Agent-based model (ABM) - Bitcoin trading dynamics against GBP.

Task 1: Agent Construction

Agents in this model hold both GBP and Bitcoin. Allocate an amount of b Bitcoin and g GBP to every agent at the start; all agents should start with the same amount of GBP and Bitcoin . To represent real-life scenarios, every 90 days additional Bitcoin amounting to 10% of the Bitcoin currently in circulation enter the market and those are assigned to agents, giving them an amount of Bitcoin proportional to those already owned following the Gibrat principle of preferential attachment (rich get richer). Agents can only open a new position if they have closed their previous position (except for the initial position which can be initiated before previous close). To close a position in the model an agent needs to sell all the Bitcoin they obtained when they opened the position.

Task 1.1 – Define Chartists (10 marks)

Chartists seek profit in GBP through Bitcoin trades, following specific rules for opening and closing positions with specific weightings. Build the chartists following the rules and the weightings specified below: Apply Opening & Closing Position Rules. Momentum-Based Rule and Relative Strength Index (RSI) Rule. Apply Decision Weightings.

Discuss Expectations (5 marks)

Discuss the expected behaviour and performance for each subtype and justify any additional modifications. Which subtype do you anticipate will perform best under market volatility? Why? Which agents do you expect would accumulate the most wealth? Which agents will open and close the most positions?

All agents make decisions based on momentum and RSI (Relative Strength Index). Momentum is a strategy where, if prices are rising steadily, agents buy, expecting the trend to continue. However, agents wait for n days before making that decision. The choice of this parameter (n days) can significantly influence an agent's behaviour. In terms of failures, when prices drop, agents sell immediately to avoid losses.

On the other hand, the RSI indicates overbought conditions, suggesting the price may be too high and a correction or decline could occur, or oversold conditions, suggesting the price may be too low and could recover or rise, as showing in the Figure 1.

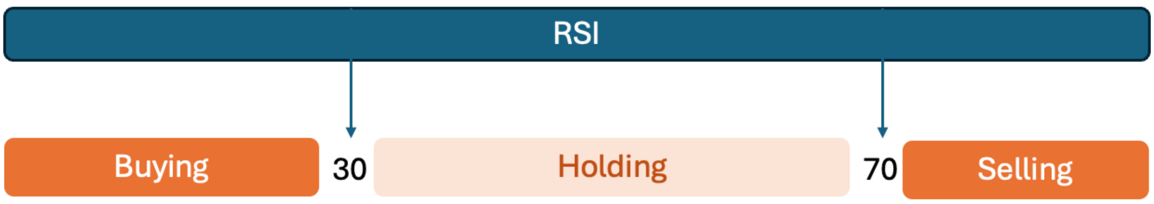


Figure 1 - RSI signal

- **RSI above 70:** Indicates overbought conditions - the price may be **too high.**
- **RSI below 30:** Indicates oversold conditions - the price may be **too low.**

Discuss the expected behaviour and performance for each subtype and justify any additional modifications.

Based on what was said before, each agent has different behaviour what could change each performance.

- Chartist 1 (C1) is a momentum-driven agent that bases 80% of its decisions on trends, buying after confirming an upward trend and closing positions after observing a single day of decline. The remaining 20% of its actions involve reacting to perceived price extremes, selling when prices seem too high or buying when they seem too low. This agent is expected to capture some portion of the gains; however, its performance depends heavily on the chosen value of n-days. A larger n might result in missing the most profitable part of the move due to delayed entry. In terms of losses, this agent is not expected to incur significant losses, as it is highly risk-aware.
- Chartist (C2): Conversely C1, this kind of agent waits for a key moment to get in or get out of the market 80% of the times. It could be seen as a long-term and conservative agent. Basically, this agent primarily seeks significant mispricings, buying when assets are undervalued and selling when they are overvalued (RSI). While only 20% of its decisions rely on short-term price trends over n-days. Therefore, it is expected that these agents have less trading frequency than C1, as well as, could capture more of the profits to come from long-term positions most of their decisions..
- Chartist 3 (C3): This agent can be considered balanced and medium-term, as it makes decisions 50% of the time using a momentum rule and 50% with an RSI rule. Compared to the previous agents, C3 is a balance between the short-term aggressiveness of C1 and the long-term conservatism of C2. As a result, it is expected to execute more trades than C2 but fewer than C1, capturing opportunities across a range of market conditions.
- Chartist (C4) - Unlike the previously mentioned agents, this chartist uses weekly volatility over the past 30 days to adjust its strategy between short-term and long-term. Typically, this agent operates with a short-term strategy but switches to a more long-term approach during high volatility, prioritizing caution (via RSI). In stable markets, C4 focuses on momentum, maximizing gains from sustained high movements. It is expected that this trader will trade more or less depending on market volatility; in stable markets, they will look like C1, while in volatile times, they will look like C2. In terms of gains, C4 is expected to offer greater consistency and lower risk over time.

Which subtype do you anticipate will perform best under market volatility? Why?

- It is expected that **C4** is likely to perform best under market volatility because its adaptability, adjusting its strategy based on volatility thresholds. This ability to adapt to both high and low volatility gives it a significant edge in managing risks and capturing gains in different market conditions.

- As a second place, **C2** could also perform well in volatile markets as it focuses on detecting price extremes using RSI, a long-term strategy. However, since they can take momentum 20% of the times, it could result in fewer gains during high volatility or fewer losses.
- In the third place **C3**, using a balanced approach by combining both momentum and RSI strategies could be more protected from volatility.
- Lastly, **C1** is expected to perform the worst in highly volatile markets. Relying on upward trends based on the n-day parameter means C1 might not trade frequently, as it waits for a strong trend to develop. This could result in missed opportunities during periods of high volatility when trends are not clear or are quickly changing.

Which agents do you expect would accumulate the most wealth?

- **C1** is likely to accumulate the most wealth in strongly trending markets, thanks to its frequent trading and momentum focus. However, it may struggle in volatile or sideways markets, leading to lower wealth accumulation in those conditions. Something expected from this agent is to have high standard deviation in its wealth.
- **C2** may accumulate less wealth than C1 in trending markets but is a solid choice for wealth accumulation in volatile or unpredictable conditions
- **C3** performs well in both trending and volatile markets due to its balanced approach combining momentum and RSI strategies, making it adaptable to various market conditions.
- **C4** is expected to accumulate the most wealth due to its adaptability in adjusting strategies based on volatility, balancing risk and return effectively. Its ability to switch between short-term and long-term strategies helps it capture consistent gains over time.

Which agents will open and close the most positions?

- C1 will likely open and close many positions in up trending markets and less in downtrends. However it will depend of n-value.
- C2 will likely open fewer positions than C1 in uptrading markets due to its focus on longer-term rule.
- C3 will likely open and close a moderate number of positions, balancing between momentum and RSI strategies to adapt to both trending and volatile markets.
- C4 will likely open and close fewer positions. However it will also depend on the volatility of the market.

Task 1.2 – Define Random Traders (5 marks)

Random traders operate without profit motivation and open or close positions randomly within their available Bitcoin and GBP holdings. They represent investors with no market analysis in their decision-making. Describe the expected behaviour of Random Traders. How does their activity differ from Chartists in this model? What market effect might result from such trades?

Random Agent: Random agents lack a strategy and make decisions based on chance, which can lead to both occasional gains and significant losses. Without risk management, they are highly susceptible to unpredictability, potentially holding positions for no clear reason, which can result in large fluctuations in wealth.

Chartist Agents: In contrast, chartists follow defined strategies like momentum or RSI to guide their decisions, aiming to minimize losses and increase wealth. They use their strategies to enter and exit positions in a way that seeks to protect their capital while capturing gains, adapting to market conditions like price fluctuations.

The main difference between those agents is that chartist agents base their decisions on technical analysis while random one make decision randomly. Additionally, chartist agents are looking for consistency, taking advantage of market patterns while random agents do not follow any predictable pattern.

What market effect might result from such trades?

Since the price is calculated based on the Petrov formula, which incorporates intentions to buy and sell, random behaviour could lead to sudden price increases or decreases. The activity of Random Traders introduces significant noise into the market, as their trades are not based on price trends or market fundamentals. This randomness can cause price movements that do not accurately reflect the asset's true value or long-term trends.

Task 1.3 – Implement Market Environment (10 marks)

Develop the market environment where agents can trade. Explain any assumption you make.

The market environment was constructed based on several key assumptions. Initially, specific parameters and behaviours were defined with the instructions given, and then some assumptions were developed.

Information given:

Parameters:

- Time: 01/01/2020 – 01/11/2024, corresponding to 1766 days.

