trade decision, which could be different from the original trade decision without considering the opinions. The said approach would demonstrate that under the opinion dynamics, the initialisation of one type of agent could significantly impact the financial market.

The software demonstration would consist of three parts. Part one would be to achieve the swarm-like behaviours with solely the individual trader agents. The focus of this part would be to show that the presence of the opinion dynamics could be one of the possible causes to build up some swarm-like behaves. In part two, various agents would be added to the model introduced in part one. This primary focus of part two would be to show how different types of agents, with each having different trading strategies, could alter the pattern of the swarm-like behaviours and how these agents would perform with the existence of the swarm-like behaviours. This would give a better understanding of what extent that such a swarm-like effect could impact the financial market. Besides, better ideas could be obtained if trading in the same direction or against the swarm.

Part three would be to put all the agents into the model to produce a similar price trend as what could be observed for the GameStop share prices during January and February 2021. Attempting to replicate such an affair would allow one to grab better the critical reason to derive such a swarm-like effect in real life.

3.2 Tech Stack

The agent-based model in this dissertation was developed in Java and with a closed source library `Simudyne`. It allowed modellers to utilise agent-based modelling to simulate different future scenarios and measure the corresponding impacts without concern about the environment's safety. Furthermore, modellers would be able to put focus on writing the logic to achieve the required objectives. Next, the agents and the structure of the ABM in this dissertation would be discussed.

3.3 Design of the Agent-Based Model

This section would discuss the design of the agents, connections of the agents and the corresponding action sequences.

3.3.1 Design of the Agents

Within a financial stock market, several types of agents would be considered. They would be various trader agents, exchange agents, data provider agent, social network agent, influencer agent and hedge fund agents.

3.3.2 Different Type of Trader Agents

There could be millions of types of traders in the real-life financial stock market, taking their trading strategies. It would be impossible to model each since it would vastly increase the uncertainties when measuring the aggregated impact and predicting the outcome.
For such reasons, the model outlined three types of traders: fundamental, momentum, and noise Traders. These three types of traders were commonly used in the financial agent-based models since they could generally present the three major typical trade strategies that individual investors would use. Besides, coordinated traders and hedge funds were introduced for the sake of the objectives.

3.3.3 Trader (Abstract Class)

Characteristics

Since fundamental trader, momentum trader, noise Trader, coordinated trader and hedge fund would be types of trader, and these would inherit from the `trader` class, an abstract parent class. In the `Trader` class, it would have:

1. Side. It indicated the trade decision of the trader agent. It included BUY and SELL
2. Type of trader agent
3. Amount of wealth
4. The amount of the shares held
5. A margin account allowing a trader agent to borrow money against the investment

The Type at (2) literally would indicate the type of the trader: $Noise$ for noise traders, $Fundamental$ for fundamental traders, $Momentum$ for momentum traders, $Coordinated$ for coordinated traders, $HedgeFundSL$ for hedge funds that would go short the shares at a low price, $HedgeFundSH$ for hedge funds that would go short the shares at a high price and $HedgeFundL$ for hedge funds that would go long the shares. The wealth of each trader was initialised from Pareto distribution, which was commonly used in literature for wealth distribution. One of the ideas of using Pareto distribution for initialising the wealth of the trader agents would be partly due to the 80-20 principle. 80-20 principle indicated that 80% of the outputs resulted from 20% of the inputs

for any given event. In a financial market, it was reasonable to assume that the majority of the movement of market price was driven by the minority of the market players. Hence the Pareto distribution would be deemed a suitable probability distribution for the wealth distribution of traders.
`Trader` class would be inherited by `FundamentalTrader` and `NoiseTrader`, `OpDynTrader` and `HedgeFund` class. `OpDynTrader` class would be an abstract class and would have `MomentumTrader` and `CoordinatedTrader` as children classes. `HedgeFund` class would be an abstract class and would have `HedgeFundShortLow`, `HedgeFundShortLong` and `HedgeFundLong` as children classes. The visualisation of the inheritance hierarchy could be found in Appendiex B.

Behaviours

At each tick, trader agents would take trading decisions in the action SUBMITORDERS(). The code snippet of the action was below:

Algorithm 1 Pseudocode of SUBMITORDERS

```
procedure SUBMITORDERS
    alpha ← getAlpha()                 ▷ probability to trade of that trader agent at the tick
    p ← U(0, 1)                        ▷ randomly generated value. ranged from 0 to 1
    if p < alpha then
        volume ← getVolume()           ▷ volume of that trader agent
        side ← getSide()
        if side = BUY then
            handleWhenBuyShares(volume)        ▷ buy or cover
        else
            handleWhenSellShares(volume)       ▷ sell or short sell
        end if
    end if
end procedure
```

Entering ***submitOrders***, it would first fetch alpha from the *getAlpha()*, which would state the probability that trader agent would trade at that tick. $alpha$, indicating the probability of trade at each tick, would range from 0 to 1, where one represented that the trader agent would trade and 0 would mean no trades would occur. $alpha$ would then be compared with p, drawn from the uniform distribution at each tick. If alpha were large, the trader agents would trade at that tick; otherwise, they would not. If the condition was met, the program would fetch the $volume$ from *getVolume()* and $side$ from *getSide()*. Note that the logic inside *getVolume()*, *getSide()* along with *getAlpha()* would be dependent on the type of traders. Hence these three functions were declared abstract in the parent class, and corresponding logic would be executed through run-time polymorphism.
The trader agents could buy, sell, short sell or close the positions of the stock shares. In other words, buying shares could also mean the trader agent would close some of the positions, and selling shares could also mean the trader agent would short the shares. For such reasons, the actually buying and selling trade activities would delegate to *handleWhenBuyShares()* and *handleWhenSellShares()*. The detail of the explanation and the code snippet of these two functions

could be found in Appendix C.

3.3.4 Fundamental Trader Agents

Fundamental trader agents, as known as informed trader agents and would be spawned from `FundamentalTrader` class,inheriting the `Trader` class.

Characteristics

Each fundamental trader would have an intrinsic value and a z-score. The intrinsic value would be the estimated value of the true value of the stock. In other words, it would be a measure of what the stock would be worth. Detail of how the intrinsic value would be calculated could be seen in Appendix D. Opinion dynamics would not be applicable for them. It would be because the mechanism of the opinion dynamics would be based on the exchange of the opinions of the trader agents, and fundamental trader agents would not consider it.

Behaviours

The given rule for fundamental trader agents would be to buy or sell based on the estimated intrinsic value at each tick. They would buy when the difference between intrinsic value and the market price would be positive and sell when the difference would be negative. The difference was known as price distortion.

$$price\ distortion > 0\ ?\ BUY : SELL \tag{3.1}$$

The volume that the fundamental trader agent would be determined using the price distortion as well. Looking at the equation below:

$$volume = \frac{\kappa}{number\ of\ fundamental\ trader} * abs(price\ distortion) \tag{3.2}$$

where the κ would indicate the market's sensitivity, the higher the value of κ, the more volume would be traded and vice versa. To make the model's outcome more independent of the number of fundamental trader agents spawned, the market demand would be divided by the number of the fundamental trader agents.
The intrinsic value would be updated at the end of each tick because the market true value would keep changing.

3.3.5 Noise Trader Agents

Noise trader agents, as known as uninformed trader agents, would be spawned from `NoiseTrader` class, inheriting the `Trader` class.

Characteristics

Noise trader agents would be irrational and would only contribute noise to the stock market.

Behaviours

The given rule for the noise trader agent would be that they would trade randomly. To decide the trade activity of the noise trader agent, at each tick, the program would generate the value drawn from the uniform distribution, $U(0,1)$. Then it would buy if the value would be greater than 0.5, otherwise, it would sell.

$$p > 0.5 \; ? \; BUY : SELL \tag{3.3}$$

The volume demand of each noise trade agent would be σ_n , the demand of noise trader.

$$volume = \sigma_n \tag{3.4}$$

The noise trader agent's volume demand was independent of the number of the noise trader agents in the model. The goal for noise trader agents would be to add noise to the stock market. Having a fixed volume for each noise trader agent would allow the flexibility for the modeller to add noise to the price trend at ease. The more noise trader agents spawned, the nosier the price trend curve.

3.3.6 Opinion Dynamics Trader (Abstract Class)

Opinion dynamics represented the trader who would participate in the opinion dynamics. It was named `OpDynTrader` class and inherited from the parent `Trader` class. It would behave an abstract class from momentum and coordinated trader agents to inherit.

Characteristics

The characteristics of `OpDynTrader` agents would be that they all would hold an opinion, indicating what the trader agent would think about the value of the stock. The higher value of the opinion, the more optimistic the stock price would go up, vice versa. The opinion dynamics could start at any time.

Behaviours

Trader agents inheriting `OpDynTrader` class must be able to exchange opinions in social media. Besides, it would also fetch the change of the market true value from the social media agent, which the data provider agent further obtains. The detail of the opinion update would be discussed under the section of Opinion Dynamics.

3.3.7 Momentum Trader Agents

Momentum trader agents would be spawned from the `MomentumTrader` class which would be a child class of the `OpDynTrader` class.

Characteristics

Momentum trader agents would trade based on the price trend, known as the momentum. Besides, they would take part in the opinion dynamics. Each of them would have an opinion indicating the belief about the company stock. A high valued opinion would mean a more robust belief about the company stock and vice versa. Each opinion would be drawn from the normal distribution, $N(0,1)$ at the initialisation of the simulation. Opinions would be assumed to be normally distributed.

Behaviours

The given rule for the momentum trader agents would be to buy if the momentum was greater than zero. Otherwise, they would sell.

$$momentum > 0 \ ? \ BUY : SELL \tag{3.5}$$

Taking opinion dynamics into account, momentum trader agents would buy if the sum of the momentum and opinion of themselves would be greater than zero, otherwise would sell.

$$(momentum + opinion) > 0 \ ? \ BUY : SELL \tag{3.6}$$

One of the examples here would be, say the momentum was -0.5 and opinion of that momentum trader agent were 0.7. Since that agent was optimistic about the company's performance, the price trend was lacking momentum, and the agent would still buy the shares.
During each tick, momentum would be updated with the equation:

$$momentum = \alpha * (current\ price - previous\ price) + (1 - \alpha) * momentum \tag{3.7}$$

where α indicated how sensitive the change of price to momentum would typically range from 0 to 1. The new market price would largely affect the momentum in having a high valued , and vice versa.
The volume demand of momentum trader agents would also be dependent on the momentum and their opinions:

$$volume = \frac{\beta}{number of momentum trader} * demand \tag{3.8}$$

where $demand$ would indicate the volume demand at each tick and β would behave as a multiplier for demand to yield to the actual market demand of each momentum trader agent. The modeller could specify the number of momentum trader agents to be spawned. β would be subject to change dynamically. It would be partly proportional to the value of the opinion. Without opinion dynamics, demand would be calculated through this equation:

$$demand = tanh(abs(momentum) * \gamma) \tag{3.9}$$

whereas taking the opinion into account, the equation would take opinion into become:

$$demand = tanh(abs(momentum + opinion) * \gamma) \tag{3.10}$$

γ would be a factor behaving as a multiplier for the momentum and opinion. Note that the demand would be calculated using the $tanh$ function. Since the value of the $tanh$ function would range from -1 to 1, the maximum demand would be capped at 1. Such constraint could be solved by having β to multiply the demand obtained.

Opinion dynamics

Momentum trader agents would participate in the opinion dynamics. Momentum trader agents would have the opportunity to exchange opinions with other trader agents, participating in the opinion dynamics. Opinions of the momentum trader agent would, although not necessary, change accordingly. The detail of the mechanism of opinion dynamics was discussed in the section of Opinion Dynamics.

3.3.8 Coordinated Trader Agents

Coordinated trader agents would be spawned from `CoordinatedTrader` class which would inherit from `OpDynTrader` class.

Characteristics

Coordinated trade agents would participate in the opinion dynamics. Coordinated trader agents would take part in the opinion dynamics. Initially, all of them would hold relatively strong beliefs. Besides the exchange of opinions, they would pay attention to the change in actual value. The goal of the coordinated trader agents would be to skew the overall opinions to eventually form a swarm, generating swarm-like behaviours to move the market price.

Behaviours

The given rule for the coordinate trader agent would be to keep buying the company shares and hold the shares. The volume demand would be a dynamic value of σ_{ct}. The volume demand would be divided by the number of the coordinated trader agents spawned in the simulation.

$$volume = \frac{\sigma_{ct}}{number\ of\ coordinated\ traders} \tag{3.11}$$

where σ_{ct} indicated the standard deviation of the coordinated trader agent. The magnitude of σ_{ct} would be subject to change dynamically, partly proportional to the magnitude of the opinions. Hence, σ_{ct} would be partially positively related to the value of the self-opinion.

3.3.9 Exchange Agent

The exchange agent would represent the market exchanges system where goods such as company stock were traded by market participants. It would be spawned from the `Exchange` class.

Characteristics

The exchange agent would take in all the trade orders and then process and disgust the total market demand. Thus, it would yield the change of market demand and would update the market price accordingly. Details of the update of the market price could be found in Appendix E.

3.3.10 Data Provider Agent

The data provider agent represented the institution specialising in delivering financial news and data, such as Bloomberg L.P. It was spawned from the `DataProvider` class.

Characteristics

The characteristics of the data provider agent would be to process the financial data and update the market true value, a.k.a the market equilibrium. The details of the update of the market true value could be found in Appendix F.

3.3.11 Social Network Agent

Social network agent represented a modern social network such as Twitter. It was spawned from the `SoicalNetwork` class.

Characteristics

The characteristics of a social network agent would be to provide a platform for the other agents to exchange opinions. The social network agent would allow the exchange of messages in a clear, logical flow, rather than letting the trader agents exchanging opinions with each other directly. Besides, a change of market true value would also be available to be fetched.

Behaviours

The given rule for the social network agent would be that at every tick, the social network agent would collect the opinions from all the trader agents and the influencer as the opinion list and send the opinion list to every momentum trader agent who participated in the opinion dynamics.

The agent would also collect the change in market value from the data provider agents and send it to agents who would require that.

3.3.12 Influencer Agent

The influencer agent represented the iconic big influencer in the financial market. For instance, Mr Elon Musk. The influencer agent would be spawned from the `Influencer` class.

Characteristics

An influencer agent would initially hold a highly positive opinion. It would have much higher influencing power than the individual trader agents, i.e. it would be bring up the market sentiment. A detailed explanation could be found in Appendix G.

Behaviours

The rule for the influencer agent was that, at every tick, it would obtain the change in market true value from the data provider agent and update its self-opinion accordingly. If the opinion reached a specific value, it would share its self-opinion to the social network.

3.3.13 Hedge Fund (Abstract Class)

The hedge fund agents represented the hedge funds in the financial market. It was known that market professionals like hedge funds most likely caused the primary market price movement since they generally would have enormous capital compared to the individual investors. They could trade with a large number of shares in a short amount of period. Curiosity was raised to replicate these market professionals better to reflect the reality of the actual financial market.
In the ABM, the `HedgeFund` class would be of an abstract class. Since the hedge funds would be classified as market participants, it would be a kind of trader, strictly speaking. Hence, the `HedgeFund` class would inherit the `Trader` class.
Two of the classic strategies of Hedge Funds were considered: going short the shares, at low prices and high prices respectively, and going long for the shares.

3.3.14 Hedge Fund Short (Low / High) Agents

Both Hedge Fund Short agent and Hedge Fund Long agent would take the first trade strategy mentioned above: going short for the stocks at low and high prices, respectively. It was spawned from the `HedgeFundShortLow` and `HedgeFundShortHigh` class which inherited the `HedgeFund` class.

Characteristics

The Hedge Fund Short agent used a going-short trade strategy. It would sell shorting the shares at a high price and close the short positions at a lower price. It aimed to gain profit from the price difference.
During the first time short selling the shares, the amount of the volume traded would update through a linear function:

$$volume = \Delta_{trueValue} * multiplier \tag{3.12}$$

where the change in true value, $\Delta_{trueValue}$, would be obtained from the `SocialNetwork` agent. If the price kept growing and went beyond a certain price, they would decide to short even more stocks to attempt to suppress the price. The number of volumes traded was designed to be more than that of the first time. The equation would take the total volume shorted in the account, and the equation would become:

$$volume = \Delta_{trueValue} * multiplier * \frac{abs(shares)}{ssDuration} \tag{3.13}$$

where $shares$ indicated the amount of the short positions holding and $ssDuration$ indicated the duration it would short the stocks at each time. The unit of the duration would be a tick.
A detailed explanation could be found in Appendix H.

3.3.15 Hedge Fund Long Agent

Hedge Fund Long agent would take the second trade strategy mentioned above: going long. IT was spawned from the `HedgeFundLong` class which inherited from the `HedgeFund` class.

Characteristics

The Hedge Fund Long agent would buy the shares at a low price and aim to sell them at a high price. It aimed to gain profit from the price difference.
The volume would be obtain through the following the equation:

$$volume = \Delta_{trueValue} * multiplier \tag{3.14}$$

where the change in true value, $\Delta_{trueValue}$, would be obtained from the `SocialNetwork` agent.
A detailed explanation could be found in Appendix I.

3.4 Connections of Agents

3.4.1 Part one: Deriving the Swarm-like Effect

This dissertation first showed the scenario in which the swarm-like behaviour could be derived in general. The visualisation of the connection were shown as Figure J.1 in Appendix J. The model parameter values of part one could be found in Table **??** in Appendix **??**.
The environment of this model were set to a continuous call auction market, hence a `Exchange` agent was required. Next, `FunamentalTrader` agents, `NoiseTrader` agent, `MomentumTrader` and `CoordinatedTrader` agent would fully connected to the `Exchange` agent for them to submit trader orders. The `Exchange` agent would have to fully connect to these trader agents to send them the market price. Note that, there were no direct connections between trader agents.
Next, to have a data provider to process the net demand and update the market true value, a `DataProvider` agent was connected by the `Exchange` agent since `Exchange` agent would pass the information of change in price to `DataProvider` agent. Besides, the `DataProvider` agent would connect to the `FundamentalTrader` agents to allow the `FundamentalTrader` agents to get the information of market true value.
To implement the opinion dynamics, a `SocialNetwork` agent was required to provide an pipe for the `OyDynTrader` agents. The `MomenumTrader` agents and `CoordinatedTrader` agents would connect to `SocialNetwork` agent in order to share the opinions. The `SocialNetwork` agent would fully connect to the `MomenumTrader` and `CoordinatedTrader` agents in order to for the `SocialNetwork` agent to publish the opinion as well as the change in market true to the trader

agents. Besides, The `DataProvider` agent were connected to the `SocialNetwork` agent for it to pass the change in market true value.

3.4.2 Part two and Part Three: Introducing Influencers and Hedge Funds

Next, on top of part one, connections relating the `HedgeFund`, `Influencer` agents were discussed.
First talk about the `Influencer` agent. Since the goal of the `Influencer` agent was to heat the market by posting to social media. The `Influencer` agent would connect to the `SocialMedia` to share its opinion. `SocialMedia` agent would also connect to the `Influencer` agent in order to pass it the change in market true value and opinions of the other trader agents.
For the `HedgeFundShortLow` agents, `HedgeFundShortHigh` agents and `HedgeFundLong` agents, they would connect to the `Exchange` agent in order to submit the trade orders. The `SocialNetwork` agent would connect to them in order to pass them the change in market true value. The visualisation of the entire connection of the agents could be found in Figure J.2 in Appendix J.

3.5 Action Sequences of the ABM

During the simulation, the program would execute a chain of the sequences of actions at each tick.

3.5.1 Part One: Deriving the Swarm-like Effect

In this scenario, it would execute two sequence of actions in parallel: ***subSequencePrice*** and ***OpDynTrader.shareOpinion***. The trader agents would make trade decision, and on the other side, they would share the opinion to the social network. The reason why theses two subsequence could be executed in parallel could be found in Appendix M.

subSequencePrice

In *subSequencePrice*, the `Exchange` agent would first send the current market price for the all the trader agents. Then, once the trader agents received the market price, they would make trade decisions. Once trade decisions have been made, the trader agents would submit orders to the `Exchange` agent. At the same time, the `MomentumTrader` agents would take the current market price and update the momentum accordingly. The `Exchange` agent would receive all the trade orders and would calculate the net demand. Next, it would update the current market price and send the information of the net demand to the `DataProvider` agent for further professor the financial data. The `DataProvider` agent would get the information of net demand and update the market true value accordingly. The visualisation of the action sequences were shown in Figure N.1 in Appendix N.

Whole Action Sequences of Part One

Following that, there was a split of sequences. On one side, the `FundamentalTrader` agents would fetch the market true value from the `DataProvider` agent to update the self intrinsic

values.
On the other side, the `SocialNetwork` agent would receive the opinions from the trader agents participating the opinion dynamics, `MomentumTrader` agents and `CoordinatedTrader` agents, and would receive the change in market true value from the `DataProvider` agent. After gathering them, the `SocialNetwork` agent would send them to `MomentumTrader` agents and `CoordinatedTrader` agents for them to update the opinions based on the set of given rules. The actions of updating the opinion from all the agents would be inside another sub-sequence called SUBSEQUENCEUPDATEOPINION. The visualisation of the complete sequence of actions could be seen in Figure N.2 in Appendix N.

STEP() method

During the simulation, the program would call the STEP() method. Internally it would call the RUN() method, which further executed sequences of actions to run at every tick.

3.5.2 Part two and Part three: Adding Influencers and Hedge Funds

To implement the influencers and hedge funds added to the model in part one, three actions were made.

- `Influencer` agent would also share the self-opinion
- `Influencer` agent would also update the self opinions
- `HedgeFund` agents would update the number of the trade volume when the `MomentumTrader`, `CoordinatedTrader` and `Influencer` was updating the self opinion.

The visualisation of the complete sequence of actions could be seen in Figure N.3 in Appendix N. The model parameter values of part three could be found in Table **??** in Appendix **??**.

Chapter 4

Model Dynamics

4.1 Price Dynamics

The model dynamics took reference to the model suggested from Majewski, Ciliberti and Bouchaud [6] which was an extension of the model created by Chiarella [21].

