CW2 Report

Build the Agents and Market

Chartists Agents's Implementation

1. **Open & Close Position rules:**

    - Rule 1 – Filtering

      If the current price is below the average price of the last n days, trader will consider buying; if the current price is above the average price of the last n days, trader will consider selling.

    - Rule 2 – Exponential Moving Average (EMA)

      $$EMA_t(n, \text{Close}) = \frac{2}{n+1}\text{Close}_t + EMA_{t-1}\left(1 - \frac{2}{n+1}\right)$$

      Use the Exponential Moving Average (EMA) to determine the trending direction of the market. If the current price is above the EMA, trader will consider buying; if the current price is below the EMA, trader will consider selling. Compared to Rule 1, the EMA contains more weight to recent price data and can react more quickly to recent market movements. If the market is moving quickly, it allows traders to capture trend changes more quickly. Furthermore, EMA smoothes the price data and reduces noise to help traders identify the market trend. Although EMA has many advantages over Filtering, this does not mean that EMA can achieve better results than Filtering, The reality of the market is just as important.

2. **Open & Close Position logic:**

    The Agent's opening and closing behavior must be obtained from the above two provisions rules. The Agent determines the behavior chosen based on a random number from 0 to 1. In this project, there are two cases when opening a position, one is when the random number is less than or equal to 0.2 choose the result of EMA to open a position, when the random number is greater than 0.2 but less than or equal to 1 choose the result of Filtering to open a position. The second case is Choosing Filtering as result when the random number is less than or equal to 0.2, and choosing EMA as result when the random number is greater than 0.2 but less than or equal to 1. At the same time, when closing a position, it is also divided into these two cases, so the two different rules for opening a position and the two different rules for closing a position together make up the four different Chartists Agents.

3. **Expected Behaviour:**

    Based on the implementation of Chartists Agent, the behaviour of the agent is mainly based on the results of Filtering and EMA. If the market trend does not change much and there is a clear upward or downward trend, then Filtering may be able to achieve good results. However, if there is a strong trend in the market price, then EMA should be able to get better performance due to its stronger adaptability. So it can be expected that the EMA results should be better, so among all four types of Chartists Agents, the Chartists Agent with more probability of selecting the EMA results in open position and close position should be able to achieve better results.

Random Traders Implementation

- Random traders trade by randomisation, so their buying and selling decisions are not regulated by rules and do not rely on market analysis. In the implementation of this project, the basic behaviour of random trader is the same as that of Chartists Agent. Random trader can only open a position after it has been closed, and it can also choose whether to buy or sell when it opens the position. A random number from 0 to 1 will be used in the project, if the number is less than or equal to 0.5, then it will choose the open position, otherwise it is considered to close the position, in the open position, a random number is used to judge whether it should buy or sell.
- **Compared to Chartist Agent:**
    - Chartist Agent buys and sells with a strategy, whereas random trader buys and sells without any strategy or purpose.
    - Chartist Agent trading decisions often rely on market trends, and if the market exhibits a certain trend, they may react accordingly.

- Random traders are not predictive. They do not change their trading behavior due to specific trends or patterns in the market.
- Overall random trader make decisions randomly have no purpose.

- **Expected Behaviour:**

  Since random trader's decisions are randomly generated, their trades are not correlated with the market trend. It is possible to be very lucky and have a good result with random trader, but it is also possible to have a very bad result. But since the total number of bitcoins in the simulated market will increase, eventually the random trader may also increase the total wealth but this result is attributable more to the market than to itself.

Market Environment Implementation

1. **Initial State:**

   Since the primary time period of the study begins on 1 January 2020, the real bitcoin price from 21 December 2019 to 31 December 2019, for 10 days in total, will be used as the initial price for the creation of the simulated market. At the same time the project is prepared to allocate 10 Bitcoins to each agent involved in the simulation with £50,000 approximately equal to the value of the ten Bitcoins at that time as initial funding. The program will set up the above 5 types of agents(4 types in Chartists and 1 type of Random Trader), two of each, for a total of 10 people to join the market.

2. **Open & Close Position:**

   Agents must close their positions before they can open new ones. When agent choose to open a new position, agent can choose to buy or sell to open position. After that the agent needs to close the position by completing the trade at the time of opening. For example, when an agent chooses to buy 1 Bitcoin when he opens a position, he must close the position by selling 1 Bitcoin, after which he can start a new round of trading.

3. **Execution of Order:**

   - When agent decide to buy bitcoins, the agent's buy order will add to the order book's buy list wait for Processing. Similarly, Agent's sell order will add to the order book's sell list. In the real situation, each order has different bids, the order book will arrange the orders according to the Buy order's bids from high to low, and according to the Sell order's bids from low to high, and then the orders in the Buy order and the Sell order will be processed one by one from the top to the bottom. However, in this project, Agents are required to bid according to the market price and are not allowed to choose freely, so it is not possible to sort Buy order and Sell order effectively. Therefore, this project chooses to buy and sell all orders submitted by Agents, so that there is no case of not being able to sell or not being able to buy.
   - In addition to this, the amount of agents bought and sold in the simulated market needs to be considered. In this project, the project specified that agents should choose up to one-third of the quantity they could buy and sell in order to prevent a very large random number instantly changing the direction of the market.

4. **Market price update:**

   On each day after all the agents have made a buy order or sell order, the buying and selling is not completed immediately, the market will calculate the difference between the quantity of buying and selling, and this quantity difference will be regarded as delta_N, delta_N can represent the relationship between the market's demand. As we all know, if the demand for buying is greater than the demand for selling, the market price will increase, and if the demand for selling is greater than the demand for buying, the market price will decrease. So with the delta_N and price update function it is possible to simulate tomorrow's market price based on today's market demand.

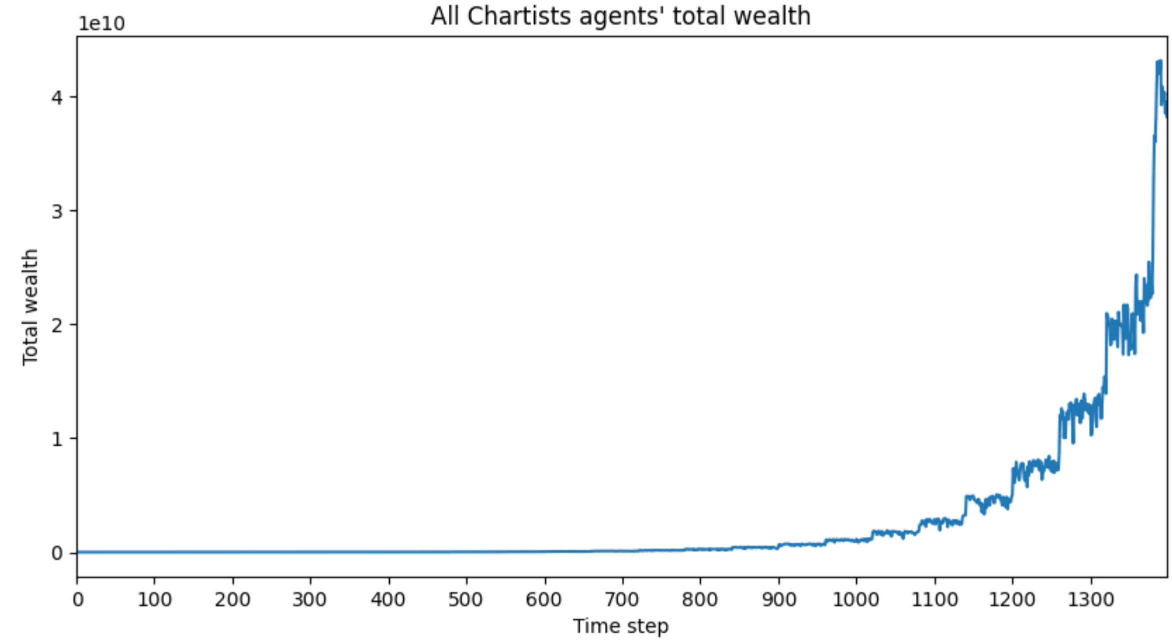
$$r_n(\Delta N_n) = S_n - S_{n-1} = \left\lfloor \alpha \operatorname{sgn}(\Delta N_n)\sqrt{|\Delta N_n|} \right\rfloor$$

Compare Agents

Vary the parameter n and Discuss

- When simulating trades, adjusting the parameter n is essential to optimise the agent's strategy. Parameter n indicates the number of past price points that the agent needs to consider when making decisions. Adjusting this parameter affects the agent's sensitivity to market trends and its trading behaviour. If n is small, the agent's behaviour is closer to short-term trading, and if n is large, the agent's behaviour is closer to long-term trading. In short-term trading the agent will trade more frequently and trading will be more volatile. In long-term trading, the agent may trade rarely and may miss some short-term trading opportunities but will be more robust. Since this project has been simulated for more than 1000 days in total, it can be considered that the agent's behaviour can be viewed as long term trading when n=100. So a range of n from 5 to 100 is set here and the change in the total wealth of all Chartists Agents in each case is plotted, while a random seed is used in order to have comparability between different data.

- According to the graphs it can be noticed that at n = 40 agents have the highest total wealth and it is significantly higher than the other cases, apart from this there are no other very significant differences in total wealth. Since the random seed was used, it is unsure whether this highest total wealth is due to coincidence or something else. However, it can be noticed that there is very small difference in the wealth totals after n is greater than 60, and the wealth totals are not stable when n is small. At n=5, the total wealth is also quite high, which may be the reason of short-term trading. Since the results achieved at n=5 are not bad, for the simplicity of further market model testing so n=5 is chosen as the parameter for this project. Overall, choosing the optimal range for n needs to be analysed through market data. So if there is a need for further research in this project, this is a topic that deserves deeper investigation.



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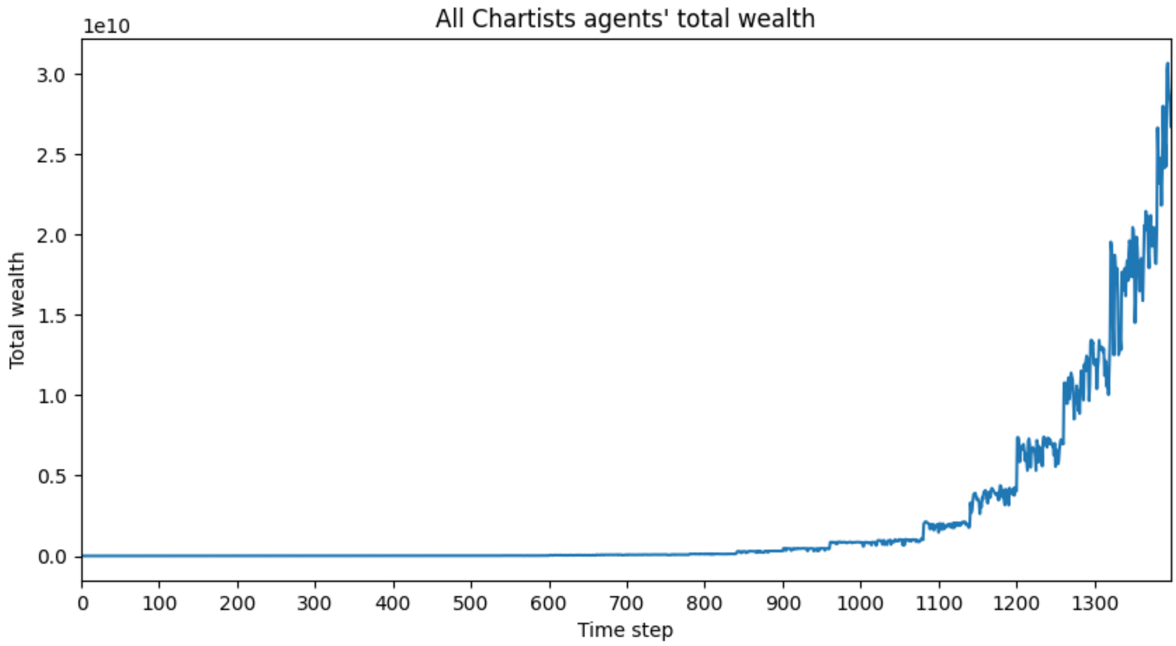

