Trading Strategy Interactions: An Agent-Based Model of Market Dynamics

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Introduction

This report investigates how different trading methods behave and interact in financial markets using agent-based modeling, or ABM. ABM provides a solid foundation to analyze complex systems by evaluating how individual agents' actions affect the market environment. This simulation explore the dynamics of various trading strategies and their role in influencing market outcomes . A variety of agent types - RandomTraders, Chartists (MomentumDominant, RSIDominant, Balanced, Alternating), and ContrarianTrader were added to the simulation. Each agent type represented a unique approach to trading. Random Traders' had an unstructured approach to making decisions, the four other Chartists' relied on systematic strategies which have technical indicators, and the Contrarian Traders relied on a counter-trend strategy. These agents attempted to create a realistic market environment, where trends, volatility, and liquidity emerge from their interactions. The main goal of this simulation is to analyse the performance of these agents in different market scenarios, especially when the market volatile and stabble. Metrics such as wealth accumulation, exposure time, win rate, and drawdown are used to compare the effectiveness of each strategy. Adding mechanisms such as Gibrat's Law of Proportional Growth, Petrov's Price Response Function, and market corrective features guarantees that the simulation accurately depicts the dynamics of the financial markets. This study emphasizes how different trading tactics contribute to market stability, efficiency, and volatility by examining not just the performance of individual strategies but also how they interact with one another. With an emphasis on how systematic, contrarian, and random tactics affect financial markets and offer chances for risk and profit management, the findings seek to shed light on the practical consequences of trading behaviors.

Task 1 - Agent Construction

The assumptions made to develop the agent based model (ABM) to trade Bitcoin against GBP are backed by historical data and past studies . At the start, each agent is initialized with 5,000 GBP and 0.5 Bitcoin. This provides the traders with a moderate investment size. According to research 5,000 GBP is the average investment size observed in retail cryptocurrency markets, and individual portfolios typically lie within this range [15]. Studies also suggest that over 97.7% of Bitcoin holders own less than 1 Bitcoin, with median holdings significantly below this threshold, making 0.5 BTC a reasonable representation of an active participant's starting balance in 2020 [24]. The starting price of Bitcoin is set at 5,472 GBP based on its historical worth as of January 1, 2020. This assumption matches with the simulation period stated in the assignment to maintain consistency with real-world market conditions [47]. The model assumes 100 to replicate a small but diverse group of agents. The model ALSO increases Bitcoin supply by 10% every 90 days, and distributes it based on proportional ownership. This differs from real-world issuance rates, but it satisfies the assignment's requirements to simulate a "rich get richer" scenario, also known as the Gibrat principle of preferential attachment [14]. These assumptions provide a realistic yet simplified framework for modelling agent behaviours and market dynamics.

Task 1.1 - Define Chartist

Rules and decision weights of chartists were designed to accurately mimic the behaviour of these chartist. This helped the model to stay grounded in market dynamics and meet the assignments objectives. These Chartist we subcategorised based on 4 rules to represent different trading goals and risk appetites. These rules revolved around two principles - Momentum based rule and Relative Strength Index (RSI-rule) The purpose of the momentum-based rule was to simulate a trend-following approach, where Chartists open positions after observing consecutive upward price trends for n days. This strategy is studied in financial literature, demonstrating its effectiveness to identify bullish market conditions [27]. Positions are closed when a single downward movement is detected, which reflects traders' tendency to reduce losses during bearish trends [11]. Behavioral finance theories, suggest that trend-following is a prominient strategy among retail traders [3].The RSI rule, based on a 14-day period, is used to spot overbought or oversold market conditions. When the RSI value drops below 30, chartists typically open positions. This signals that the market is oversold and hints there could be an upward momentum. These positions are closed when the RSI value rises above 70, indicating that the market is overbought and there could be a downward pressure [46]. Market psychology is reflected in this strategy since traders typically take advantage of chances when RSI levels reach certain extremes [39]. In the given formula Average Gain represents the average of positive price changes while the Average Loss is the average of negative price changes.

$$\text{RSI} = 100 - \frac{100}{1 + \frac{\text{Average Gain}}{\text{Average Loss}}}$$

Four subtypes of Chartists were introduced, each prioritizing

Agent Type	Behavior	Performance	Wealth Accumulation	Activity
Momentum Chartists	Follow price trends; buy in uptrends, sell in downtrends.	Best in trending markets with clear directional movements.	High during prolonged uptrends, as they capitalize on sustained price increases.	Moderate: Trade frequency tied to trend signals. They rely on momentum
RSI Chartists	Use RSI to identify overbought/oversold conditions for mean-reversion.	Best in range-bound or volatile markets with frequent reversals.	Moderate: Benefit from small market corrections rather than sustained trends.	Low: Signals are less frequent than momentum indicators. They do not rely on momentum
Balanced Chartists	Combine momentum and RSI strategies equally for balanced decision-making.	Steady performance in varying conditions but may not excel in extremes.	Moderate: Benefit from diversified strategy but may miss optimal conditions.	High: Respond to both momentum and RSI signals, leading to frequent trades. They rely on momentum
Volatility Chartists	Switch between momentum and RSI based on market volatility.	Best in mixed conditions, effectively navigating both trends and reversals.	Moderate to high: Adaptability allows them to capitalize on varied conditions.	Moderate: Switching mechanism limits over-trading. The rely on moment based on market volatility.

Table 1: *Agent Types and Characteristics*

decision rules differently. Momentum-Dominant Chartists (80% Momentum, 20% RSI) prioritize trend-following, reflecting strategies often employed in volatile markets where momentum indicators outperform oscillators [45]. Momentum-Dominant Chartists are expected to accumulate the most wealth in trending markets. They rely on momentum which allows them to maximize their returns, and focus extending upward price trends. Studies have shown, momentum strategies are effective during periods of consistent directional trends, which allow these agents to outperform others when markets exhibit clear patterns [27]. These Chartists account for 30% of the total, indicating their significance in catching market movements, as evidenced by research on momentum's impact on asset prices [8]. To identify short term-term maker corrections RSI-Dominant Chartists (80% RSI, 20% Momentum) are used as they focus on mean-reversion strategies. They have the ability to identify overbought or oversold conditions, and hence they can make effective time trades in scenarios where momentum signals might be weaker. The RSI rule, which measures the magnitude of price gains relative to losses over a 14-day period, provides a robust framework for identifying high-probability reversal points [46]. RSI-Dominant Chartists make up 25% of the total Chartists, to help create a balance between trend-following and mean-reversion strategies [29]. Balanced Chartists (50/50) , use a hybrid approach where they apply equal weight to both rules, helping them diversify their decision-making approach. They react to trends as well as corrections which results in higher trading activity T[40]. This makes them responsive in markets with mixed signals or changes from trends to corrections [39]. Hence, they are expected to open and close the most positions. Balanced Chartists represent 25% of the total Chartists,This emphasizes how well technical indicators may be combined to improve trading decisions [36]. Alternating Strategy Chartists dynamically switch between momentum and RSI rules based on weekly market conditions. When market volatility, measured as the standard deviation of 30-day daily returns, exceeds 2.5%, they prioritize the RSI strategy to exploit overbought and oversold signals. They revert to momentum strategy to capitalise on upwards trends during periods having low volatility and high stability. The benefits of adapting strategies to the state of the market are highlighted by adaptive trading system research, which is in line with this strategy [17]. These Chartists constitute 20% of the total Chartists, to reflecting the adaptability required in volatile trading environments [10]. Hence, they are expected perform the best under market volatility, leveraging the strengths of both strategies.

