Building an Agent-Based Model to Simulate Stock Market Participants and Simulate Price Action

Gregory Chapman*
gchapm06@uoguelph.ca
University of Guelph
Guelph, Ontario, Canada

Mayank Juneja*
mjuneja@uoguelph.ca
University of Guelph
Guelph, Ontario, Canada

Saurav Luthra*
luthras@uoguelph.ca
University of Guelph
Guelph, Ontario, Canada

Romar Tumamao*
rtumamao@uoguelph.ca
University of Guelph
Guelph, Ontario, Canada

Abstract

Agent-based modeling is a very common technique used to analyze and understand complex systems. The stock market itself is a very complex system that can be described as an agent-based model where different agents can interact with each other and when these agents are put in different situations and analyzed, they can be used to understand the real-world stock market phenomenon. In this paper, agent-based model simulations are used to understand the effects of trading frequency on market volatility and share prices with time. The design also aims to prove the hypothesis that the higher amount of frequency traders in a stock market will cause more drastic changes to the overall price.

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1 Introduction

The investigation of stock markets to understand different aspects of economics is of great interest to society. The investigation of data from daily market trends, and predictions based on these trends, is a huge business as well as a very important aspect of understanding financial public markets. There are many different ways of analyzing these trends and understanding the markets. Some of them include traditional economics, adaptive learning, behavioral economics, behavioral finance, and agent-based models [3].

Traditional economics is a system in which an agent gathers all the information available to decide. A behavioral decision rule is used by the agent to plan based on the given information and their preferences [7]. These agents operate autonomously and are not influenced directly by others. *Adaptive learning* is a system in which agents use statistical models, observe different quantities and update their parameters to predict the future [7]. *Behavioral economics* is a field that develops models based on non-rational behavior such as altruistic behavior, reciprocity, tit-for-tat, etc. This focuses on behavior that is not fully rational in the standard sense [4]. The *behavioral finance* system is based on the idea that financial phenomena can be understood using models that are not fully rational. This means including psychological effects play a role in economic decisions such as people perceiving profits and losses differently [1].

However, for this paper we will be using *agent-based models* (ABMs for short) to study these markets. This is done by designing different ABMs to simulate the real life attitudes of agents such as high frequency traders, retail investors and institutions. The models will trade stocks at high frequencies to understand its effects on the markets and understand the causes as well as duration of big crashes in the market.

In recent times, despite economic concerns, the stock market has continuously grown and fluctuated. There has been many flash crashes and high volatility in the markets in the last two decades due to the rising high-frequency trading [8]. The most recent example is the stock market crash due to the COVID-19 pandemic starting in March 2020, and the high volatility in the market due to the GameStop/WallStreetBets phenomenon on January 2021 where extreme volatility in the market was introduced in a short time due to a very high frequency of trading, influenced by social media. There are many different reasons for these crashes [5]. But for this paper we will just be focusing and trying to simulate how

*All authors contributed equally to this research.

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different agents such as high frequency traders, retail investors and institutions react to high volatility and what are the results of different actions on the markets.

High frequency trading in general is believed to be good as it provides the market with volatility, and help to reduce transaction costs and make markets connected with each other [2]. However, they also increase chances of flash crashes, unstable market volatility and have an overall negative effect on the market [6]. The main goal of this paper is to understand these unstable events and how behavior of different agents effects these events.

This paper is organized as follows: Section 2 covers the Background & Literature Review, Section 3 covers the Design Description, and Section 4 discusses the Results and covers the Conclusion. References are provided at the end of this report.

2 Background and Literature Review

Many ABMs have been created to simulate stock markets using trader agents who buy or sell stocks at various frequencies, as well as apply other financial options such as shorting to the stock. Examples of simple models include the Santa Fe market, and the Genoa Artificial Stock Market (GASM) [3]. For a standard efficient market model, agents' behaviours are all uniform, and are all equally "informed"; but various ABMs incorporate behavioural patterns known in real life markets. There also exist large-scale models such as Eurace, which incorporates three economic spheres: "The real sphere (consumption goods, investment goods, and labour markets), the financial sphere (credit and financial markets), and the public sector (Government and Central Bank)." [3]. The agents in Eurace act between these spheres, and are characterized by their adaptation to the decentralized markets. This model help to reach the goal for ABMs - to reproduce the salient features of the real economy, and to see how known methods such as quantitative easing would benefit the uniform market.

Also, all of these models show the validity of Agent-based Computational Economics (ACE) as innovative technology for the study of economics [3].