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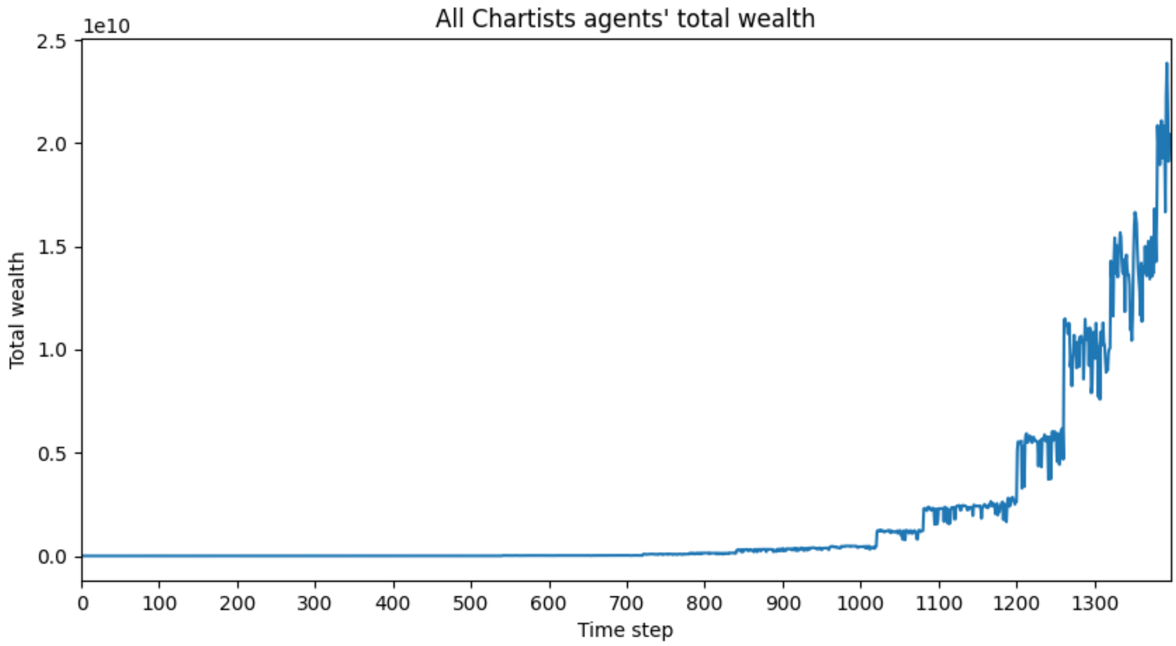
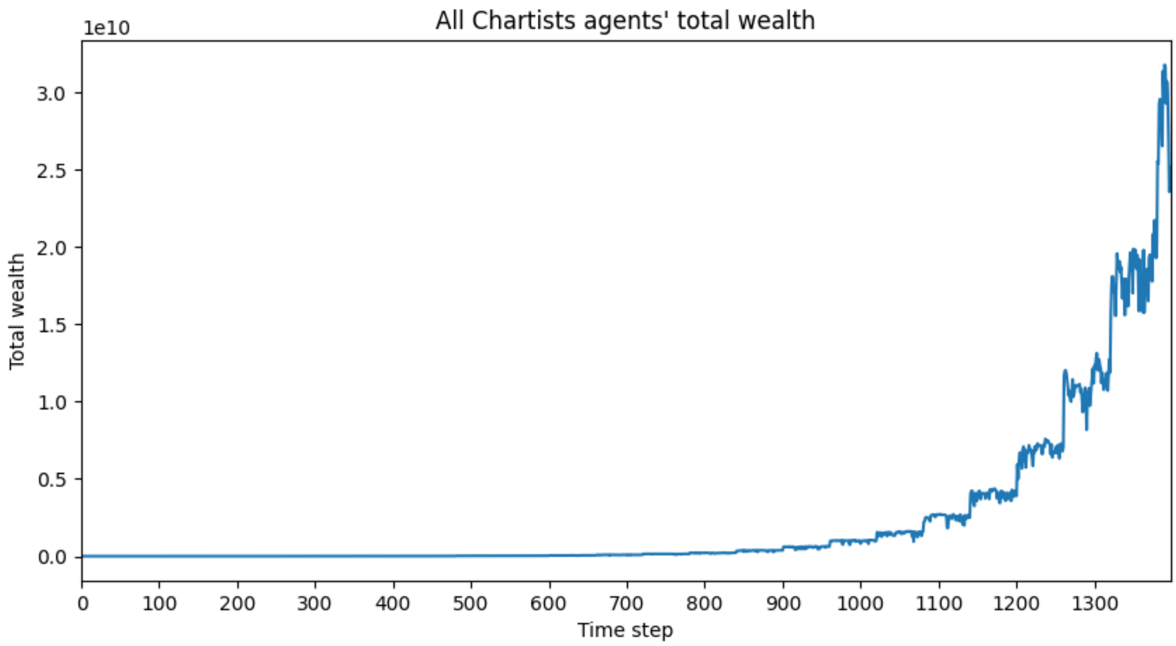

All Chartists agents' total wealth
1e10
2.5
2.0
1.5
1.0
0.5
0.0
Total wealth
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
Time step

n = 20


All Chartists agents' total wealth
1e10
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Total wealth
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400
500
600
700
800
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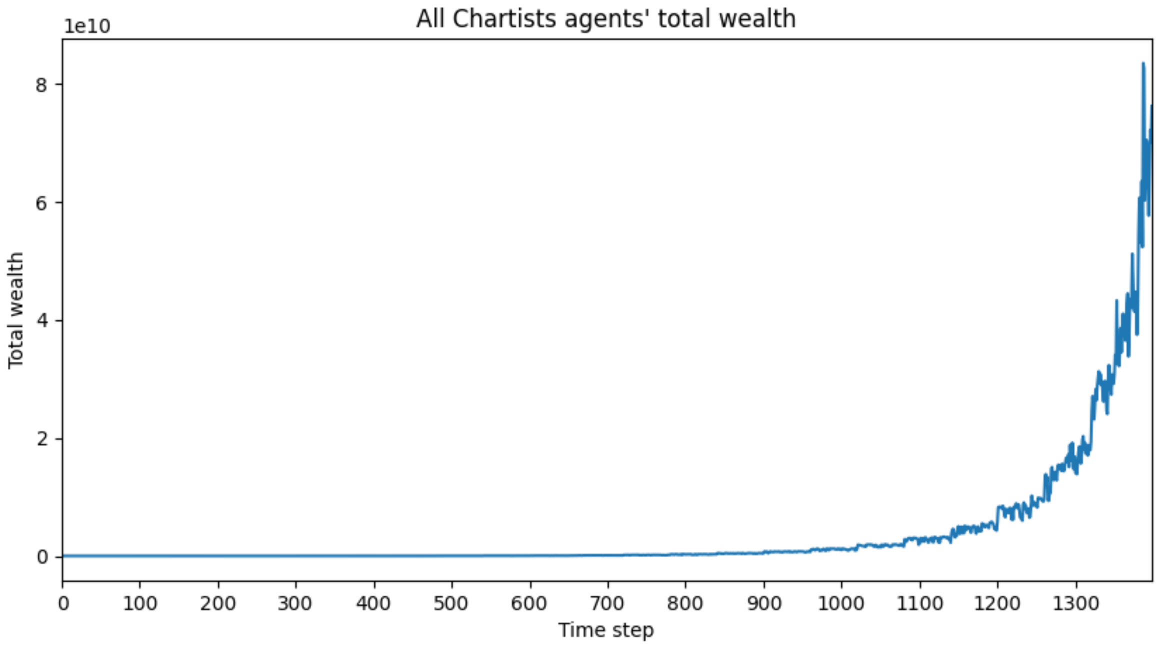
1000
1100
1200
1300
Time step

n = 30


All Chartists agents' total wealth
1e10
8
6
4
2
0
Total wealth
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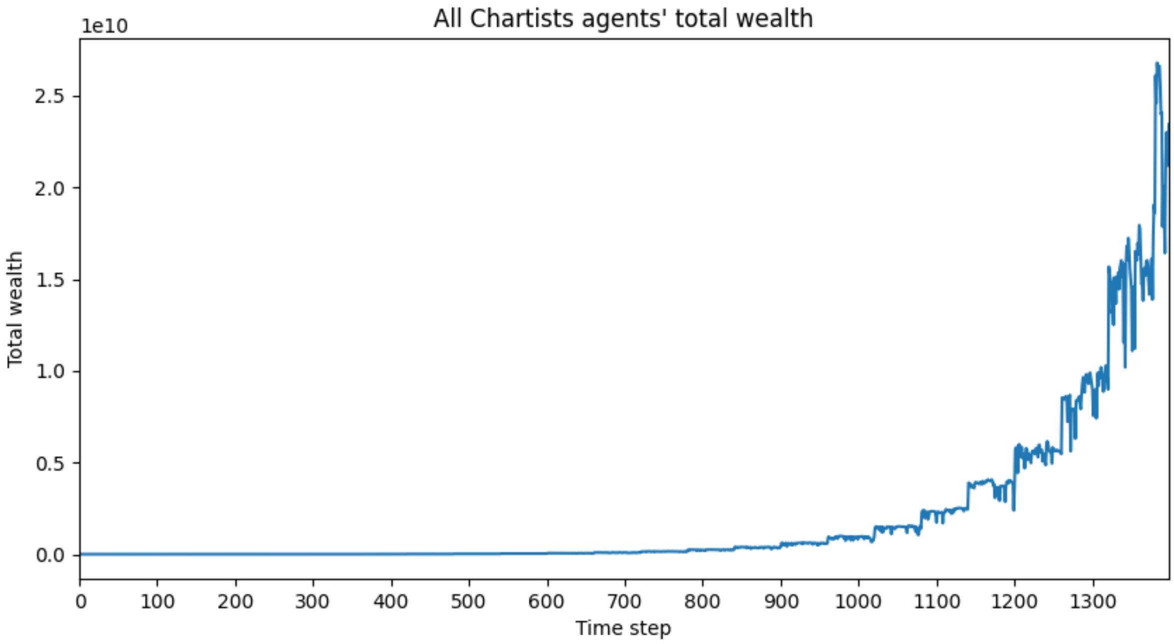
900
1000
1100
1200
1300
Time step

n = 40


All Chartists agents' total wealth
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2.5
2.0
1.5
1.0
0.5
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Total wealth
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Time step