In this simulated environment 70% of the agent population is assign to Chartist. This is because they play an important role of technical analysis in trading and have an effective influence on the market behaviour. This majority ensures the simulation implements a range of decision-making strategies, to provide a comprehensive representation of different market conditions.

This ratio was implemented to create a realistic environment to reflect how technical strategies can shape asset prices and shape market trends [35, 27]. The simulation would be able to capture the interaction between structured and methodical trading strategies and the unpredictable nature of Random Traders.

Task 1.2 - Define Random Traders

Random Traders	Chartists
Make random buy/sell decisions based on probabilities.	Employ technical analysis indicators (e.g., RSI, momentum) to make informed trading decisions.
Lack a specific trading strategy, often leading to suboptimal performance.	Follow trends, identify overbought/oversold conditions, or combine both strategies for a balanced approach.
Limited risk management practices due to random decision-making.	May employ stop-loss and take-profit orders to manage risk, potentially leading to better risk-adjusted returns.
Typically underperform in the long run due to the lack of a structured approach.	Can outperform random traders, especially in markets with clear trends or cyclical patterns.

Table 2: Comparison of Random Traders and Chartists

Random Traders represented the agents who traded unpredictably in the market. These agents are similar to retail investors but they act without any clear strategy or technical expertise. Their decision on whether to buy, sell, or hold are random and is not influenced by price trends, market signals, or economic factors [28].The conduct of noise traders, who are frequently characterized in financial literature as being motivated by emotions, outside influences, or irrational reasoning, is reflected in this unpredictability [4]. In this simulation, Random Traders make up 30% of the agent population, emphasizing their role in adding both liquidity and unpredictability to the market. Unlike Chartists, who rely on structured strategies like momentum analysis, RSI thresholds, or adaptive approaches to make informed decisions, Random Traders lack any systematic method. They are less likely to achieve consistent profits and are subjected to significant losses and high financial volatility due to their lack of strategy[22]. It is harder for the to take advantage of favourable conditions and protect themselves from losses as they trades do not follow market trends. Although they are inefficient they play an important role to help simulate real world market trends into this simulation. Their trades are unpredictable and hence are treated as noise which often disrupt price movements and increase the market volitaliity. While this randomness introduces inefficiencies, it also provides opportunities for informed traders, like Chartists, to take advantage of mispriced assets. This reflects the influence of retail traders in the actual world, whose choices can both increase market complexity and liquidity [44]. A more accurate representation of market dynamics is made possible by involve Random Traders in the simulation, emphasising the difference between their impulsive, unstructured behavior and other agents' planned actions.

Task 1.3 - Implement Market Environment

To insert dynamic price adjustments into the environment, Petrov's Price Response Function is used, to calculates price changes based on the net demand (ΔN) generated by agent activity. The parameter (α) is usedto scale the impact of price demand and uses the direction as well as the magnitude of trading activity to simulate realistic market responses. Using this function guarantees that price dynamics are consistent with recognized financial models and represent the combined activities of all agents [41].

$$r_n(\Delta N_n) = S_n - S_{n-1} = \lfloor \alpha \cdot \text{sgn}(\Delta N_n) \cdot p \cdot |\Delta N_n| \rfloor,$$

To simulate real-world wealth dynamics, the model incorporates a 10% Bitcoin influx every 90 days, distributed among agents based on their current Bitcoin holdings. This reflects the "rich get richer" phenomena seen in financial markets and is consistent with Gibrat's Law of Proportional Growth, which asserts that larger holders of an asset are likely to gain proportionately more from any rises. Research on patterns of wealth accumulation and their effects on market inequality is consistent with this strategy [14]. To follow a disciplined trading behavior, agents are required to close an existing position before initiating a new one. By preventing overlapping holdings, this restriction mimics real-world situations in which traders try to lock in gains or reduce losses before reentering the market. When combined, these systems produce a controlled and accurate setting that offers a strong basis for evaluating how well different trading tactics perform in a simulated market. Random noise and periodic sinusoidal variations are introduced by an external market effect to simulate wider economic cycles and trading behavior variability. Agent-based economic models have employed similar methods to model cyclical behavior and exogenous shocks [37]. When the price drops below 50% of the initial price, a market recovery mechanism stimulates speculative buying demand, maintaining price stability during severe downturns. Research indicates that speculative activity frequently increases during steep drops, resulting in brief price corrections [13], which supports such mechanisms. Every 200 days, a market correction mechanism is also implemented, which lowers the price by 5% in order to imitate the rebalancing forces seen in financial markets. Over time, these mechanisms sustain price trends that are both dynamic and under control. To encourage realistic price movement, adjustments to α are based on the magnitude of net demand: α is halved during high activity ($|\Delta N| > 50$) to stabilize excessive price changes and increased by 50% during low activity ($|\Delta N| < 10$) to stimulate market movement. According to research on dynamic market pricing, these modifications guarantee response to fluctuating degrees of market volatility and involvement [16]. In accordance with strategies to stop

Day (After Addition)	Total Bitcoin	Total GBP	Price (GBP/BTC)
90	55.00	792040.31	5654.50
180	60.50	816422.96	5929.26
270	66.55	805442.71	5766.56
360	73.20	837439.85	6150.85
450	80.53	841585.55	6127.26
540	88.58	871813.53	6498.41
630	97.44	876494.32	6540.10
720	107.18	902098.12	6838.73
810	117.90	894745.95	6703.48
900	129.69	918114.79	6970.47
990	142.66	937585.75	7188.14
1080	156.92	905702.85	6813.15
1170	172.61	925428.28	6999.44
1260	189.87	917055.41	6608.82
1350	208.86	927624.92	6630.47
1440	229.75	885303.23	6198.61
1530	252.72	895320.70	6231.80
1620	278.00	884296.60	5788.67
1710	305.80	897384.82	5872.15

Table 3: *Increase in bitcoin every 90 days and its price for n=5 (Petrov's Price Response Function)*

uncontrollably steep drops in simulated markets, a price floor of 547.2 is implemented to guarantee that the price of Bitcoin does not fall below a fair level [42]. In addition, agents are allocated a 20% chance of not trading on any particular day to account for variations in participation brought on by strategic decision-making or market uncertainty. Collectively, these improvements guarantee a stable and flexible market environment appropriate for assessing the effectiveness of different trading tactics in a range of situations.