3 Design Description

For this project, a system is made that simulates the stock market via agent based modelling. This system tries to implement the different behaviour of agents such as high frequency traders, retail investors and institutions i.e. banks, hedge funds, pension funds. And how their behaviour is related to the frequency of trading. The main hypothesis for this design is defined as follows: **The higher amount of frequency traders in a stock market will cause more drastic changes to the overall price.**

This design uses two different models to simulate the system. These models are discussed below.

3.1 Simple Model

The initial design was originally kept simple in order to lay a foundation for the model. A class called "Agent" was designed in order to replicate the behaviour of the traders. These agents were given a name based on their role in the stock market. The term "HFT" represents the high frequency traders; the term "RET" represents retail traders, or individuals such as civilians; The term "INT" represents instutional traders (banks, hedge funds, etc.). The trading frequency of the agent is based off of the name they are given. The amount of each trader is determined in a parameter given to the "modelStock" function to model different simulations for different amounts of traders.

A simulation method was implemented in class "modelStock" to carry out the simulation of the stock price over a given period of time. This function would run for the amount of time given, and at each iteration, would check to see whether each agent wanted to trade. If more agents bought than sold, the stock price would raise by 1%. If more sold, then it would lower by 1%. This parameters were kept static in order to ensure that the simulation was working properly.

With this simple implementation, multiple simulations were conducted. The results of a few of these simulations are shown in the results question. The only parameters that were changed were the amount of each trader for consistency.

3.2 Complex Model

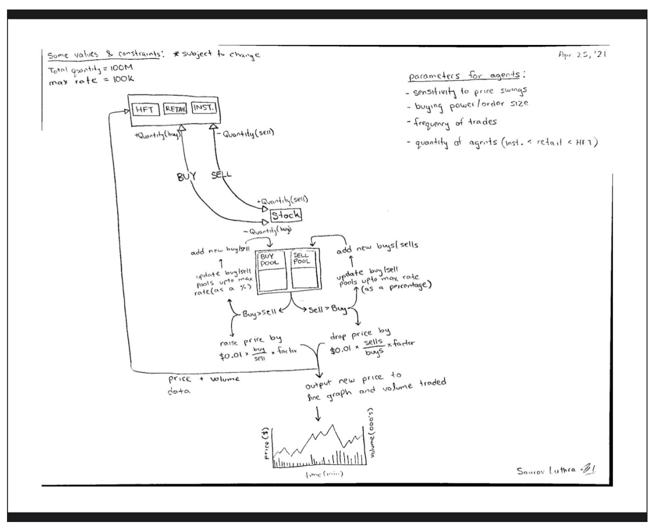


Figure 1. Hand Drawing of the System Design

The *modelStock* class (centre) receives buy orders and sell orders from stock market participants/ agents, each with a quantity of shares to be transacted. Based on the total number of shares listed for purchase and listed for sale on the stock exchange at a given time step, the price is updated.

The price increments upwards when there is more relatively more buying pressure and downwards when there is relatively more selling pressure. The dollar amount that it moves is the proportional to the ratio between buy orders and sell orders.

For each time step, the price is recorded in a log for plotting. After the price and volume data for a given time step is tabulated, that data is sent to the agents to allow them to make their next trade decision based on the data and their inherent algorithms. The shares for sale and for purchase is updated as well before the next time step, to clear out the previous quantity of orders.

There are 3 types of Agents: High Frequency Traders, Retail/ Individual Traders, and Institutional Traders. They each trade shares with different probabilities, quantities, and behaviours. This was done to attempt to accurately model and simulate the real actors in a public stock market, and thus the real behaviours that a stock price would exhibit.

In these simulations, we tried to vary the amount of agents of each type, as well as the allocation of shares each type had at the start of the simulation in order to identify patterns in behaviour.

4 Results

The models described above are used to generate different graphs that provide insight into behaviours and patterns of the agents at different frequencies of trading. The analysis and results of these graphs are discussed in this section.

4.1 Simple Model Discussion

Based on these graphs of the simple model, there is little information to come to a conclusion on the hypothesis. Although the simulation of each stock seems accurate with the implementation, there is little evidence that higher frequency trading has drastic effect on the stock price (based on this model). In order to prove this hypothesis, parameters will be changed to more realistically model the stock market. These change in parameters include increasing the amount of shares traders can buy or sell and the likelihood of them buying and selling.

The following figures below and to the right represent the simple model with varying parameters of traders.