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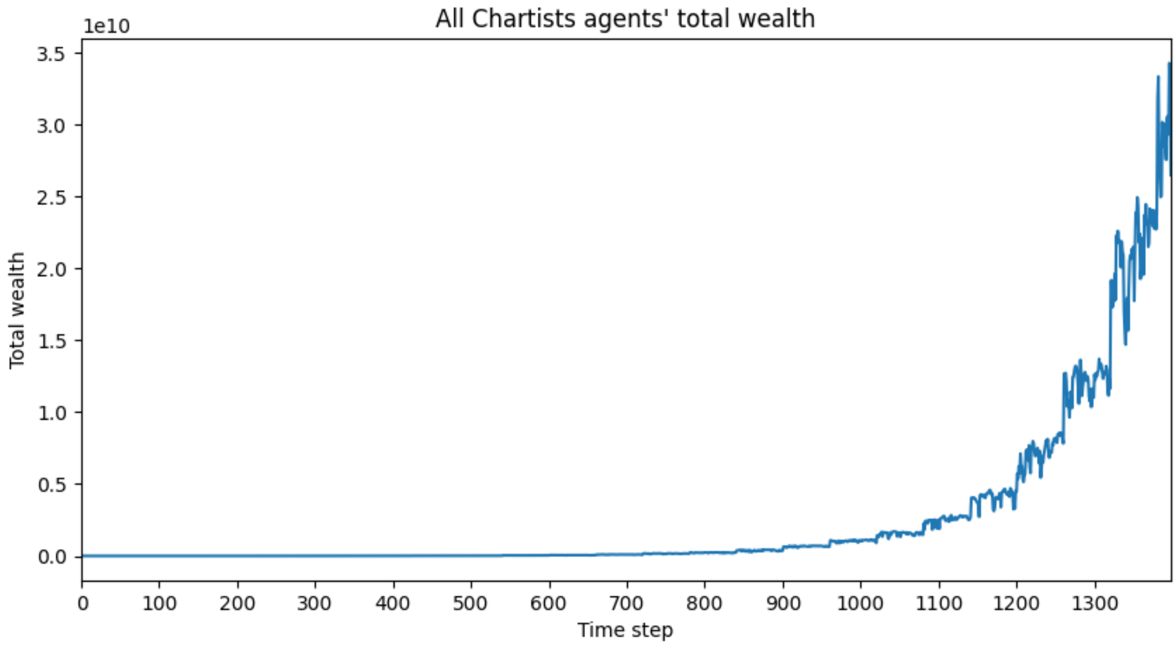
All Chartists agents' total wealth
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3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Total wealth
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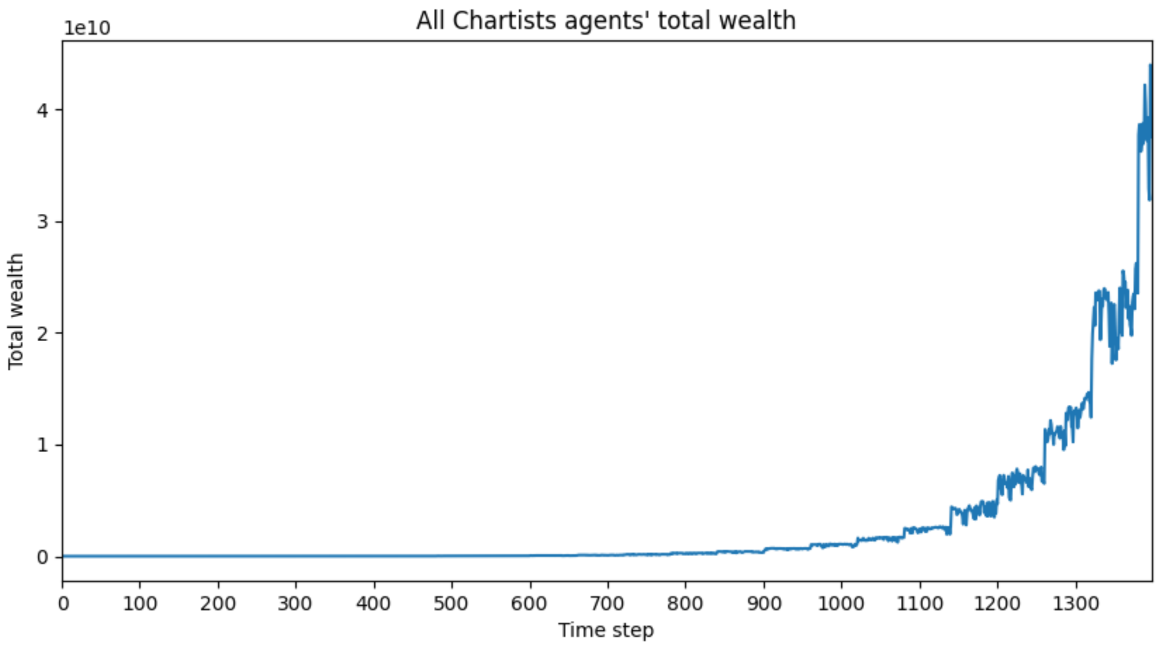
1200
1300
Time step

n = 60


All Chartists agents' total wealth
1e10
4
3
2
1
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Total wealth
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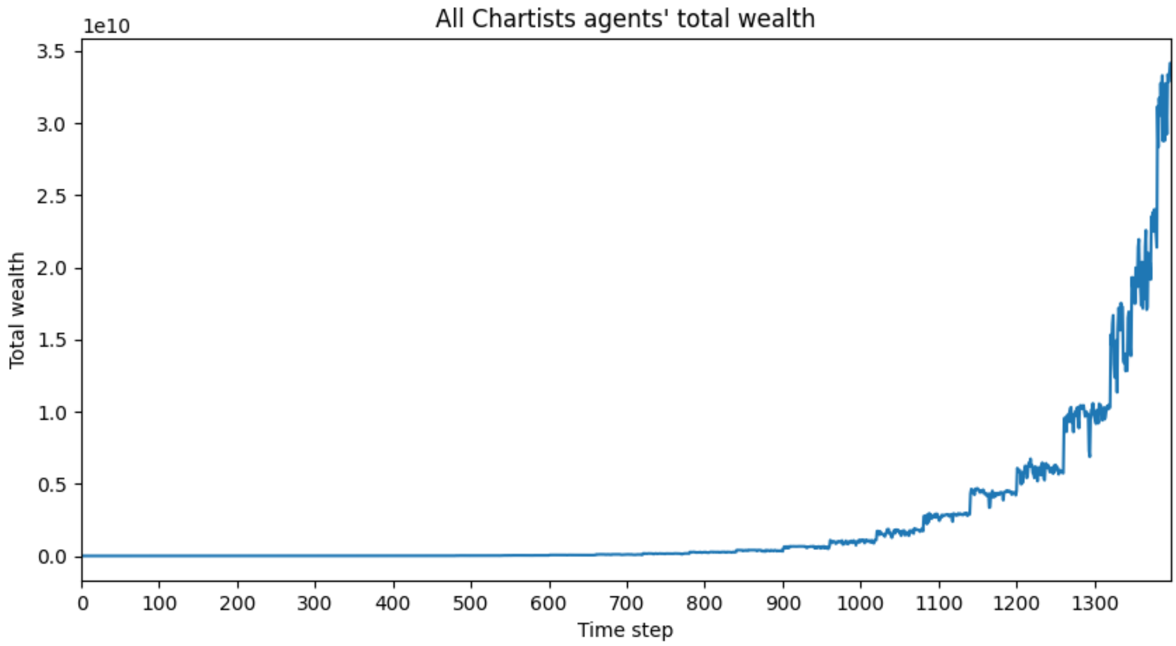
1200
1300
Time step

n = 70


All Chartists agents' total wealth
1e10
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Total wealth
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100
200
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400
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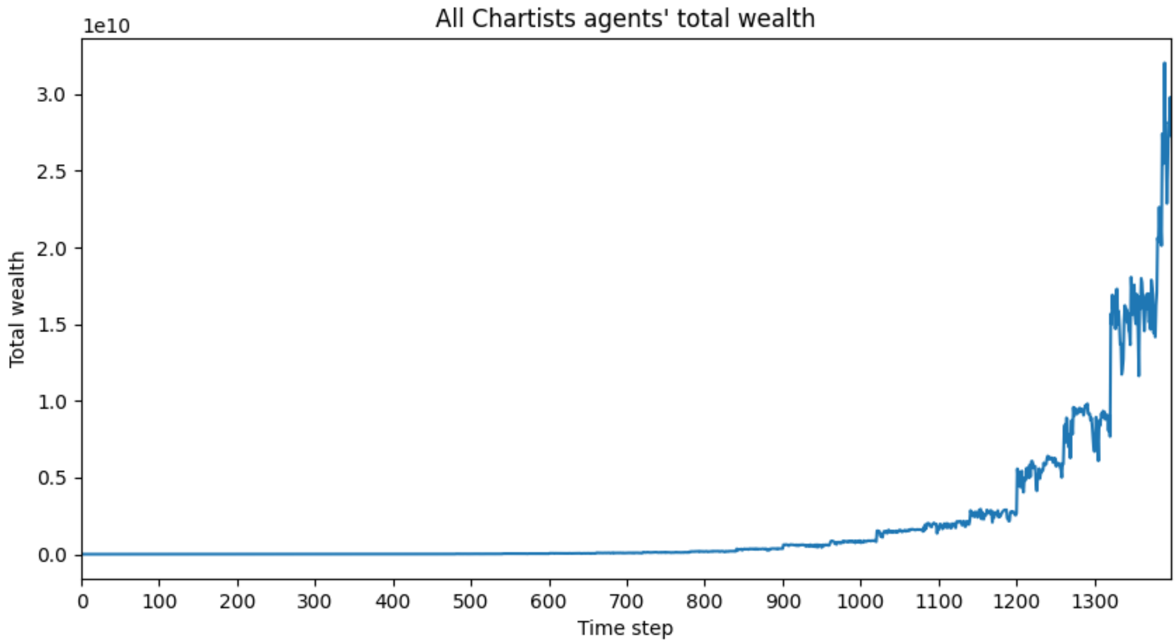
1200
1300
Time step

n = 80


All Chartists agents' total wealth
1e10
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Total wealth
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1200
1300
Time step

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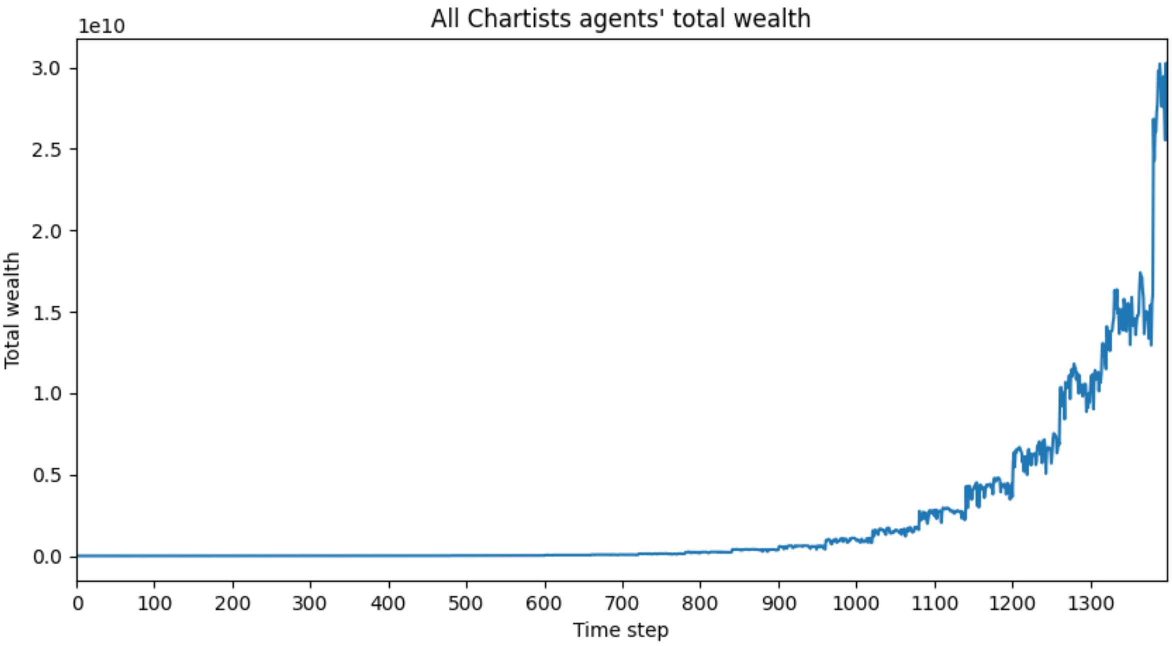

n = 100

Compare Agents

NOTE: In order to distinguish between different types of Chartists agents, the following table uses special names to represent Chartists agents in a certain state, as shown in the table below.