Task 2 - Running and Analyzing the Model

In financial markets, the "rich get richer" tendency is evident. This strategy is in line with studies on the trends in wealth accumulation and how they affect market inequality [14]. Agents operate under a rule that mandates the closure of an existing position before opening a new one, ensuring disciplined trading behavior. In order to replicate real-world situations when traders want to lock in profits or limit losses before reentering the market, this constraint prohibits overlapping positions. When combined, these systems produce a controlled and accurate setting that offers a strong basis for evaluating how well different trading tactics perform in a mock market.

Task 2.1 - Model Execution and Parameter Tuning

Momentum dominant agents achieve peak wealth at $n = 6 - 7$, with a maximum of 2156.67 at $n = 7$. This range allows the agent to balance frequent trading and capture market trends. The wealth declines sharply at higher n values, dropping to 1705.21

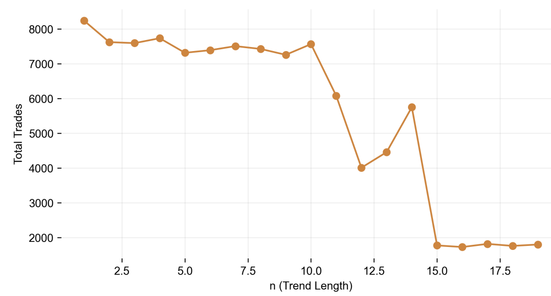

Figure 1: *Total Trades for Momentum Dominant Chartist*

at $n = 15$. This is because of reduced trading activity which limits the agent's ability to capitalize on market opportunities. This emphasises that overly conservative settings affects the profitability for Momentum-Dominant agents.

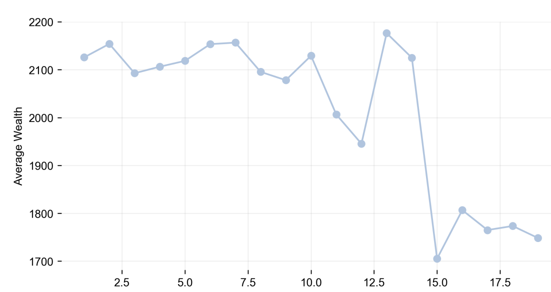

Figure 2: *Average Wealth of Momentum Dominant Chartist*

Momentum-Dominant agents achieve peak wealth at $n = 6 - 7$, with a maximum of 2156.67 at $n = 7$. This range allows the agent to balance frequent trading with capturing meaningful market trends. However, wealth declines sharply at higher n values, dropping to 1705.21 at $n = 15$, as reduced trading activity limits the agent's ability to capitalize on market opportunities. This demonstrates that overly conservative settings hinder profitability for Momentum-Dominant agents.

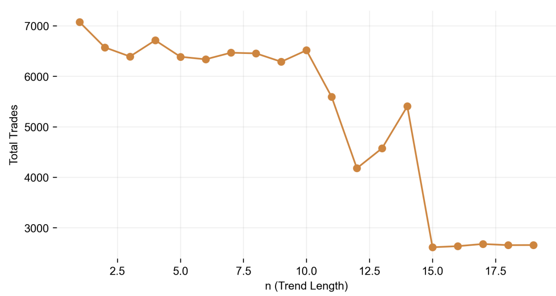

Figure 3: *Total Trades for RSI Dominant Chartist*

RSI-Dominant agents also exhibit high trade volumes at $n = 1$, starting with 7074 trades. As n increases, trade counts steadily decline, reaching 2613 at $n = 15$. The decrease in trades is less pronounced compared to Momentum-Dominant agents, as RSI-Dominant agents rely on mean-reversion signals, which remain partially independent of trend lengths. This behavior shows that RSI-Dominant agents maintain a moderate level of activity even with increasing n, reflecting their adaptability to both short- and mid-term signals.

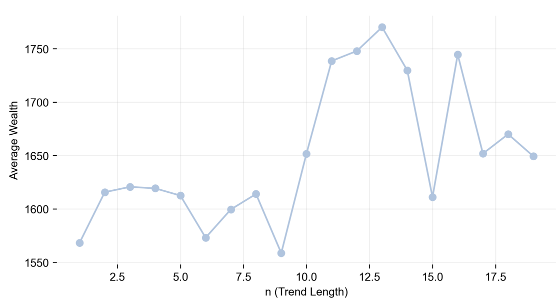

Figure 4: *Average Wealth of Moment Dominant Chartist*

Wealth for RSI-Dominant agents peaks at $n = 12 - 13$, with a maximum of 1770.22 at $n = 13$. This indicates how well they can take advantage of mean-reversion possibilities at moderate trend lengths. Beyond $n = 15$, average wealth declines steadily, reaching 1611.00 at $n = 15$. The slower decline in wealth compared to Momentum-Dominant agents highlights the RSI-Dominant agent's greater resilience and ability to generate profits even in more conservative market conditions.

Balanced agents exhibit the highest trading activity among all structured agents, starting with 10394 trades at $n = 1$. Trade volumes decline steadily as n increases, but even at $n = 15$, they maintain 2447 trades, significantly more than Momentum- and RSI-Dominant agents. This reflects the Balanced agent's adaptability, as it utilizes both momentum and RSI signals to maintain consistent activity levels across a wide range of trend lengths.

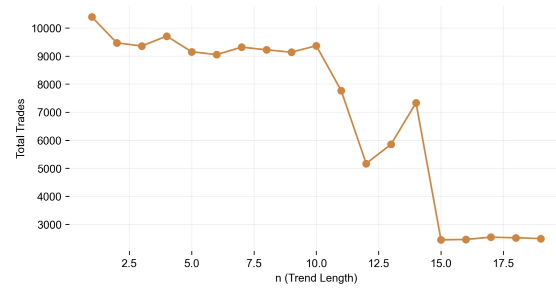

Figure 5: *Total Trades for Balanced Chartist*

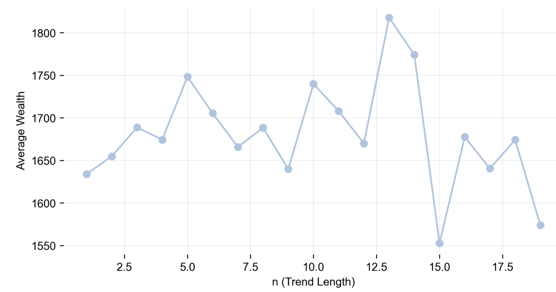

Figure 6: *Average Wealth of Balanced Chartist*

Balanced agents achieve peak wealth at $n = 6$, with an average of 1748.31. Wealth remains relatively stable for moderate n values and only begins to decline significantly beyond $n = 12$. Even at $n = 15$, the Balanced agent maintains better profitability than other structured agents. This consistency highlights its robustness and ability to perform well in diverse market conditions, making it one of the most reliable agent types.