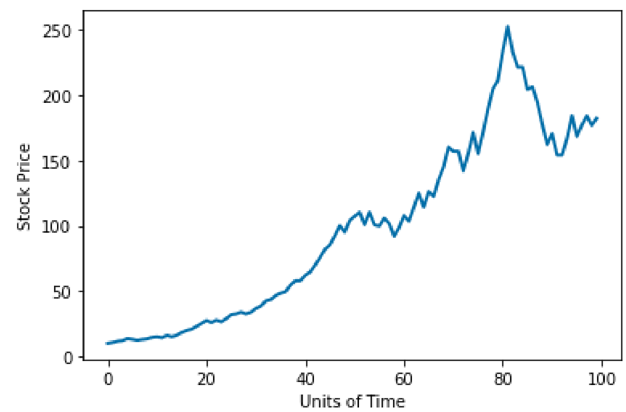


Figure 2. Stock Price vs Time (2 INT - 2 RET - 10 HF)

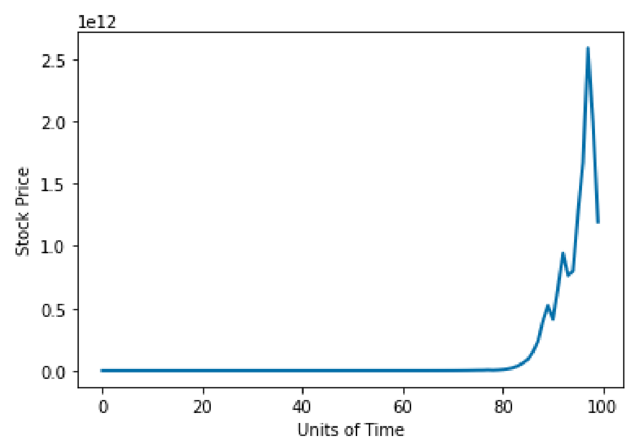


Figure 3. Stock Price vs Time (5 INT - 5 RET - 50 HF)

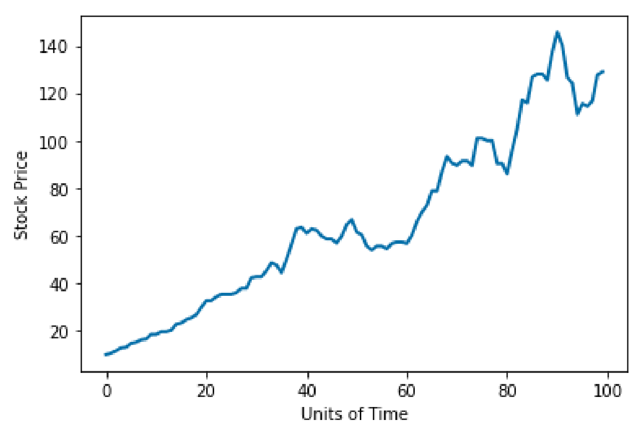
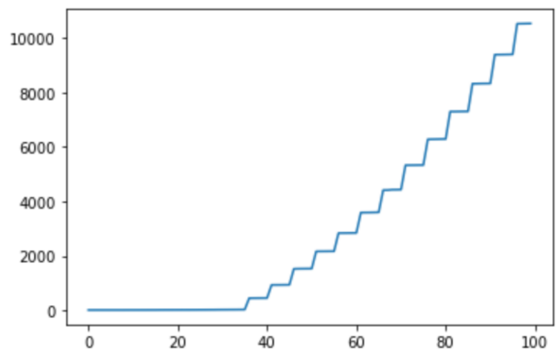


Figure 4. Stock Price vs Time (10 INT - 10 RET - 2 HF)

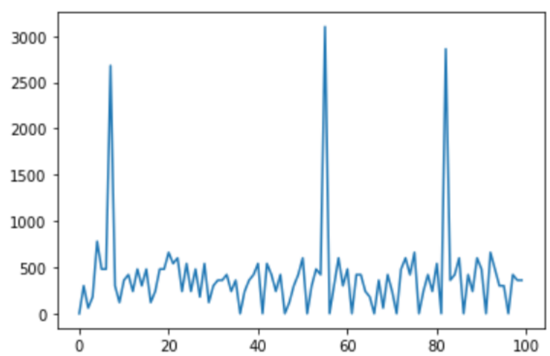
4.2 Complex Model Discussion

As evidenced by these few simulations, as the number and proportion of HFT increases in a market place, the volatility of a stock (measured by its standard deviation) increases. With 1000, 50, and 1 HFT, the standard deviation went from approximately 3400 to 705. Although the model did not provide completely accurate and desirable stock price action (overwhelming buying and constant upward pressure on price), it does begin to give us insight on our hypothesis of more HFT leading to more volatile stock prices.

```
STONK = modelStock(10, 2, 1, 50, 100, 100000)
STONK.makeAgents(0.5, 0.2, 0.3)
# STONK.printAgents()
STONK.simulate()
STONK.plot()
```