Name	Open Position	Close Position
Chartists agent 11	80% Filtering + 20% EMA	80% Filtering + 20% EMA
Chartists agent 12	80% Filtering + 20% EMA	20% EMA + 80% Filtering
Chartists agent 21	20% EMA + 80% Filtering	80% Filtering + 20% EMA
Chartists agent 22	20% EMA + 80% Filtering	20% EMA + 80% Filtering

- **Ratio between GBP and Bitcoin Held:**

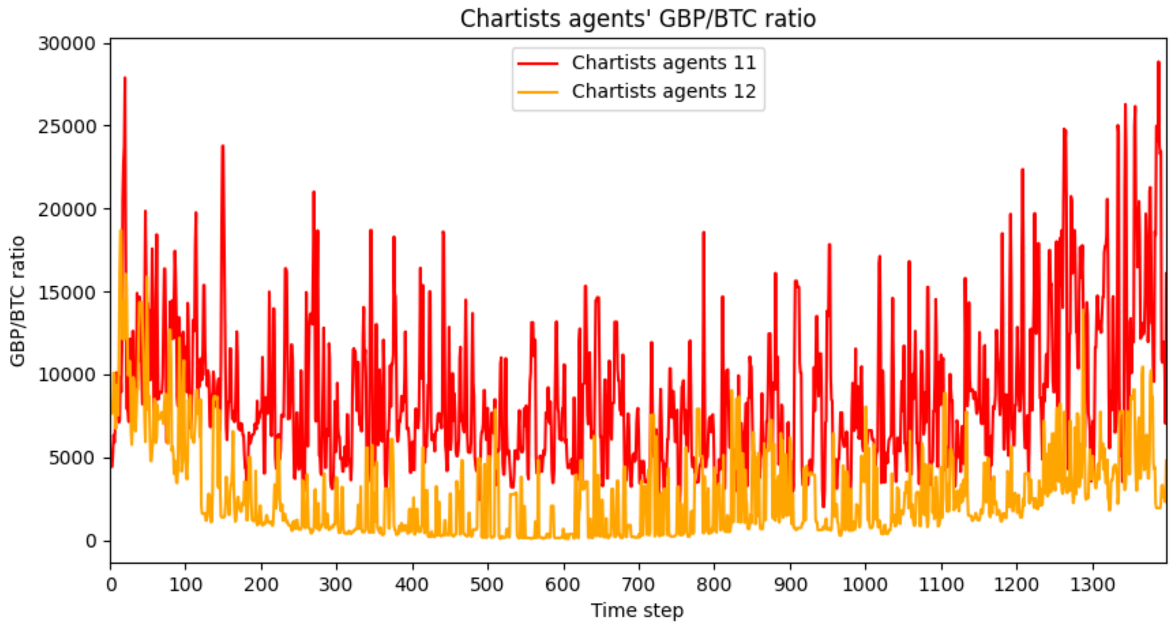

Figure 1

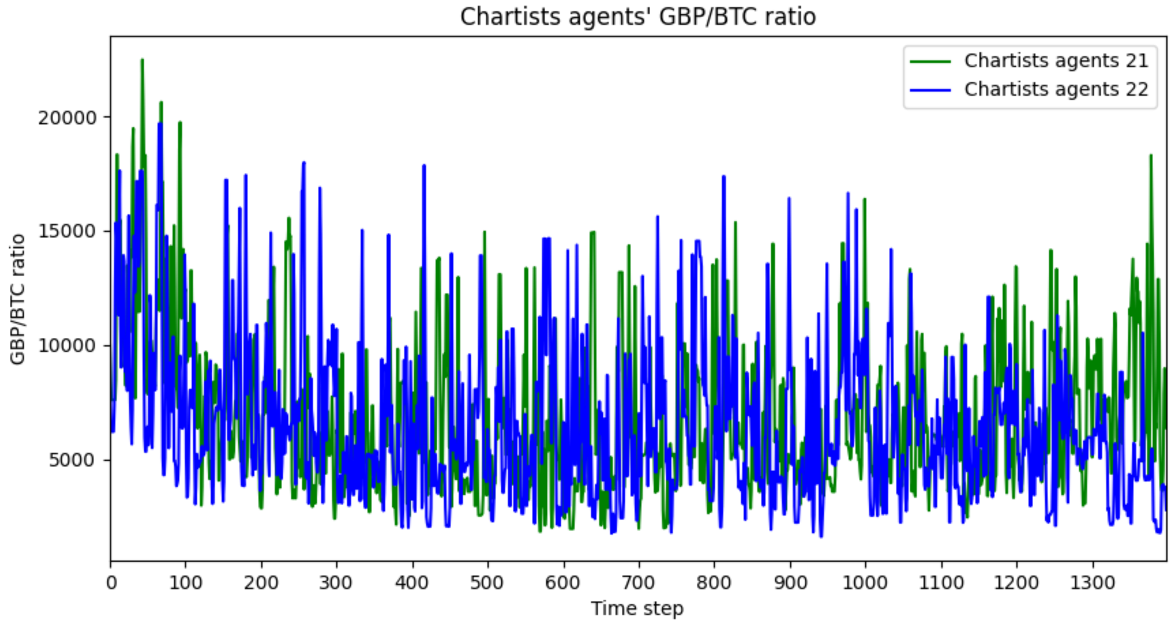

Figure 2

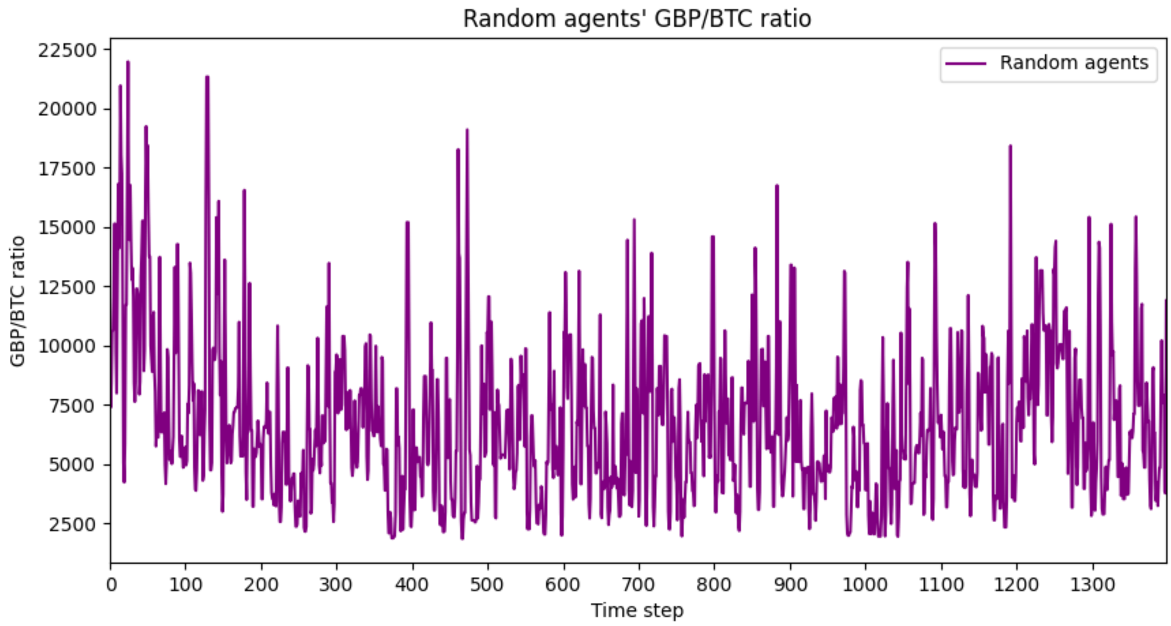

Figure 3

- **Chartists Agents:**

  From Figure 1 and Figure 2, it can be noticed that Chartists Agents show a high degree of volatility. And the differences between the trading strategies of different Chartists Agents can be observed on the figure. Agents labelled Chartists Agents 11 and Chartists Agents 21 show more significant spikes than Chartists Agents 12 and Chartists Agents 22 which demonstrate a relatively mild volatility, showing that perhaps they prefer a higher risk or higher return investment strategy. However, overall there is no clear long term trend in the GBP/BTC ratio, suggesting that these agents are adopting a strategy that exploits short term market volatility rather than investing for the long term.

- **Random Traders:**

  Random Traders shows less volatility than Chartists Agents in Figure 3, which matches its expected behaviour of making random decisions without a systematic trading strategy. And it is easy to see that Random Traders' ratio reaches a minimum of 2,500 instead of 5,000 for Chartists Agents, which also suggests that Random Traders' behaviour is more chaotic without a strategy.

Overall, Chartists Agents uses a rules-based strategy that shows a more dynamic approach to trading. In contrast, Random Traders' approach is less strategic, resulting in a more homogeneous sequence with no extremes. So Chartists Agents' profit potential higher, whereas Random Traders is unable to capture market trends that can be profitable.

- Total Wealth Acquisition (GBP plus Bitcoin):