Behaviours:

- Every 90 days additional Bitcoins get in to the market (10% of the bitcoins currently in circulation enter the market). The new bitcoins are proportional distributed following the Gibralt principle of preferential attachment (rich ger richer).
- Some agents use Relative Strength Index (RSI) Rule: Use the 14-day RSI, which signals buying (opening) when below 30 and selling (closing) when above 70.
- Agents can only open a new position fi they have closed their previous position.To close a position in the model an agent needs to sell all the Bitcoin they obtained when they opened the position.
- Chartist C4: change the strategy to RSI when the weekly volatility exceeds 2.5%. Once the weekly volatility falls back below 2.5%, return to using the Momentum strategy.

My assumptions:
To run the market, certain parameters need to be defined. Some values were derived from the literature, others from empirical data, and the rest were assumed using common sense to simplify the model.

Parameters:

- **n – number of agents:** 1000. This number was chosen for computational feasibility, as simulating more agents significantly increases computational demands. Additionally, 1,000 agents balance realism and simplicity while providing a sufficiently large sample size to observe emergent behaviors and represent a practical model for exploring market dynamics.

- **% of each type of agent – R (randoms), C1, C2, C3 and C4:** 40% random agents and 60% chartists (divided evenly among C1, C2, C3, and C4). Those values were chosen According to Cocco et al. [1] where they used the same proportions mentioned.

- **b – number of bitcoins to start the simulation:** 18. This value is based on empirical data from blockchain.info. On 03/01/2020, the circulating supply was 18,138,668 BTC. Dividing this among 1,000 agents results in approximately 18000 BTC per agent, for simplicity 18 BTC were used.

- **g – number of GBP to start the simulation:** £97,992 . This value was calculated to balance starting conditions between BTC and GBP holdings for each agent. Each agent begins with 18 BTC, valued at approximately £5,444 per BTC in early 2020, resulting in an equivalent starting balance of £97,992 per agent. This ensures neutral starting conditions.

- **Price bitcoin: £5,444.** This value was chosen using empirical data from investing.com [3] selecting the same open value in 01/01/2020

- **N-days for opening a momentum rule** is a parameter to be defined later. Its careful selection is crucial, as inappropriate values could result in delayed market entries for some agents, affecting their performance.

Behaviour assumptions:
These assumptions were made to maintain the simplicity and tractability of the model, ensuring it remains manageable while still capturing key market dynamics.

- **Order Book**: As mentioned in paper [2], the order book consists of two queues—buy orders and sell orders—at each instant. At every simulation step, new orders are inserted into their respective queues.
- **Order Book Sorting**: The order book is sorted by the quantity of bitcoins to buy or sell, rather than by price, since this simulation does not use limit prices. We sort both lists so that the highest quantity of bitcoins is at the top of the list. This ensures that orders with fewer bitcoins are not matched with buyers who have the capacity to purchase more.
- **Order Matching and Cleaning**: After all possible orders are matched, the order list is cleared for the next day. This allows all agents to make new decisions based on price changes.
- **Order Matching Based on Quantity**: In contrast to paper [2], where order matching is based on price, our model matches orders according to the quantity of bitcoins involved.
- **Full Transactions Only**: Agents must buy and sell everything in a transaction. Partial purchases are not allowed. This assumption simplifies the model.
- **Price Generation**: As outlined in paper [1], the Bitcoin price is generated based on the order book dynamics.
- **Agent Decisions**: Each agent has three possible decisions: to buy, sell, or hold. Even random agents can make these choices.
- **Single Purchase Per Day**: Agents are allowed to buy only once per day. If an order is matched, the agent is removed from the order book for that day, even if they have more money to buy additional bitcoins. This contrasts with paper [2], where agents can place multiple orders on the same day.
- **Simulation Time Step**: Each simulation step represents one day, including weekends and holidays, since the Bitcoin market operates every day of the week.
- **Momentum Decision (Initial Phase)**: When there aren't enough past days to calculate the trend for momentum, the momentum signal will be generated, continuing until a decrease is observed.
- **Volatility Decision**: Similarly, in the volatility decision, at the beginning of the simulation, when there are not enough days to calculate the signal, the volatility signal is calculated based on the available days.

Task 2 – Running and Analysing the Model

Task 2.1 – Model Execution and Parameter Tuning (7 marks)

Run your model from January 1, 2020, to November 1, 2024, varying parameter n (justify your choice of range). Analyse the behaviour of the agents as n changes. Do agents with higher values of n exhibit fewer or more trades? What other conclusions can you draw form this analysis?

Using the given parameters and previously defined constants, the number of days for the momentum rule (denoted as *n*) is tuned to assess its influence on the market. The *n* parameter determines when a momentum rule opens a position, analysing whether an upward trend has occurred over the last *n* days. The selection of this parameter is critical, as it can lead to late entries into the market for some agents, depending on the direction and stability of the market trend (upward or downward).

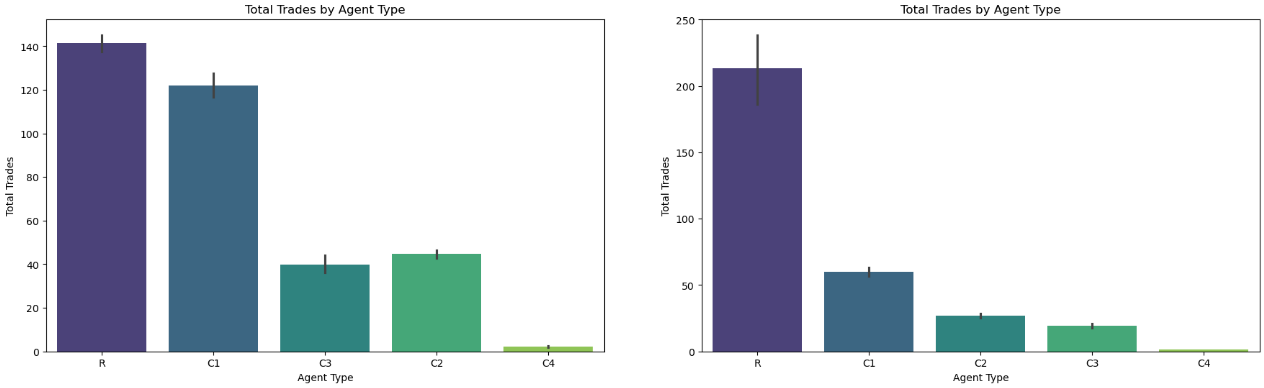
It is important to note that any change in the *n* parameter will impact the behaviour of chartist agents, who represent 60% of the simulation. The parameter influences agents in the following order of importance: C1 (80% momentum – 20% RSI), C4 (momentum rule followed when weekly volatility is less than 2.5%), C3 (balanced approach of 50% momentum – 50% RSI), and C2 (80% RSI and 20% momentum). The simulations were conducted using a random seed of 13 to maintain stability in the results, and the results reflect a single simulation.

To analyse the agents' behaviour, simulations will be run with both short-term time horizons (2-5 days) and long-term time horizons (5-20 days). This will allow for the observation of how different timeframes affect the agents' trading strategies and their overall performance.

Short Time Horizons:
Using a short time horizon of n=2 resulted in high activity among the chartist agents, particularly C1, which aligns with expectations, as well as C3 and C2. However, when the n value was increased to a long-term horizon of 20 days, the dynamics of C1, which primarily uses momentum, decreased significantly, as did the activity of the other chartist agents. It is worth noting that this analysis is based on a single simulation. Additionally, the number of trades reflects the total sum of buys and sells executed by these agents during the simulation.

Figure 2 - Total trades by agent type

n=2 n= 20



In terms of the market, when a short-term n value is chosen, there are more momentum signals to buy, as the market is more responsive to small price movements (Figure 3). However, with a long-term momentum (n=20), the momentum signal becomes active only during significant upward trends that last for at least 20 days. This is expected, as long-term trends require more sustained price movements, and thus the momentum signals are less frequent but typically represent stronger trends when they do occur.

n= 2 **n= 20**

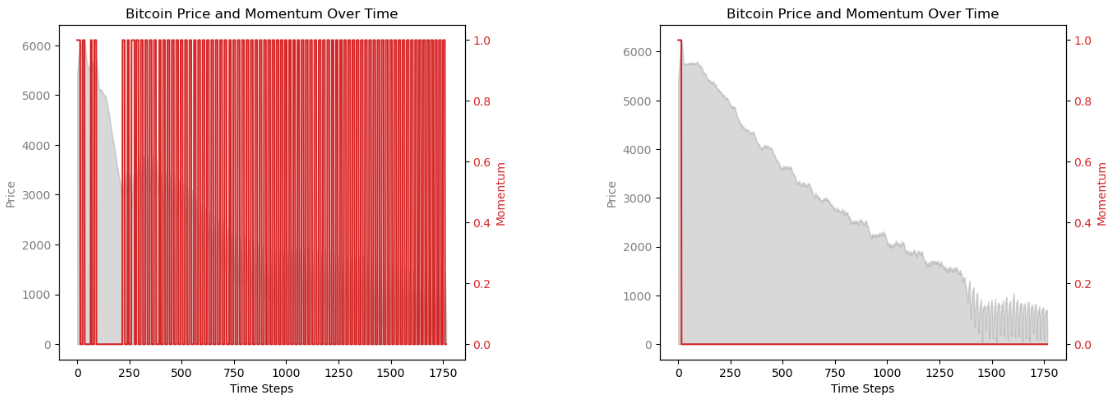


Figure 3 - Momentum over time

In general, it is observed that when the number of days (n) changes, some statistical metrics also change, such as an increase in kurtosis. However, it is important to point out that even for different values of n, the model consistently returns heavy tails, as shown in the table 1, demonstrating the robustness of the model in this metric.