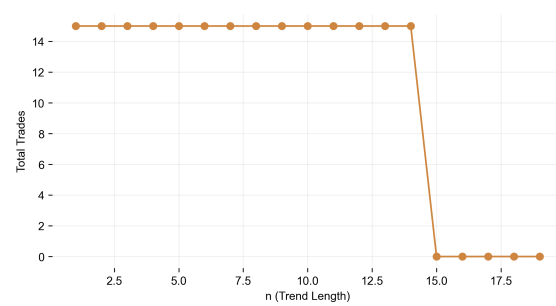

Figure 7: *Total Trades for Alternating Chartist*

With only 15 deals for $n \leq 14$ and none at $n = 15$, alternating agents trade at incredibly low volumes.This low activity is a result of their strong reliance on switching tactics, which in the majority of market conditions do not produce enough signals. The complete cessation of trades at higher n values underscores the Alternating agent's inability to adapt to longer trends or low-signal environments, making it the least active agent.

The Alternating agent's average wealth is consistently low, starting at 1507.87 at $n = 1$ and declining steadily with increasing n. By $n = 15$, wealth falls to 1136.63, the lowest among all agents. This reflects the agent's poor adaptability and overreliance on alternating strategies, which fail to capitalize on either short- or

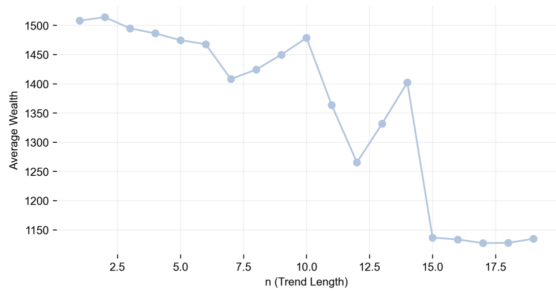

Figure 8: *Average Wealth of Alternating Chartist*

long-term trends effectively.

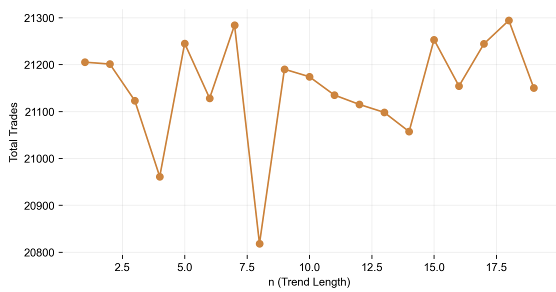

Figure 9: *Total Trades for Random Traders*

Random agents maintain consistently high trade volumes across all n, ranging from 20800 to 21300 trades. Their behavior is independent of market signals or trend lengths, resulting in uniformly high activity levels. This lack of reliance on n ensures that Random agents provide liquidity to the market but also highlights their inefficiency, as they fail to adjust their behavior based on market dynamics.

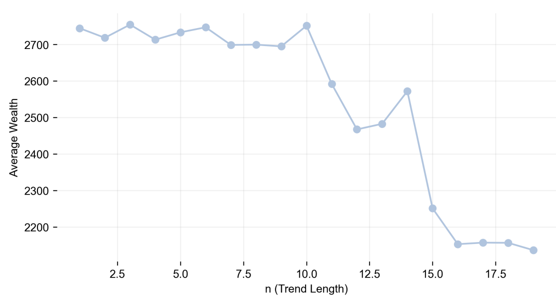

Figure 10: *Average Wealth of Random Trader*

Random agents achieve relatively high average wealth at low n, peaking at 2744.74 for $n = 1$. However, wealth declines steadily beyond $n = 10$, reaching 2250.91 at $n = 15$. This decline reflects the cumulative effect of unprofitable trades and transaction costs. Despite their inefficiency, Random agents maintain higher

In this analysis, the trend parameter n was varied from 1 to 20 in order to look into agent behavior. The findings made it evident that each type of agent behaves differently according to the market setting. Momentum-Dominant agents performed best with moderate values of n (around 6-7), as they captured trends without becoming overly conservative. Their performance dropped y at higher n values, where fewer trends met the threshold for action. RSI-Dominant agents excelled at longer trends ($n = 12 - 13$), using mean-reversion strategies, but their profitability began to decline at very high n values. Balanced agents were the most reliable across all conditions, peaking at $n = 10$, where their combination of momentum and RSI strategies allowed them to adapt well to changing market dynamics. Alternating agents struggled across all values of n, with minimal trades and poor overall performance. Random agents maintained high trade volumes regardless of n, but their lack of strategy caused a steady decline in wealth as n increased.Based on these findings, $n = 10$ stands out as the optimal choice for further experiments. It offers a compromise that enables Momentum-Dominant, RSI-Dominant, and Balanced agents to perform well and take advantage of trends without overreacting to transient noise or passing up long-term possibilities. Profitability and trading efficiency across various agent tactics are balanced by this value.

Task 2.2 - Performance Comparision

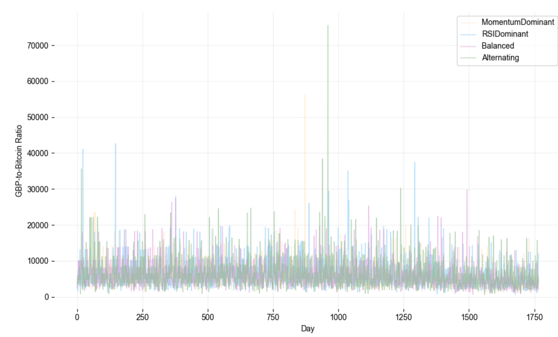

Figure 11: *GBP to Bitcoin Ratio for Chartists*

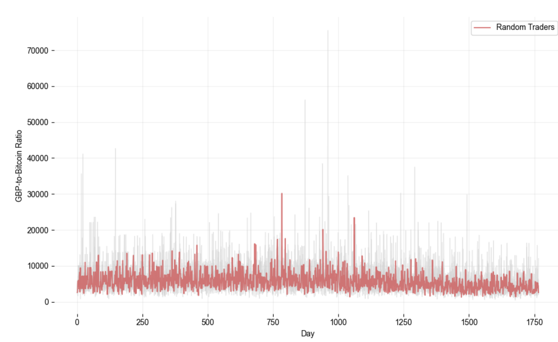

Figure 12: *GBP to Bitcoin Ratio for Chartists vs Random Traders*

Each type of chartist shows different strategies in how they balance their holdings between GBP and Bitcoin. Momentum dominant agents use a dynamic approach and have an average

GBP-to-Bitcoin ratio of 5,936. They also have a wide range from 451 to 56,164, indicating their tendency to hold Bitcoin during upward trends but shift to GBP when the market shows uncertainty. RSI-Dominant agents use a more cautious approach. They have an average ratio of 6,217 and they hold the maximum ratio of 42,656 . This highlights their preference for holding GBP, especially during market corrections or when trends reverse. Balanced agents have an average ratio of 5,915 and the lowest minimum of 631. This shows their ability to adapt effortlessly between GBP and Bitcoin based on market conditions. Alternating agents, are the most conservative, with an average ratio of 6,309 and a maximum of of 75,496, indicating a heavy bias toward GBP and less risk-taking in volatile markets. Overall, Momentum-Dominant and Balanced agents stand out for their ability to optimize asset allocation, while RSI-Dominant and Alternating agents take a safer, GBP-heavy approach that may limit opportunities for higher returns. When looking at chartists compared to Random agents, the differences in their strategies and outcomes are striking. Random agents tend to lean more heavily toward Bitcoin, as shown by their slightly lower average GBP-to-Bitcoin ratio of 5,605. Their range, from 1,287 to 30,154, reflects a steadier but less adaptable approach. RSI-Dominant and Alternating agents heavily favour GBP, with maximum ratios of 42,656 and 75,496, which emphasises their cautious investment approach. Momentum Dominant and Balanced agents are more flexible, and actively shift between GBP and Bitcoin based on market trends. This is something Random agents can not implement without a clear strategy. Although random agents' inconsistent choices provide regularity, they lose out on chances to maximize their holdings when the market fluctuates. The difference illustrates the advantage of chartists, whose methodical approaches enable them to adjust and profit from shifting market circumstances, in contrast to random agents, who maintain predictability but are ultimately less successful.