Part One

In the ABM of this dissertation, three types group of investors, which trend-followers, fundamentalists and noise-traders were replaced by momentum traders, fundamental traders and noise traders respectively. One more additional type group of investors, coordinated traders were implemented. The altered version of the total demand of the four group of traders, for Δ amount of ticks, was given by:

$$D(t, t+\Delta) = \kappa \int_t^{t+\Delta} (V_s+P_s)\, ds + \beta \int_t^{t+\Delta} tanh(\gamma(M_s+O))\, ds + \sigma_N \int_t^{t+\Delta} dW_s^{(N)} + \sigma_C \int_t^{t+\Delta} dW_s^{(C)} \tag{4.1}$$

where $D(t, t+\Delta)$ represented the total market demand for Δ amount of ticks. $\kappa \int_t^{t+\Delta}(V_s+P_s)\, ds$ represented the market demand by the fundamental traders. $\beta \int_t^{t+\Delta} tanh(\gamma M_s)\, ds$ indicated the market demand by the momentum traders. $\sigma_N \int_t^{t+\Delta} dW_s^{(N)}$ indicated the market demand by the noise traders, $\sigma_C \int_t^{t+\Delta} dW_s^{(C)}$ indicated the market demand by the coordinated traders.
where Ms was replaced by $Ms+O$, taking the additional effect of opinion caused by the opinion dynamics. $\sigma_C \int_t^{t+\Delta} dW_s^{(C)}$ indicated the total demand by the coordinated traders.
And in the case when $\Delta \to 0$, the result of the price dynamics were given below:

$$dP_t = \kappa\, (V_t + P_t)\, dt + \beta\, tanh(\gamma M_t + O)\, dt + \sigma_N\, dW_t^{(N)} + \sigma_C\, dW_s^{(C)} \tag{4.2}$$

$$dM_t = -\alpha M_t dt + \alpha dP_t \tag{4.3}$$

where dM_t indicated the change of momentum.

$$dV_t = gdt + \sigma_V dW_t^{(V)} \tag{4.4}$$

Majewski, Ciliberti and Bouchaud [6] also took price price volatility σ_V and average growth g into account. For simplicity, the ABM in this dissertation only adopted σ_V whereas g would be 0. The equation became:

$$dV_t = \sigma_V dW_t^{(V)} \tag{4.5}$$

Part Two and Part Three

Since influencer was set not to be market participant. The model dynamics would remain the same as equation 4.1. Whereas the value of the opinion might differ due to the participation of the influencer to the opinion dynamics.
Implementing the hedge fund agents, the price dynamics would become:

$$\begin{aligned} D(t,t+\Delta) = \kappa \int_t^{t+\Delta} (V_s + P_s)\, ds + \beta \int_t^{t+\Delta} tanh(\gamma(M_s + O))\, ds + \sigma_N \int_t^{t+\Delta} dW_s^{(N)} \\ + \sigma_C \int_t^{t+\Delta} dW_s^{(C)} + \sigma_H \int_t^{t+\Delta} dW_s^{(C)} \end{aligned} \tag{4.6}$$

where $\sigma_H \int_t^{t+\Delta} dW_s^{(C)}$ indicated the market demand by the hedge fund only if certain conditions were met.
And in the case when $\Delta \to 0$, the result of the price dynamics were given below:

$$dP_t = \kappa\,(V_t + P_t)\, dt + \beta\, tanh(\gamma M_t)\, dt + \sigma_N\, dW_t^{(N)} + \sigma_C\, dW_s^{(C)} + \sigma_H\, dW_s^{(H)} \tag{4.7}$$

where $\sigma_H\, dW_s^{(H)}$ indicated the market demand by the hedge fund of one tick, again, only if certain conditions were met. dM_t and dV_t remained unchanged.

Calibrated Parameters

To increase the robustness of the ABM, some of adapted parameters were referenced from the calibrated parameter in literature because such calibrated parameter has been investigated and tested with fundamental scenarios by researchers, hence the model less error-prone and more robustness. For instance, in parameters used in the equation (4.1) were referenced from the calibrated parameters of the model created by the from Majewski, Ciliberti and Bouchaud [6]. Then, parameters such as β for the momentum traders and exchange's λ were altered based on the objectives.

4.2 Opinion Dynamics

4.2.1 Mechanism

The mechanism of opinion dynamics based on the exchange of the opinions between agents. This opinion would be something that agents would consider when making decision. The exchange of the opinions would alter the initial opinions of the agents, hence to alter the decision they would initially make.

The opinions of the agents would be normally distributed, representing the normal opinions in real-life. Then, there would be some agents as outliers, having very strong opinions. Through the exchange of the opinion, the agents holding the normal opinions would likely be influenced by the agents holding the strong opinions. The skew of the opinion could lead to the situation that agents could make different decisions. The total values of the opinions indicating the market sentiment could increase.

Applying the opinion dynamics into the stock market, a situation that would yield the swarm-like behaviour would be to have a group of trader agent which behave as individuals, through the interaction of the nearest trader agents, ended up buying the stock shares as the agents around would do. Such resulted in the continuous rises of the market stock price. That would be similar to how a swarm-like group would behave.

4.2.2 Code Implementation

Opinion Dynamics for Coordinated Traders

Now, let's look at with the implementation of opinion dynamics in the software aspect. At each tick, the opinion would be updated in the UPDATEOPINION(). The UPDATEOPINION() was an abstract method declared in the `OpDynTrader` class which gave the opportunities for different type of trader agent to update the opinion with different algorithms. Here would be the pseudocode of UPDATEOPINION() for coordinated traders:

Algorithm 2 pseudocode of UPDATEOPINION()

```

procedure UPDATEOPINION
    if opinion dynamics started then
        prevOpinion ← opinion                          ▷ store the opinion before update
        adjustOpWithInfluencerOp()                     ▷ consider influencer's opinion
        adjustOpWithDvTrueValue()                      ▷ consider change in market true value
        σ_c_t ← updateSigma(prevOpinion, σ_c_t)        ▷ update sigma
    end if
end procedure
```

For all the agents participating the opinion dynamics, the opinion would only be updated when the opinion dynamics has started. The starting time could be specified by the modeller.

Entering into UPDATEOPINION(), the value of the opinion before update were stored in a variable $prevOpinion$. It was for the use of updating the value of the multiplier σ_{ct}, refered to σ_{ct} in equation 3.11. Next, the agent would consider the two factors separately: the opinion from the influencer and the change in market true value.

In the case of receiving the opinion from the influencer, the program would enter the ***adjustOpWithInfluencerOp()***.

The opinions would be updated with a linear function. In this model, it was assume that the opinion from the influencer would have a higher influencing power to the other individual traders in the market. The equation of updating the opinion were:

$$opinion = opinion + influencerOpinion * weighting_i \tag{4.8}$$

where $weighting_i$ represented the multiplier.
Next, the agent would take the change in market true value, $\Delta_{trueValue}$ into account. the program would enter the ***adjustOpWithDvTrueValue()***. The rules of the updating the opinion was similarly to the update with the opinion from influcener above which was as well a linear function. The $\Delta_{trueValue}$ could tell the trader agents if the effect of the opinion has contributed anything to the $\Delta_{trueValue}$. In the case of receiving a positive $\Delta_{trueValue}$, value of opinion would increase, because the positive $\Delta_{trueValue}$ gave the trader agent a sign that the performance of the stock was increasing. In the opposite, when receiving a negative $\Delta_{trueValue}$, the trader agent could tend to think the performance of the stock was worse, hence the value of the opinion decreased. The equation of the updating the opinion with change in true value were:

$$opinion = opinion + \Delta_{trueValue} * weighting_{dvTrueValue} \tag{4.9}$$

where $weighting_{dvTrueValue}$ represented the multiplier for the $\Delta_{trueValue}$.
After the opinion was updated, σ_{ct} had to be updated accordingly. In the ABM of the dissertation, σ was set to be changeable dynamically. σ_{ct} for the coordinated trader was named σ_{ct} and for momentum traders was named β specify. σ_{ct} was set to have a partly proportional to the absolute value of opinion. the higher absolute value of the opinion, the higher value of the σ_{ct}. The update of the σ_{ct} were completed in UPDATESIGMA(). The pseudocode revelant to the update of the σ_{ct} were below:

Algorithm 3 Pseudocode of updateSigma()

```
procedure UPDATESIGMA(prevOpinion, σ)
    prevOpinionCopy ← Abs(prevOpinion)    ▷ store the absolute opinion of previous tick
    opinionCopy ← Abs(opinion)            ▷ store the absolute opinion of current tick
    if prevOpinionCopy < opinionCopy then
        σ ← multiplier * (opinionCopy * σ/prevOpinionCopy)
    else
        σ ← (1/multiplier) * (opinionCopy * σ/prevOpinionCopy)
    end if
    return σ
end procedure
```

Since the opinion could be positive or negative, when updating the σ, the absolute of the value of the opinion were used. It was because the σ would only be positive. It represented as a multiplier of how many order a trader agent should submit. A opinion of value -2 or 2 should have the same value of σ, since the absolute value of the opinions were the same. Trader agents with an opinion of 2 should submit the amount of buy orders as same as the amount of the sell orders submitted by a trader agent with opinion of 2.
As displayed in the pseudocode, σ were updated using the equation:

$$\sigma = \frac{opinionCopy * \sigma}{prevOpinionCopy} \tag{4.10}$$

The use of multiplier here was meant to increase the effect of the opinion dynamics, ie. to increase the rate of change in market demand of the trader agents. The dynamically update of the σ allowed trader agents participating the opinion dynamics to trader more when their opinions were of high value, no matter on the positive or negative direction.

Opinion Dynamics for Momentum Traders

For the momentum traders, it would also go inside the ***updateOpinion()***. The algorithm used to updatet the opinion was slightly different from how the coordinated traders did. Here is pseudocode of *updateOpinion()* for momentum traders:

Algorithm 4 pseudocode of UPDATEOPINION()

procedure UPDATEOPINION
  if $opinion\ dynamics\ started$ **then**
    $prevOpinion \leftarrow opinion$
    $adjustOpWithInfluencerOp()$
    $adjustOpWithTradersOp()$
    $\beta \leftarrow updateSigma(prevOpinion, \beta)$
  end if
end procedure

While the algorithm in *adjustOpWithInfluencerOp()* and *updateSigma()* were as same how the coordinated trader agents did, the momentum trader agents were also take account of the opinions from the other traders which would be done in ***adjustOpWithTradersOp()***. The pseudocode of it was shown below:

Algorithm 5 pseudocode of ADJUSTOPWITHTRADERSOP()

procedure ADJUSTOPWITHTRADERSOP
  for $opinion\ in\ opinionList$ **do** ▷ loop through every opinions received
    if $abs(opinion - selfOpinion) < vicinityRange$ **then**
      $condifenceFactor \leftarrow (1/Abs(o - selfOpinion)) + weighting_{cf}$
      $selfOpinion \leftarrow selfOpinion + (o - opinion) * confidenceFactor$
    end if
  end for
end procedure

Here would be the explanation of the pseudocode above. Entering ***adjustOpWithTradersOp***, the momentum trader agent would receive the opinions from the other trader agents, including other momentum trader agents and coordinated trader agents, in the form of a opinions list. structure of the collection of these opinions would be in the form of an array list, and would be done using the `simudyne` library, which no arguments would be needed. Next, loop through each opinion in the opinion list, check if it would meet the first condition: whether the difference between the received opinion and the opinion of the momentum trader agents itself would be within the vicinity range.
The concept of vicinity range from the idea of swarming between the birds or bees. In the group of birds and bees, each of them would be affected by the behavior of their nearest neighbours.

A bird/ bee would be the one of the nearest neighbours of another if that they would be close enough, and vicinity range would be used to determine whether two birds/ bees would be close enough.
If the difference between the two opinions were smaller than the vicinity range, then that the trader agent would take that particular opinion into account. However, the trader agent would decide how much it would adapt the particular opinion based on the difference of both the self opinion and the opinion. Such considering factor was implemented as the confidence factor. Essentially, the further the both opinions, the lower of the confidence factor and vice versa. Note that the $weighting_{cf}$ was a parameter to determine the rate of converge amount of the opinions of the trader agents. A higher value of $weighting_{cf}$ could slow down the rate of converge of the opinion. It was not expected the opinions to be converged in just few ticks which the observation and analysis from the simulation might not be done properly. The introduction of such parameter could allow pattern that could occur in the simulation could be captured in a more observable manner.

Opinion Dynamics for Influencer

The algorithm used to update the opinion of the influencer was different from the trader agents. It would update the opinion through the action UPDATEOPINION with the pseudocode displayed below:

Algorithm 6 pseudocode of UPDATEOPINION

```
procedure UPDATEOPINION
    if opinion dynamics started then
        adjustOpWithDvTrueValue()
        adjustOpWithTradersOp()
    end if
end procedure
```

Compared to the update procedure for the coordinated and momentum trader agents, the update procedure for the influencer agent were relatively straight forwards. It would consider both the change in true value and the opinions of the other trader agents as a whole, through the linear function. in *adjustOpWithDvTrueValue()*, the opinion would be updated by using the following equation:

$$opinion = opinion + \Delta_{trueValue} * multipler_i \tag{4.11}$$

and in *adjustOpWithTradersOpinion()*

$$opinion = opinion + (avgOpList - opinion) * multipler_i \tag{4.12}$$

where $avgOpList$ represented the average value of the all the opinions received at that particular tick. By having the $multipler_i$, the change in true value and the opinions from the other trader agents would have an linear effect to the opinion of the influencer itself.

Chapter 5

Results and Analysis

5.1 Part One: Deriving the Swarm-like Behaviour

Part one focused on addressing the challenge 1 by deriving the swarm-like behaviour among individual trader agents using the mechanism of opinion dynamics. It also addressed the challenge 2 by analysing the change in price before and after the swarm-like effect and achieved the collapse of the swarm-like behaviours.
Fundamental, momentum, noise, and coordinated trader agents represented the individual investors in this scenario. In the set-up of this scenario, opinion dynamics were set to come in effect after 15^{th} tick. Before the presence of the opinion dynamics, no opinions were exchanged. The simulation ran for 200 ticks for observing the formation and collapse of the swarm-like behaviour.

Rise and Drop in Price

Figure 5.1 showed the before the start of the opinion dynamics, the market price followed a random walk fashion. There opinion values of the trader agents remained unchanged. After 15^{th} tick, the opinion dynamics started, momentum trader agents and coordinated trader agents started to exchange opinions and gradually form a swarm. The formation of the swarm was reflected in the price trend. It was evident that after the start of the opinion dynamics, despite the noise observed in the price trend, the price gradually increased from a start price of $30 and topped at $413.82 at 100^{th} tick, a percentage change of 1279%. The topped price was more than thirteen times the original price. It moved the price up to around $3.8 per tick. The market price gradually increased, which indicated the effect caused by the swarm consisted of momentum and coordinated trader agents. After the 100^{th} tick, the price dropped gradually, similar to how the price increased. It dropped from $413.82 to $93.57 at the end of the simulation. The percentage change of this downtrend was -77.39%. It was dropped $3.2 per tick, similar to the amount of price increase during the uptrend. The gradual price drop indicated the collapse of the swarm.
The market true value had a similar shape to the price trend since the price kept converging the market true value, which kept changing as well. Figure 5.1 showed another information that the market true value was always lower than the market price. The difference gradually increased from 0 at the beginning of the simulation to $128.39, where the price topped at 100^{th}

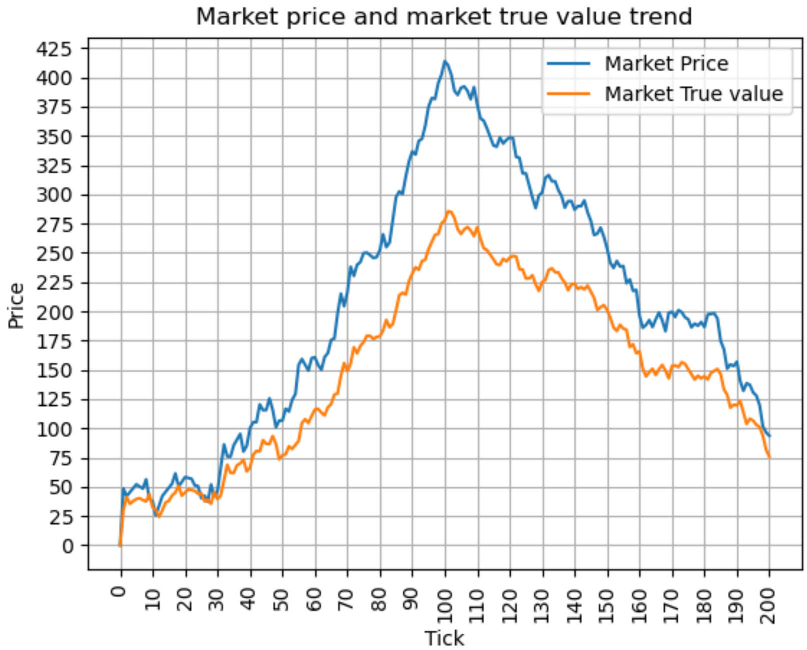

Figure 5.1: Part 1: Market price and true value trend

tick. The difference gradually reduced when the price dropped. Such indicated that the swarm-like behaviour caused the price to be over-valued. Trader agents were getting hype about the stock. Next, how the swarm was formed were discussed.

Formation of the Swarm

The pattern observed in Figure 5.1 were due to the formation of the swarm. Figure 5.2 showed the change of the average opinion values of the momentum and coordinated trader agents during the entire simulation. It indicated the convergence of opinions because each momentum trader agent held a different opinion at the beginning, and as the simulation went on, the opinions of the momentum trader agents became of the same values.
By exchanging the opinions, momentum trader agents were gradually influenced by the coordinated trader agents, and hence the opinions of the momentum trader agents were skewed to the opinions of the coordinated traders. The opinions started to converge. Such an increase in the opinions further increased the β since β and opinion were partial positive correlated. A higher value of β yielded higher market demand from momentum trader agents.
On the other side, coordinated traders agents held highly positive opinions, and they took the change of market true value into account when updating the self opinions. The Higher change in true value, the higher value of their opinions. The high value of the opinions yielded the higher value of σ_{ct} and further yielded market demand from the coordinated traders. This brought two effects: a higher chance to bring up the momentum by buying more shares and further increasing the momentum traders' opinions. As the momentum increased, momentum trader agents were more likely to decide to buy the stocks. Such chaining effect gave snow-ball effect for the overall opinions for both momentum and coordinated traders agents, resulting in the overall value of the opinions, in the form of market sentiment, gradually increased and

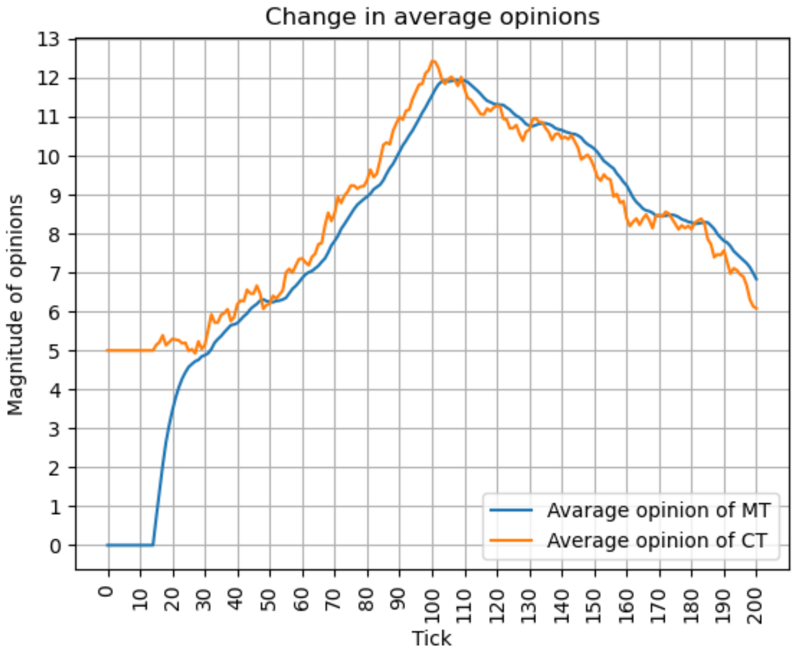

Figure 5.2: Part 1: Change in the average value of opinions of the momentum and coordinated trader agents

higher.
The exchange of opinion resulted in more momentum trader agents joined the coordinated trader agents, forming a swarm and bringing more stocks. The average opinions of the momentum and coordinated trader agents increased from close to 0 and 5 to 11.93 and 12.02, respectively. The percentage increase was around 1193% and 140.4% respectively. Such a huge percentage increase of the opinions indicated that the coordinated trader agents heavily influenced momentum trader agents, and event formed the swarm.

Collapse of the Swarm

However, the swarm-like behaviour did not ever last because each trader agent was given limited wealth. After the 100^{th} tick, both type trader agents ran out of money to buy the shares at such a high price. This resulted in a reduction in the market demand from both types of trader agents, further negatively impacting the market true value. The market sentiment reduced. Hence, the average opinions, as reflected in Figure 5.2, dropped and caused the momentum to drop gradually. Figure 5.2 showed that the average value of the opinions of momentum and coordinated trader agents dropped gradually from 11.93 and 12.02 to 6.82 and 6.07, respectively. The percentage change of the drop was about 50%. The rate of change for the coordinated trader agents was similar to the rate of rising of their opinions.
Besides, it was observed in Figure 5.2 that when the formation of the swarm, the average opinion values of the momentum trader agents were slightly less than that of the coordinated trader agents. Whereas during the collapse of the swarm, the average opinion of the momentum trader agents was slightly higher than that of the coordinated trader agents. A lag of the opinion values could be observed. Such clues indicated that the coordinated trader agents

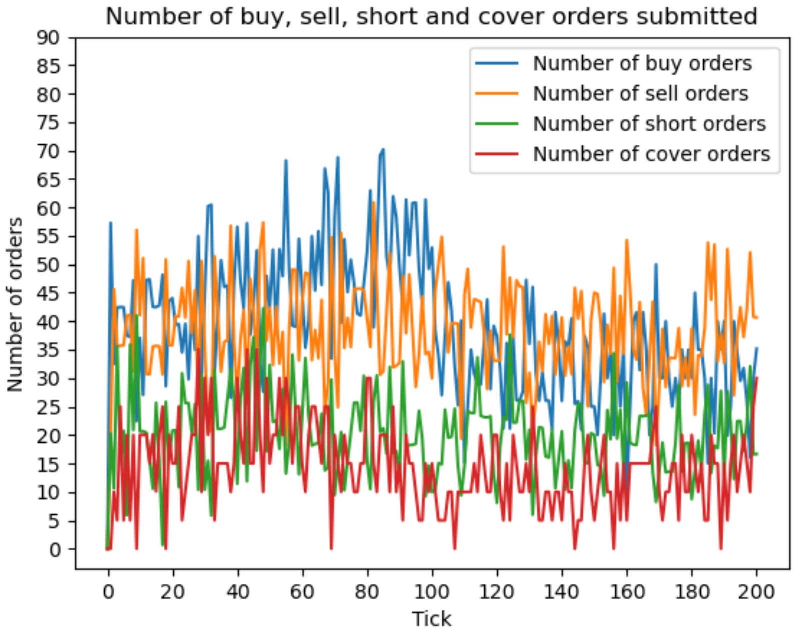

Figure 5.3: Part 1: Number of buy, sell, short and cover orders submitted. Note that the number of buy orders included the number of cover orders; The number of the sell orders included in the number short orders.

highly influenced the momentum trader agents.