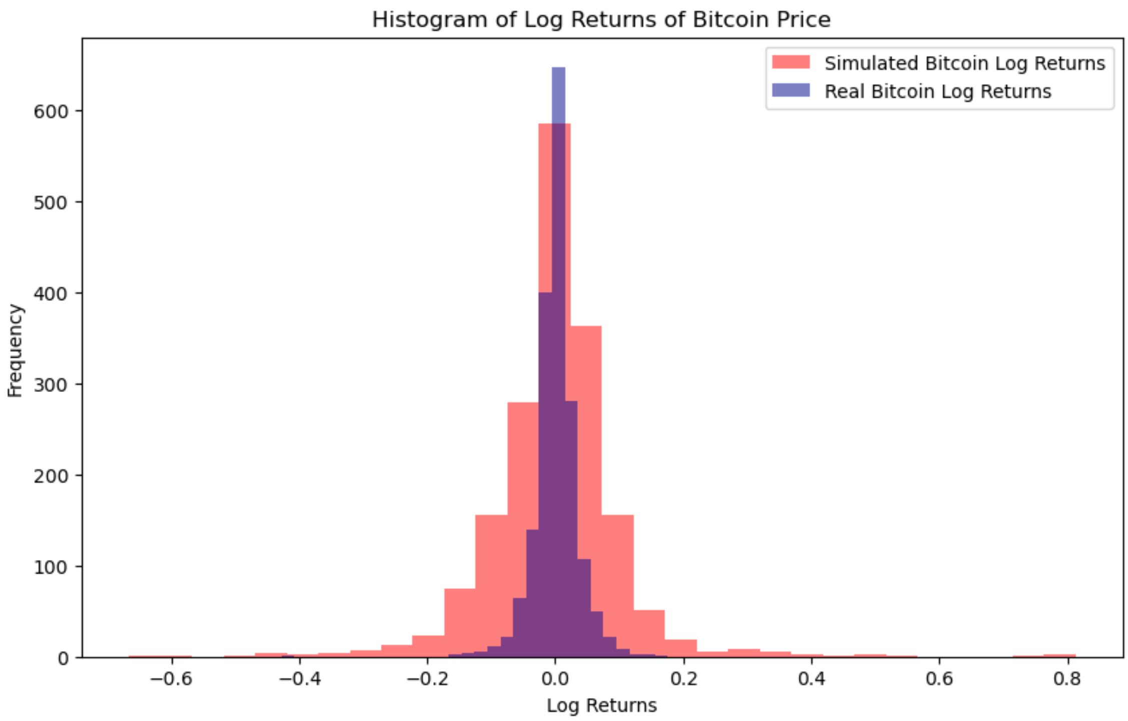
Table 1- Statistics metrics over simulation of momemtum

Sim	N_momentum	Kurtosis	Volatility	Mean	Skewness
0	2	17.803143	0.159372	-0.001552	1.8815770
1	3	432.753204	0.261688	-0.001548	9.720385
2	5	230.346924	0.332487	-0.00157	8.415009

3	10	17.803143	0.120162	-0.001552	1.881577
4	20	30.551347	0.162217	-0.001464	2.851431

As it was mentioned before, those results correspond to one simulation using the same random seed. A future improvement of this work would be to test it with different seeds as the works [1] and [2] mentioned where they repeated 100 simulations with the same initial conditions, but different seeds of the random number generator.

By using output validation with the real BTC prices, it is observed that n = 2 could be a good option, as it reflects a similar behaviour in log returns compared to the real prices. However, it is also important to mention that metrics such as skewness, which indicate the gain/loss asymmetry, are not met, leaving room for improvement in the model.



Task 2.2 – Performance Comparison (15 marks)

The following analysis will be run using the parameters mentioned above, along with the last parameter, n = 2, which was calibrated earlier.

Ratio of GBP to Bitcoin Held:

Evaluate the proportion of wealth held in GBP versus Bitcoin for each agent type to understand their asset allocation strategies. Consider how this ratio changes over time and how that compares to the final ratio at the end of the simulation.

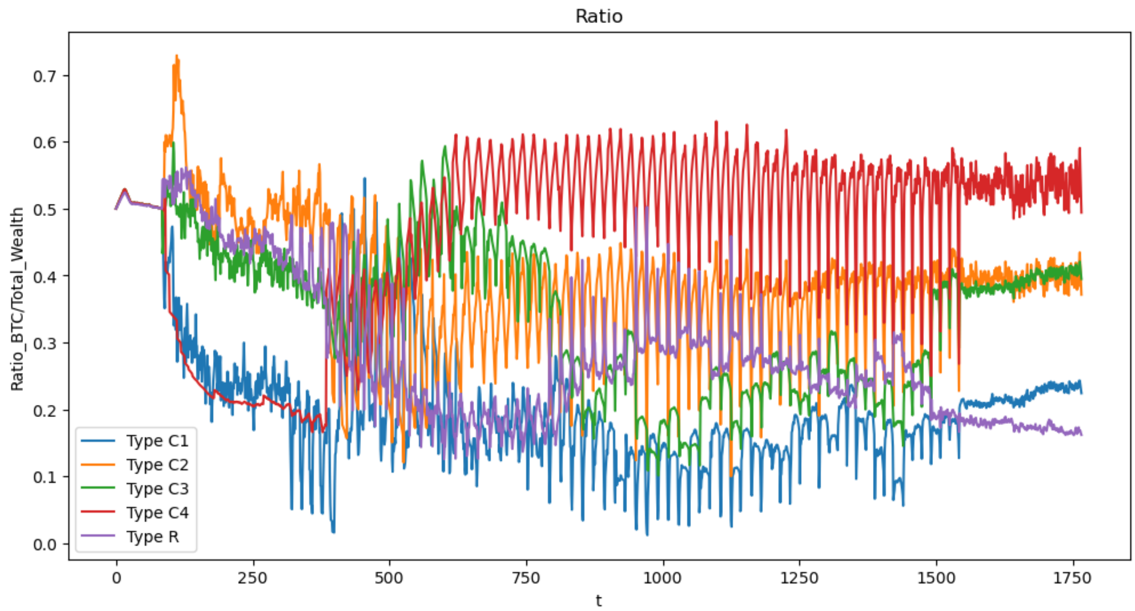


Figure 4 - Ratio BTC/Total Wealth

Overall, the figure shows that the chartists held more BTC in their wealth than the random agents. In fact, at the end of the period, the random agents had the lowest BTC/Wealth ratio compared to the others. This outcome could be expected for type C4, as this type of agent maintained long-term positions, whereas types C1 and the random agents mostly held short-term positions.

Total Wealth (GBP + Bitcoin):

Asess the overall wealth of each agent type, combining both GBP and Bitcoin holdings to observe their financial performance.

Figure 5 - Total Wealth GBP + BTC

Since the simulated market had a downtrend, it is expected that chartist type 1, as well as the random agents, would have the least wealth, while conservative and more risk-averse agents like type C2 and C4 would have higher wealth at the end of the period. However, it is important to point out that the wealth of type C2 exhibited high volatility, which was unexpected, given that they mostly followed the RSI rule.

Exposure Time:

Measure the percentage of time the agents have an open position in the market over the simulation period.

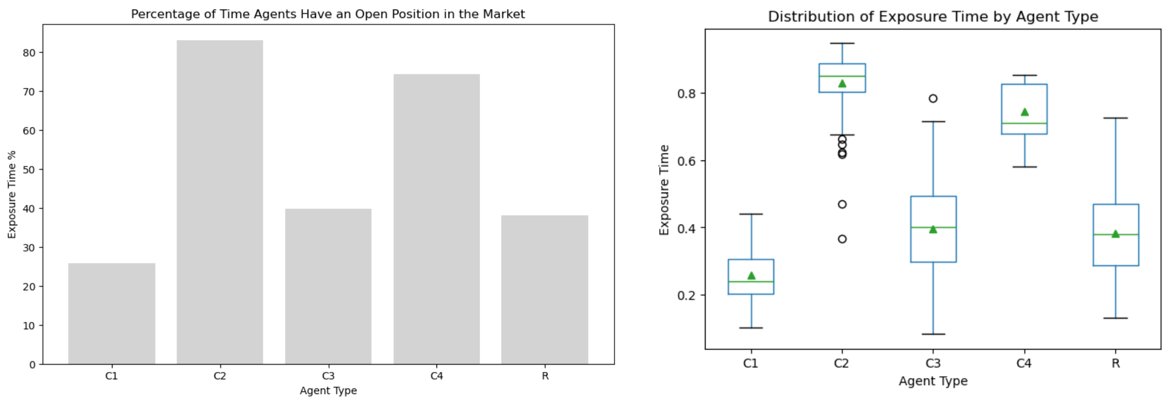


Figure 6 - Exposure time %

Figure 6 shows that the agents with the most exposure time were chartist types C2 and C4, which was expected given their long-term positions in the market. It is also observed that random agents held open positions about 40% of the time, which makes sense, as they made random decisions based on three options: buy, sell, and hold (Figure 7). An interesting point to highlight is that chartist C1 had fewer open positions than the random agents, which was expected, as they waited for an upward trend, while the market mostly showed a downtrend. As a result, they had the lowest exposure time among all the agents.