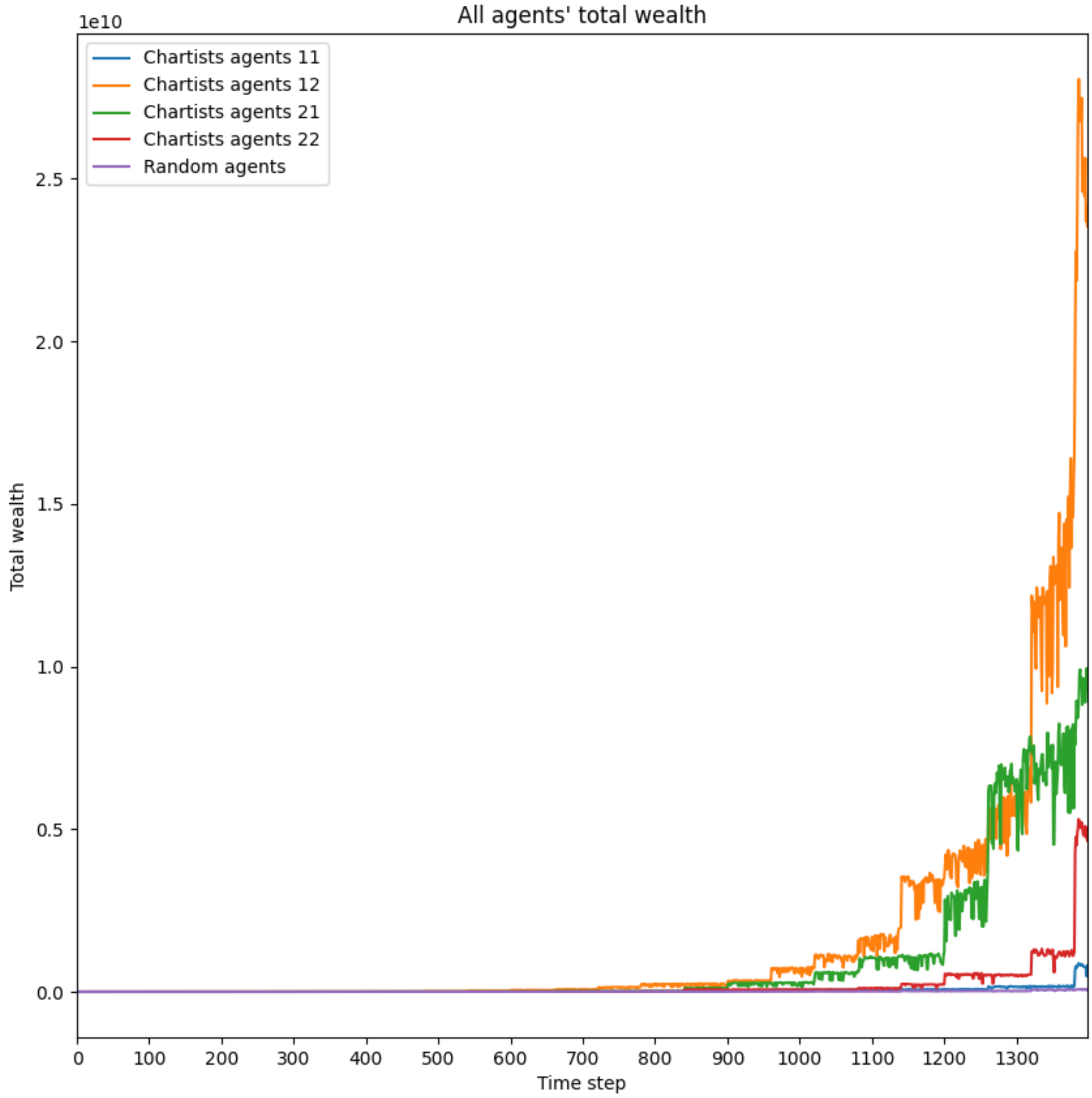

Figure 4 All agents' total wealth

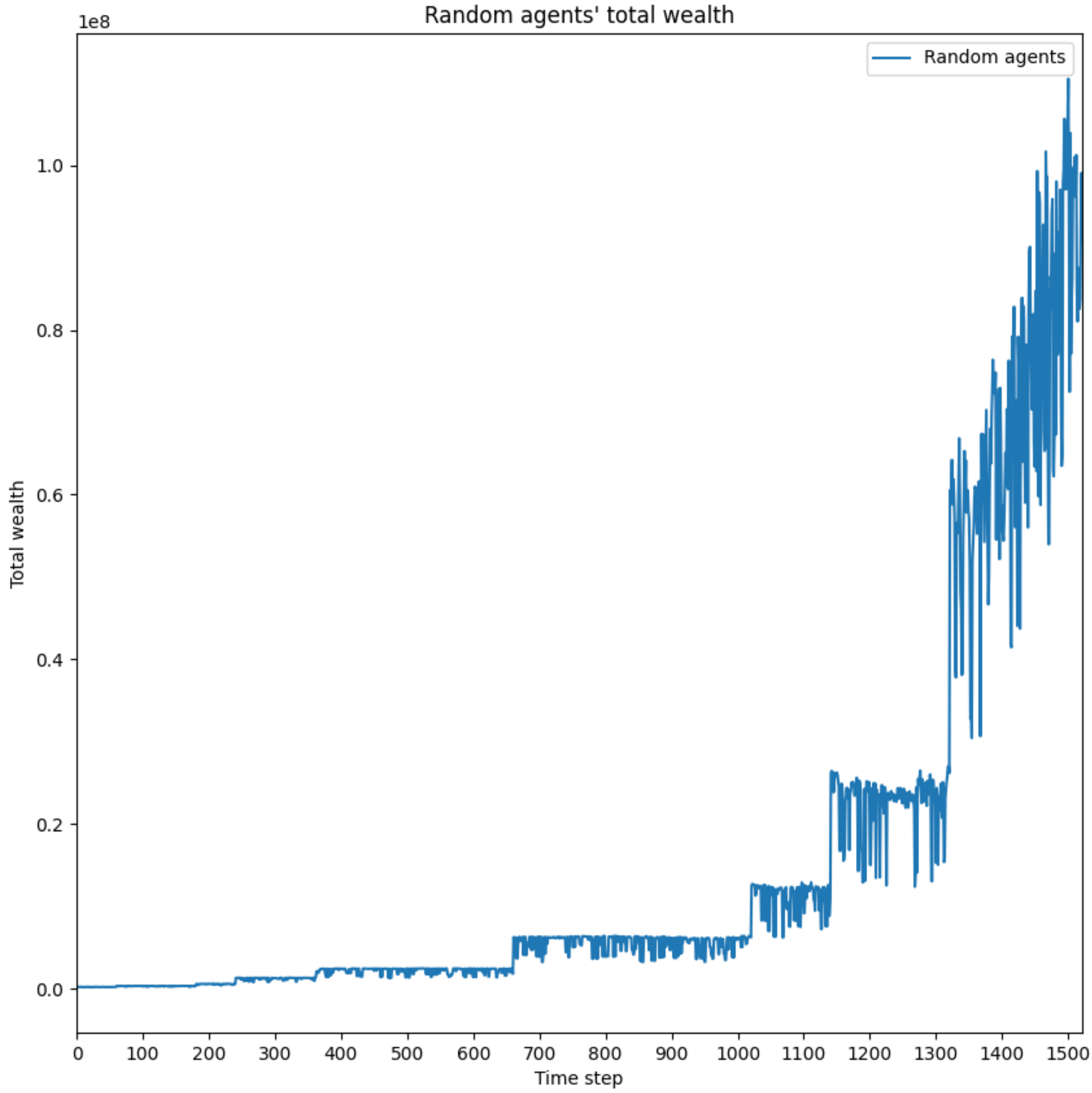

Figure 5 Random traders' total wealth

NOTE: In Figure 4 Figure 5, the number of AGENTS in the graph are all two.

- **Chartists Agents:**
  - The total wealth of all types of Chartists Agents has increased over time, but the track of wealth for these Chartists Agents is not linear, which may be due to the increased allocation of the number of Bitcoins.
  - Chartists Agents 11 and Chartists Agents 21 show a more aggressive rate of wealth increase in the later stages, suggesting that their strategy may be to take higher risk, but also potentially higher returns.
  - Chartists Agents 12 and Chartists Agents 22 show a more gradual increase in wealth over time, but not significantly compared to Chartists Agents 11 and Chartists Agents 21. This could represent a more conservative strategy, which did not achieve the same level of returns, but probably was more effective in preventing losses.
- **Random Traders:**
  - In Figure 4, Random Traders showed less significant wealth increases compared to Chartists Agents, and Random Traders has magnitudes less wealth.
  - In Figure 5,The stepped wealth growth of random traders can be clearly seen, indicating that random trader wealth growth relies more on the distribution of new bitcoins than on their own abilities.

Different strategies of Chartists Agents will have different risks and returns. Those Agents that are likely to take more risk have higher returns, while more conservative agents have less volatile wealth accumulation. Random Agents cannot increase their wealth as fast as Chartists Agents and are very dependent on market environment, unlike Chartists Agents who are able to adapt to changes in the market and seek opportunities to profit from them. Overall, Chartists Agents with a clear strategy have a faster rate of wealth increase and are more adaptable to market environment than Random Traders without a strategy.

- Number of Opened Positions

Agents	Number of Opened Positions
Chartists agents 11	1875
Chartists agents 12	1972
Chartists agents 21	1805
Chartists agents 22	2002
Random Traders	1870
Total	9524

Number of Opened Positions can reflect the frequency of agent's trading, and frequent trading may imply higher risks and rewards. However, the number of opened positions shows that the activity level of all the agents is quite close to each other, and no significant difference can be seen.