When the rate of drop of prices gradually decreased, the value of the momentum dropped as well. Taking the momentum and opinions of the trader agents into account, they switched the trade decision again from selling the stocks to buying them.

Change in Number of Orders Submitted

Figure 5.3 showed the number of buy orders, sell orders, short orders and cover orders during the simulation. It could be observed that at the first half of the simulation (0^{th} to 100^{th}), Figure 5.5 shown that during the period in which the price gradually increased, the total amount of buy orders, shown as the blue lines, were higher than that of the number of sell orders. This indicated that the market had a positive net increase of the market demand. The amount of the sell orders mainly came from fundamental traders who believed the price was over-valued and kept shorting the stocks. At the second half of the simulation (100^{th} to 200^{th}), the number of buy orders reduced since the swarm ran out of capital.

Change in Wealth

Figure 5.4 showed the change in wealth for all types of trader agents during the simulation. The overall wealth of the momentum and coordinated trader agents gradually reduced due to the continuous buying of the share until they could not afford the high stock price. They have been buying the stock shares and holding them. After the 100^{th}, the remaining wealth

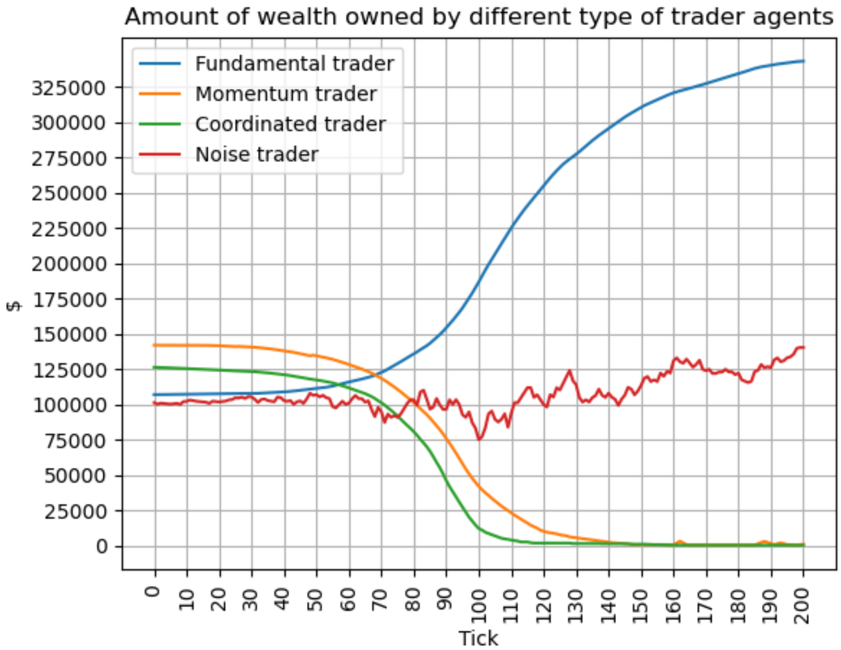

Figure 5.4: Part 1: Amount of wealth owned by different type of trader agents during the simulation

from these two types of trader agents was not enough to buy the stocks. This showed why the market demand, as well as the total number of buy orders, reduced suddenly in Figure 5.3.
On the contrary, since the fundamental traders believed the stock price was over-valued, they kept shorting the stocks. Hence margin accounts were initialised. As a result, the wealth of fundamental trader agents kept increasing temporary. It was shown that the amount of the change in wealth of the fundamental trader agents was higher than that of the momentum or coordinated trader agents. The overall wealth of the fundamental trader agents changed from around $10,000 to almost $35,000 due to the continuous increase of the stock price. In fact, the fundamental trader agents were losing wealth because the price of the shares that they kept shorting increased. Once they covered the positions, they would suffer huge losses.

Change in Number of Shares Held

Figure 5.5 showed that during the simulation, the shares hold by the momentum and coordinated trader agents were increasing due to the continuous buying of the shares. In the event of lack of capital, they were not selling the shares since their opinions were still at highly positive. This resulted that they kept holding the shares. On the other hand, shares shorted by the fundamental trader were as well increasing during the simulation. They did not join the swarm because the fundamental trader agents traded based on the stock's estimated intrinsic value, which was always lower than the actual market price.
It could be observed that the add up of the amount of the buy orders from momentum and coordinated traders agents were higher than of the sell orders from fundamental trader agents. Hence, there were positive net changes in demand, causing the price to increase continuously. During the collapse of the swarm, the number of shares shorted by the fundamental trader agents was still increasing because even though the price was gradually reduced, they believed

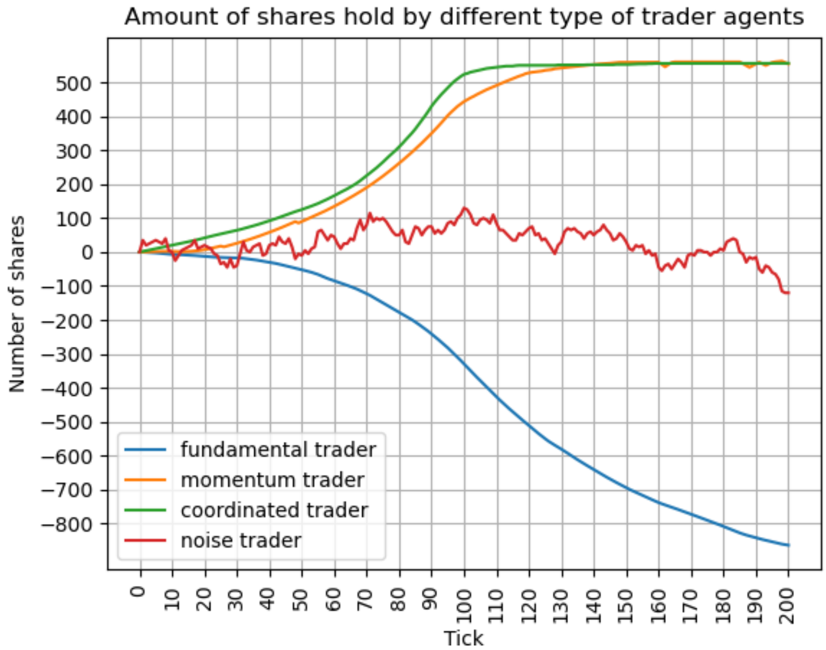

Figure 5.5: Part 1: Amount of shares hold by different type of trader agents

the price was still over-valued. The sign of the over-value of the price were reflected in the difference between the market price and true value in Figure 5.1.

Change in Value of β and σ

Other worth-seeing metric was the change in value of β and σ, shown in Figure 5.6. The average value of the β and σ rose from 0.5 to 12.79 and from 2 to 26.11 when the market price topped. The percentage increase for both $beta$ and $sigma$ were 2458% and 1205.5%. It showed that the swarm's total market demand was significant compared to the other market demand against it. Since in the ABM of this dissertation, the amount of the trader agents remained static. The increase of the β and σ could mean two possibilities in the real-life. First, the market demand from each investor would increase when hype would build up. Second, there would be more individual investors joining the swarm and would buy the shares. Either of them would likely increase the market demand and would cause the price to grow.

Factors that Could Control the Swarm-like Effect

In the scenario above, the swarm-like effect caused the price to the top at $413.82. Could it be higher or lower? Yes, there were mainly three factors to affect the effect of the swarm-like behaviour. The first one was the initial wealth given to the trader agents. By giving an amount of money to start with, trader agents would have more capital to buy the shares for a longer time, i.e. the solid swarm-like effect, pushing the price even higher. On the other hand, giving less wealth to the trader agents could be expected that the swarm-like effect would be weaker. The initial amounts of wealth were drawn from the Pareto distribution, which allowed each trader agent to have different wealth corresponding to the fact the amount of investment each

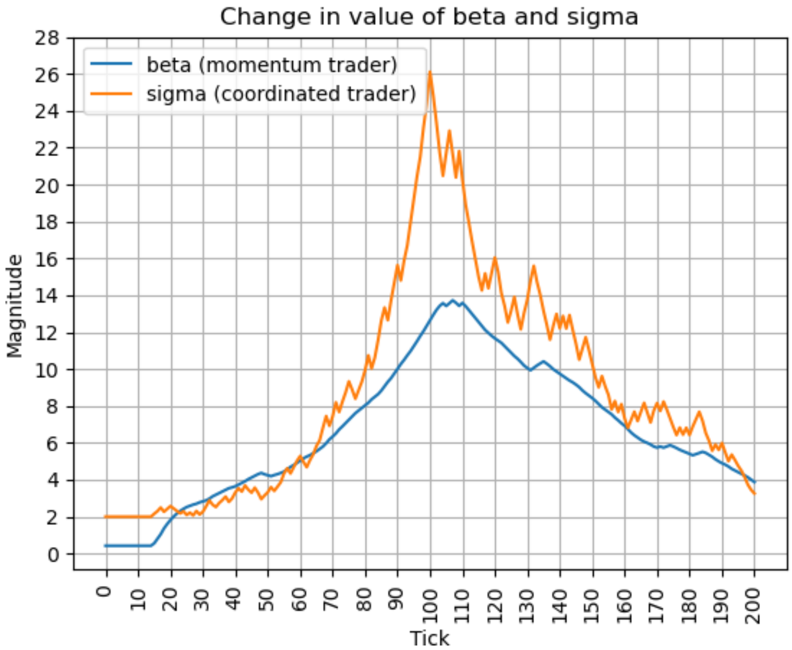

Figure 5.6: Part 1: Change in value of β and σ

investors would likely differ from others in real-life. Pareto distribution was used because of that. Table 5.1 showed the price price at different amounts of wealth given at initialisation using the Monte Carlo simulation of 100 runs. It showed a positive correlation between the initialisation wealth, and the average price and the total opinion values of the trader agents.

The second factor was the total number of trader agents spawned in the model. It was expected that by spawning more trader agents, the amount of exchange of opinions were higher. As a result, the converging of the opinions was faster, and the total opinion values, the market sentiment, was also higher. Table 5.2 showed that spawning a higher number of the momentum and coordinated trader agents would result in a higher total value of the opinions and higher average price. Thus, a positive correlation could be observed between the number of trader agents involving the opinion dynamics and the swarm-like effect.

The third factor was the value of κ. Table 5.3 showed that, by increasing the value of kappa

Table 5.1: Average price and Total opinion values with different wealth given to the trader agents at initialisation

Wealth	Average Price	Total Opinions Values
1000	255.24	360.90
2000	379.63	447.73
3000	423.5	492.5
4000	471.65	539.91
5000	520.51	572.43

Note. Results were obtained from the average values in the monto carlo simulation of 100 runs.

Table 5.2: Average price and total opinion values with different amount of trader agents spawned

FT	MT	CT	NT	Average Price	Total Opinion Values
10	10	10	10	275.32	185.67
20	20	20	15	423.5	492.5
20	30	30	15	482.75	885.32
30	30	30	15	468.54	841.05
30	40	40	15	569.48	1316.52
40	40	40	15	547.16	1205.44

Note. Results were obtained from the average values in the monto carlo simulation of 100 runs. Symbols - FT: Fundamental traders, MT: Momentum traders, CT: Coordinated traders, NT: Noise traders

Table 5.3: Average price and total value of opinions with different κ

κ	Average Price	Total Opinion Values
0.08	423.51	492.5
2	55.26	209.51
5	41.86	189.52
10	30.66	79.76
15	28.26	50.78

Note. Results were obtained from the average values in the monto carlo simulation of 100 runs. Symbols - FT: Fundamental traders, MT: Momentum traders, CT: Coordinated traders, NT: Noise traders

from 0.08 to 12, the swarm-like effect would eventually be cancelled out. i.e. the swarm, could not form, and the price would follow a random walk fashion. This indicated that with enough market players trading against the swarm, the swarm might not have the dynamic to form.

Summary of the Section

This section addressed the challenge 1 by demonstrating the formation of the swarm using opinion dynamics. Next, it addressed the challenge 2 by demonstrating that the swarm-like behaviour could cause the price to increase ten times more than the original price. Besides, it also demonstrated that the behaviour of one trade type could initiate the formation of the swarm and eventually made a significant impact on the market, especially since not every single trader agent joined the swarm.

5.2 Part Two: Influencer and Hedge Funds

This section showed how the swarm-like effect could form and affect the market price and the wealth of the trader agents. In part, the influencer and hedge funds were introduced in the model. This section aimed to address the part of challenge 3 and challenge 4. It was done by analysing the effect created by the influencer agent and hedge fund agents on the swarm pattern and deriving insights into how hedge funds performed when the swarm existed.

5.2.1 Influencer

The goal of an influencer was to influence the individual investors, increasing the market sentiment using its significant influencing power. It held a highly positive opinion, and at the same time, it inspected the change in true value of the market and a brief skim of the opinions in the market. When its opinion has reached a particular value, it shared its opinion with the market, which further influenced the opinions of the trader agents.

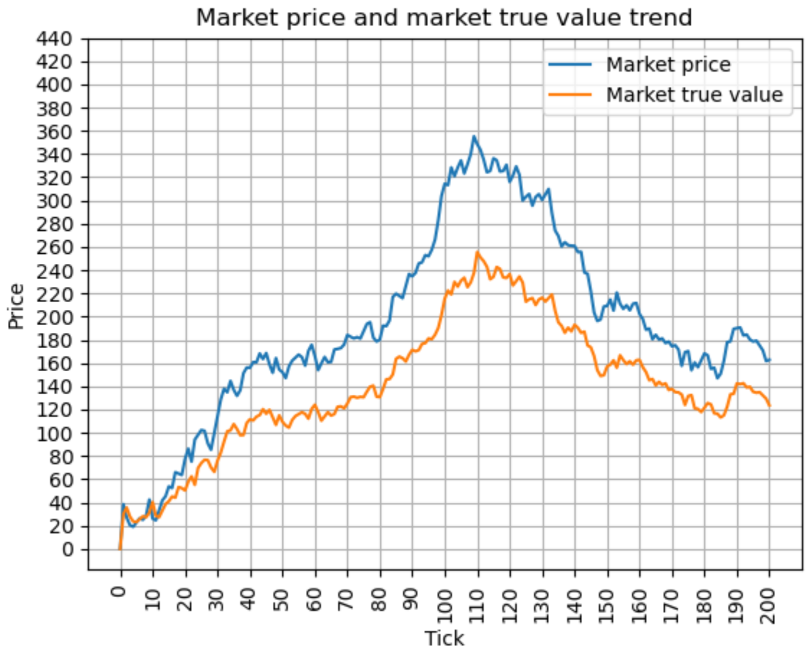

Figure 5.7: Part 2 (Influencer) - Market price and market true value trend

Change in Price

Figure 5.7 showed the trend of market price and true value. The shape of the price trend was similar to what could be observed in the general scenario shown in Figure 5.1. It was because even though the opinion of the influencer agent heavily influenced the opinions of the momentum and coordinated trader agents, it was just a one-off effect. It meant the increase of the opinion were digested in one tick. Hence, even though the overall value of the opinions had a sudden increase, the price increase was not sensitive enough to reflect the boost of the overall opinions. In this scenario, the influencer agent shared its opinion happened between 94^{th} and 95^{th} tick, whereas the price increased from $257.56 to $266.24 from 94^{th} and 95^{th} tick, a percentage change of 3%. In general, the change in price due to the influencer agent's influencer effect was not apparent.

A boost to the Overall Opinions and Market Sentiment

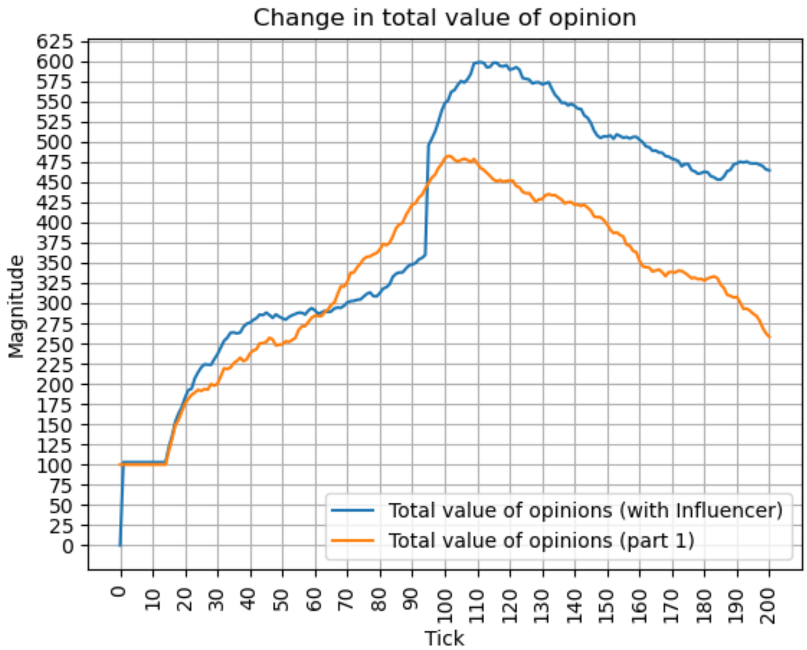

Figure 5.8: Part 2 (Influencer): - Change in total value of opinions of momentum and coordinated trader agents, , in comparison of the general scenario (part 1)

Figure 5.8 showed the change in the total value of the opinions of momentum and coordinated trader agents with comparison in part one general scenario. It showed that after influencing sharing the opinion, the total value of the opinions had a sharp rise from 359.77 to 495.48, a percentage change of 37,72%. This showed that the influencer agent gave a boost to the overall market sentiments. By comparing the total amount of the opinion in part one, the maximum total value of the opinions was higher than that in part one, with a difference of 19% (598.57 vs 482.21) when the value topped at both scenarios. Different from the change in price, the effect the influencer agents brought to the change in opinions was observable. Second, it fastened the rate of converging of those opinions. Note that the maximum price might not necessarily be higher than when the influencer agent was absent since the amount of wealth allocating to the trader agents were remain the same. Besides, these two scenarios were two different simulations. The critical point here was that the significant influencing power from the influencer could increase the market sentiment, even though the influencer agent itself did not execute any trading activity.
Figure 5.9 showed the average value of the opinions of the momentum and coordinated trader agents in comparison to the general scenario in part one. The opinion of the influencer agent

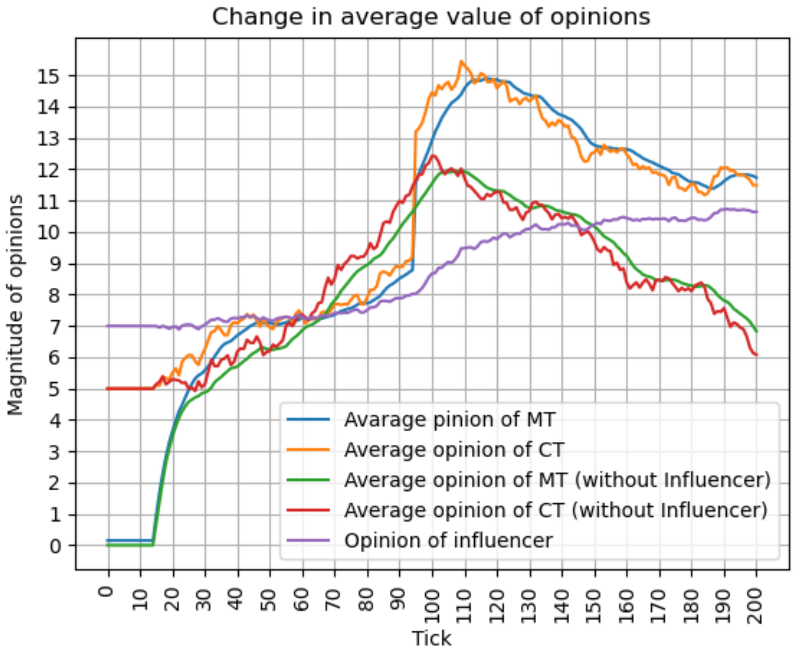

Figure 5.9: Part 2 (Influencer): Change in average value of opinions of momentum, coordinated trader agents and influencer agent

was also shown. Since the influencer agents paid some attention to the market, it considered the change of market true value into account and updated the self opinions. During the time the price had an upward trend, the opinion of the influencer slowly increased. Until it had a value of 8 of its opinion, it shared the opinion to the social network. The change in opinion for the influencer was relatively minor since it paid little attention to the market. The influencer's opinion rose from 7 to 10.64 during the entire simulation, having a percentage change of %52. Such indicated that the influencer agents was affected by the swarm indirectly.

Change in Number of Orders Submitted

Figure 5.10 showed the number of orders submitted by the trader agents during the simulation. Similar to the general scenario in part one, before the 110^{th} tick, the total number of the buy orders was slightly higher than that of the sell orders due to the swarm-like effect, which caused the price increase. After that, the swarm started to collapse, where it could be seen that the number of the sell orders was higher than the buy orders.

Change in Value of β and σ

Figure5.11 showed the after influencer agent shared the opinion, the value of the had a shape increase from 9.08 to 13.19, a percentage change of 45.3%. In comparison, the value of the β increased from 8.78 to 11.58, a percentage change of 31.9%. The σ were more sensitive to the change because coordinated trader agents had a higher multiplier for the market demand than the momentum trader agents. Both the change in β and σ had a similar shape in general.