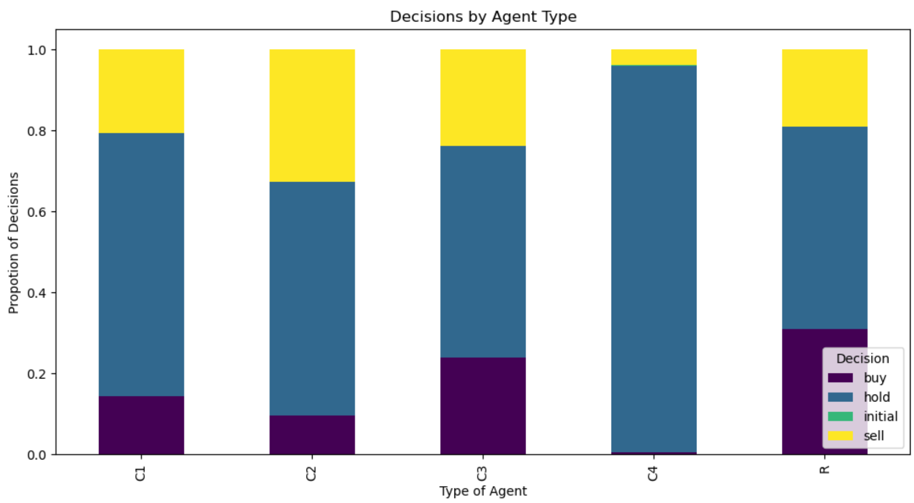


Figure 7 - Proportional decisions over agents

Win Rate:

Calculate the percentage of profitable trades for each agent type to understand their trading effectiveness and consistency in generating positive returns.

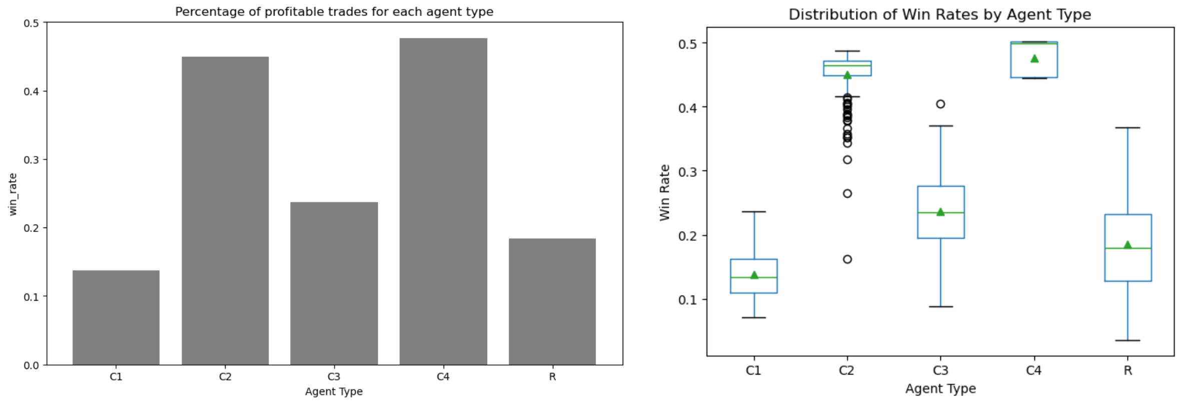


Figure 8 - Win rate

Figure 8 illustrates that Chartist C4 definitely had the highest win rate, maintaining the metrics with little deviation, which was expected given the risk management behaviour of this agent. Meanwhile, Chartist C2, despite obtaining a good win rate, shows significant outliers, possibly reflecting some momentum-based decisions. On the other hand, random agents exhibited high deviation in their win rate compared to other agents, which was expected due to their random decision-making process.

Maximum Drawdown:

Measure the maximum drawdown (the largest peak-to- trough decline) experienced by each agent type.

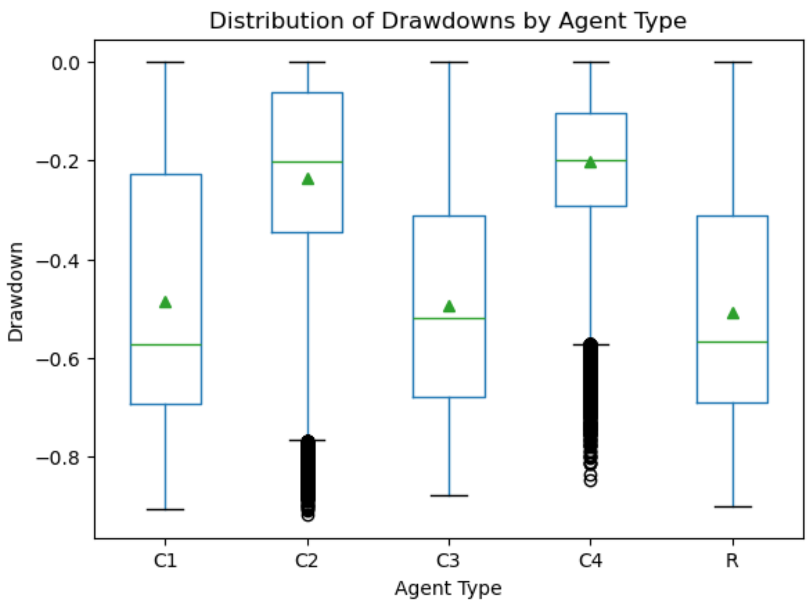


Figure 9 - Drawdown of agents

Figure 9 shows that the agents with the lowest drawdown were C2 and C4, with some outliers, which is expected given the downtrend. Meanwhile, C1, C3, and C4 showed similar behaviour, which was unexpected since random agents did not follow any strategy.

Task 3 – Model Validation

Task 3.1 – Market Dynamics Validation (8 marks)

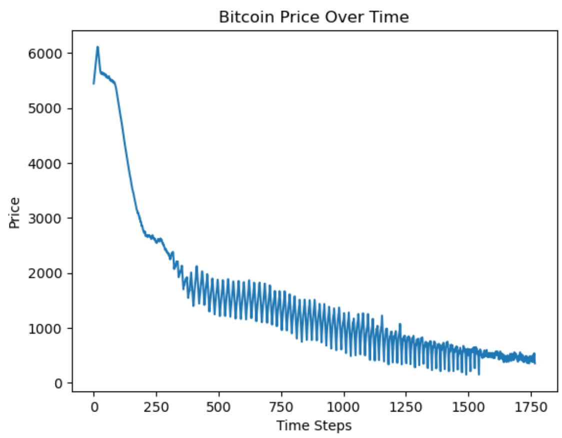
Compare your model results with findings from Cocco, Tonelli, and Marchesi or other sources. Focus on agent wealth distribution, Bitcoin price movements, and trading volume trends. Discuss any differences in metrics and and how they might be affected based on model assumptions.

For making this comparison two works by Cocco et al. [1] and [2] were taking into account.

Work [2] compared to this work:

To start with, the Bitcoin price movements shown in Figure 10 compare this simulation with the one done in the paper [2]. It is immediately noticeable that both simulations are completely different, as the simulation by Cocco et al. presents an upward trend, while the simulation in this work shows a downtrend.

This simulation



Cocco at al. simulation [2]

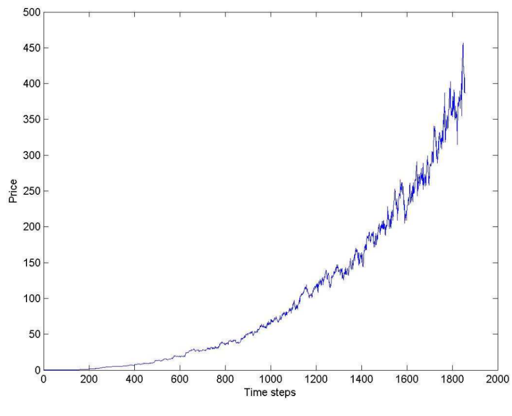


Figure 10 - Bitcoin simulated price with paper [2]

Some of the main differences between the assumptions made in work [2] and this one are:

- the initial points are different because they started the simulation from September 1st, 2010 and September 30th, 2015.
- The time period is different in this model 1750 steps were used in [2] work 1856. However, something similar is that a simulation step corresponding to one day. We included also weekends and holidays, because the Bitcoin market is, by its very nature, accessible and working every day.
- In work [2] they distributed the cash in different way, therefore they had richest trader whereas in this work the same quantity of bitcoins and bgp were distributed.