Model Validation

Wealth Acquisition

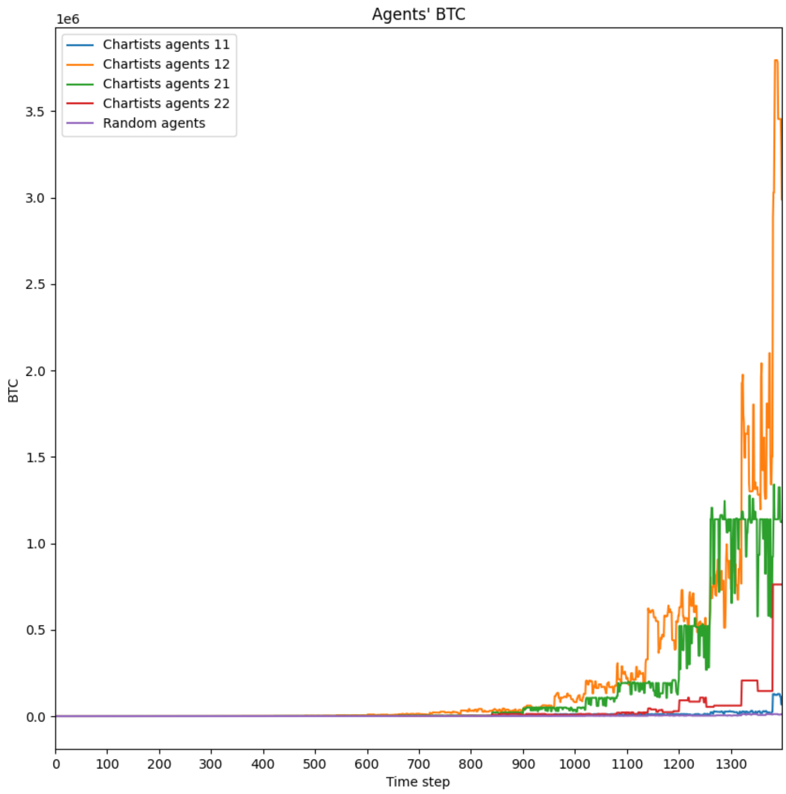

Figure 6 Chartists Agents' BTC

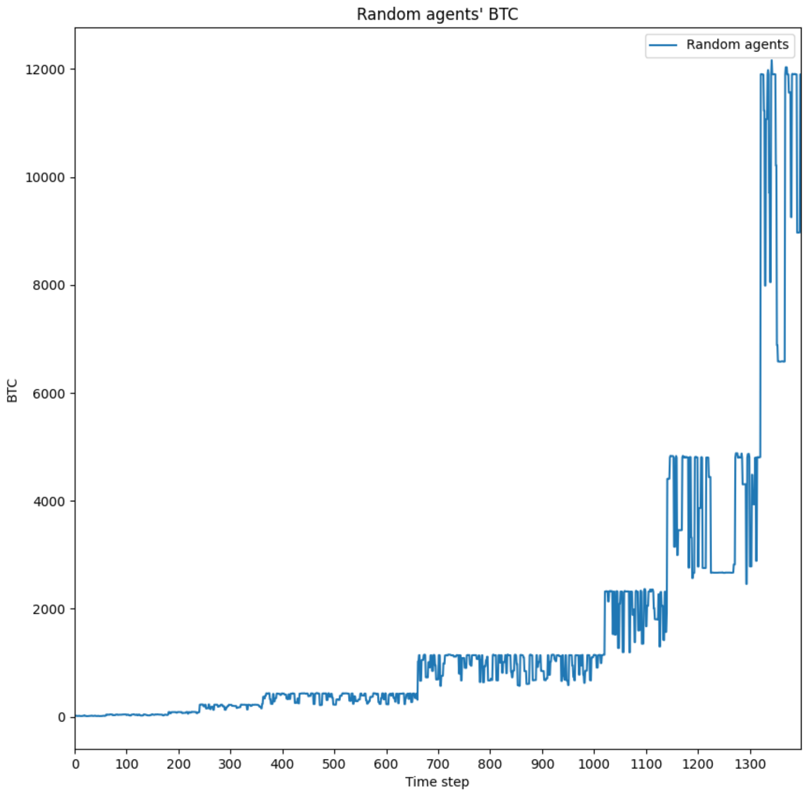

Figure 7 Random Traders' BTC

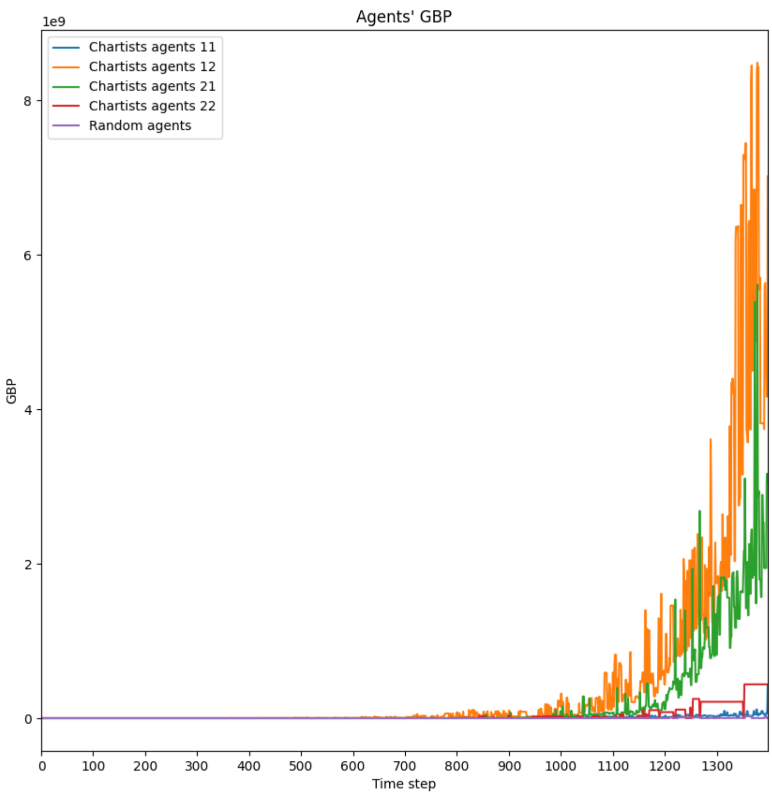

Figure 8 Chartists Agents' GBP

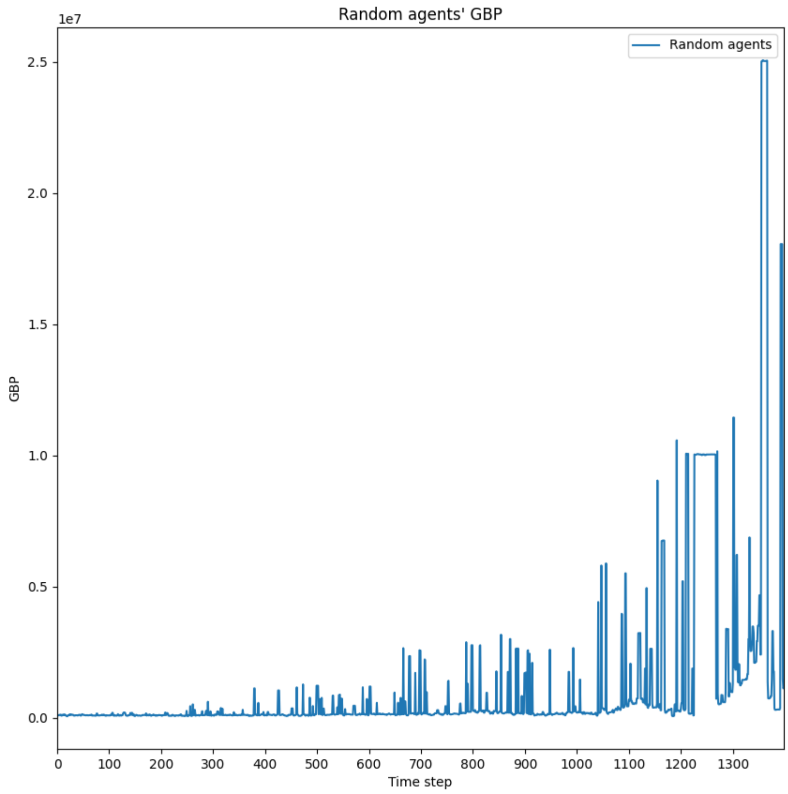

Figure 9 Random Traders' GBP

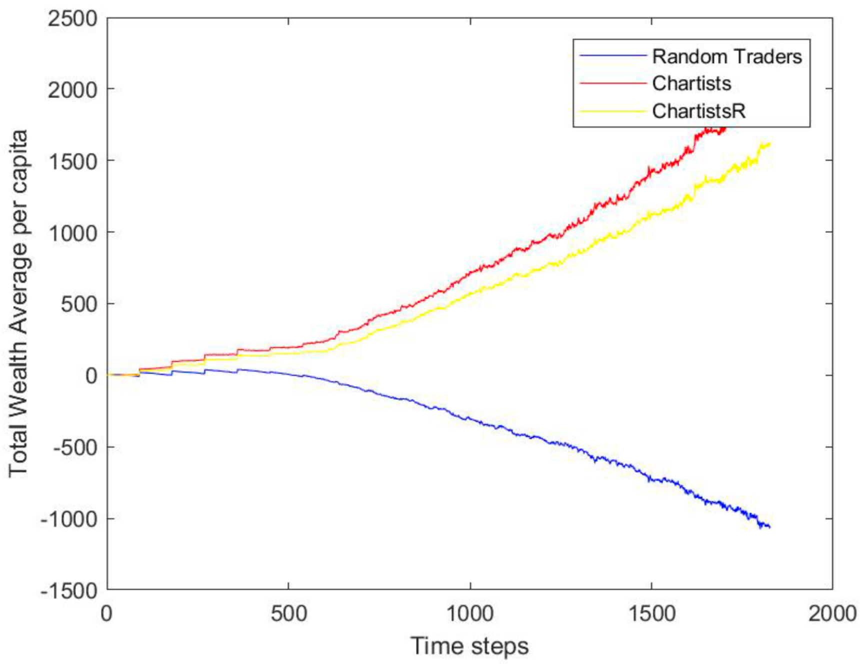

Figure 10 Total Wealth Average by the work of Cocco, Tonneli, and Marchesi(1)

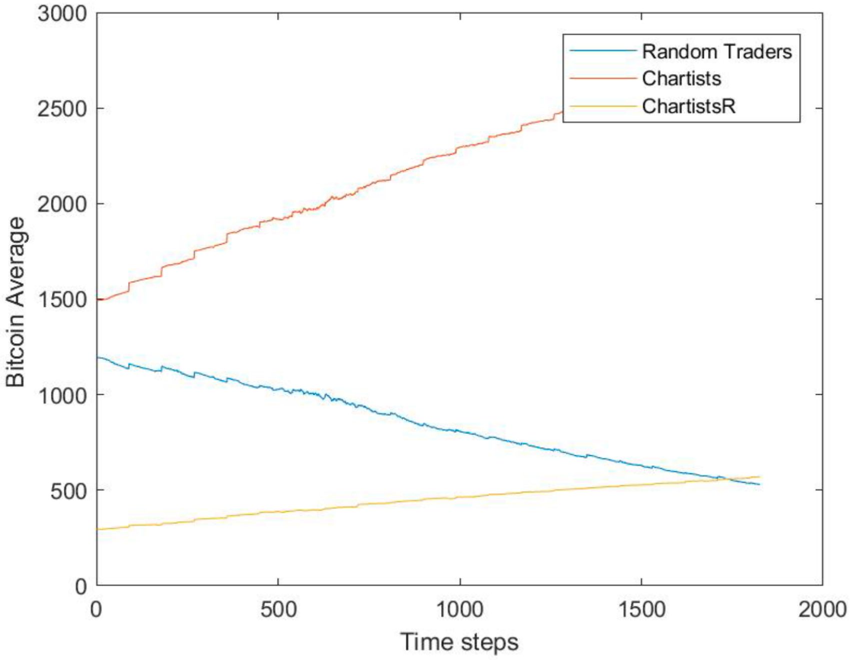

Figure 11 Total Bitcoin Average by the work of Cocco, Tonneli, and Marchesi(1)

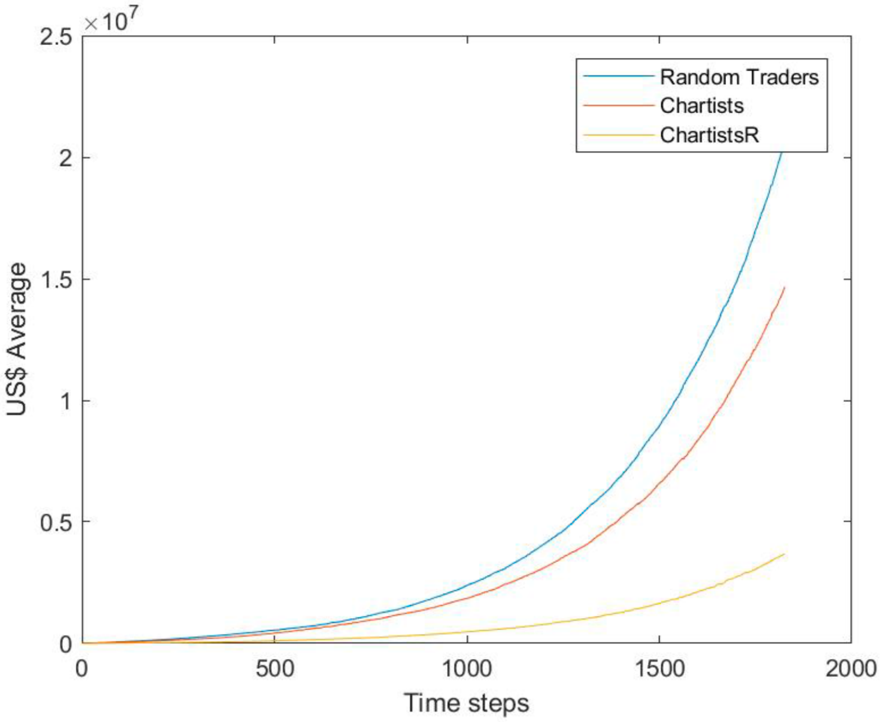

Figure 12 Total USD Average by the work of Cocco, Tonneli, and Marchesi(1)

NOTE: In Figure 6, 7, 8 and 9, the number of AGENTS in the graph are all two.

- **Compare Total Wealth (Figure 4, Figure 5, Figure 10):**

  In the work of Cocco, Tonneli, and Marchesi(1), the total wealth of random trader shows a downward trend, while the total wealth of chartists agent shows an upward trend. However, in this project, both random trader and chartists agent, showed an upward trend in total wealth. Compared to The work of Cocco, Tonneli, and Marchesi(1), the project's total wealth has increased at a faster rate, which may be a result of the new bitcoin distribution.

- **Compare BTC (Figure 6, Figure 7 and Figure 11):**

  In the work of Cocco, Tonneli, and Marchesi(1), the number of bitcoins of random trader shows a downward trend, while the number of bitcoins of all agents in this project shows an upward trend. Both random trader and chartists agents have increased their bitcoin quantities much faster in this project than in the work of Cocco, Tonneli, and Marchesi(1).