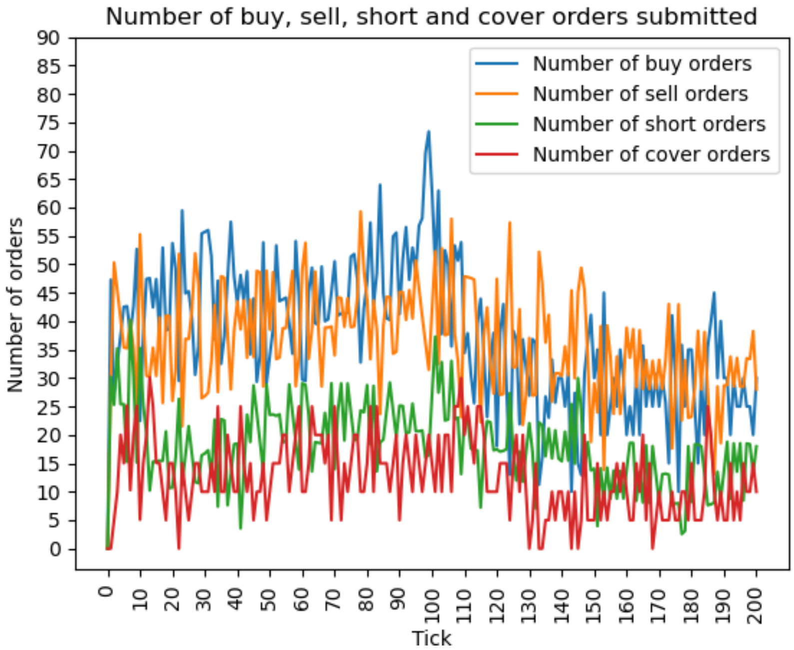

Figure 5.10: Part 2 (Influencer): Orders submitted during the simulation. Note that the number of buy orders included the number of cover orders; The number of the sell orders included in the number short orders.

Summary of the Section

This section addressed part of the challenge 3 by giving an understanding of how the influencer agent in the model could affect the pattern of the swarm. It boosted the market sentiment, resulting in a higher value of the total opinions than when the influencer agent was absent.

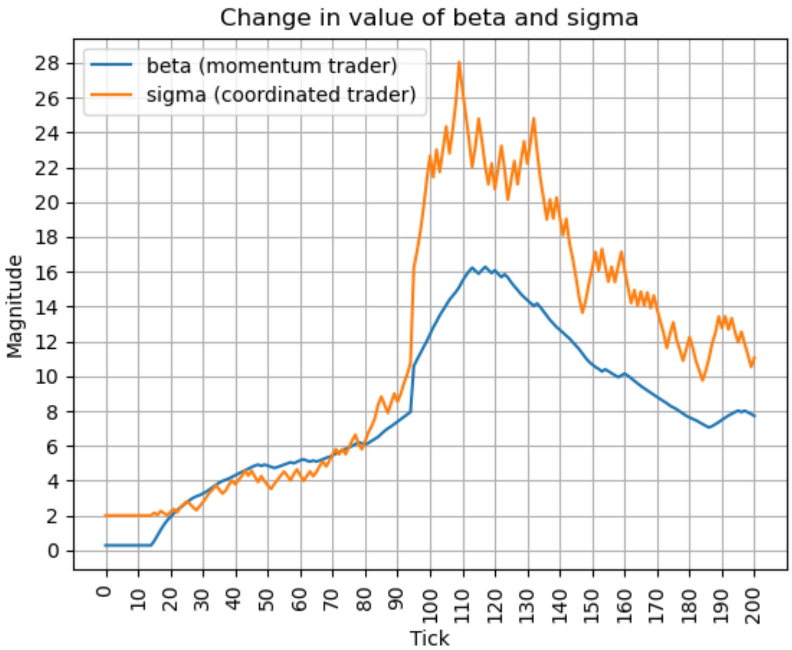

Figure 5.11: Part 2 (Influencer): Change in β and σ

Putting Hedge Funds into the ABM

In this dissertation, simplified trading strategies were given to the hedge fund agents: going short or going long. Each type of hedge fund was put in separate scenarios to observe its effect on the swarm. Besides, it focused on addressing part of the challenge 3 and 4 by showing how the hedge fund could potentially gain and loss capital in the existence of the swarm.

5.2.2 Hedge Fund (Short Selling at Low Price)

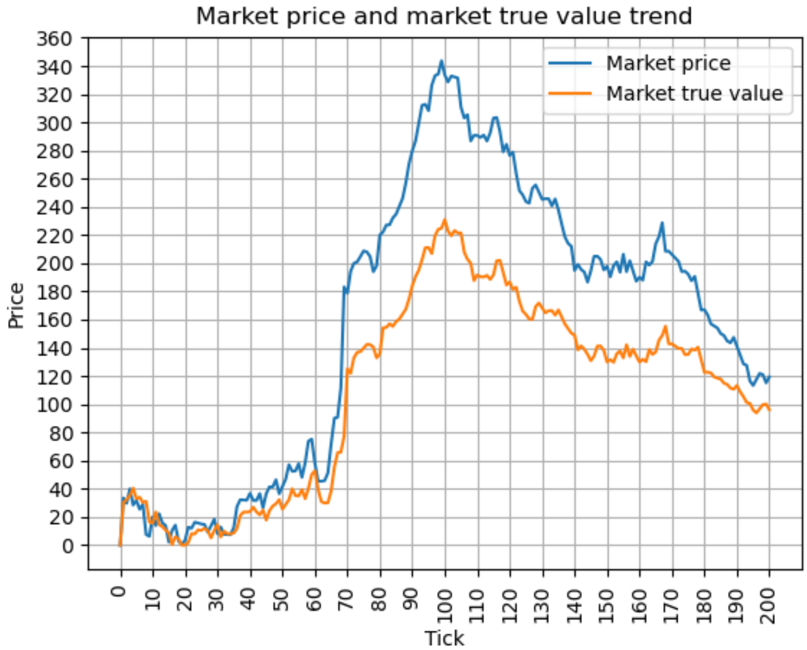

Figure 5.12: Part 2 (Hedge fund, short selling at a low price): Market price and true value trend

Hedge Fund Short Selling to Suppress the Price

Figure 5.12 showed an different pattern of the swarm from the general scenario in part one (Figure 5.1). In the scenario, the hedge fund agent attempted to profit by shorting the stocks and hoping the price would drop further. From 1^{st} tick to ^{3rd} tick, it shorted the amount of 32.13 shares. This trading activity caused the price to drop from \$33.53 to \$28.42, a percentage change of -15.24%. Such an amount of shorting could not cause the price to a lower level of which the hedge fund agent could cover the positions to reap the profit. Then after the start of the opinion dynamics, the swarm gradually formed and the price gradually increased. Between 59^{th} tick to 62^{th} tick, it showed that the hedge fund agent shorted even more shares to suppress the price further, increasing the total amount of shares begin short from 32.13 to 126.95, almost 300% of the first time shorting. This trade action of the second time shorting caused the price to have a more obvious drop from \$75.22 to \$45.77, a percentage decrease of 39.15%.

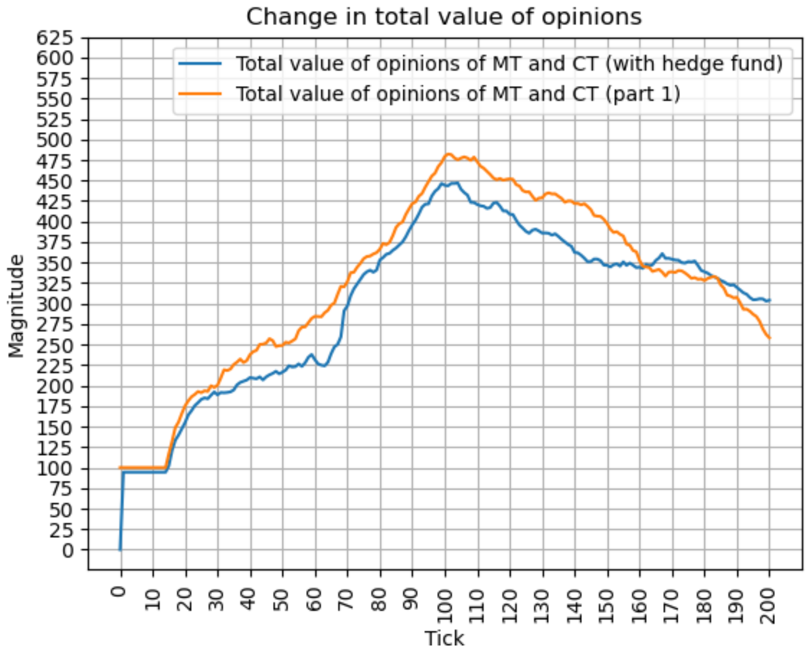

Figure 5.13: Part 2 (Hedge fund, short selling at a low price): Change in total value of opinions of momentum and coordinated trader agents

Short Squeeze Triggered by the Swarm

However, the short sales did not seem to stop the swarming as the price continued to rise. A short squeeze happened. At 69^{th} tick, where the price passed the \$100, the hedge fund covered all the positions to prevent from suffering enormous loss. Such trade action caused the price to rise from \$111.56 to \$183.23, a percentage increase of 64.24%. The momentum increased from 7.67 to 42.97, a percentage increase of 469%. Such high momentum caused the momentum trader agents to buy the shares. The consequence of covering the positions strengthened the swarm-like behaviour. The price further topped \$343.73 before the swarm started to collapse. In this scenario, the price had risen from \$30 to \$343.73, more than ten times the original price.

The price trend showed that the shorting action by the hedge funds slowed down the swarm-like effect. However, once it failed to move the price against the swarm, the swarm effect became stronger until the collapse of the swarm.

Change in Total Value of the Opinions

Figure 5.13 showed the pattern of the total opinion values differed from the general scenario in part 1 due to the involvement of the hedge funds. From 15^{th} to 80^{th}, the speed of the forming of the swarm was relatively slower than in part 1, after 68^{th} where the hedge fund covered the positions, the forming speed of the swarming accelerated for a while. As a result, the total value of the opinion increased from 259.41 to 291.22, a percentage increase of 12.26%. Both scenarios' pattern was similar outside this period where the hedge fund agent was not involved.

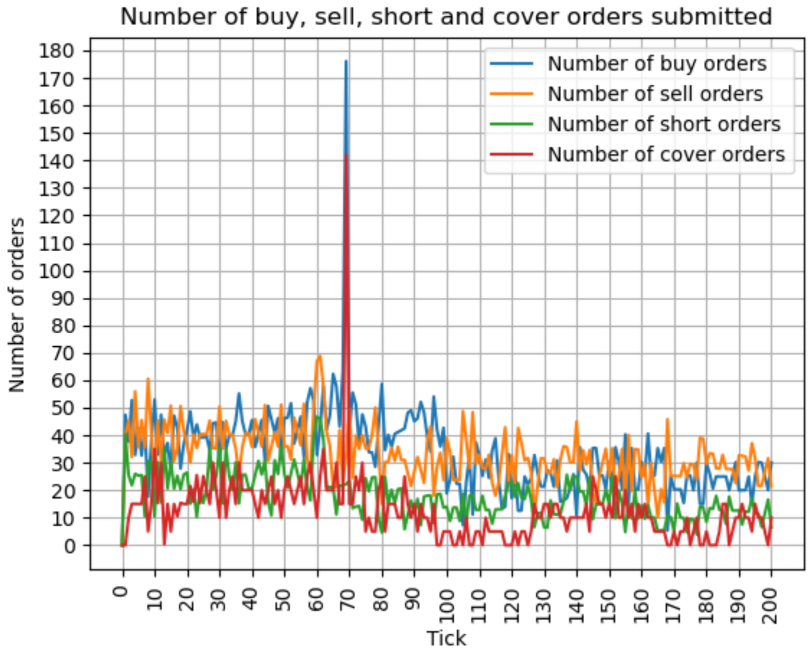

Figure 5.14: Part 2: hedge fund (short sell at low price) - Orders submitted during the simulation. Note that the number of buy orders included the number of cover orders; The number of the sell orders included in the number short orders.

Change in Number of Orders Submitted

Figure 5.14 showed that at 69^{th} tick, the hedge fund agent covered all the positions, indicated in the red line representing the number of cover orders at that tick. It covered 126.95 of shares at one tick. The number of shares being shorted was not apparent in the figure since the hedge funds shorted the shares gradually for three ticks each time it shorted. If paying close attention to the green line, representing the number of short orders, between 1^{st} tick and 4^{th} tick, and between 58^{st} tick and 62^{th} tick, the amount of the short orders were relatively higher than that at other ticks due to the short selling of the shares by the hedge fund agents.

Change in Wealth

Figure 5.15 showed that the trading strategy of the hedge fund agent was not successful as it suffered a loss as a consequence of covering the positions at a price higher than when it shorted the shares. In this scenario, it suffered a loss of $7440. The change in wealth or fundamental trader had a change in wealth of $8917.05, from $4708.95 to $13626.004. Whereas for the momentum and coordinated traders, the change in wealth were $4841.61 (from $4846.22 to $4.61) and $4182.91 (from $4187.82 to 4.91) respectively. The comparison of the market players' wealth showed that the loss from the hedge funds was relatively large.

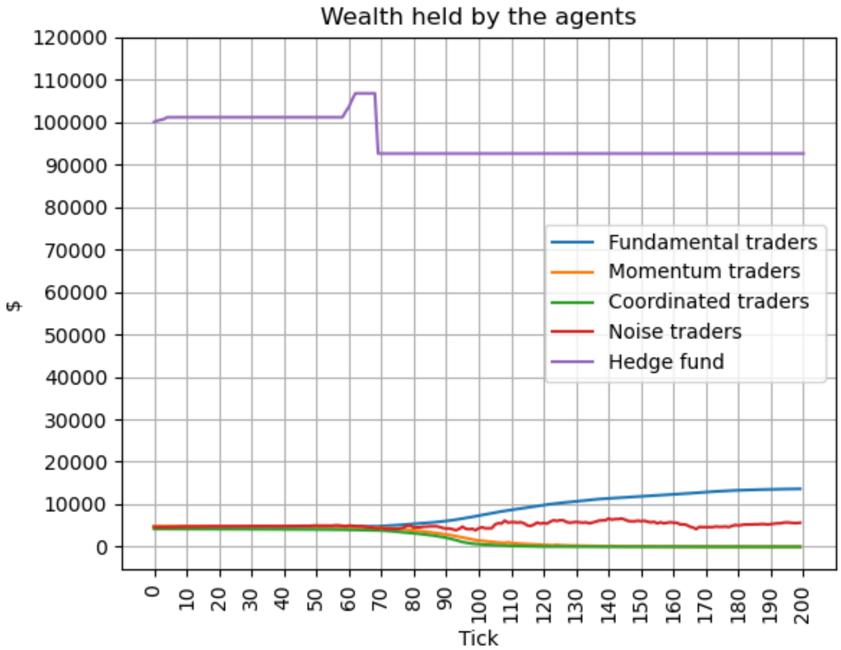

Figure 5.15: Part 2 (Hedge fund, short selling at a low price): Change in wealth of trader agents and hedge fund

Change in Number of Shares Held

Figure 5.16 showed that the amount of the shares the hedge fund agent shorted were not significant to the amount of the shares bought by the momentum trader and coordinated trader agents due to the strong swarm-like effect.

Summary of the Section

This section addressed part of the challenge 3 by demonstrating how the covering of the short positions by the hedge fund could increase the swarm-like effect. Besides, it addressed part of the challenge 4 by demonstrating one of the possibilities for a hedge fund to suffer loss if trading against the swarm. Another possibility for the hedge fund to succeed in this trading strategy could be by shorting more stocks or having the weaker swarm-like effect overall.

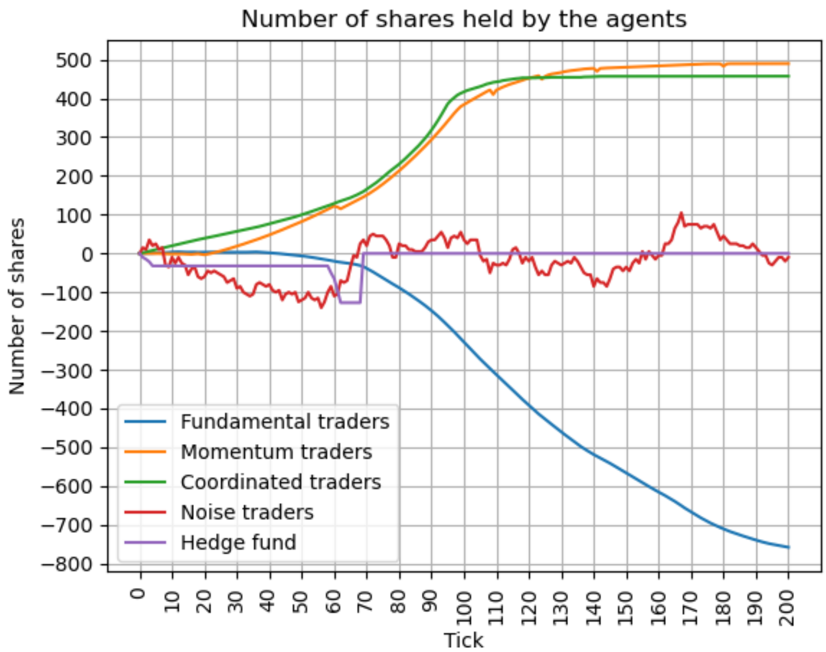

Figure 5.16: Part 2 (Hedge fund, short selling at a low price): Change in number of shares held by trader agents and hedge fund agent

5.2.3 Hedge Fund (Short Selling at a High Price)

What could happen if the hedge fund agent decided to go short but with a high price? This section focused on addressing part of the challenge 3 and 4 by having a scenario with a hedge fund agent attempted to do that and aimed to gain profit by covering the short position at a lower price.

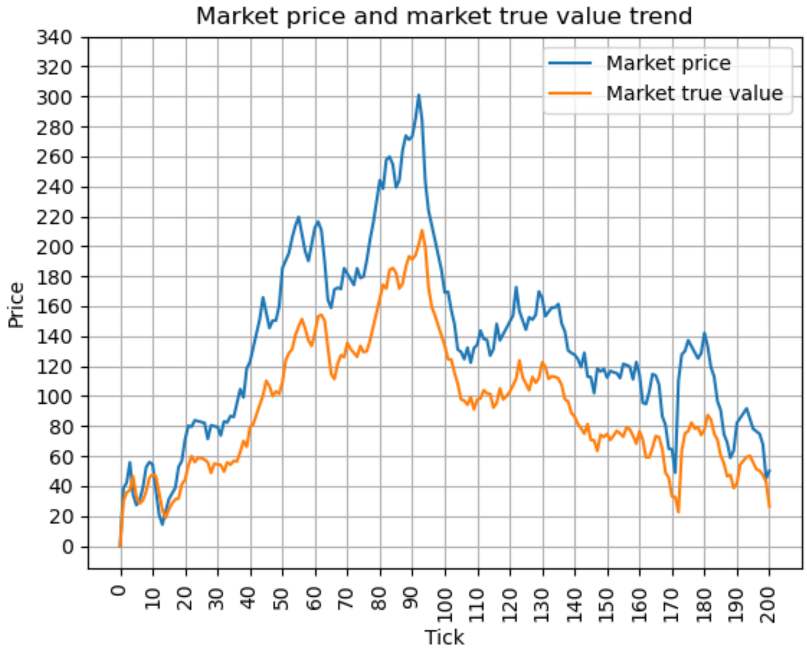

Figure 5.17: Part 2 (Hedge fund, short selling at a high price): Market price and true value trend

Short Selling when the Swarm Was About to Collapse

Figure 5.17 showed the during 93^{th} tick to 95^{th} tick, almost at the start of the collapse of the swarm, the hedge funds agent short sell the total amount of 163 shares, causing the price to drop from \$300.94 to \$243.48, a percentage decrease of 19.09%. This fastened the collapse of the swarm. Following the short selling, the price further dropped to \$124.65 at 106^{th} tick. Before this tick, the momentum trader and coordinate trader agents halted to buy the stocks due to the sudden momentum drop. After 106^{th}, the momentum started to drop slower, and the price was lower than when it was at the top, causing the trader agents to use the remaining capital to buy shares. Such trade activities caused the price to rise to \$143, a percentage increase of 14.7%. When the trader agents ran out of capital, the price started to drop again. After the price reached \$48.93 at 172^{th}, the target price for the hedge fund to cover the short positions was met, it then covered all the short positions, causing the price to have a sudden rise from \$48.93 to \$137 at 175^{th} tick, a significant percentage increase of 179.99%. However, since the swarm remain ran of the capital, the price started to drop again.

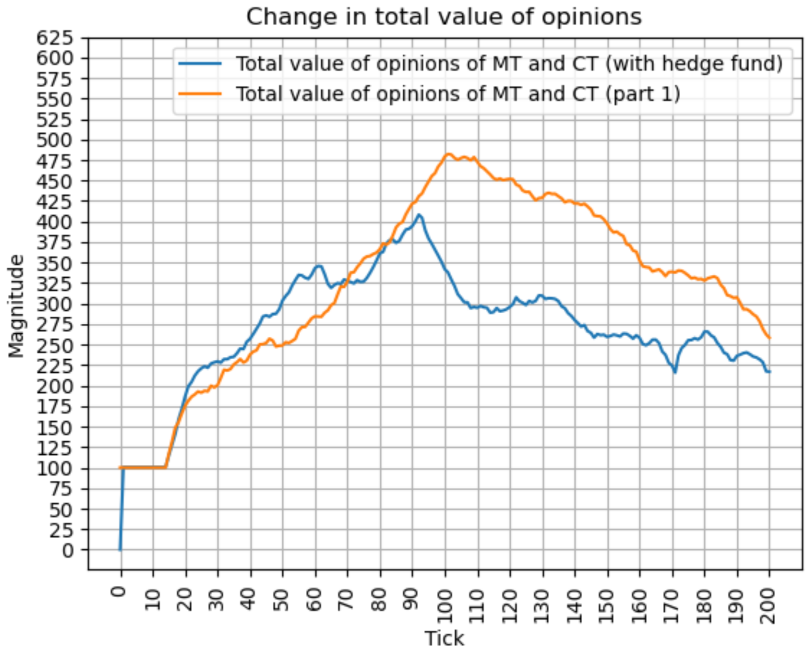

Figure 5.18: Part 2 (Hedge fund, short selling at a high price): - Change in total value of opinions of momentum and coordinated trader agents

Change in Value of Opinions

Figure 5.22 showed that the trade activities of short selling by the hedge fund caused the swarm to collapse at a faster rate, compared to that when there were only individual trader agents. During 93^{th} tick and 108^{th} tick, the total value of the opinion dropped from 404.51 to 294.46, a percentage decrease of 27.21%. During this period, the total value of the opinion dropped 7.33 per tick. Whereas in the general scenario (part 1), the total value of the opinions dropped around 2 per tick. Such indicated the faster rate of the collapse of the swarm with the involvement of the hedge fund agent. At 172^{th} tick where the hedge fund covered the short positions, it caused the total value of the opinion to rise from 215.79 to 261.23, a percentage increase of 21.05%. The percentage change was similar to when it shorted the shares. This result indicated that the hedge funds' trade activities could alter the swarm pattern, i.e. increase the speed of its collapse. The side effect was that once it covered the positions, the swarm could potentially form again.