- In work [2] include traders over time starting from 160 and ending with 39649.
- The agents in work [2] were able to buy to a different agents in the same t, having more than 1 order in the order book ar the same time. In this work it is assumed that a trader can put just one order by day.

In terms of wealth for each agent, in work [2], it is observed that random agents had higher wealth compared to chartist agents. This could be explained by the uptrend in Bitcoin prices shown in their model. In contrast, in this work, since the trend was downward, random agents showed more losses than gains.

This simulation

Cocco at al. simulation [2]

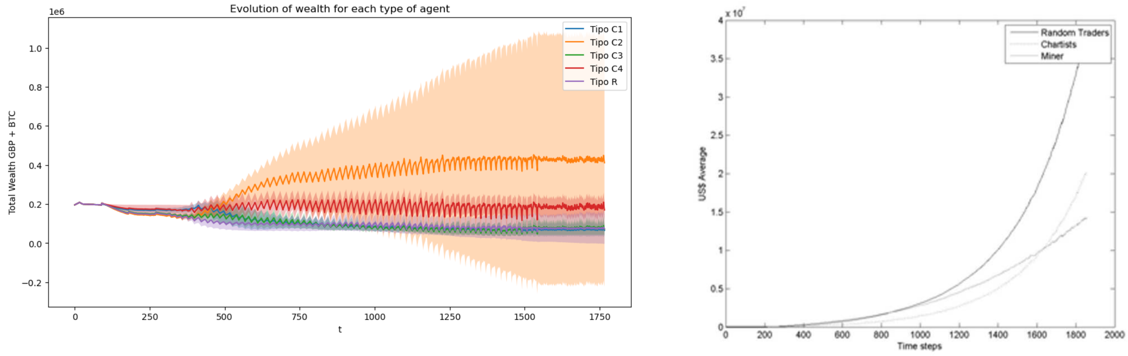


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Figure 11- Total Wealth of each agent compared to paper [2]

It is important to note that work [2] acknowledged its inability to reproduce the decreasing trend of the price, even though it was able to replicate many of the statistical properties of real Bitcoin prices and returns quite well. The stylized facts were robustly replicated by their proposed model. With this in mind, this work analysed the stylized facts where work [2] showed a high kurtosis with a median of 7.6, while this work presented a kurtosis of 17. Although the values are different, both meet the patterns typically seen in financial markets in terms of kurtosis. In terms of skewness, it is worth noting that both studies show similar values. Finally, with respect to the mean, the difference in values is reflected in the sign, with this work's model reflecting downtrends.

Table 2 - Statistics metrics of paper [2]

Descriptive statistics	**Percentile Value**			
	.25	**.50**	**.75**	**.975**
mean	0.0052 (0.0228)	0.0053 (0.023)	0.0053 (0.024)	0.0054 (0.025)
st. dev	0.032 (0.023)	0.033 (0.024)	0.034 (0.025)	0.036 (0.027)
skewness	0.4 (2.05)	0.6 (2.4)	0.81 (2.6)	2 (5)
kurtosis	6 (9.9)	7.6 (12)	9 (17)	25 (58)

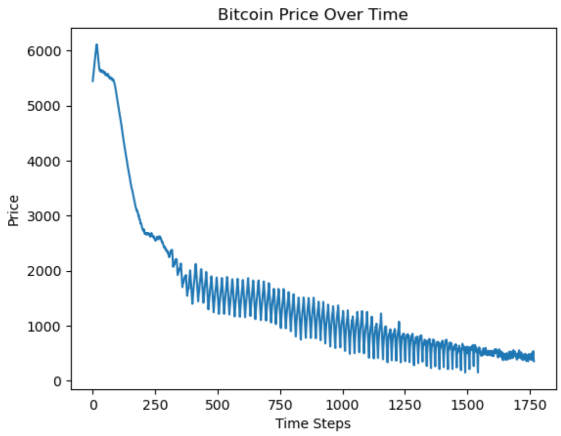
Table 3 - Statistics metrics for this simulation

Kurtosis	Volatility	Mean	Skewness
17.803143	0.159372	-0.001552	1.8815770

Work [1] compared to this work:

Comparing the model with paper [1], it was noticed that, similar to paper [2], the Bitcoin prices maintained an upward trend over time, whereas this simulation showed a downtrend, despite having fluctuations over time.

This simulation



Cocco at al. simulation [1]

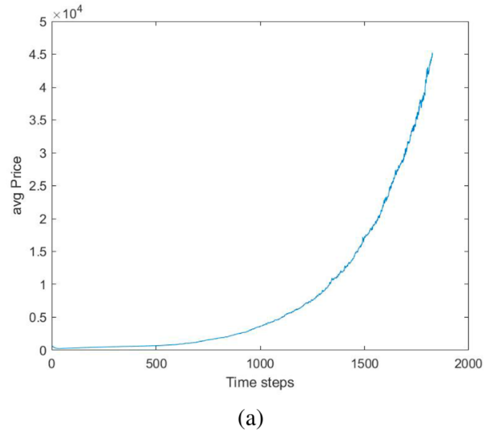


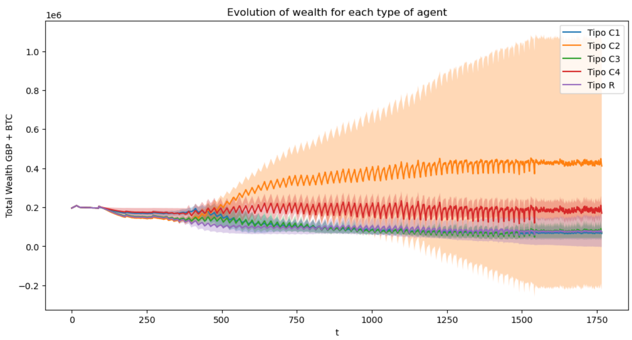
Figure 12 Bitcoin simulated price with paper [1]

Some differences between those models were:

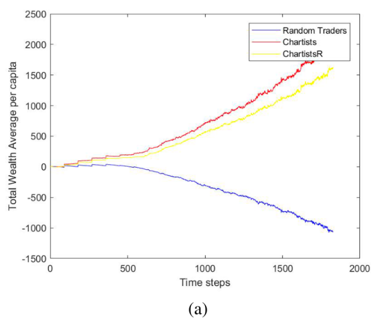
- The paper [1] used two kind of chartist, Chartists and Random traders. Nonetheless part of Chartists trades applying the best sets of trading rules selected by a genetic algorithm that simulates a trading system.
- The paper [1] assumed that only 60% of the BTC were trader assuming the 40% left were unavailable to trader.

Figure 13 - Total Wealth of each agent compared to paper [1]

This simulation



Cocco at al. simulation [1]



In terms of total wealth, both simulations have in common that random traders obtained the lowest wealth. However, paper [1] shows a dramatic change in wealth from the beginning to the end of the period, while this simulation shows only slight changes over time.

Task 3.2 – Comparison to Real-World Data (10 marks)

Discuss the changes in Bitcoin prices over the period by analysing the log-returns. Compare the log-returns obtained from your model with those in the article and real-world values. Why do you think the prices in your model do (or do not) match published findings? How does the volatility (the degree of price variation) in your model compare to real Bitcoin price changes? Does your model show similar patterns of price jumps or drops as seen in actual Bitcoin data? Give examples.

Log returns are the metric used to compare this model with empirical data extracted from [3], in order to validate if the ABM model follows the same patterns as the financial market. To review the stylized facts, statistical metrics such as mean, variance, skewness, and kurtosis are used.