[159]:
```
STONK.plotvol()
```



[160]:
```
statistics.stdev(STONK.y)
```

[160]: 3401.724517188177

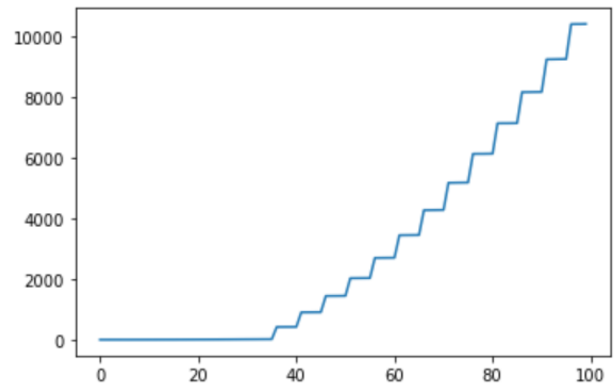
Figure 5. 2 Institutional 1 Retail 50 HFT

5 Conclusion

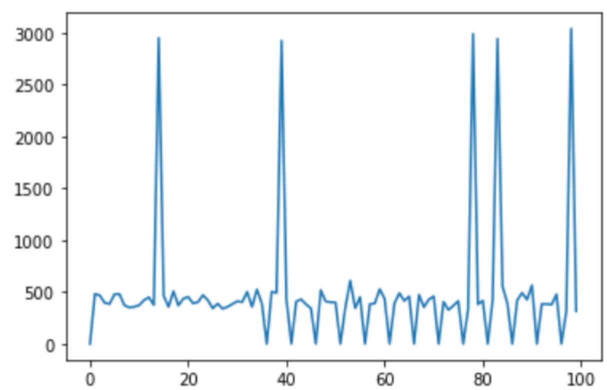
This project tries to simulate the behaviour of agents at different levels of trading frequency and tries to prove the set hypothesis. Due to time constraints, the results from both the simple and complex model cannot yet prove the hypothesis. However, the results as discussed above give some explanation about the behaviour of the agents.

One conclusion that was made based on the modelling was that the volatility of the stock increased as there were

```
STONK = modelStock(10, 2, 50, 1000, 100, 100000)
STONK.makeAgents(0.5, 0.2, 0.3)
# STONK.printAgents()
STONK.simulate()
STONK.plot()
```




```
STONK.plotvol()
```




```
statistics.stdev(STONK.y)
```

3349.40629184992

Figure 6. Stock Price vs Time (2 Institutional 50 Retail 1000 HFT)

more high frequency traders. This was evident based off of the results of the complex model. However, the initial hypothesis that higher frequency traders resulted in more drastic changes was not proven, based on the provided implementation. Although the hypothesis is not dis-proven, it is hard to come to a conclusion based off of this model.

These models can be further developed by changing parameters and refining code. This could include changing variables such as stock increase and decrease or adjusting when traders are more likely to buy.

References

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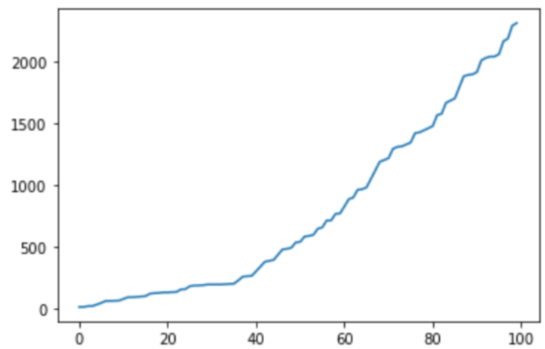
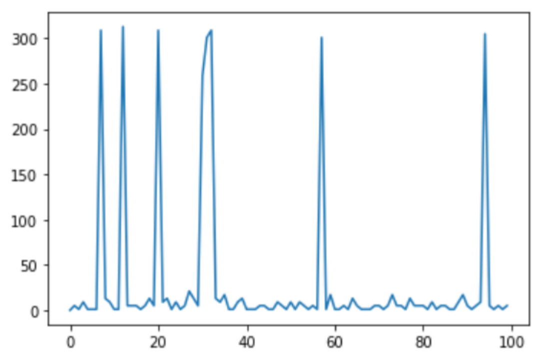
```
STONK = modelStock(10, 2, 50, 1, 100, 10000)
STONK.makeAgents(0.5, 0.2, 0.3)
# STONK.printAgents()
STONK.simulate()
STONK.plot()
```




```
[156]: STONK.plotvol()
```




```
[157]: statistics.stdev(STONK.y)

[157]: 705.6794652541529
```

Figure 7. Stock Price vs Time (2 Institutional 50 Retail 1 HFT)

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