Change in Number of Shares held

Figure 5.24 showed clear indications where the hedge fund agent traded. Between 93^{th} tick and 94^{th} tick, the hedge fund agent shorted 163.31 shares in two ticks, almost three times the orders submitted by the individual trader agents in the market. Whereas at the 172^{th} tick, it covered all the short positions at one tick, which indicated the red line representing the number of cover orders. Such indicated that in a short period, the trade activities of the hedge fund were apparent, as expected. It could cause significant interruption in the market, such as the

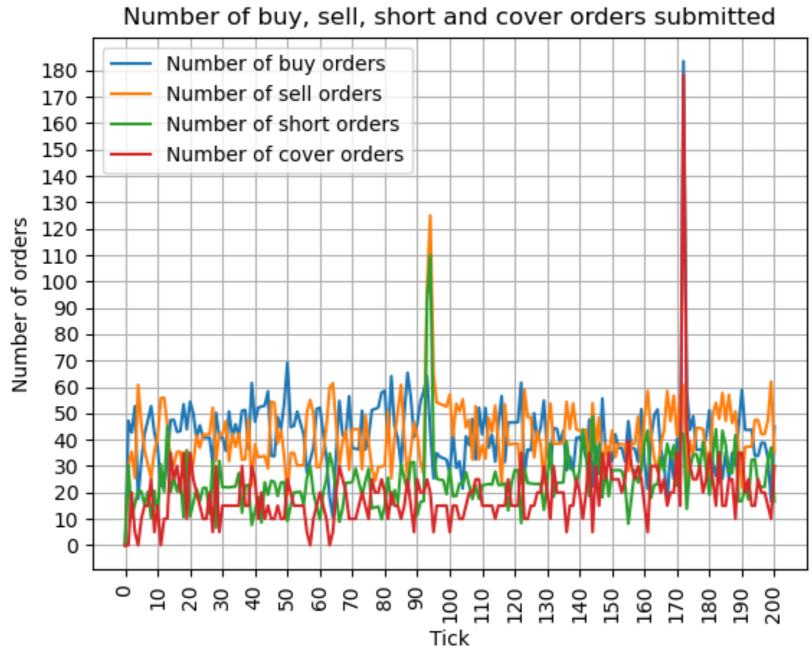

Figure 5.19: Part 2 (Hedge fund, short selling at a high price): Number of buy, sell, short and cover orders submitted during the simulation. Note that the number of buy orders included the number of cover orders; The number of the sell orders included in the number short orders.

market price and the speed of the collapse of the swarm.

Change in Amount of Wealth

Figure 5.20 showed the consequence of the simulation, the hedge fund gain $4000 due to the short selling. The momentum and coordinated trader resulted in having a change in the amount of wealth of around $9500 and $9000. The fundamental traders had a temporary change in wealth of around $10,000. Compared to the total wealth of different types of individual trader agents, the relatively from the hedge fund was not highly significant. However, it was still close to 50% of the change in wealth of every type of trader. By gaining profit, the trading strategy of short selling at a high price where the swarm was about to collapse could be said to be successful.

Summary of the Section

This section addressed the part of challenge 3 by demonstrating how a hedge fund could speed up the rate of collapse of the swarm by shorting large amounts of shares at a higher price. It could be possible to have multiple hedge funds entering the market, short-selling a relatively higher amount of the shares, which could cause the collapse of the swarm even faster. Again, the side effect could be when covering the short positions, the sudden increase of the price to cause another swarm to form.
It addressed the part of challenge 4 by demonstrating one of the possibilities of how a hedge

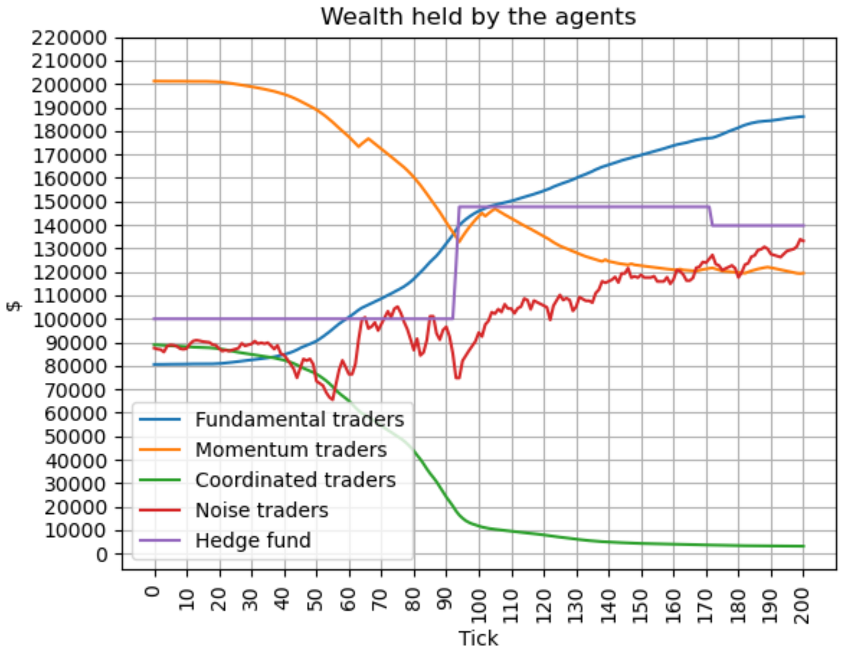

Figure 5.20: Part 2 (Hedge fund, short selling at a high price): Change in wealth owned by the trader agents and hedge fund agent

fund could gain profit by short selling at the price where the swarm was about to collapse. It could fasten the speed of the collapse of the swarm, making it closer to the target price at which the hedge fund covered the short positions.

5.2.4 Hedge Fund (Going Long on the Stock Shares)

The above two examples showed the possibility of a hedge fund's consequence by utilising the trading strategy of going short. This section focused on addressing part of the challenge 3 and 4 - a scenario where a hedge fund with a trading strategy of going long the stocks was demonstrated.

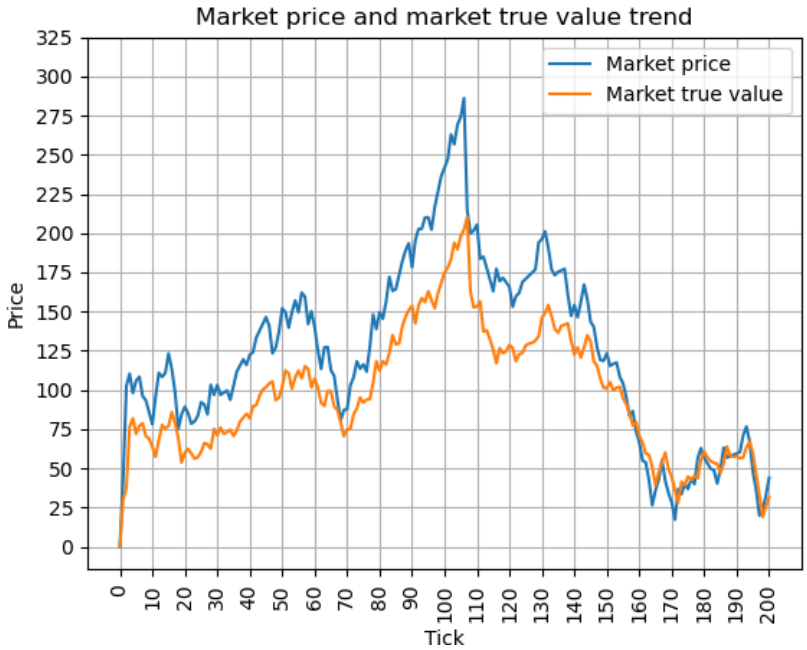

Figure 5.21: Part 2 (Hedge fund, going long): Market price and true value trend

Buy at Low price, Sell at High Price

Figure 5.21 showed that at 2^{nd} tick, the hedge fund agent went long of 151 shares, causing the price to rise from $34.56 to $102.62, a percentage increase of 196.93%. Such indicated that the trade activity by the hedge fund significantly affected the price. However, since the opinion dynamics came into effect after 15^{th} tick, the momentum gain from these trade activities was not continuous. The price had dropped to $75.19 at 18^{th}. After that, the exchange of opinions started, and the price started to rise again. There was a period where the swarm-like effect was relatively weak. It could be observed that during 64^{th} tick to 70^{th} tick, the price dropped from $127.39 to $87.56, a percentage decrease of 31.33%. That could be due to the noise trader continuously bought the shares by chance.
Overall, the swarm-like effect led the price to top at $286.08 at 106^{th} tick. At this price, it met the target price for the hedge fund to sell the shares it held. Hence, at 107^{th} tick, it sold all the 151 holding shares and caused the price to have a sharp drop from $286.08 to $214.59, a percentage decrease of 24.99%. This trading activity speeded up the swarm's collapse, as the price further dropped to $168.86 at 124^{th} tick. During the period, the price dropped $6.51 per tick. Even though there was a price rise right after, the swarming collapsed eventually as the price eventually dropped to about $17.38 at 171^{th} tick.

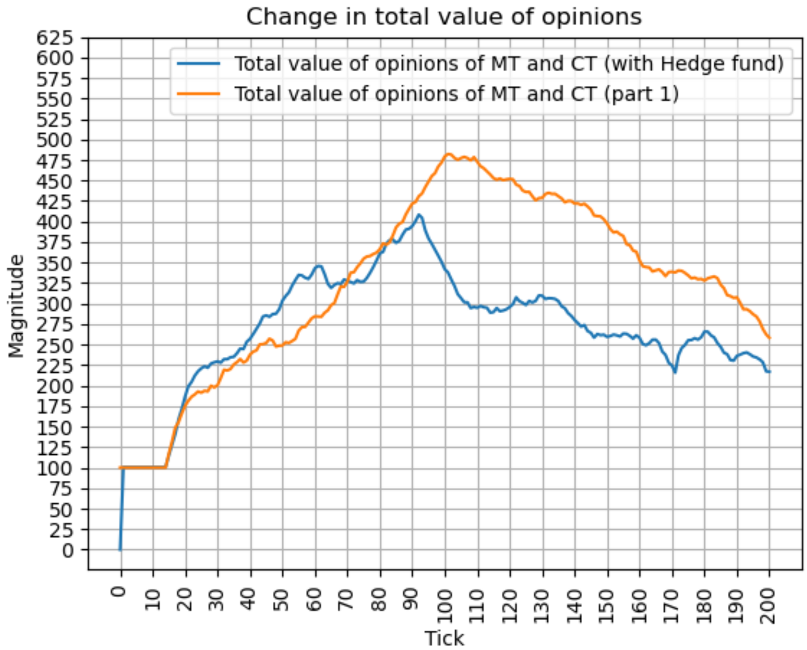

Figure 5.22: Part 2 (Hedge fund, going long): Change in total value of opinions of momentum and coordinated trader agents, in comparison of the general scenario (part 1)

The findings indicated that the trade activities of this hedge fund agent could cause the price to have a share rise as well as the shape drop.

Change in Swarm Pattern

Figure 5.22 showed that the swarm pattern was not as same as in the general scenario. Buying the shares from hedge fund agents caused the overall opinion to converge quicker, from 112.25 to 189.53 at 30^{th}, a percentage increase of 68.85%. After the price change was disgusted, the rate of converging of the opinions started to reduce. A similar situation could be observed at the start of the collapse of the swarm. The selling from hedge fund agent caused the total value of the opinion to drop from 343.48 to 267.42 from 106^{th} to 115^{th}, a percentage decrease 22.14%. Even though the percentage decrease was not as significant as when the hedge fund bought the shares, the faster rate of collapse of the swarm was noticeable. Note that the total value of the opinions was less than that of the general scenario. Part of the reason for this was that, in this scenario, the noise trader agents' trade activities were almost against the swarm by chance.

Figure 5.28 showed the average opinion of the momentum and coordinated trader agents at the maximum swarm-like effect were not beyond 10, whereas in the general scenario, both average opinions went over 10. Thus, it just showed that the opinions hold by the trader agents were less optimistic.

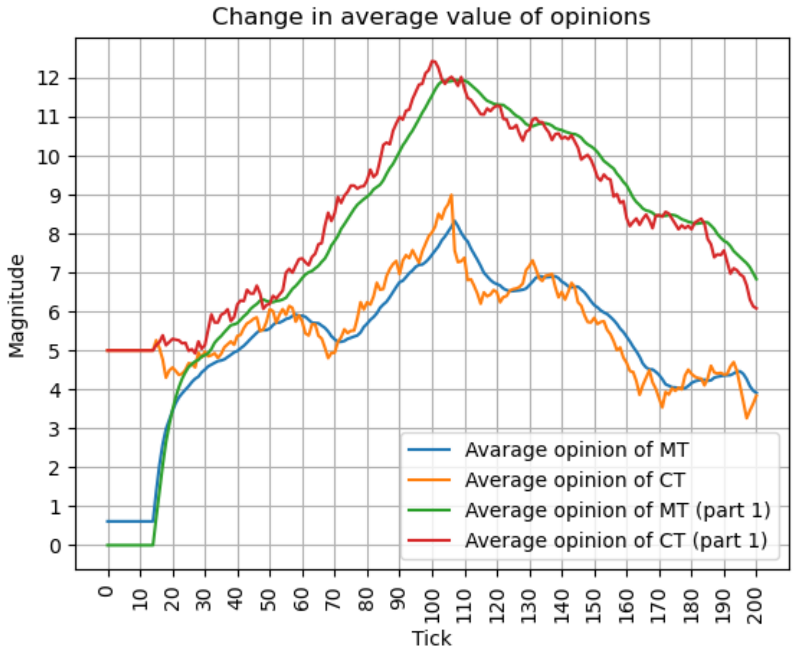

Figure 5.23: Part 2 (Hedge fund, going long): Change in average value of opinions of momentum and coordinated trader agents, in comparison of the general scenario (part 1)

Change in Number of Orders Submitted

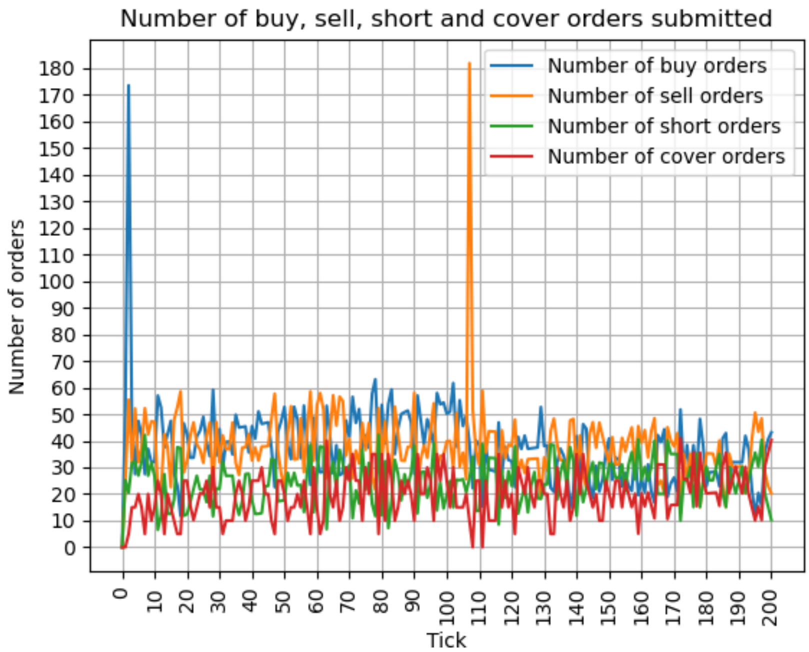

Figure 5.24: Part 2 (Hedge fund, going long): Number of buy, sell, short and cover orders submitted during the simulation. Note that the number of buy orders included the number of cover orders; The number of the sell orders included in the number short orders.

Figure 5.24 clearly showed the trade activities by the hedge fund indicated by the blue line where it bought the shares at 2^{nd} tick and indicated by the orange line where it sold the shares at 106^{th} tick. Both volumes of shares that it traded at two different ticks were about three times higher than that of the orders submitted against it. The vast difference indicated that the trade activities by the hedge fund agent caused the significant interruption of the price at a concise amount of period. During the formation of the swarm, in the most of time between 18^{th} and 106^{th}, it could be seen that the number of buy orders was larger than the sell orders. The situation flipped when the swarm collapsed gradually.

Change in Amount of Shares held

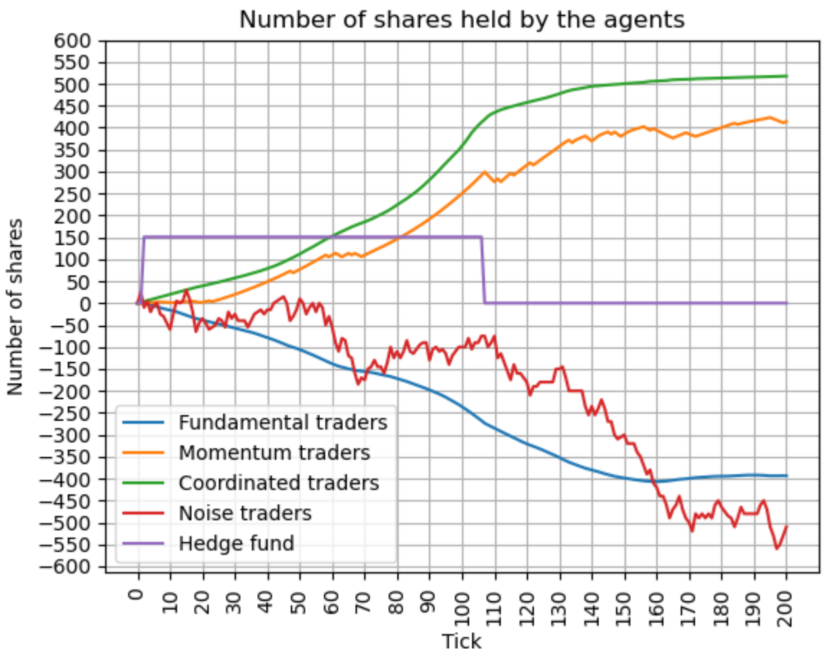

Figure 5.25: Part 2 (Hedge fund, going long): Change in shares that trader agents and hedge fund held

Figure 5.25 showed the aspect of shares held by the trader agents and hedge funds. It could be observed that the amount of the shares that the hedge fund bought, indicated as the purple line, was indeed significant comparing the amount of the shares that the other trader agents held. During the period where it held 150 shares, most of the time, the shares held by the other traders only passed after the second half of that period (within 60^{th} to 106^{th}). The shares held by all momentum and coordinated trader agent only exceed 150 after 60^{th} tick.

Change in Wealth

In this scenario, the hedge fund was a winner as they gained a total net profit of \$36622. Overall, the coordinated trader agents had a change in wealth of -\$84307. The momentum trader agents had a change in wealth of -$68859. The fundamental trader had a change in wealth of $65093 temporary. The noise trader agents in total had a change in wealth of $76625. The percentage change of wealth was almost 50% of the percentage change of wealth of each type of trader agent. Such indicated the significant magnitude of the profit gained from the hedge fund. This scenario was worth mentioning the noise trader since it almost behaved like the fundamental trader, again, by chance. It was reflected by the number of shares the noise trader and fundamental trader held where similar patterns were observed.

Summary of the Section

This section addressed the part of challenge 3 by demonstrating one of the possibilities of how a hedge fund could alter the swarm pattern by buying a massive amount of shares at a low price and selling them at a high price. It also addressed part of challenge 4 by demonstrating how these trade activities could gain an observable profit in the event of the swarm.

5.3 Part Three: GME-like Scenario

This section focused on addressing part of the challenge 3 and 4 by demonstrating one of the possibilities of how the accumulated effect of the influencer and the hedge funds could alter the pattern of the swarm, the stock price. Furthermore, it attempted to produce a scenario similar to the GameStop 'Short Squeeze' affair in January 2021.