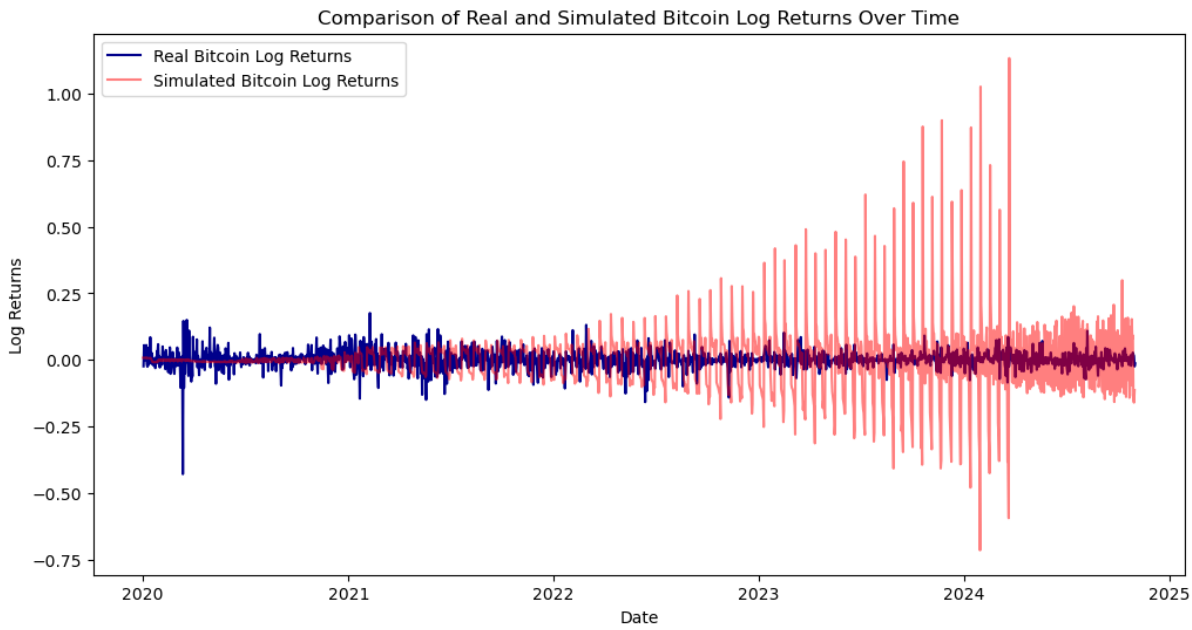


Figure 14 - Log returns of real world and simulated model

Figure 14 shows the log returns of real-world Bitcoin prices for the same dates, along with the simulated BTC returns. It can be seen that at the beginning of the period, around 2021, both graphs exhibit similar patterns. However, towards the end of the period, the model captures significantly higher volatility. The differences between these models can be explained by the assumptions made to simplify the ABM. Additionally, the real-world graph shows that Bitcoin prices are heavily affected by exogenous factors, such as the pandemic. The ABM cannot capture these exogenous factors, as the model's assumptions remain constant throughout the entire studied period.

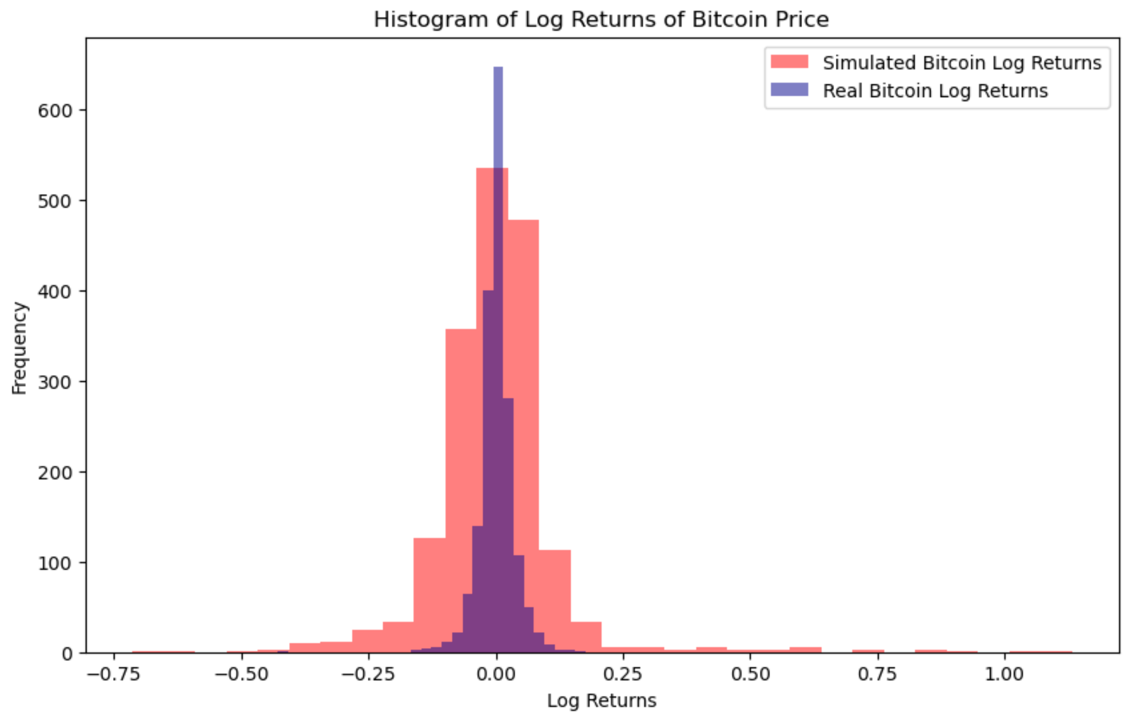


Figure 15 - Histogram of log returns of real world and simulated model

Even though the model has simple assumptions, it is observed that peaks and long tails appear, indicating that, like in the real world, a few extreme events occurred. This can also be confirmed through the kurtosis of the simulation, as shown in Table 4.

Table 4- Statistics metrics of real world and simulation

	Kurtosis	Mean	Skewness
Real world	17.302171	0.00129851	-1.16195696
Simulated	17.80314	-0.0015523	1.88157705

Another important point is Skewness, which helps identify the asymmetry between gains and losses. In the ABM, it is shown that, in contrast to the real world, skewness is positive, which makes sense since the price of BTC experienced downtrends most of the time. This is different from the real world, where downward movements are larger but less frequent, while upward movements are smaller but more frequent. This is something that should be taken into account for improvement.

Task 3.3 – Agent Behavioural Impact (5 marks)

Evaluate how differences in agent behaviour (e.g., frequency of trades, risk tolerance) could affect market volatility in your model. How realistic do you find these behaviours, and what adjustments might improve accuracy?

Some assumptions that could be changed to make the model more realistic are:

- Assuming the same number of agents in a currency that is becoming popular is unrealistic. It would be expected that new agents enter the market, generating different trends.
- A market where nothing happens except for price changes is less realistic, as it should be expected that events such as the pandemic and political movements around the world would affect traders.
- The assumption that agents buy and sell all their BTC is also unrealistic, as in a real market, agents should decide how to maximize their resources.

Task 4 – Propose a New Agent Class

Task 4.1 – New Agent Design (5 marks)

Design a new agent class, citing relevant literature or online resources. Define their entry/exit rules and their decision logic. To fully define this new agent class take into account the four steps for agent design we have seen in class.

Taking into consideration that the model has a downtrend, a new agent is developed to contrarian the market. Based on [4], the contrarian investing is investment strategy where investors deliberately go against the prevailing market trends, buying when most are selling and selling when others are buying. Contrarian traders think differently from most, avoiding trading based on fear. Their behaviours are:

- Open position: They will open position when they identify that the last period the majority of the market sold or had the intention to sell.
- Close position: They will close position when they identify that the last period the majority of the market bought or had the intention to buy.

The main metrics is the number of sellers and number of buyers each period. Figure 16 shows the trends of sellers and buyers in the market simulated with 40% of random agents and 60% of chartist agents.

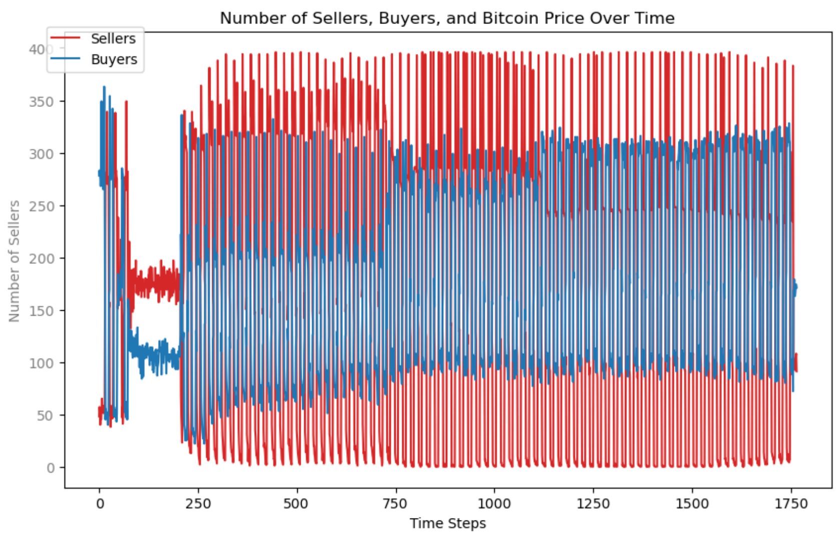


Figure 16 - Seller and buyer over time

Task 4.2 – Market Impact Analysis (7 marks)

Analyse the impact of your new agent class on the market. Describe how the addition of this agent type changes overall market trends, volatility, or price stability. How does it affect the monthly earnings and wealth accumulation of the other agents?