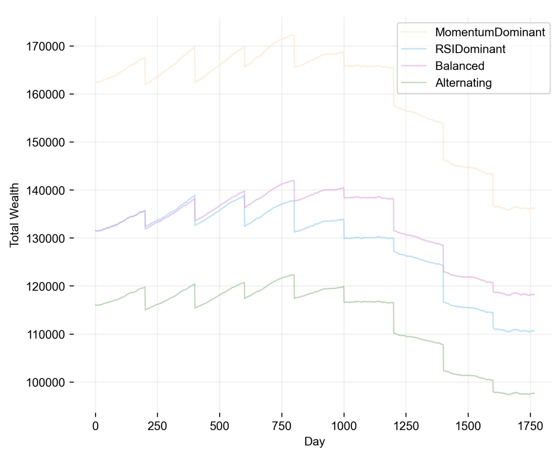

Figure 13: *Total Wealth for Chartists*

Interesting trends related to chartists' trading methods can be seen in their total wealth outcomes. With an average of roughly 159,935 and a max of 172,293 in total wealth,

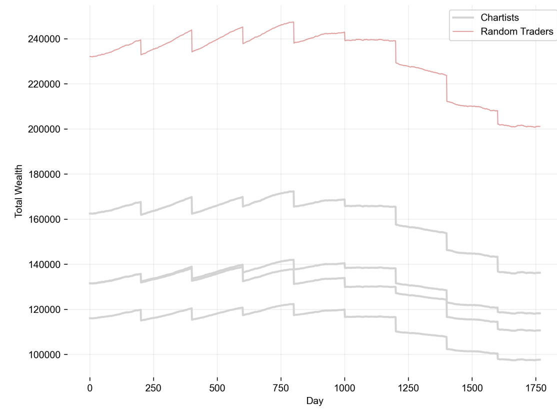

Figure 14: *Total Wealth for Chartists vs Random Traders*

Momentum-Dominant agents had the highest average overall wealth among chartists. This is consistent with their propensity to profitably ride trends, even while their minimal wealth of 135,819 indicates sporadic susceptibility to adverse market conditions. demonstrating their flexibility in switching between momentum and RSI-driven tactics. Results from this flexibility are consistent, ranging from a minimum of 118,007 to a maximum of 141,957. Although RSI-Dominant agents did well, their average wealth of 131,765 was lower than that of the Balanced and Momentum-Dominant strategies. This suggests that their inclination for overbought/oversold conditions may restrict their capacity to take advantage of some market chances. Alternating agents, with an average wealth of 113,277, represent the lowest-performing chartists, reflecting their more cautious and conservative approach. While this strategy mitigates extreme losses (minimum wealth of 97,362), it also limits the ability to capitalize on large gains compared to other chartists. The Random agents significantly outperformed all chartist subtypes in terms of total wealth, with a mean of 231,016, far exceeding the Momentum-Dominant agents' average. Their wealth range (minimum: 200,691, maximum: 247,385) underscores their ability to accumulate wealth steadily over time, despite lacking structured decision-making. This discrepancy in performance emphasizes the importance their Bitcoin-heavy allocation was in enabling them to profit from advantageous Bitcoin price moves. However, it also shows that, in certain situations, unstructured behavior can produce significant rewards despite the risks involved. In contrast, chartists demonstrated greater control and strategy in asset allocation, resulting in consistent but comparatively lower total wealth outcomes. Even though random agents were very good at maximizing wealth, their inability to adjust strategically would make them vulnerable in less advantageous market situations, where chartists may perform better thanks to risk management and organized decision-making. The contrast between chartists' consistent, methodical performance and unstructured, opportunistic profits is highlighted by this comparison.

When it comes to exposure time—the proportion of time

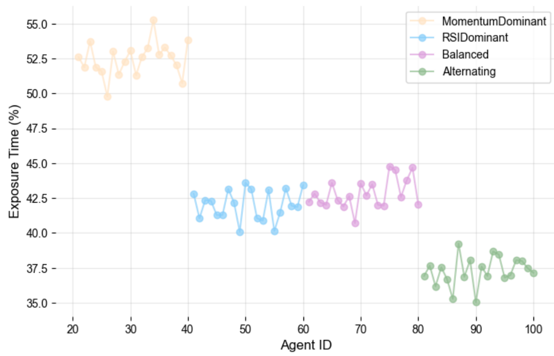

Figure 15: *Exposure Time for Chartists*

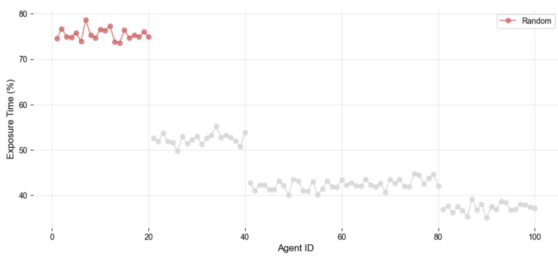

Figure 16: *Exposure Time for Chartists vs Random Traders*

that each type of chartist holds open positions in the market during the simulation—they all behave differently. Momentum-dominant agents have the highest exposure time among chartists, averaging around 52%, with individual agents ranging between 49.7% and 55.2%. This shows that they take an initiative toward market trends, holding onto positions for extended periods of time in order to profit from rising prices. As a result of their cautious and reactive trading style, which involves opening positions only in response to certain conditions such as oversold or overbought market indicators, RSI-Dominant agents, on the other hand, maintain an average exposure time of roughly 42%, with a tighter range of 40.1% to 43.6%. With an average exposure time of almost 43%, balanced agents show comparable exposure times to RSI-Dominant ones; however, their range of 40.7% to 44.7% indicates a little more flexible approach. Alternating agents show the lowest exposure time among chartists, averaging only 37%, with values spanning from 35.0% to 39.2%. This conservative approach aligns with their tendency to frequently shift between holding GBP and Bitcoin, minimizing market risk at the cost of reduced engagement.It is clear that chartists and random agents operate in the market differently. The average exposure duration for random agents is 74.9%, with values ranging from 73.6% to 78.7%. This is a much higher exposure time. This consistent and extended market presence highlights their unstructured strategy of maintaining open positions without responding to market trends. The exposure times of chartists, are far more customized and variable depending on their trading techniques and restrictions. The extended exposure period of random agents may appear to be helpful in capturing market swings, but it is devoid of the strategic adjustments made by chartists, who maximize their time in the market by focusing on particular signals. This results in more strategic and risk-aware trading patterns for chartists, albeit with lower overall market presence compared to Random agents.The comparison highlights the importance of strategic exposure since, in contrast to random agents who only rely on extended exposure, chartists are able to match their market activity with advantageous conditions.