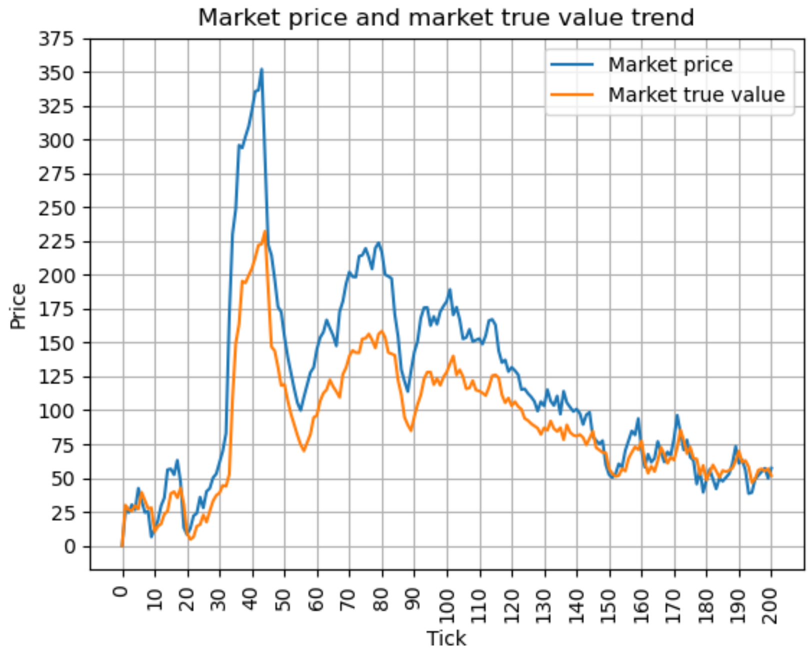

Figure 5.26: Part 3: GME-like Scenario - Market price and true value trend

Sharp Rise and Drop in price, and Bouncing back

Figure 5.26 showed the pattern of the price trend differed from the previous scenarios. In general, it could be observed that the price rose sharply from \$69 at 31^{th} tick to \$351.92 at 43^{th} tick, with a percentage increase of 410% within 12 ticks. The rate of price increase was significant as it rose \$23.58 per tick. Right after the price topped, it sharply dropped from \$351.92 to \$99.91 at 55^{th} tick, with a percentage decrease of 71.6%. It dropped \$21 per tick, having a similar rate of change in price as to how it grew. After that, a bounce-back was observed as the price rose again from \$99.92 at 55^{th} tick to \$219.59 at 75^{th} tick, with a percentage increase of 120% in 20 ticks. It then dropped back to the \$113.83 at 88^{th} tick, with a percentage decrease of -48.16% in 13 ticks. After that, the first bounce up and drop finished, following by the second bounce up. The price started to rise from \$113.83 at 88^{th} tick to \$175.92 at 94^{th} tick, with a percentage increase of 54.54% in 6 ticks. After the price topped at the second peak, it gradually dropped to the low level, at \$57.35 at the end of the simulation. The price trend showed two bounces up after the first sharp rise and drop of the price. The amplitude of the second bounce up was smaller than that of the first bounce up. Such indicated that the swarm were not wholly collapsed after the first sharp rise and fall in price. The swarm

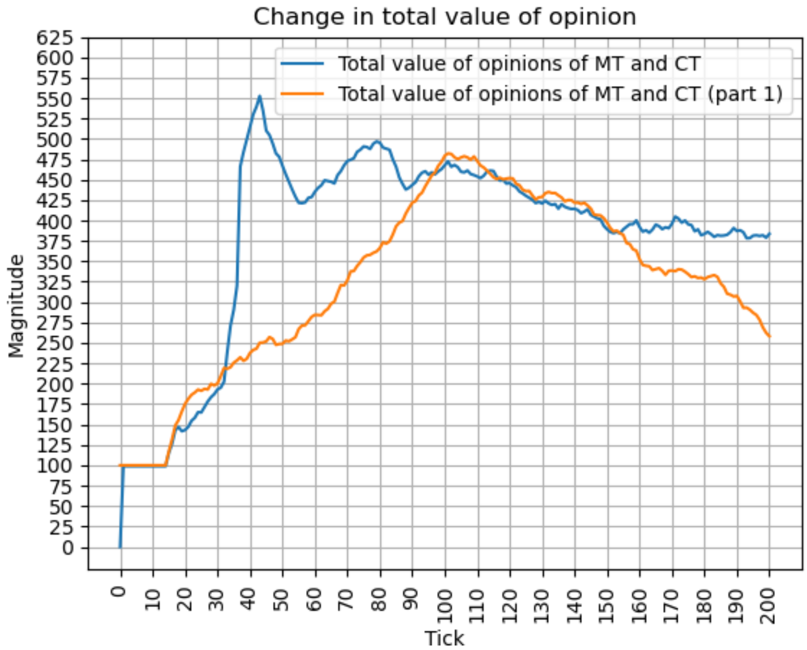

Figure 5.27: Part 3: GME-like Scenario - Change in total value of opinions of the agents, , in comparison of the general scenario (part 1)

attempted to form again through the two bounces. However, it eventually collapsed as the price eventually fell to a lower price level. The sign of the swarm's ability to initiate two bounces up indicated that the first sharp rise and fall in price was also caused by the other agents other than just the swarm. They were the influencer agent and hedge fund agents.
Another interesting observation was that before the first sharp rise in price (before 20^{th}) and after the two bounces and fell caused by the swarm (after 150^{th} tick), the market price was very close to the true value indicating the collapse of the swarm and the stock price were no longer over-valued. In other words, the market had re-adjusted.

Change in Value of Opinions

Figure 5.27 showed that the pattern of the convergence of the opinions was different from the general scenario. With the external effect from the influencer and hedge fund agents, the total value of the opinions topped at a higher value (552.7) in the earlier tick (43^{th} tick) than the general scenario (topped at 478.2 at 101^{th} tick). The converge rate of the opinion was high since it rose from 192.99 at 30^{th} tick to 552.7 at 43^{th}, with a percentage increase of 186.4% in 13 ticks. As a result, the total value of the opinions increased to 27.67 per tick, whereas the average value of the opinions increased to 0.69 per tick. The change in opinions was relatively significant. Moreover, the pattern of the reduction of the opinion was different as well. Instead of having a smooth downtrend, there were two times where the swarm tried to increase the total value of the opinions, but eventually, the total value of the opinions gradually reduced despite the bounces up. Note that the fact that the price dropped to the low level was not reflected in the change in the total value of the opinions in Figure 5.27 because the trader

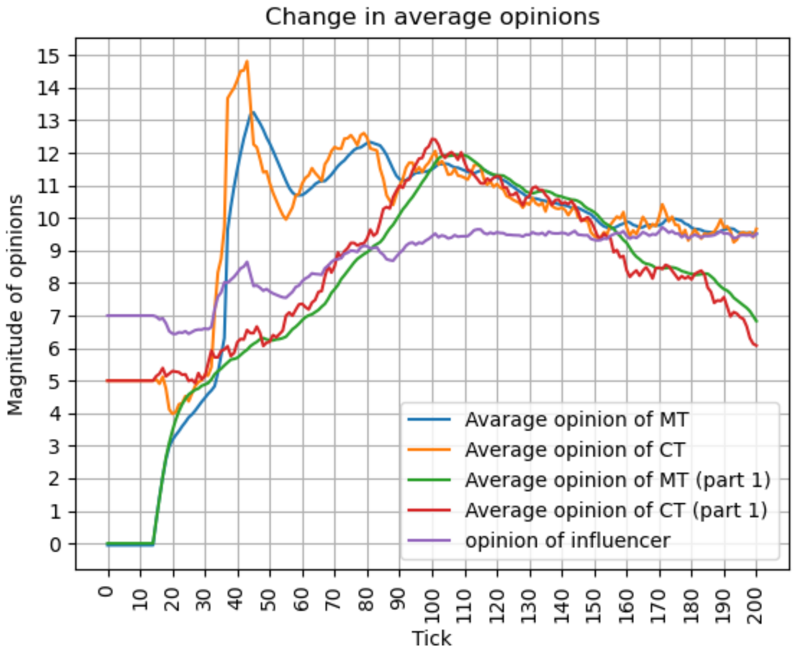

Figure 5.28: Part 3: GME-like Scenario - Change in average value of opinions of the agents, in comparison of the general scenario (part 1)

agents ran out of capital even though they involved relatively strong opinions.
Figure **??** showed that both the average value of the opinions for the momentum and coordinated trader agents rose to 13.24 at to 14.819 at 45^{th} and 43^{th} tick, respectively. Both values were higher than that in the general scenario. Such an increase in the total value of the opinions was caused by the impact caused by the influencer agent and hedge funds agents. They interrupted the market and the forming of the swarm. The external effect from the influencer was not noticeable, whereas the effect from the hedge funds was more significant than that.

Change in Number of Orders Submitted

Figure 5.29 showed how the three hedge fund agents interrupted the market and caused such a different pattern of price trend as well as the swarm-like behaviour. From 1^{st} tick to 3^{rd} tick, the hedge fund shorted a total amount of 24.96 shares as the first time short selling. The second time short-selling happened between 18^{th} and 19^{th} tick where it further short sell up to a total amount of 125 shares to suppress the price further. It caused the price to drop from $63.14 to $13.41, with a significant percentage decrease of 78.8%. However, it did not stop the swarm-like behaviour, and the short squeeze happened. At 34^{th} tick where price went beyond $100, the hedge fund agent was forced to cover all the short positions to suffer more enormous losses. This was reflected in the red line at about 34^{th} tick in the figure. The price when the hedge fund agent shorted the shares was about $24, whereas the price was %168 when it covered the short positions. As a result, it suffered a loss of $144, a percentage change of 600% of each of the shares it shorted.
Around the same time, at 33^{th} where the price went over $70, another hedge fund agent bought

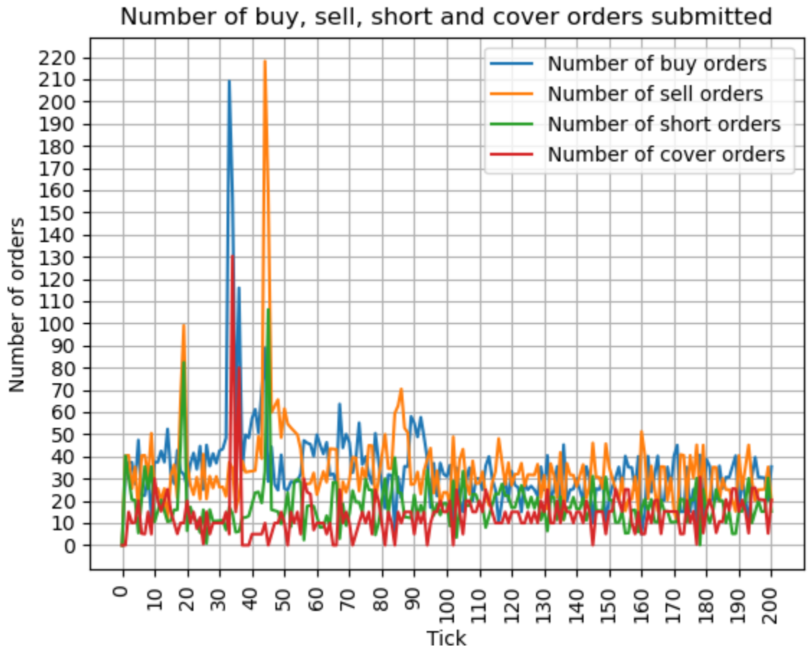

Figure 5.29: Part 2: Influencer and hedge funds - Orders submitted during the simulation. Note that the number of buy orders included the number of cover orders;The number of the sell orders included in the number short orders.

a total amount of the 174 shares, causing the price to rise from \$83.06 to \$168.95, with a percentage increase of 103%. With 33^{th} and 34^{th} tick, the total amount of the buy orders reached 209.16 and 156.75, respectively, almost five times more than the sell orders (37.38 and 34.76).
This external effect increased the market sentiment which further caused the formation of the swarm. When the price topped at 351.92 at 43^{th}, two significant events happened: the target price for the hedge fund to sell the shares has reached, it sold all of its shares. Besides, another hedge fund shorted the total amount of 102.32 shares between 44^{th} and 46^{th} tick. This was reflected in the number of sell and short orders indicated in orange and green lines at about 44^{th} and 45^{th} tick respectively. The number of short orders was 218 and 158, more than that of the buy orders (88.78 and 28.8) by more than 100 shares. These indicated significant interruption to the market caused by the trade activities from hedge funds. Such a massive amount of the sell orders caused the price to quickly drop from \$351.92 to \$214.54, with a percentage decrease of 39.04% within two ticks. The figures mainly showed the hedge funds' trade activities at three different periods, which caused the massive interruption in the market and the swarm pattern. At the end of the simulation, the hedge fund which shorted the shares a high price has not covered the positions since the price has not fallen to its target price.

Change in Amount of Shares Held

Figure 5.30 showed that since the moments that hedge funds traded happened at a brief period, usually within three ticks. In the remaining of the time, they did not trade. Their trade activities

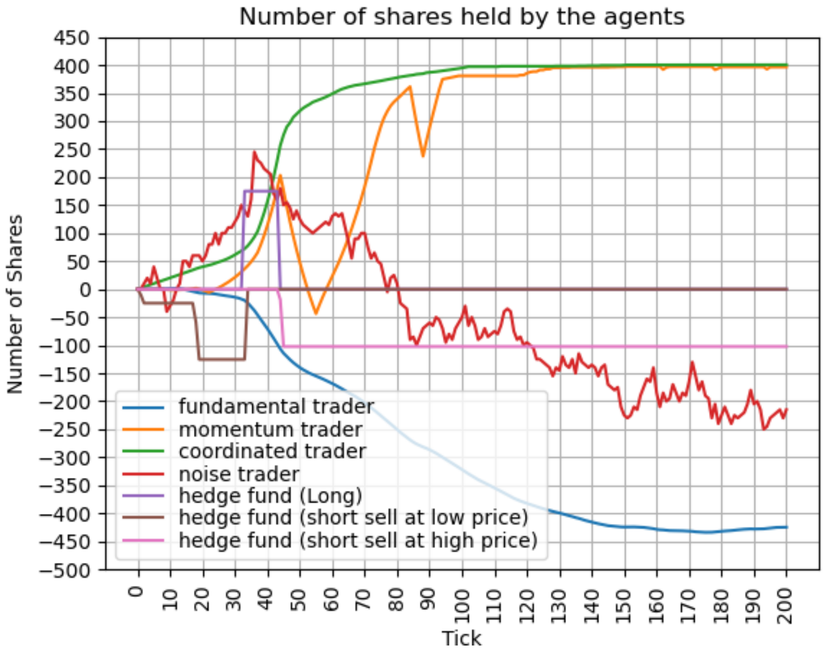

Figure 5.30: Part 3: GME-like Scenario - Change in shares that traders and hedge funds held

tended to be static, which caused the total amount of the shares not to change dynamically. Hence, the number of shares they held was no longer higher than other types of trader agents as a whole, as the simulation went on.

Nevertheless, when they traded, the amount of the shares they either hold or short sell were comparable to that of other types of trader agents. For instance, during the period between 19^{th} tick and 33^{th} tick, the amount of the 125.36 shares that hedge fund shorted at a low price (indicated as the brown line) were comparable to the number of shares that the coordinated and momentum trader agents hold (about 50 and 10 for each). Besides, during the period between 33^{th} tick and 43^{th} tick, the hedge fund holding 174.89 shares were more than the total shares held by the momentum and coordinated trader agents (about 75 each). This again indicated the significant effect caused by the hedge fund agents.

Change in Value of β and σ

In this scenario, β and σ rapidly changed during the form and the collapse of the swarm. Before and after the swarm-like behaviour, the value of β and σ fluctuated about the original level. Such indicated that the market demand also increased during the swarming and reduced during the bounces back and the collapse of the swarm. The maximum value of β and σ were 39.68 and respectively 29.96. It indicated that the external effect brought by the hedge fund agents led to higher market sentiment. Hence the value of both β and σ was higher than the previous scenarios.

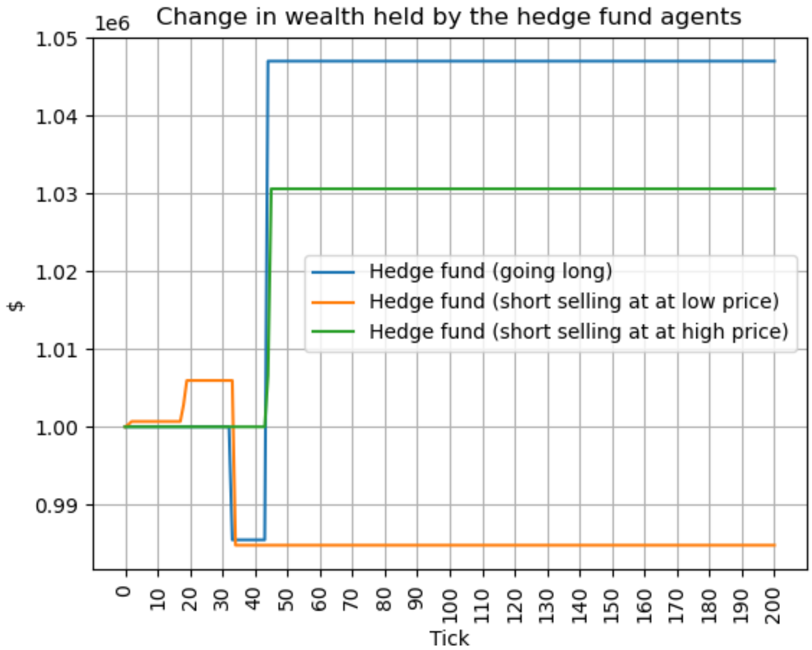

Figure 5.31: Part 3: GME-like Scenario - Change in wealth that hedge funds held

Change in Wealth

Figure 5.31 showed that how each hedge fund performed in the scenario. The hedge fund agent, which shorted the shares at a low price, lost the amount of $15,222. Whereas the hedge fund, which went long for the shares, gained a profit of $47018. For the hedge fund that short sell the shares at a high price, the target market has not been met at the end of the simulation. It has not covered the short positions. However, by looking at the price trend, it was most likely the price would continue to fall, of which the target price would likely be met. In other words, it might likely be that the hedge fund agent could cover the short positions at the target price and hence could earn a profit.

Summary of the Section

This section addressed the challenge 3 by demonstrating how the accumulated effect of the influencer agent and various hedge fund agents could affect the market price. Also, it addressed challenge 4 by demonstrating how the hedge fund agents could potentially earn or lose when trading with or against the swarm-like behaviour.

Chapter 6

Evaluation

6.1 Validation: Comparisons with the Theoretical Results

The ABM in the dissertation was evaluated by comparing the theoretical results of the research papers. Resulted completed by Kenneth and Dave[10] suggested that, first of all, the opinion values of the traders converged over time and traders with extreme positive or negative opinions made very different transactions. It showed that the transactions that traders with extreme positive opinions made converged at the price of $175 with slight fluctuations, whereas the transactions with extreme negative opinions made converged at the price of $50 with slight fluctuations. The price difference due to the vary of the opinions was apparent.
The ABM in this dissertation showed similar behaviour of the trader agents. Over time, the opinion values of the momentum and coordinated trader agents converged and changed simultaneously. Furthermore, it showed a partial positive correlation between the total opinion values and the market price where the transactions were made at, shown in the simulation results in Results and Analysis.
It was because the converge of the opinions formed the swarm and caused the price to gradually increased. The main difference was that in Kenneth and Dave[10]'s model, the range of each opinion value was bounded, whereas the range of the opinion value in the ABM of this dissertation was not. Nevertheless, model parameters were tuned tuning to ensure the opinion values did not increase inexplicably.
On the other hand, the model created by Tamas, Andras, Eshel, Inon, and Ofer [3] demonstrated the emergent phenomenon over the interaction of the particles. The outcome showed that the particles changed their behaviour from moving randomly to eventually moving in the same direction as their neighbours over time. Compared with the ABM in this dissertation, even though the ABM focused on the financial aspect, the emergent phenomenon between the trader agents could be observed. Over time, the momentum trader agents behaved the same as the coordinated trader agents and other momentum trader agents. The outcome of the simulation indicated the sign of the existence of such a phenomenon.

6.2 Comparisons with GameStop "Short Squeeze" Affair

In the section of Results and Analysis, the swarm-like effect was managed to derive, and the influence of such on the stock market was analysed by running various simulations, with each presenting different scenarios. To evaluate the feasibility of the swarm-like behavior derived in the paper, the price trend of GME-like scenario (Figure 5.26) was compared to the price trend of the GameStop (GME) during 25-11-2020 and 2021-08-27 [22].

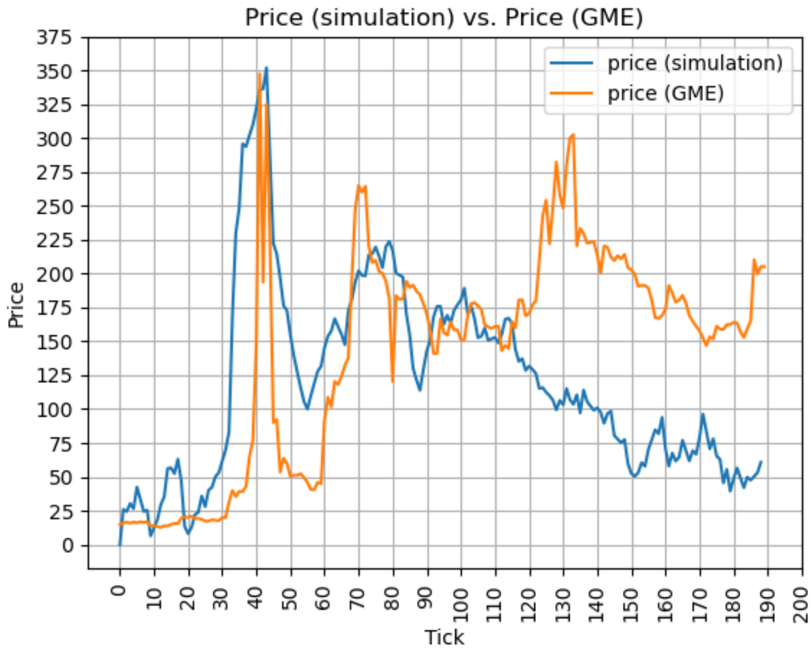

Figure 6.1: Comparison of price generated from the simulation and the price of GME

Rise in Price

Figure 6.1 showed the price trend generated from the simulation and price trend of GME. For GME, with one tick indicating one trade day. It could be observed that during around 31^{th} tick to 55^{th}, both price trends had a shape rise and sharp drop. For the price trend generation from simulation, the price rose from $8.11 at 20^{th} tick and topped at $351.92 at 43^{th} tick, with a percentage increase 4239% in 23 ticks. On average, the price rose about 14.95 per tick. Whereas for the GME's price trend, the price rose from $17.69 at 30^{th} tick and topped at $347.51 at 42 tick, with a percentage increase 1864% in only 12 tick. On average, the price rose about 27.485 per tick. The difference in the price increase per tick indicated that the price increase in the GME's was almost double the price increase in the simulation. Besides, the price of GEM did drop to $193.6 at 43^{th} tick and bounced back to $325 at 44^{th} tick. Such situations were not captured in the simulation. Nevertheless, the maximum price ($351.92 vs $347.51) were close.