- **Compare GBP or USD (Figure8, Figure9 and Figure12):**

  In the work of Cocco, Tonneli, and Marchesi(1), the amount of USD increased for all types of agents, and surprisingly, random traders had the highest amount of USD and the fastest growth. Comparing this to the decline in total bitcoin holdings of random traders, it suggests that the behaviour of random traders in the work of Cocco, Tonneli, and Marchesi(1) is much more conservative, buying and selling fewer bitcoins and therefore retaining more USD. However, the total number of GBP held by random traders in this project is still on the rise, but obviously not as much as the number of GBP held by chartists agents.

Price Change

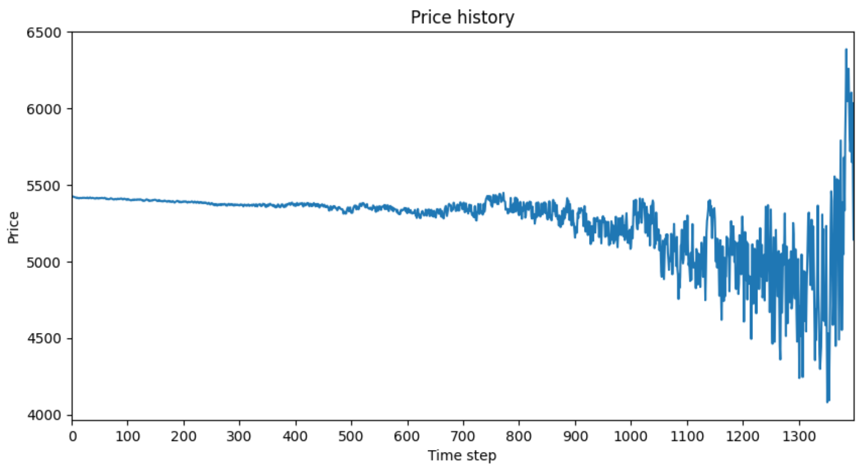

Figure 13 Simulated Price History

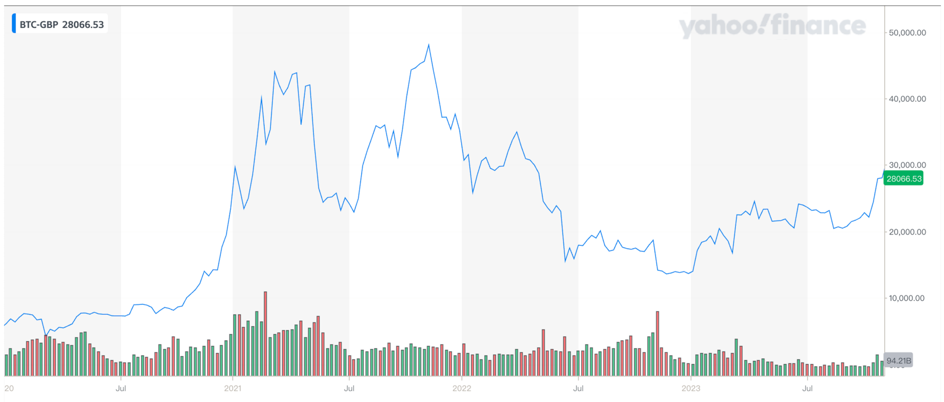

Figure 14 Real Price History (https://uk.finance.yahoo.com/quote/BTC-GBP/)

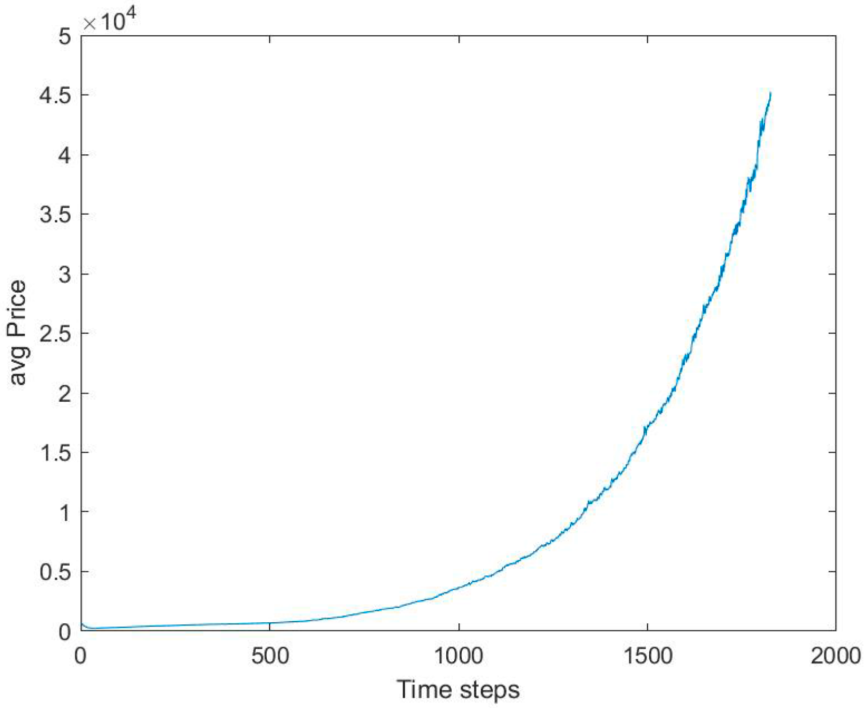

Figure 15 Average Price by the work of Cocco, Tonneli, and Marchesi(1)

NOTE： Figure 14 The real bitcoin price runs from January 1, 2020 to October 31, 2023, the same time period as the simulated price.

Using price history results of this project (Figure 13) compare with the work of Cocco, Tonneli, and Marchesi(1)(Figure 15). Because the initial parameters of the simulation are different, the final results are also have a significant difference. Overall, the simulated prices of this project do not show a significant increase, whereas the work of Cocco, Tonneli, and Marchesi(1) has a very significant growth process. In addition to this, the simulated price of this project is much more volatile than that of the work of Cocco, Tonneli, and Marchesi(1). The simulated price of this project is less volatile in the initial stage, but it becomes more volatile in the later stage due to the richness of the agents, who will use more money to buy and sell.

If comparing the simulated price of this project with the real Bitcoin price in the same time period, it can be noticed that the simulation results are also completely different. There could be several reasons for the different simulation results.

- Only five different types of traders are considered in this simulation, and the real situation cannot be that simple. The price impact of traders on the market is also not possible to model with a single formula.
- The number of traders in the real Bitcoin market changes every day and may increase or decrease. And this is not considered in this model.
- The unprecedented global interest in Bitcoin around 2020 has led to a lot of public participation in the Bitcoin market, many of which may just be a novelty, so this complexity is also difficult to simulate for this project.
- The increase of Bitcoin quantity on the market is obtained by mining, and the rough model of distribution in this simulation does not correspond to reality.

Overall, Bitcoin is the most famous digital currency and there are a lot of factors that can have an impact on its price not just the buying and selling in the market. This project has not modelled the price of Bitcoin correctly, but it has studied and discussed the patterns of growth and decline in its price, and how investors trade.

Cyberattack on Bitcoin

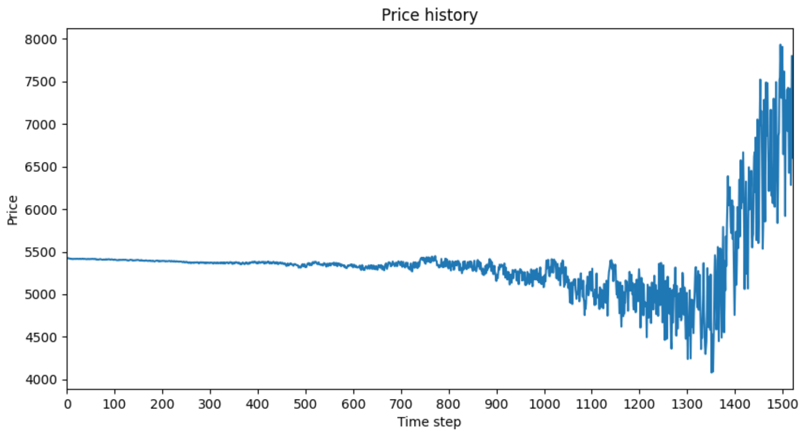

Figure 16 Price after attack

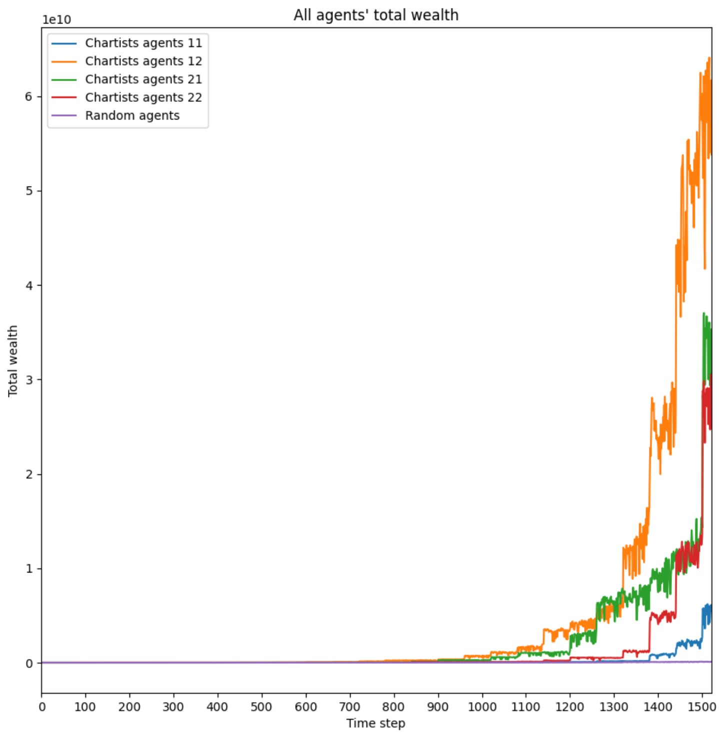

Figure 17 All agents' total wealth after attack

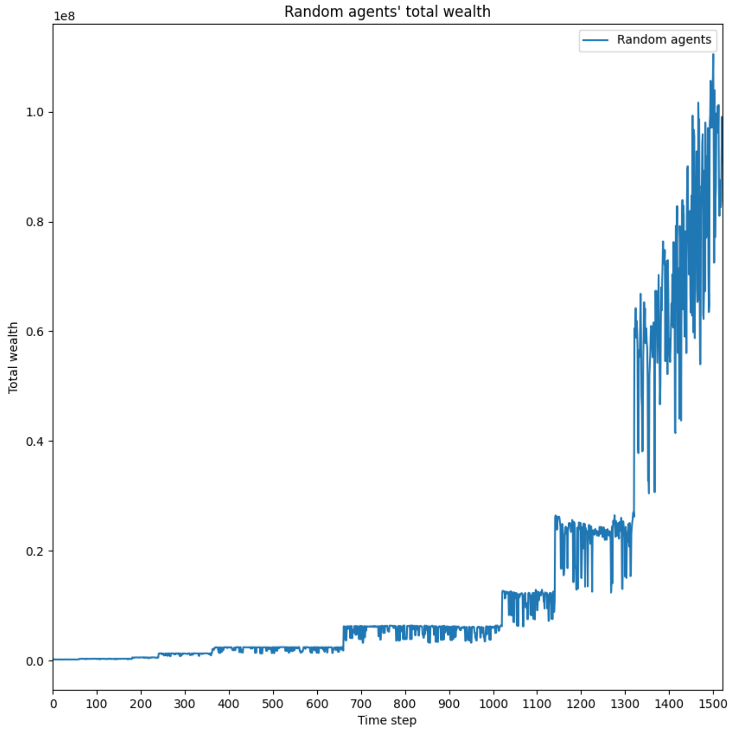

Figure 18 Random Traders' total wealth after attack

Implementation

Since the previous simulation of this project was from 1st January 2020 to 31st October 2023 and cyberattack on Bitcoin on December 1, 2023, the project extended the simulation to 1st March 2024 in order to observe the impact of the cyberattack. So the attack happened on day 1430. Since They would hack the accounts of 40% of the traders(agents), 4 out of 10 agents simulated in the project would be considered to have received the attack and stopped buying and selling.