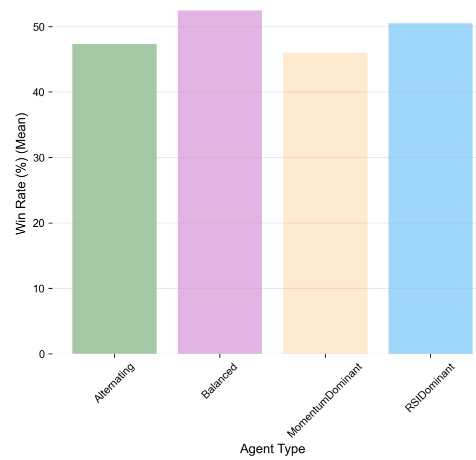

Figure 17: *Win Rate of Chartists*

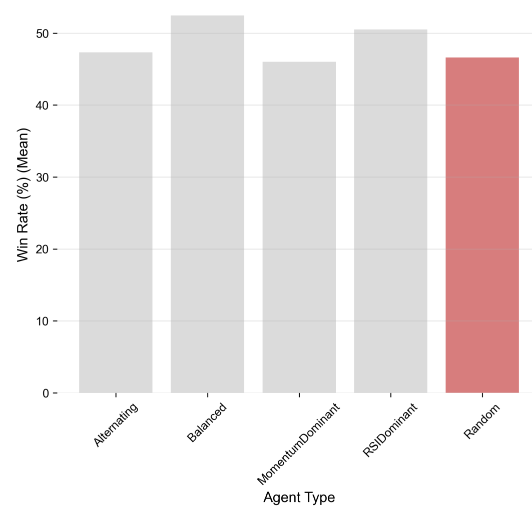

Figure 18: *Win Rate of Chartists vs Random Traders*

Chartist agents exhibit significant patterns in their win rates, which are indicative of their tactical methods and the limitations of the simulation system. The highest average win rate of 52.47% is attained by balanced agents, demonstrating their capacity to adjust between Bitcoin and GBP in response to shifting market trends. With an average win rate of 50.50%, RSI-Dominant agents come in second, demonstrating the effectiveness of their cautious entry and exit tactics in erratic markets. With an average win rate of 46.02%, momentum-dominant agents can use market trends very effectively, although they perform marginally worse than more flexible methods. Alternating agents have the lowest win rate of 47.33%, suggesting that their conservative GBP-heavy approach limits their capacity to capitalize on significant opportunities. Overall, these trends highlight the importance of flexibility and calculated decision-making, although the model's predictable environment may inflate structured strategies' effectiveness beyond real-world expectations. Despite having no formalized strategies, random agents outperform alternating agents and competing momentum-dominant agents with an astounding average victory percentage of 46.63%. They are able to take advantage of favorable Bitcoin moves opportunistically due to their unstructured decision-making, which aligns their win rate with specific chartist subtypes. However, because of their strategic planning and risk management, chartists consistently have greater win rates. The contrast highlights the trade-offs between the opportunistic, occasionally fluctuating results of Random agents and the methodical, consistent performance of chartists. While Random agents can thrive in predictable environments, their lack of adaptability would likely hinder their performance in less favorable market conditions where systematic strategies excel.

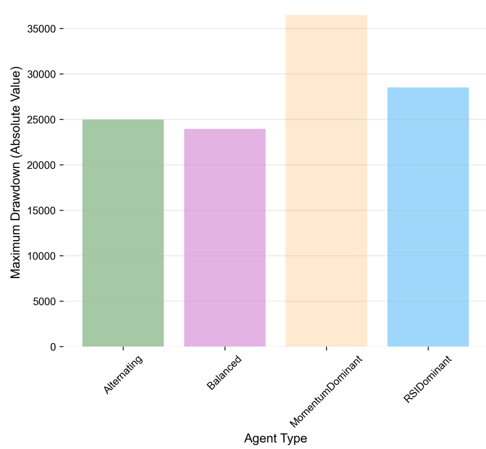

Figure 19: *Maximum Drawdown of Chartists*

Each agent type has a different risk profile which is analysed by seeing the maximum drawdown. This proves how vulnerable they are to market downturns. Alternating agents have the lowest maximum drawdown (£24,964) among all agent types , proving them to be conservative. Momentum-dominant agents, have the highest drawdown (£36,474) among chartists . This shows how aggressively they are using market trends to their advantage, which inturn causes the, to have large losses in the event of a market reversal. A midway ground is represented by RSI-Dominant agents, whose maximum drawdown is £28,496. Their cautious entry and exit methods help to reduce losses, but they are not completely immune to market volatility. When compared to Random agents, the difference in maximum drawdown is highlighted. Random agents have the highest drawdown (£46,694), which exceeds any chartist type. This highlights the inherent risk of their unstructured and Bitcoin-heavy strategy, which, while profitable in upward trends, leaves them exposed to

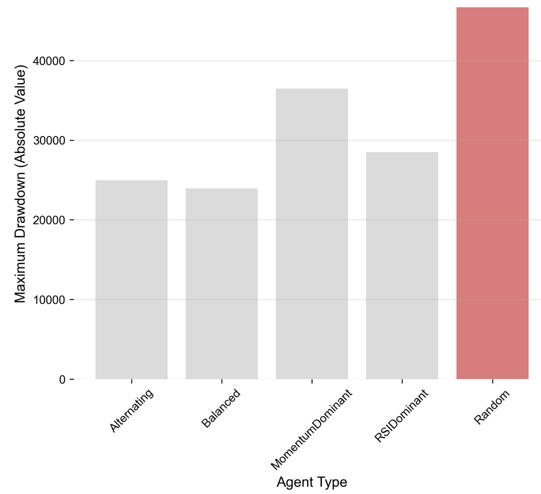

Figure 20: *Maximum Drawdown of Chartists vs Random Traders*

steep losses during downturns. Chartists, with their strategic and systematic approaches, consistently manage lower drawdowns, showcasing their ability to mitigate losses through structured decision-making. This comparison underscores the trade-off between the opportunistic but risky nature of Random agents and the calculated, risk-mitigated behaviour of chartists. While chartists' strategies allow for better control during market downturns, the Random agents' lack of structure makes them more vulnerable to significant losses, despite occasional high returns in favourable markets.

Each agent type balances profitability, risk, and flexibility differently, highlighting its own benefits and drawbacks. Random agents have the highest total wealth and exposure time, as they heavily rely on constant market engagement. This also exposes them to the highest maximum drawdown, making them more vulnerable in volatile markets. Among the chartists, MomentumDominant agents perform well in wealth accumulation and exposure time by capitalizing on market trends, while Balanced agents emerge as the most consistent performers, achieving the highest win rate and minimizing drawdowns effectively. RSI-Dominant and Alternating agents adopt a more cautious strategy, leaning heavily toward GBP holdings and maintaining moderate success with lower exposure to risk. Overall, while Random agents thrive in favourable conditions with their unstructured strategies, the structured and balanced approaches of chartists—particularly Balanced agents—provide a steadier, more reliable path to profitability and risk management.