The difference in the speed of price increase indicated external factors were interrupting the market other than just the agents introduced in the paper. It could be due to the even stronger swarm-like behaviour causing higher market demand. It could be due to the following possibilities: first, it could be due to an immense swarm - more individual investors joining the market and invested om GEM. Since in the ABM of this dissertation, the number of the agents spawned remained static during the simulation, whereas in the actual financial market, individual investors would entering and dynamically left the market. Having the number of agents fixed would limit the dynamics during the simulation. The second possible reason would be that the existing investors' market demand was way higher than the market demand of the trader agents in the simulation. The third possible reason would be the consequence of a short squeeze. There could be a massive amount of shares being short by the market professionals like hedge funds trading against the swarm. On the other side, the swarm-like continuous to behave robustly due to high market sentiment and eventually triggered the short squeeze. As a result, market professionals were forced to close the positions to suffer from more enormous losses.

Drop in Price

In both scenarios, after the price topped, it both dropped to a lower value. For the simulation scenario, the price dropped from $351.92 at 43^{th} $99.91 at 55^{th} tick. On average, the price dropped by $21 per tick. Whereas for the GME scenario, the price quickly dropped from $347.51 at 43^{th} tick to $50.31 at 51^{th} tick. On average, the price dropped $37.15 per tick. Both the statistics and the figures showed that the rate of the price drop was much higher than that of the simulation scenario. The potential causes of such differences could be that the individual investors in real life sold the stock instead of substantial holding them. They just reaping the profit by selling the shares at such a high price. These kinds of investors were not fully modelled in the ABM. Since in the model, the momentum trader and the coordinated trader agents were holding the stock even they ran out of money. The second reason could be that there were many short-selling activities after the price topped, for instance, the illegal naked short selling. These could cause the price to fall sharply, further leading the other investor to sell their shares due to the reduction of the stock value.
Overall, the rise and drop in price in the GEM scenario were much quicker than in the simulation, and this indicated that trade activities in the market happened GME scenario was very likely to be much more intense than in the simulation scenario.

Formation of the New Swarm?

An interesting point could be observed that, for both scenarios, after the price dropped from the first peak, it started to rise again, indicating a sign of the form of the swarm. For the simulation scenario, the price rose again from $99.92 at 55^{th} tick to $223.73 at 79^{th}, with the price value smaller than that of at the first peak — a similar situation for the GME scenario. The price rose again from $44.97 at 60^{th} tick to $265 at 71^{th} tick, with the price value smaller than that at the first and second peak. The amplitude at the third peak was smaller, indicating a weaker swarm-like effect. A sign of this could be observed that the following reaching the third peak, the price started to fall again and rise to fourth with ever-smaller amplitude. Thus, the price seemed to fluctuate for a while, settled at new market equilibrium, indicating the sign of the completion of a market re-adjustment. During the period between 92^{th} tick and 112^{th} tick, the price at both scenarios fluctuated between the range from $150 to $175.Overall, the rise and drop in price in the GEM scenario were much quicker than in the simulation, and this indicated that trade activities in the market happened GME scenario was very likely to be much more intense than in the simulation scenario.

Another interesting point could be observed after around 112^{th} tick, the price trend was very different from both scenarios. For the simulation scenario, the price continued to fall to about \$50, indicating the further collapse of the swarm. Whereas for the price trend in the GEM scenario, the price started to rise again to \$302 at 134^{th} tick, with the price value higher than that at the second peak (\$223.73). The price then started to fall but had a sign of rising at the end.

What Caused the Price to Rise Again?

The difference in price trend between the simulation's and GME's scenarios could be due to various reasons. For the simulation scenario, it was sure that the collapse of the swarm was due to the swarm lacking the capital to buy the shares. The traders' wealth was given at the start of the simulation and would not get more investment during the simulation. However, in real life, individual investors would have more capital over time. These investors could have more investments to buy the stocks if they felt the GME stock price would increase.

Besides, there could be good news about the GME, which could stimuli the market sentiment, causing more investors to believe that GME would perform well in the future. However, in the ABM, other than the effect caused by the influencer agent, the element of the market sentiment was not solemnly taken into account.

Furthermore, the switching of the decision of the real-life investors could be a lot rapid. In real life, the investors' opinion could change rapidly at a concise amount of time if they received much information regarding GME in a short period. Such might not be fully reflected in the ABM since the exchange of the opinion followed the sole mechanism of opinion dynamics, and the opinions would only get updated at every tick. Also, sometimes investors could behave irrationally and switched their trade decisions. Such probability of irrationality might also not be well reflected in the ABM.

Moreover, market professionals could buy a massive amount of the GME shares again, causing the price to rise again. In real life, these market professionals could have multiple trade strategies to target a single stock. In the ABM, only three hedge fund agents were not spawned, and they were given simple trade strategies.

Comparisons in the Number of Volumes

Figure 6.2 showed the pattern of the volume traded in simulation and GME scenario, respectively. The volume for the simulation was scaled up with a factor of 200,0000 to make the pattern comparable. It could be observed that at between 30^{th} tick and 35^{th} tick, large volumes were recorded at both scenarios, although with different magnitude. Similar could be seen at about 43^{th}, where volume was higher than average across the 190 ticks. For the GME scenario, at 33^{th}, 40^{th}, 41^{st}, 42^{th} and 62^{th} tick, the volume recorded were 14908000, 197157900, 177874000, 178588000, 150308800 respectively. Such a huge volume indicated intense trading activities, especially the heavy involvement by the market professionals and hedge funds due to their ability to trade a massive number of shares in a short period. Such activities could include short selling the shares as well as covering the short positions. The magnitude of the volume might not be fully captured in the model.

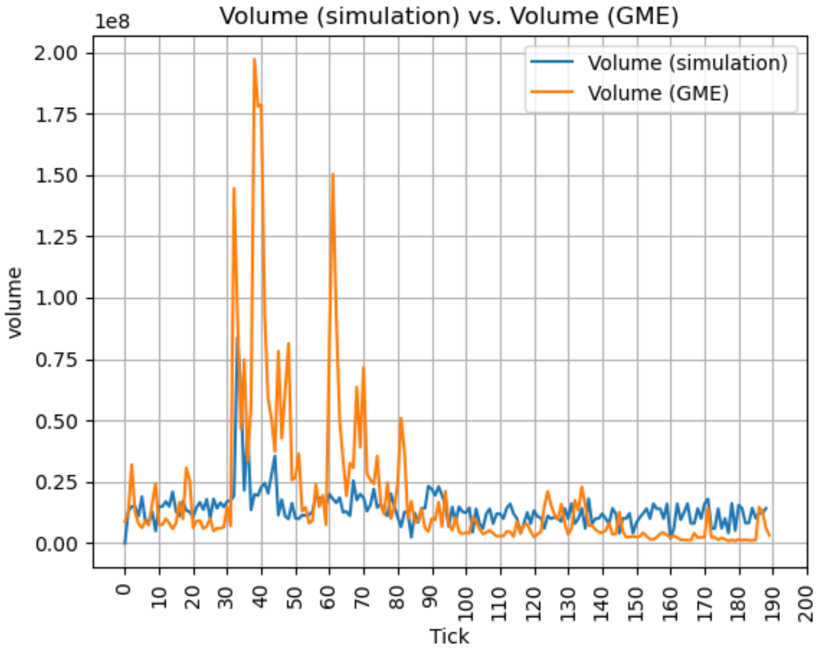

Figure 6.2: Comparisons of volume traded in simulation and the volume of traded in GEM affair

Summary of the Evaluation

To sum up, the ABM in this dissertation attempted to produce a similar scenario as the GEM's shown in Figure 6.1. From a broader point of view, before the first half of the simulation, both scenarios showed similar characteristics, such as the rapid price rise and price drop. However, the details of the GME scenario was not fully captured in the model, causing the difference such as the rate of rising in price and the number of the volume traded. Furthermore, limited implementation of the model led to the fact that the price trend of both scenarios after about 110^{th} tick did not share similarities. Nevertheless, the model was believed to capture some of the critical characteristics of the GME scenario. Moreover, with the description explaining the possible cause of the difference of both scenarios in the section, the model could be set as a foundation for further implementation if one wishes to capture more of the detail of the GME 'short squeeze' affair.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

This dissertation utilised ABM to investigate the swarm-like behaviour using the mechanics of opinion dynamics and derived insights into how the swarm-like behaviour could impact the market by running various scenarios to extend the exploration capabilities. The model addressed challenge 1 by using the mechanics of the opinion dynamics to allow the trader agents to exchange their opinions and produce swarm-like behaviour. It addressed challenge 2 by demonstrated that swarm-like behaviour could cause the market price to increase more than ten times the original price. It addressed challenge 3 by simulating how the influencer could give a boost to the overall opinion values and market sentiment and how the hedge funds could slow down or speed up the swarm-like effect by short selling or buying a large number of shares or covering a large number of short positions in a short period. It addressed challenge 4 by demonstrating how the hedge funds could gain profit trading with the swarm, such as short selling the shares at a high price or going long for the shares at a low price and how it could lose by trading against the swarm such as short selling the shares at low price. Finally, it addressed challenge 5 by demonstrating that controlling the amount of wealth given to the trader agents could affect the maximum price.

This ABM showed that the swarm-like effect built up through the opinion dynamics was shown to dominate the market and move the price in their desired direction. It also showed that the activities of hedge funds could make significant interruptions in the market. The dissertation also attempted to evaluate the model by producing a scenario similar to the GME 'short squeeze' scenario. It was believed that the model captured some of the critical characteristics of the GME scenario, especially where the GME short squeeze happened. However, some details were not captured in the model, causing the simulation price trend to differ from the price trend of the GME. Nevertheless, the simulation and the comparison better understood the swarm-like effect in the actual financial market. Additionally, the model could potentially be utilised for further implementation to capture more details of the GEM 'short squeeze' affair.

7.2 Future Work

Since there is not much current research about the swarm-like effect in the trading market, this model, results and discoveries in this dissertation could set up a foundation for further research investigating the swarm-like behaviour in the financial market. However, the ABM of this dissertation has room for improvement. Therefore, some of the ideas that are worth exploring, yet not implemented and simulated, are put in this section for readers to take for further research if found beneficial.

First, in this dissertation, only the core agents were introduced. There are many types of entities in the real world than the amount introduced in this dissertation. For instance, app-based trade app-based brokerage and banks could significantly alter the pattern of the swarm-like behaviour. In terms of trader types, there are way more various trade strategies in real life. More trader types, such as Simple Moving Average (SMA) and Exponential Moving Average (EMA) traders that would trade based on the calculation of SMA and EMA, could be implemented to add varieties in the market and further yield discoveries.

Second, the equation used by the exchange agent in this paper provided a basic calculation of the price change. Equations with more parameters taken might be used to possibly provide more accurate calculations of price change in the market. Besides, the ABM assumed that most of the trade transactions happened when the last bid and last ask were equal. Mechanism of limit order look could be used to capture the limit orders and market orders submitted by the agents to reflect more degree of reality of the actual financial market.

Third, the rules of the trading strategies given to the hedge fund agents were simplified and static. In reality, hedge fund agents would take multiples strategies and take many other factors when deciding what strategies should be used in various situations—for instance, taking the opinions in the market into account when designing the trade strategies. The trade strategies would be more complex and more advanced. For instance, they could trade with options, forwards or futures. Testing the variety of the trade strategies used by the hedge funds was not the main objective of this paper, and the implementation of multiply and advanced trading strategies into the ABM could bring different outcomes and be worth paying attention to.

Fourth, this dissertation solely applied the mechanism of opinion dynamics to derive the swarm-like behaviours. However, other potential mechanisms or methods could be explored - for instance, particle swarm optimisation, a popular method for optimising a problem. Applying such a method could derive fresh insights into how the swarm-like behaviour can form and impact the market price.

7.3 Legal, Social and Ethical Considerations

The main focus of this project was to use ABM to simulate a specific phenomenon that happened in the financial market and derived insights from it. Regarding the legal aspect, this project did not involve the following: personal data or sensitive data collection and processing, animals, developing countries, elements that might potentially harm the environment, humans, animals or plants. It did not have the potential for military application or terrorist abuse. Hence no ethical issues were concerned.

Regarding the legal aspect, the use of the project involved no copyright licensing implications, data protection or other legal implication. Hence no legal issues were concerned.

Regarding the social aspect, no particular social issues were concerned, although it might be worth mentioning that the swarm-like behaviour itself might not be much welcomed due to its irrationality and significant interruption to the market, and the not completely clear consequences to the society.

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Appendices

Appendix A

Particle Swarm Optimisation

Particle swarm optimisation (PSO) could be a potential method to derive the swarm-like behaviour in the financial market. PSO is a technique that aims to find optimisation of a problem by improving the solution with an iterative approach of improving the solution, along with a given set of measures used to measure the quality of the solution. [23] In PSO, within a given search space environment, there would be a population particle, and each of the particles would have position and velocity. Furthermore, they would be given a set of rules giving them instructions on which direction they should move within the search space. Apart from those simple formulas, the local best know position of each particle and the best-known positions found by the other particles would also be two essential elements to influence the movement of each particle. Through time, since each particle could be influenced by the best-known position discovered by other particles, the underlying interaction caused the particles to form a swarm. Eventually, the swarm would be expected to move the optimised solutions.

The popularity of PSO has raised to be applied in different kinds of problems. For instance, heating load forecasting, carrying trading portfolio, stock market prediction. Moreover, at the same time, more and more research emphasised improving the original PSO technique to attempt to fit it into a more tailored problem. As a result, altered versions of the PSO were developed.

PSO provided the opportunity to solve optimised-based and complex problems, making the financial-based problem one of the trendy choices to apply PSO due to the complex nature of the financial world and stock market. Seidy [24] has applied an altered version of PSO, called particle swarm optimisation with the centre of mass (PSOCoM), into the stock market prediction model. He utilised the prediction model with such altered PSO, along with some indicators and measures to maximise the return and at the same time to reduce the risk within the stock market. The paper showed the possibility that such a proposed technique could provide high accuracy with the other PSO-based models.

In the context of a finance-based problem, apart from stock market prediction, applying PSO into the trading strategy has gained similar popularity due to the increasing interest in algorithm trading and the difficulty of making trade decisions. Worasucheep, Nuannimnoi, Khamvichit, Attagonwantana [25] has come up with a trading strategy that could optimise the weights of the signals by implementing, again, a modified version of PSO. Such a weight signal could help make a better trading decision regarding the timing to make trade orders. They utilised the modified PSO to optimise the weight of the trading signal, which would expect to give the best trading strategy on top of the trading algorithm in their proposed strategy.

Wang, Yu and Cheung [26] proposed a weight reward strategy (WRS) which include various combinations of the rule parameters by taking advantage of the using an improved time-variant PSO algorithm to optimise the weight and further maximise the annual net profit. With experiments, the adaption of the modified PSO could achieve more profit than the basic trading rules such as moving average.

The popularity of the PSO and its ability to optimise a solution could be seen. However, it could be easy for the trader agents to fall into local optimum where the swarm-like behaviour might not even create. Besides, the converged rate might tend to be low in such an iterative process. The swam could not be easily formed. Such disadvantages showed that the difficulties in built-up the swarm-like behaviour to address the challenges further. Hence, it was not used in the ABM. Instead, another mechanism, opinion dynamics, were caught attention.

Appendix B

Inheritance Hierarchy of Traders

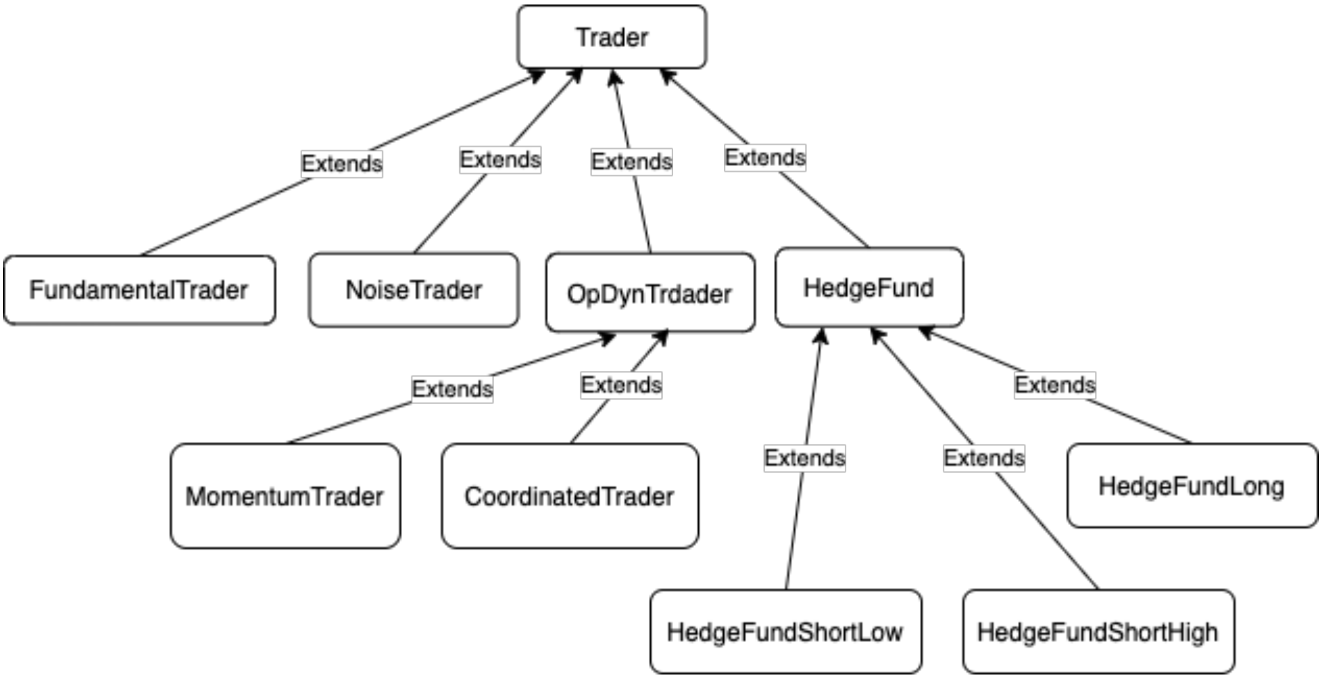


Figure B.1: Inheritance hierarchy of traders

Appendix C

Detail of how the trader agents make trade decisions

Let have a look at the logic of the ***handleWhenBuyShares()*** and ***handleWhenSellShares()*** one by one.

Algorithm 7 pseudocode of HANDLEWHENBUYSHARES

```
procedure HANDLEWHENBUYSHARES(volume)          ▷ volume obtained from getVolume()
    if hasEnoughWealth(price * volume) then
        if shares >= 0 then                    ▷ if that trader agent had any shares
            buy(volume)
        else
            if shares + volume <= 0 then       ▷ if that trader agent had more short positions
                closeShortPos(volume)
            else if shares + volume > 0 then   ▷ if that trader agent had less short position
                volume ← shares + volume       ▷ actual volume to buy
                closeShortPos(shares)
                buy(volume)
            end if
        end if
        updateTraderStatus()
```

In the ***handleWhenBuyShares()***, the program would first check if the trader agent had enough wealth to afford the number of shares being bought. If yes, it would check if the trader agents had any existing short positions. Trader agents would have to close all positions of shares, i.e. the shares could become non-negative before buying any new shares. The ***updateTraderStatus()*** was to update the margin account only if the trader agent has closed some short positions, if not all positions of shares being shorted. In the case a margin call was triggered, short positions would be forced to close. Margin account and margin call would be explained in more detail in the following two paragraphs.
Next, the logic of ***handleWhenSellShares()*** was shown below:
In the ***handleWhenSellShares()***, the program first checked if the number of shares the trader

Algorithm 8 pseudocode of HANDLEWHENSELLSHARES

```

procedure HANDLEWHENSELLSHARES(volume)
    if hasEnoughShares(volume) then          ▷ if that trader agent had enough shares to sell
        sell(volume)
        return
    end if
    if shares <= 0 then                      ▷ if that trader agent was short selling
        if isShortSellAllowed(volume) then
            shortSell(volume)
        end if
    else if shares > 0 then                  ▷ if that trader agent had no short positions
        volume ← volume − shares             ▷ actual volume to short sell
        sell(shares)
        if isShortSellAllowed(volume) then
            shortSell(volume)
        end if
    end if
end procedure=0
```

agent held was more than the number of shares to be sold. If yes, it would simply sell them. Otherwise, short selling might likely happen. Thus, trader agents would be able to short sell shares only if they had no shares on hold and also be financially capable of shorting those amounts of shares.

When a trader agent first short sell shares, a margin account would be initiated. When a trader agent kept short sell more shares, the margin account would be updated accordingly. Once the trader agent closed all the share selling positions, the margin account would be reset. Margin account existed to ensure the trader agent had a certain amount of wealth before it was allowed to short sell. The initial margin requirement was 0.5 in the model. That meant for short selling shares that valued $1000 USD, the trader agents must have a wealth of at least $500 USD. Moreover, if a margin call was triggered, the trader agent would have an obligation to close all the short positions. A margin call would trigger if

$$\frac{trader's\ wealth}{value\ of\ all\ short\ positions} * 100\% < maintenance\ margin \tag{C.1}$$

where trader's wealth represented the amount of wealth in the margin account. It would change accordingly when the price of the shares changed. The maintenance margin was set to be 0.3.

Appendix D

Explanation of the intrinsic value of the fundamental traders

The intrinsic value would be initialised with the following equation:

$$intrinsicvalue = truevalue + z\_score * \sigma_u \tag{D.1}$$

where true value indicated the true value of the company stock. The market true value would be ever-changing, whereas the market price would keep converging with the market true value. z-score indicated the belief that the trader agent would hold for the stock. It would be drawn from the normal distribution, $N(0, 1)$ and would remain unchanged during the simulation. Normal distribution was used because the distribution of similar kind of belief hold by the traders in the real world was likely to be normally distributed. The higher value of z-score, the more optimistic the company and the stock, and would overestimate the stock price. The lower value of z-score, the more pessimistic the company and the stock, and hence it would under-estimate the stock price. Therefore, the z-score would differ from the intrinsic values. σ_u indicated the uncertainty that the trader agent would have about the true value. The higher uncertainty, the more likely the intrinsic value would be far from the market true value.

Appendix E

Details of the update of the market price by exchange agent

The trade orders and transactions and orders would typically be recorded in a limit order book in terms of the price mechanism. Due to the objective of this model aimed to the short and intensive time. It would be reasonable to assume that most of the transactions would execute where the ask price and bid price matched. Hence an assumption was made that trader agents would submit market orders, and the exchange agent would process those market orders.