Agents' React

According to Figure 17, it is clear that chartists Agents 12, which has the highest total wealth, has a significant drop in total wealth after the attack, which shows that it cannot respond well to the crisis, but it is able to recover quickly after the attack, which may be due to its aggressive strategy. Whereas Chartists Agents 22 did not receive a significant impact on its total wealth at the time of the attack, which could be the reason for its more prudent strategy. According to Table 18, it can be seen that random trader without any strategy does not cope well with the attack and shows a sudden drop.

Overall, agents with more robust strategies such as Chartists Agents 22 were able to respond better to the crisis, while agents with more aggressive strategies received a big impact when the attack happened, but they were able to recover quickly after the attack and were even able to continue growing. The random trader's no-strategy type, on the other hand, as expected, was not able to respond well to the rapid changes in the market, and although its total wealth still increased after the attack, this was more due to the distribution of new bitcoins than to its own efforts.

New Agent Class

Implementation

In the work of Cocco, Tonneli, and Marchesi(1), a rule of Relative Strength Index (RSI) was introduced, and this project decided to use RSI as a rule to test its simulation effects.

According to Gumparthi, S.(2), the principle of RSI is to calculate the daily price changes over a period and divide the price changes into gains and losses and calculate the average of each. Relative Strength (RS) is then calculated using the average gain divided by the average loss This ratio indicates the strength of up days relative to down days in a selected period. The RSI is calculated by converting the RS value to an index between 0 and 100. In general, an RSI value above 70 indicates that the asset may be overbought and should be sold, while an RSI value below 30 usually indicates that the asset may be oversold and may represent a buying opportunity. By using this RSI strategy, a new agent class is build.

$$RS = \frac{AverageGain}{AverageLoss}$$

$$RSI = 100 - \frac{100}{1 + RS}$$

New Agent Performs

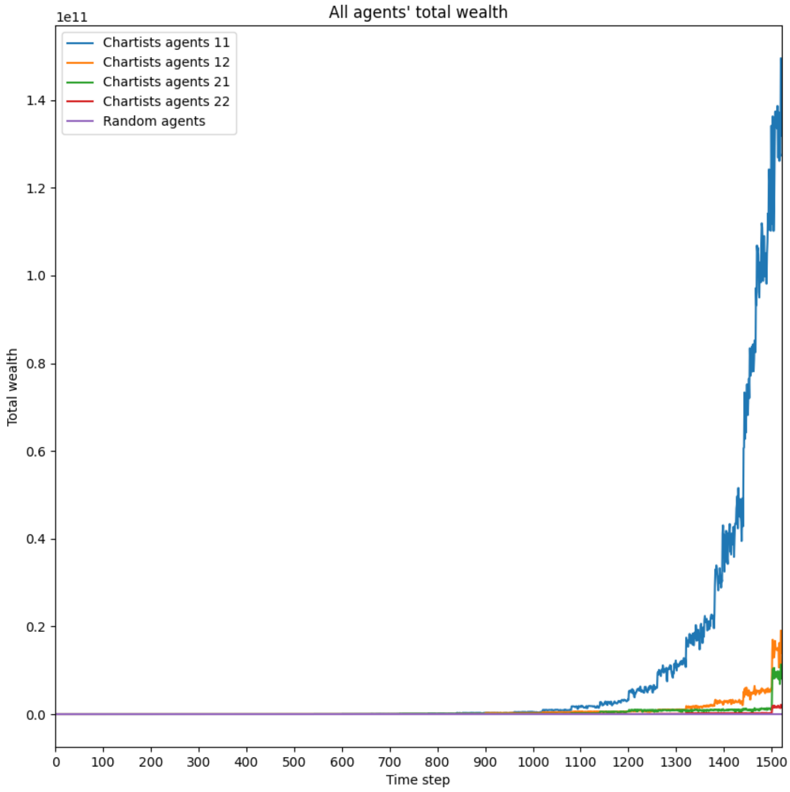

Figure 19 All agents' total wealth after attack with RSI agent

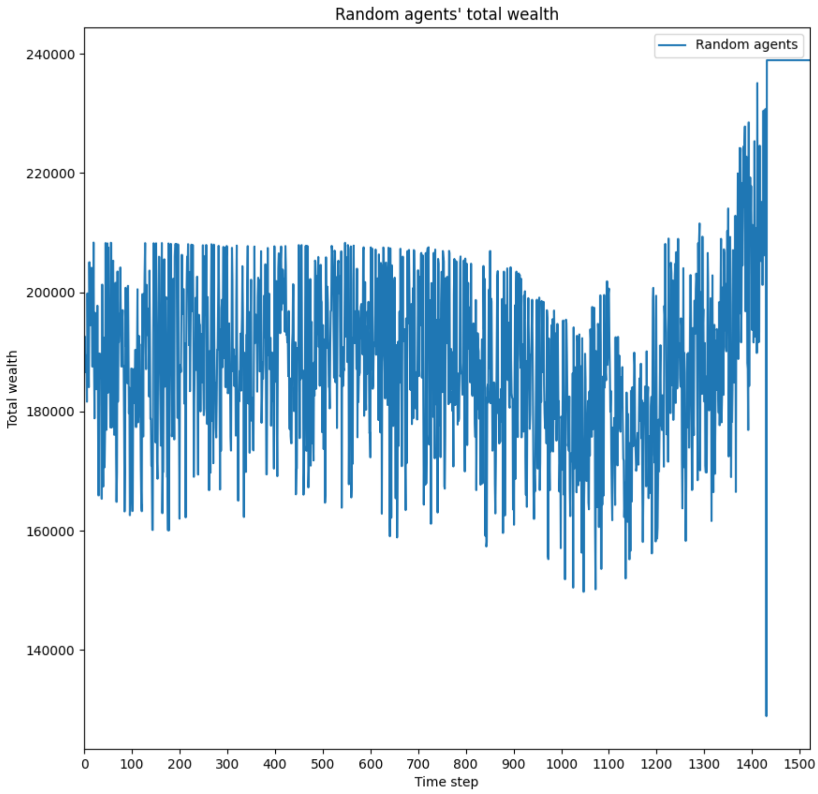

Figure 20 Random Traders' total wealth after attack with RSI agent

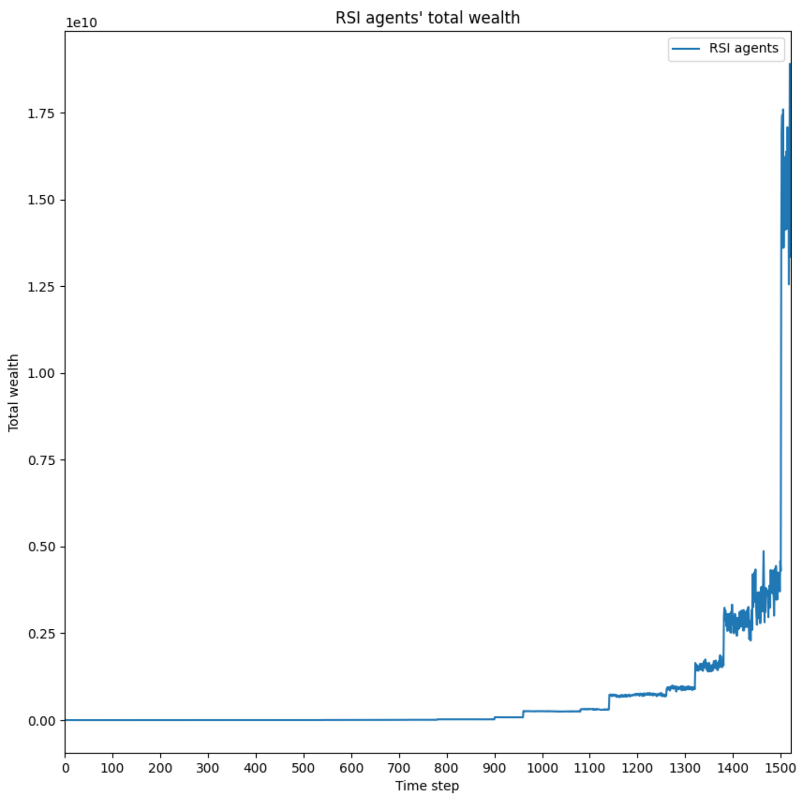

Figure 21 RSI agents' total wealth after attack

In order to continue all the research above without changing anything else after adding the RSI agent, this project continued with the random seeds used previously. But unfortunately both random traders happened to be attacked and lost their trading ability. But because of the no strategy type of random trader, its behaviour is very predictable and after the attack its not able to react quickly to the rapid changes in the market. Moreover, after adding the RSI agent, the results show that the random trader was not allocated new bitcoins at this time, which confirms that the random trader's wealth increase is extremely dependent on the distribution of new bitcoins.The overall behaviour of the chartists agents has not changed much since the addition of the RSI agent, it should be noted that Chartists Agents 11 is very much ahead of the other types of Chartists Agents at this point. it can be noted that Chartists Agents 12 has a significant drop in the 1430 days in the attack. It can be observed that Chartists Agents 12 had a significant drop in 1430 days after the attack, but Chartists Agents 11 still maintains a very good upward trend, and it was not greatly affected by the attack. RSI agent is not as rich as Chartists Agents 11, which is the best performer, but it has reached the level of Chartists Agents 12, which is the second richest, so its performance is not bad. And when the attack occurred RSI agent did not have Chartists Agents 12's obvious decline, RSI agent only had a slight decline, but later through the adjustment also quickly get back. Overall, RSI agent's performance is very good, although not as good as Chartists Agents 11, which is the best performer, but the overall performance is not bad.

Result Discussion

Among the three different agents studied in this project, Chartists Agents had the best performance, RSI agents had the second best performance, and Random Traders had the worst performance. The RSI strategy established in this project does not perform poorly, indicating that it deserves further attention. There are some limitations to the RSI strategy, firstly RSI may remain overbought or oversold for long periods of time in a strong trending market. For example, in a bull market the RSI may stay above 70 for long periods of time, while in a bear market it may stay below 30 for long periods of time, resulting in lost opportunities. In addition to this, because the previous research on Chartists Agents showed that this simulated market has better returns for fast and aggressive agents, the time period of RSI attention in the implementation of this project was set to 7 days instead of the commonly used 14 days setup. However, different parameter settings can affect the sensitivity of the strategy and the accuracy of the results, so the setting of this period also deserves further continued research. Overall relying on a single indicator to make trading decisions is risky, and if the agent setup can be further optimise, using more subdivided selection conditions for the strategies and a greater range of strategy types should be able to give better results. For example, it would be better to make both long term RSI judgements and short term RSI judgements in a single agent and choose a trading strategy based on market conditions at that point of time.

References

(1) Cocco, L., Tonelli, R., & Marchesi, M. (2019). An agent-based artificial market model for studying the Bitcoin trading. IEEE Access, 7, 42908-42920.

(2)Gumparthi, S. (2017). Relative strength index for developing effective trading strategies in constructing optimal portfolio. *International Journal of Applied Engineering Research*, *12*(19), 8926-8936.