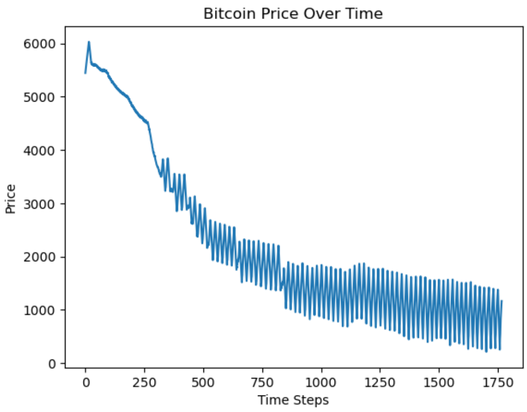
It is expected that this contrarian agent (CT), based on the actions of others in the previous period, introduces confusion into the market for chartists who are waiting for opportunities. This is because their behaviour is perceived as irrational by 60% of the agents. Nevertheless, it is also anticipated that they help maintain low volatility. As the number of contrarian agents increases, they can manage the volatility generated by price changes, even avoiding significant fluctuations.

The market was simulated using different percentages of this type of agent: 10%, 20%, and 30%. The scenarios were as follows:

Scenario 1: 30% Random – **10% Contrarian** – 60% Chartist (divided into C1, C2, C3, C4)
Scenario 2: 20% Random – **20% Contrarian** – 60% Chartist (divided into C1, C2, C3, C4)

Figure 17 and Table 5 demonstrate that these agents generally helped to maintain low volatility. This was expected, as they avoided making significant loss-inducing decisions contrary to the market trend. It is worth noting that in Scenario 2, the price was higher than in Scenario 1, averaging 2808 in Scenario 2 compared to 2211 in Scenario 1.

Scenario 1 – 10% CT



Scenario 2 – 20% CT

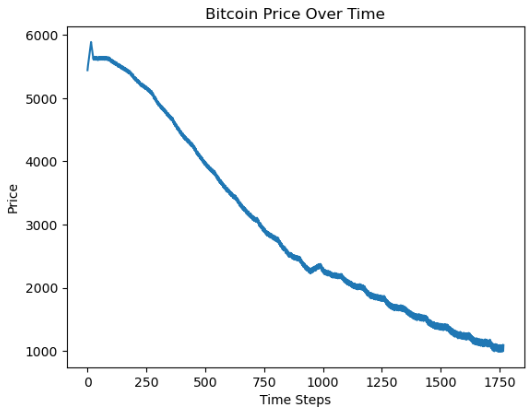


Figure 17- Price with new agent

Table 5- Changes in price with new type of agent

Scenario 1		Scenario 2	
count	1767	**count**	1767
mean	2211.694397	**mean**	2808.940577
std	1491.87251	**std**	1476.31053
min	211	**min**	794

25%	1143	**0.25**	1569.5
50%	1634	**50%**	2380
75%	2922.5	**75%**	3999
max	6029	**max**	5964

In terms of volatility, Figure 18 shows that with more contrarian agents volatility decrease.

Scenario 1 – 10% CT **Scenario 2 – 20% CT**

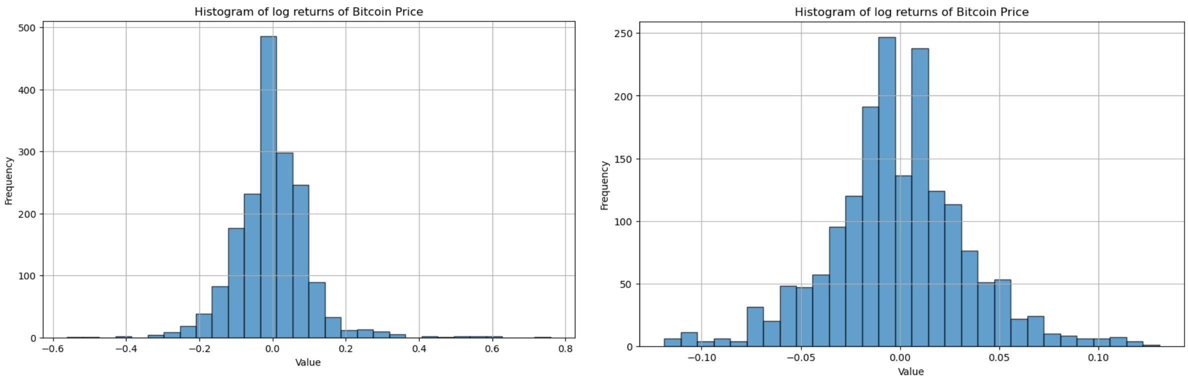
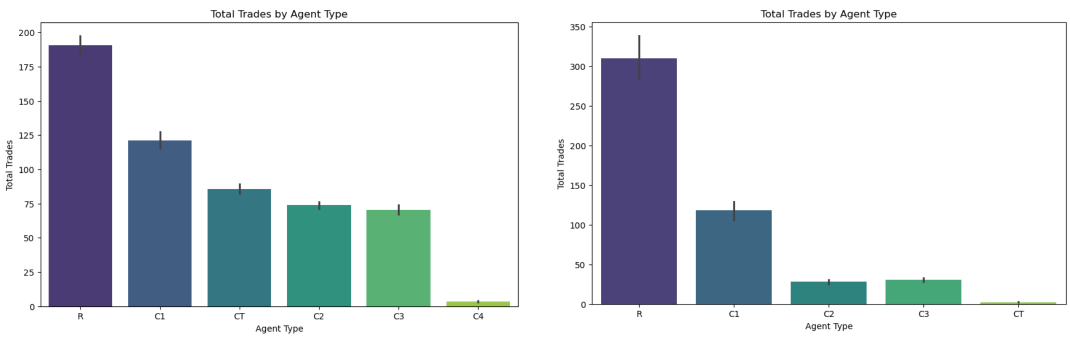


Figure 18 - Histogram of log returns new agent

In terms of traders, it is interesting to highlight that as contrarian agents increased, chartists started reducing their participation in market trades. This could be explained by the low volatility, which does not allow significant changes in the market for long-term positions. In fact, random agents and chartists C1, using 2-day momentum strategies, were the most active traders in Scenario 2.

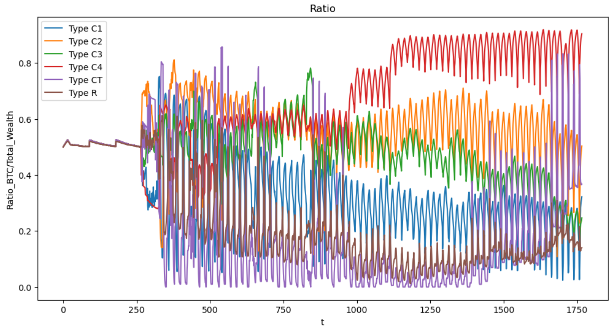
Scenario 1 – 10% CT **Scenario 2 – 20% CT**



Task 4.3 – Performance Discussion (8 marks)

Compare the new agent class with chartists and random traders across the different performance metrics. Discuss the advantages and disadvantages of your agent and evaluate their effectiveness in volatile conditions. Could this agent type reflect real trading behaviours? Why or why not?

Scenario 1 – 10% CT



Scenario 2 – 20% CT

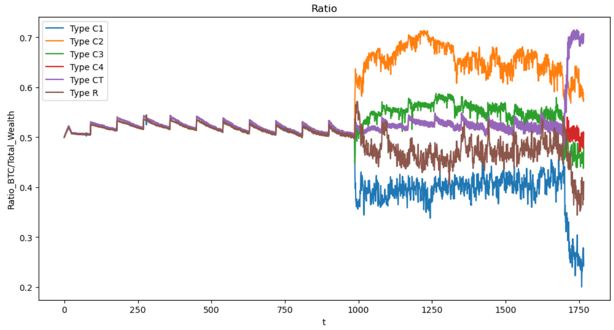
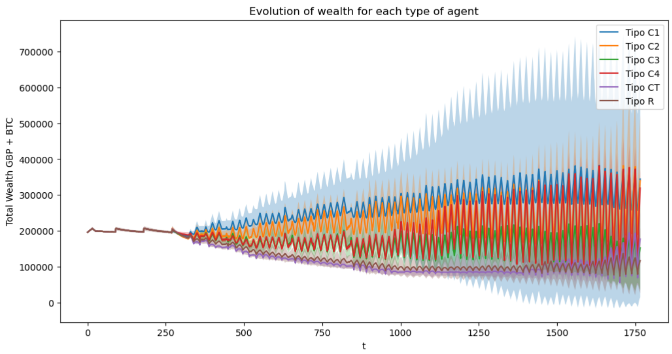


Figure 19 - Ratio BTC with new agent

In terms of the BTC ratio, contrarian agents ended up with the highest ratio. This could be explained by their irrational movements against the market, as the majority of agents either reduced their ratios or, like C4, maintained a balanced ratio of around 50% most of the time. It is also interesting to point out that in the first scenario, high volatility regarding the BTC ratio was observed. However, in a market with low volatility, all agents began making slower decisions.