Behaviours

The exchange agent would receive all the trade orders and would calculate the net demand. The net demand would be the difference between the number of buys and sells volumes at each tick:

$$net\ demand = buy\ volumes - sell\ volumes \tag{E.1}$$

The net demand would be used to calculate the change in market price:

$$price\ change = net\ demand * \lambda \tag{E.2}$$

where λ would represent the exchange's lambda, as known as price elasticity. It would indicate the speed at which the market price would converge to the market true value, also known as market equilibrium. The higher value of λ, the faster the market price would converge to the market true value.
Then market price would be updated accordingly:

$$price = price + price\ change \tag{E.3}$$

at every tick.

Appendix F

Details of Update of the Market True Value by Data Provider Agent

Behaviours

At every tick, The data provider agent would update the market true value based on two factors: exogenous effect, named dv_exo and endogenous effect, named dv_endo.
Exogenous effect indicated that the market true value would follow a random walk fashion. Random Walk Theory is a mathematical object that describes a path consisted of random steps. Applying random walk theory in finance suggests that the stock follows an unpredictable as well as random path. In the actual stock market, the market true value would never be a fixed value. Instead, it would keep changing as there were millions of different thoughts about a company stock value. Therefore, it would be reasonable to model the market true value to follow a random walk manner.
In the paper, the random walk theory was achieved by utilising the jump diffusion model described in. The exchange agent would receive all the trade orders and would calculate the net demand. The net demand would be the difference between the number of buys and sells volumes at each tick:
Then, the exogenous effect would be calculated using the value of jump diffusion process:

$$dv\_exo = N(0,1) * \sigma\_v + J_t \tag{F.1}$$

where σ_v indicated the standard deviation of random walk.
The endogenous effect indicated the effect due to market impact. The market would absorb the net demand at every tick, and the net demand would also influence the market true value. The intuition here would be that the net demand would be a kind of market signal. If the net demand were high positive, the true value could be shifted to higher-value because many market participants executed in buying the shares. An increase in the market price might produce a kind of market signal to the market participants to potentially alter their true values to the stock. The equation of calculating dv_endo would be:

$$dv\_envo = net\ demand * \lambda_{kyle} \tag{F.2}$$

where λ_{kyle} indicated the Kyle's Lambda, a commonly used statistical measure to measure market impact. It was inversely proportional to the market liquidity, In this model, Kyle's Lambda would be taking a percentage of the exchange's Lambda, λ:

$$\lambda_{kyle} = \lambda * \frac{2}{3} \tag{F.3}$$

where λ represented the exchange's Lambda.
Taking the values of exogenous and endogenous effect accordingly,

$$true\ value = true\ value + dv\_exo + dv\_endo \tag{F.4}$$

the true value would get updated.
Besides, it was responsible for passing the change of the true and true values to other agents that required them.

Appendix G

Detailed Explanation for the Influencer Agent

Influencer in Real Life

Why would Elon Musk be said to be an influencer?
One of the examples would be that after he posted on Twitter expressing that Dogecoin, a cryptocurrency, was a great idea, the price of Dogecoin rose over 100% on a brief period. Note that 100% of the rise in the financial market in a brief period is considered extremely high.
The influencing power of an influencer raised the curiosity to reproduce a similar behaviour by testing out a Big Influencer agent to cause extreme social network effect.

Opinion of the Influencer Agent

The value of the opinions would, though not necessary, change by the change in true value. This component was designed to have a small effect on the influencer's opinion each time. However, when the influencer agent reached a point where it was exciting about the market true value, it would spread its opinion to the other trader agents. Such opinion would have a massive influence on the opinion of the trader agents.
The intuition here would be the influencer agent paying some attention to the market price movement and the opinion in the social media. In the case of the price growing or dropping very quickly, and meet a certain level, the influencer would post the opinion on the social media, and such action trigger to influence to share its opinion, which would bring a so-called influencer effect, which the traders agent in the market would take part of the influencer's opinion. This would further heat the market by increasing the trade volumes at the single trade day, vice versa.

Appendix H

Detailed Explanation for the Hedge Fund Short Agents

It would have four variables of the price specified during the initialisation:

- $priceToFirstSS$ specifying the price which it would go short for the shares for the first time;
- $priceToSecondSS$ specifying the price which it would further go short for the shares;
- $targetPriceToClosePos$ specifying the target price of which it would cover the shorts positions;
- $priceToStopLoss$ specifying the price of which it would also cover the short positions to prevent bigger loss caused by the short squeeze.

Note that $priceToFirstSS$ would be lesser than $priceToSecondSS$. $targetPriceToClosePos$ would be the least among the four whereas $priceToStopLoss$ would be the greatest.
Besides, it would record the number of shares it would hold during the simulation and the amount of shares it would trade.

Behaviours

The rules given to the `HedgeFundShort` agent was that it would short sell the shares when the current market price met either the $priceToFirstSS$ and $priceToSecondSS$ for a certain amount of ticks. Once short selling happened, it would then close the positions when the current market was either equal or larger than $targetPriceToClosePos$ or smaller or equal to the $priceToStopLoss$.

Appendix I

Detailed Explanation for the Hedge Fund Long Agent

It would have two variables specifying two prices: $priceToBuy$ indicating the price at which Hedge fund agent would buy the shares; $priceToSell$ indicating the price at which it would sell the shares. $priceToSell$ must be greater than $priceToBuy$.
Besides, it would record the number of shares it would hold during the simulation and the number of shares it would trade.
The rules given to the `HedgeFundLong` agent was that it would go long by buying shares when the current market price was smaller or equal to the $priceToBuy$. Once buying happened, it would sell the shares when the current market price was more significant than or equal to $priceToSell$.

Appendix J

Figures of the Connections of Agents

Figure J.1: Connection of the agents of part one: Connections of the agents for part 1: 20 Fundamental Trader, 20 Momentum Trader, 20 Coordinated Trader Agents, 15 noise Trader Agents, 1 Data Provider Agent, 1 Exchange Agent and 1 Social Network Agent

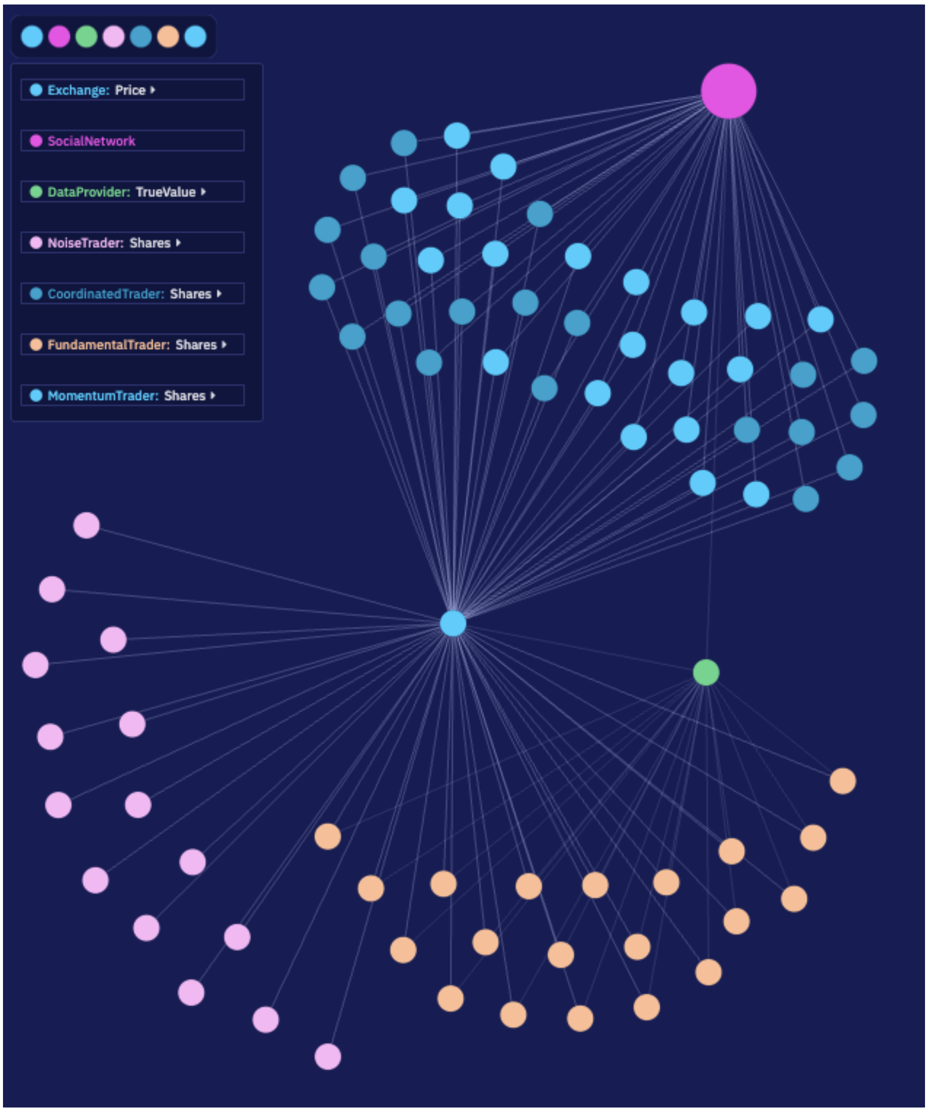
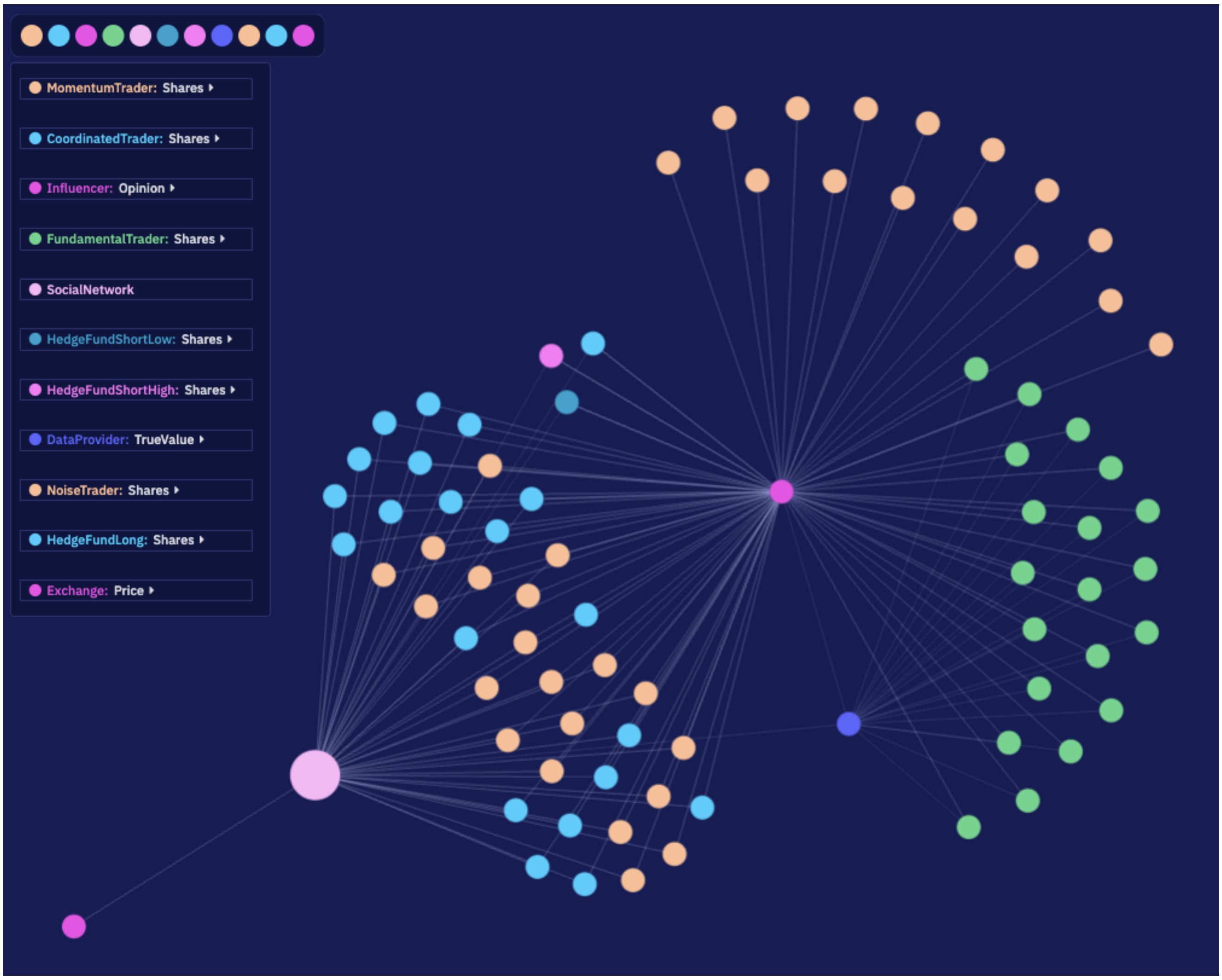


Figure J.2: Connection of the agents of part three: 20 Fundamental Trader, 20 Momentum Trader, 20 Coordinated Trader Agents, 15 noise Trader Agents, 1 Data Provider Agent, 1 Exchange Agent and 1 Social Network Agent, 1 Influener agent, 1 Hedge Fund Short Low Agent, 1 Hedge Fund Short High Agent, 1 Hedge Fund Long Agent



Appendix K

Model Parameter Values of in Part One

Parameters	Values
Number of Agents	
Social Network Agent	1
Exchange Agent	1
Data Provider Agent	1
Fundamental Trader Agents	20
Momentum Traders Agents	20
Noise Traders Agents	15
Coordinated Traders Agents	20
Influencer Agent	0
Hedge Fund Short Low Agent	0
Hedge Fund Short Long Agent	0
Hedge Fund Long Agent	0
Model	
Number of Ticks Ran	200
Market Price	30
Market True Value	30
Exchange's λ	0.5
Standard Deviation of Exogenous Effect (σ_v)	0.075
Standard Deviation of Jump Diffusion (σ_{jd})	1
Lambda of Jump Diffusion λ_{jd}	1
Traders (General)	
Wealth	Pareto(2000)
Parameter for Pareto Distribution	3
Initial Margin Requirement	0.5
Maintenance Margin	0.3
Noise Traders	
Market Demand (σ_n)	5
Probability of Trading	1
Fundamental Traders	
z-score	N(0,1)
Intrinsic Value	True Value + z-score * σ_u

Uncertainty of True Value (σ_u)	10
Sensitivity to Market (κ)	10
Momentum Traders	
Opinion	N(0,1)
α	0.5
β	0.5 * Abs(Opinion)
γ	50
Multiplier of Market Demand	1
Probability of Trading	1
Coordinated Traders	
Standard Deviation (σ_{ct})	2
Opinion	5
Multiplier of Market Demand	1.05
Probability of Trading	1
Opinion Dynamics	
Vicinity Range	6
Tick which Opinion Starts to Exchange	15
Weighting for $\Delta TrueValue$	0.03
Weighting for Confidence Factor	100

Appendix L

Model Parameter Values of in Part Three

Parameters	Values
Number of Agents	
Social Network Agent	1
Exchange Agent	1
Data Provider Agent	1
Fundamental Trader Agents	20
Momentum Traders Agents	20
Noise Traders Agents	15
Coordinated Traders Agents	20
Influencer Agent	1
Hedge Fund Short Low Agent	1
Hedge Fund Short Long Agent	1
Hedge Fund Long Agent	1
Model	
Number of Ticks Ran	200
Market Price	30
Market True Value	30
Exchange's λ	0.5
Standard Deviation of Exogenous Effect (σ_v)	0.075
Standard Deviation of Jump Diffusion (σ_{jd})	1
Lambda of Jump Diffusion λ_{jd}	1
Traders (General)	
Wealth	Pareto(2000)
Parameter for Pareto Distribution	3
Initial Margin Requirement	0.5
Maintenance Margin	0.3
Noise Traders	
Market Demand (σ_n)	5
Probability of Trading	1
Fundamental Traders	
z-score	N(0,1)
Intrinsic Value	True Value + z-score * σ_u

Uncertainty of True Value (σ_u)	10
Sensitivity to Market (κ)	10
Momentum Traders	
Opinion	N(0,1)
α	0.5
β	0.5 * Abs(Opinion)
γ	50
Multiplier of Market Demand	1.05
Probability of Trading	1
Coordinated Traders	
Standard Deviation (σ_{ct})	2
Opinion	5
Multiplier of Market Demand	1.1
Probability of Trading	1
Opinion Dynamics	
Vicinity Range	6
Tick where Opinion Starts to Exchange	15
Weighting for $\Delta TrueValue$	0.03
Weighting for Confidence Factor	100
Influencer	
Opinion	7
Hype Point	8
Influencer's Weighting	0.5
Influencer's Multiplier	0.01
Hedge Fund (General)	
Wealth	1,000,000
Hedge Fund Short Low	
Multiplier of number of shares begin shorted	3
Duration of Short Selling	4
Price triggering 1^{st} Short Selling	30
Price triggering 2^{nd} Short Selling	60
Target Price to cover the positions	0.5
Price to Stop Loss	100
Hedge Fund Short High	
Multiplier of number of shares begin shorted	4
Duration of Short Selling	2
Price triggering Short Selling	340
Target Price to cover the positions	10
Price to Stop Loss	420
Hedge Fund Long	
Price to Buy	70
Price to Sell	350
Multiplier of number of shares being longed	4

Appendix M

Running Actions in Parallel

The reason why these two sub-sequences could be executed in parallel since the information, such as the price and opinions, would only get updated after the trade orders have been submitted, and the agents would utilise the updated information on the next step. For instance, at tick 0, the agents would trade first. While the agents would be submitting the order, the agents would as well be sharing their opinions. The opinion would get updated; however, it would only affect the trade decision at the next tick.

Appendix N

Figures of the Action Sequences of the ABM

Part One: subSequencePrice

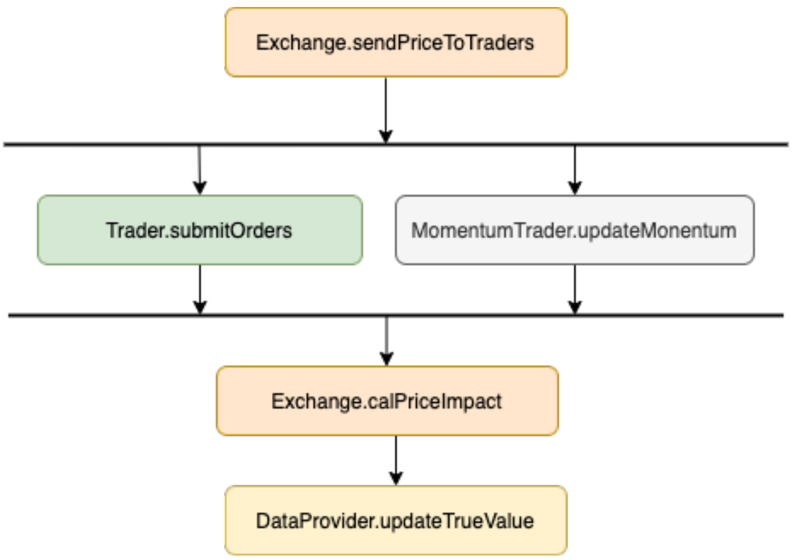


Figure N.1: Sequence of actions in the *subSequencePrice*

Part One: Entire Action Sequences

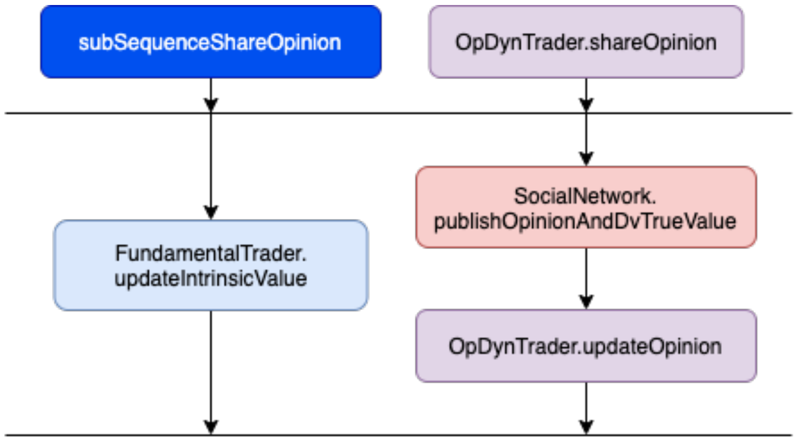


Figure N.2: Sequence of actions of part one

Part Three: Entire Action Sequences

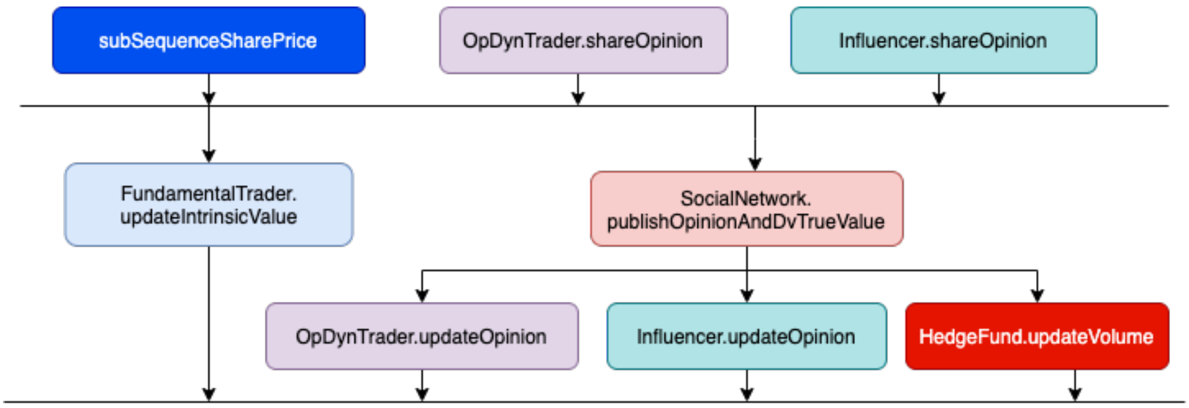


Figure N.3: Sequence of actions of part two and three