Task 3 - Market Validation

Task 3.1 - Market Dynamics Validation

The developed simulation offers information on how income is distributed among various agent types. This simulation was compared to three important research papers in this field. In the

Agent Type	Win Rate (%)	GBP-to-Bitcoin Ratio	Total Wealth	Maximum Drawdown	Exposure Time (%)
Alternating	47.33	6309.07	113277.27	24964.03	37.00
Balanced	52.47	5914.81	132730.27	23949.15	43.00
MomentumDominant	46.02	5935.85	159935.09	36473.57	52.00
RSIDominant	50.50	6216.54	128615.88	28495.82	42.00
Random	46.63	5605.13	231015.98	46693.60	74.90

Table 4: Summary of Key Metrics for Each Agent Type

simulation Momentum dominant chartist achieved the highest average wealth (159,935.09) among the chartist. Balanced agents (132,730.27) came in second followed by RSI dominant chartist(128615.88). Alternating agents (113,277.27) had lower average wealth but were relatively stable. It was interesting to note that in this simulation Random traders outperformed all the other agents (231,015.98). This finding is different from theoretical expectations" LeBaron et al. contend that money tends to concentrate in the hands of a select few in artificial financial markets where various sorts of traders engage. The way wealth inequality occurs in actual economies is comparable to this. They did discover, however, that in their simulations, basic, random trading techniques occasionally performed better than more intricate, systematic ones. This surprising outcome goes against their initial assumptions based on conventional financial theory and raises the possibility that the simulated market has hidden biases or characteristics that favor particular kinds of traders [34]. Similarly, Howison et al.

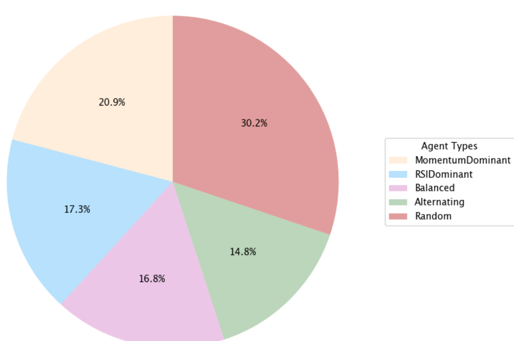

Figure 21: *Wealth Distribution by Agent Type*

in *Emergent Statistical Properties in an Artificial Financial Market* highlight the stabilizing role of market-making agents, which resonates with the stable and relatively high wealth of Balanced agents observed in the simulation. The performance of MomentumDominant agents' was strong and it supports their finding that trend-following methods could profit from market inefficiencies. The simulation conntradicst Howison's prediction that systematic methods perform better than random. This could be due to underlying randomness in the simulated trading environment [25]. Cocco et al. in *Artificial Financial Market as a Tool for Pricing Derivatives* argue that in artificial financial markets, wealth distribution is influenced by how willing agents are to take risks and how complex their trading strategies are. The finding that agents employing Momentum and RSI techniques, which range in risk and complexity, accumulate wealth at different rates is consistent with this. This difference could be because of the initial conditions such as wealth allocation, trading constrains or idealistic market environments, It needs to be refined to reflect the conditions of a real market [14]. The simulation is successful at replicating key aspects of wealth disturbing and strategy of the chartist it fails to do the same for Random agents. This finding emphasizes the necessity of iterative refinement in order to further align simulated and real outcomes while leveraging the exploratory insights of the model.

Observing the Bitcoin price trend, it was noticed that there were distinct phases on gradual growns followed by sharp declines. This resembles the important characters of artificial financial markets which is discussed in the literations, The results from the simulation were similar to the work of LeBaron et al, which stated how artificial markets show a gradual price increase influenced by strand following strategies and are then faces with a sudden correction due to liquidity mismatches or panic selling [33]. As seen in the plot, the simulation are periodic sharp declines which is due to corrections made in the market, where the prices of the market was dropped by 5% every 200 days. The increase in volatility over time is similar to LeBaron's observations that Speculative dynamics intensify market swings when the economy is expanding. The framework outlined by Cocco et a, where asset values with long-term growth interspersed by volatility spikes are modeled by artificial markets [14] is supported by the sumlations price trend. This trajectory is influenced by the momentum dominant chartist as well as the RSI dominant chartist. Unlike the findings in the paper the simulation displayed less damped recoveries after the price correction which could be due to the absence of stabilizing forces like heading or risk aversed behavior [34].

The emergent statistical properties described by Howison et al., such as fat-tailed returns and volatility clustering, are partially evident in the simulation [25]. While the price corrections followed by stable periods indicate possible volatility clustering, the lack of sustained recovery or volatility spikes after the sharp declines deviates from Howison's findings. This shows that the market in the simulation lacks the complexity required to mimic the real market resilience. These differences emphasised

Metric	Simulation Findings	LeBaron et al.	Howison et al.	Cocco et al.
Wealth Distribution	MomentumDominant agents exhibit the highest wealth growth (Mean: 159,935.09), but Random agents show maximum wealth overall.	Stylized fact: wealth accumulates unevenly across agents, similar to observed unequal wealth distribution.	Wealth distribution linked to information and strategy heterogeneity, aligning with simulation patterns.	Differences arise as the paper focuses on derivative pricing, not directly on wealth dynamics.
Bitcoin Price Trend	Price shows steady increase with abrupt declines post-saturation points, influenced by deterministic Bitcoin introduction.	Captures long-term trends with volatility, but lacks extreme short-term fluctuations noted in LeBaron et al.	Reflects equilibrium trends but misses liquidity-driven volatility spikes.	Matches steady price increase in line with predictable market behavior but lacks derivative-specific shocks.
Trading Volume Trend	Volume increases steadily, with surges during active periods, driven by periodic Bitcoin introduction and deterministic behavior.	Burstiness in volume matches some trading peaks but lacks cyclic patterns seen in LeBaron et al.'s study.	Volume spikes align with liquidity and agent interaction thresholds but lack stochastic fluctuations.	Consistent volume increase reflects trader confidence over time, diverging from stochastic fluctuations.