Scenario 1 – 10% CT



Scenario 2 – 20% CT

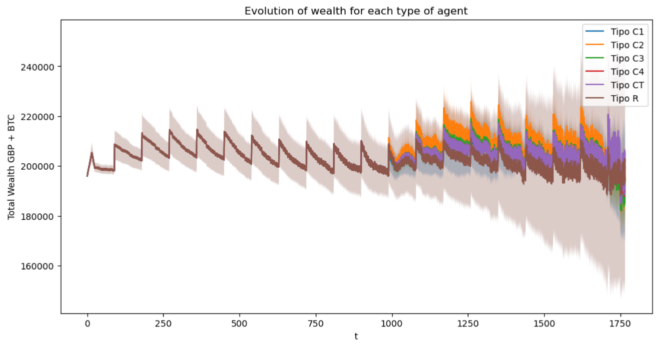


Figure 20 - Total wealth witn new agent

Regarding wealth, Figure 20 shows that in the higher-volatility market of Scenario 1, Chartist C1 and most agents exhibited significant fluctuations in their total wealth. However, in Scenario 2, with lower market volatility, chartist agents made decisions more cautiously, reducing the volatility in their wealth. Meanwhile, random agents showed the highest standard deviation in wealth. It is also noteworthy that C2, with long-term positions, and contrarian agents maintained the highest wealth, while others retained the same wealth they had at the beginning of the simulation. This aligns with the reduced market volatility.

Scenario 1 – 10% CT **Scenario 2 – 20% CT**

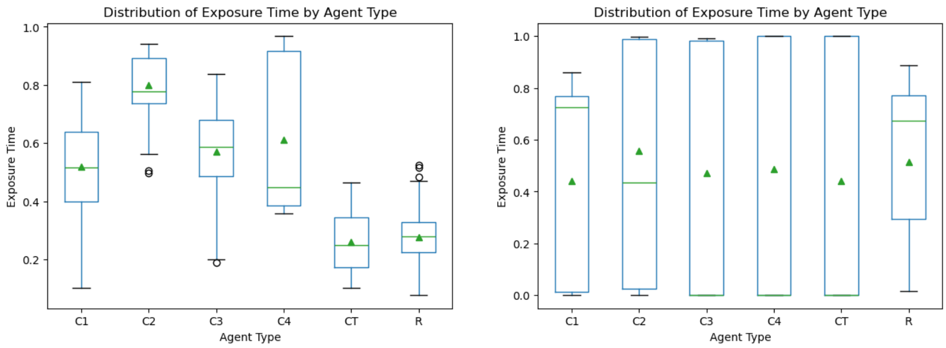


Figure 21- Exposure time with new agents

Figure 21 shows the effect of exposure time for new agents. In the first scenario, contrarian agents behaved similarly to random agents, while the rest of the agents traded as usual. However, as the proportion of contrarian agents increased, the market conditions changed, becoming less volatile. This led most chartist agents to adopt a holding strategy, waiting for better opportunities.

Scenario 1 – 10% CT **Scenario 2 – 20% CT**

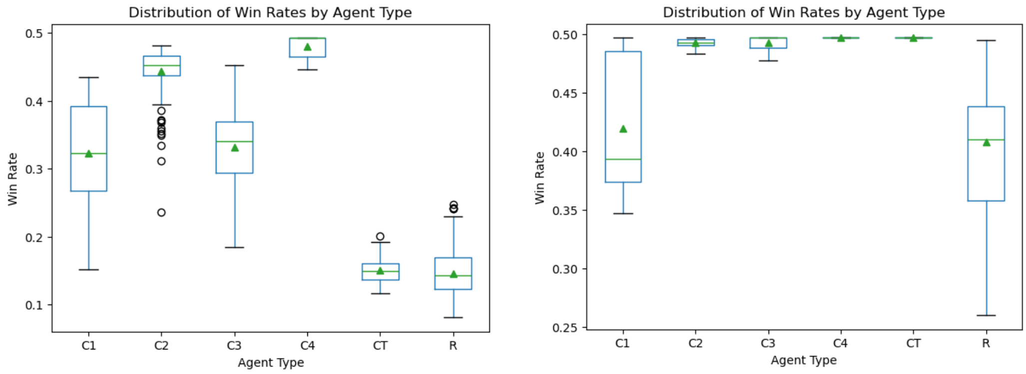


Figure 22 - Win rate with new agent

Figure 22 illustrated that most of the agents ended up with a 50% win rate in Scenario 2, indicating that, on average, they neither significantly outperformed nor underperformed the market. This could be interpreted as the agents' strategies not providing them with a substantial advantage or disadvantage in terms of wins versus losses. Nonetheless, it is important to point out that random agents, as expected, had a lower win rate compared to the others since they made decisions randomly.

Scenario 1 – 10% CT **Scenario 2 – 20% CT**

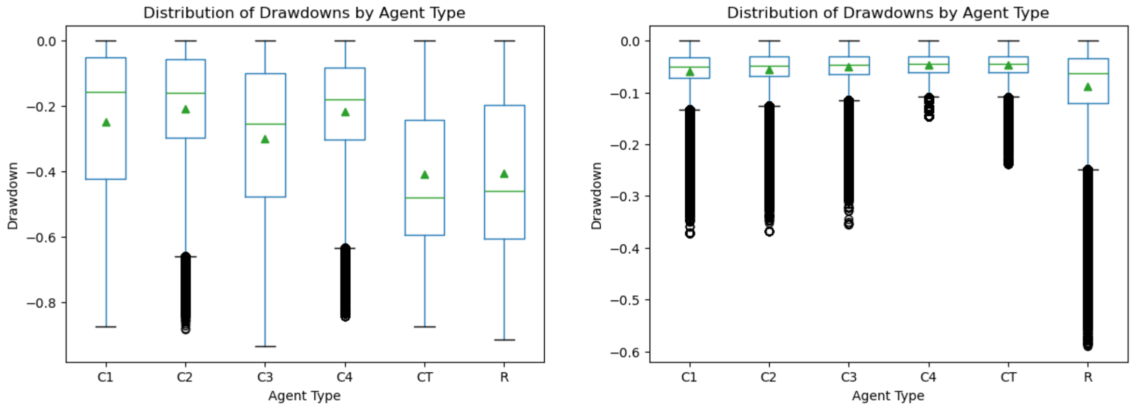


Figure 23 - Distribution of drawdown with new agent

As expected, after the previous indicator, the drawdown for most of the agents, except for the random ones, was close to zero. This makes sense due to the slow movement in the market, where 60% of the chartists were waiting for opportunities, and most of them maintained their positions.

Finally, as shown across the different metrics, the effect of the new agents on the market was to reduce volatility, as they consistently balanced the market behaviour. When there were many purchases, they sold, and when there were many sales, they bought. Additionally, as the number of contrarian agents increased, the market became relatively stuck, with few movements, as most chartists waited for opportunities. This lack of movement is not realistic, as it does not reflect the dynamic nature of real-world markets.

Task 5 – Summary Report (5 marks)

Write a brief report (approx. 250 words) summarizing the results, performance of each agent type, model limitations, and possible improvements. This report should include any limitations of the ABM you created (anything you think affected your results), performance of different agents, any improvements you can think of, etc.

This work aimed to represent the market conditions in the BTC/GBP market. The model was constructed using parameters from the literature, empirical data, and assumptions based on common sense to simplify the simulation. Regarding the model's behaviour, many assumptions were made; however, these assumptions present limitations when trying to represent real-world market conditions. The main limitations that could be improved in the future are: incorporating an order book based on the price that agents wish to buy rather than using quantities, allowing agents to make multiple orders on the same day, enabling agents to decide how much of their wealth they want to trade (instead of trading all of it), increasing the number of agents during the simulation and introducing exogenous factors like a pandemic.

In terms of agents, four types were constructed: chartists and random agents. These agents followed rules based on momentum, RSI, and randomness. Since the momentum decision relies on n-days, to be activated, simulations were conducted to determine the optimal value that could better represent the market. Additionally, the momentum strategy was designed to close the position after one day of loss. It would be interesting to explore different durations for being out of the market. Regarding the results, chartist C4, the most rational agents, achieved the highest wealth, while random agents had the worst performance throughout the simulation.

After running some simulations, the price movements did not align with the real-world trends and prices. However, the model did capture some stylized facts typical of financial markets, such as high kurtosis. The main limitation of the model was its inability to reproduce sudden price increases, keeping the same assumptions throughout the entire simulation.

Finally, a new type of agent was introduced: contrarian agents who make decisions based on the actions of others, following a cognitive bias that leads them to take the opposite position. The effect of these agents on the market was that, initially, they maintained the market's volatility, but after adding 20% contrarian agents, the market became stuck, with only random agents and a few C1 agents driving any movements.

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