Table 5: Comparison of Simulation Findings Against Three Papers

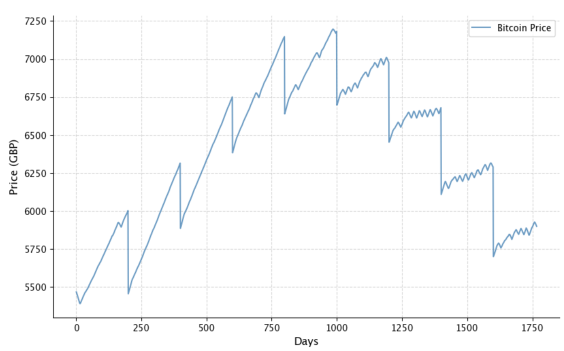

Figure 22: *Bitcoin price trends in simulated environment*

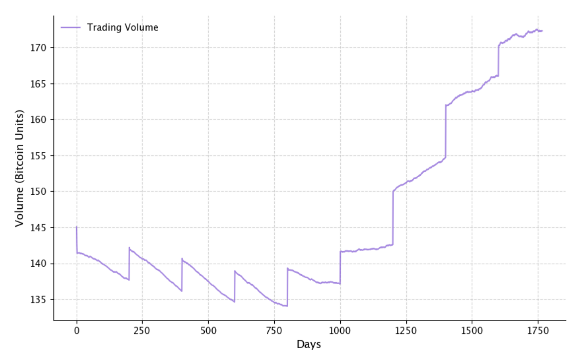

Figure 23: *Trading Volume trends in simulated environment*

the simplicity of the simulation market which does not incorporated external shocks. It can be concluded that the Bitcoin price trend in the simulation is a simplified representation of the artificial financial markets. A few of its key characteristics such as the speculative amplification and volatility could be refined to incorporate risk hedging mechanisms to improve market realism [34]. The trends observed in the trading volume during the simulation are compared to the findings from. The simulation shows an increase in trading volume which can be seen in figure 23. At the beginning, it shows a consistent increase which is then very noticeable after a certain threshold of market interactions. The periods of stability are spread out with abrupt increases in volume which emphasises points having the most market engagement.The work by [34] identifies ”bursty” trading behaviours in artificial financial markets, where clusters of high activity are followed by quieter phases, reflecting the role of momentum and information aggregation in market behavior. This partially explains the observed patterns in the simulation where certain days show jumps in trading volume but they are less cyclic in the real world. This could be due to the deterministic components in the model that influenced an uniformed participation of agents. The influence of liquidity in trade volumes is explained in [25]. It can be concluded that agent interactions speed up volume spikes when liquidity thresholds are violated. The steady rise in total volume over time, rather than recurrent trading activity equilibria, deviates from [25]'s conclusions. This could be due to the consistent addition of Bitcoins into the market every 90 days, which created a progressive growth in the volume. [14] discusses the market dynamics in context of pricing derivatives and highlights that volume reflects trader confidence and risk tolerance levels. The simulation exhibits higher volumes at later stages, where agents accumulate more market knowledge which is similar to the findings in that paper. Stochastic elements such as real world uncertainty which is mentioned [14] is lacking in the simulation, This is essential for diverse volume fluctuations.To conclude the simulated trading trends mimic aspects such as gradual increases and periodic spikets. When compared to the three referenced papers they are different in their deterministic nature and lack prominent cycles. To improve the model stochastic factors could be integrated and well as more liquidity mechanisms

Task 3.2 - Comparison to Real-World Data

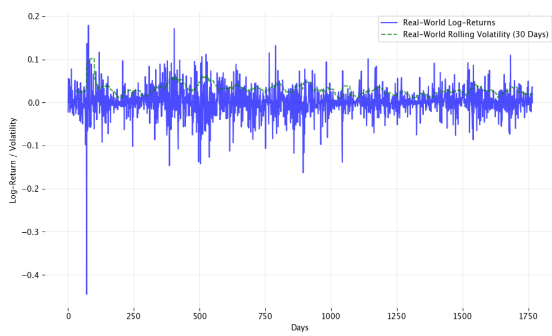

Figure 24: *Log return of prices using real world data*

Bitcoin log-returns from simulated and real-world datasets are analyzed, highlighting the difficulties in effectively simulating cryptocurrency markets by highlighting significant variations in volatility, price dynamics, and general behavior.The standard deviation of real-world Bitcoin log-returns is roughly 0.033603, which is significantly higher than the simulated volatility of 0.005434. The simulation's predictable and controlled nature, fails to replicate the chaotic and speculative nature of real Bitcoin markets. This difference can be observed in real-world graphs which demonstrate frequent sharp spikes and dips because they are influenced by unpredictable external shocks and market sentiment. Cheah and Fry (2015) [12] and Lahmiri and Bekiros (2020) [31] have shown, situations such as China's regulatory crackdowns or Tesla's announcement of Bitcoin purchases which have caused great shifts in the prices of Bitcoin. These abrupt changes reflect Bitcoin's sensitivity to macroeconomic events, a feature absent in the simulated environment.

In contrast, the simulated Bitcoin log-returns are characterized by periodic and predictable spikes, resulting from deterministic mechanisms such as Petrov's Price Response Function and Market Correction Mechanism. Petrov's function stabilizes the system by reducing the price impact of high trading activity ($|\Delta N| > 50$) and encouraging movement during low activity ($|\Delta N| < 10$). Every 200 days, the price is lowered by 5% as part of the Market Correction Mechanism, which was put in place to mimic periodic changes. This rule introduces artificial downward spikes in the simulated data, creating a stark contrast with the irregular, unpredictable jumps and drops in real-world log-returns.These methods minimize excessive fluctuations and guarantee smoother price movements, but they are unable

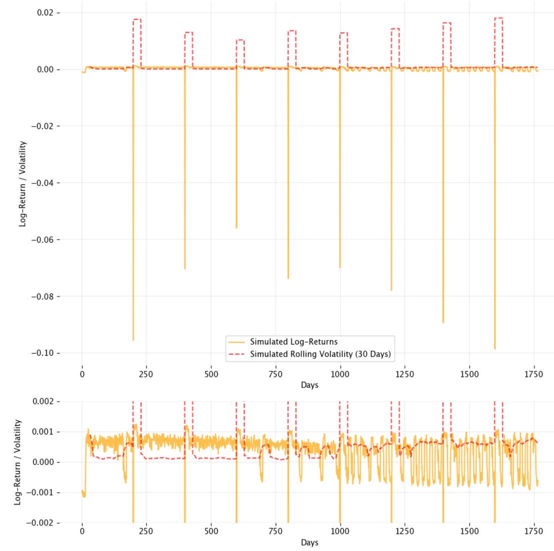

Figure 25: *Log return of prices using data from the simulated envirnoments*

to reproduce the volatility clustering and irregularity present in real markets. The Market Recovery Mechanism, which introduces speculative demand when prices fall below 50% of their starting value, further suppresses downward volatility, contributing to the flat baseline observed in rolling volatility trends.

These variations are further highlighted by the rolling volatility trends. The rolling 30-day volatility (green dashed line) in the real-world data shows small intervals of relative quiet between times of increased market volatility. This aligns with findings by Yermack (2014) [48] and Sensoy and Tabak (2019) [43], who note Bitcoin's inefficiencies and susceptibility to speculative trading. The simulated rolling volatility, represented by the red dashed line, stays largely flat except from occasional spikes based on by the deterministic market correction rule and outside influences. This restriction illustrates how important behavioral and market-driven elements like herding behavior, speculative bubbles, and outside news shocks are missing from the model (Kristoufek, 2015) [30]. The validity and implemen-

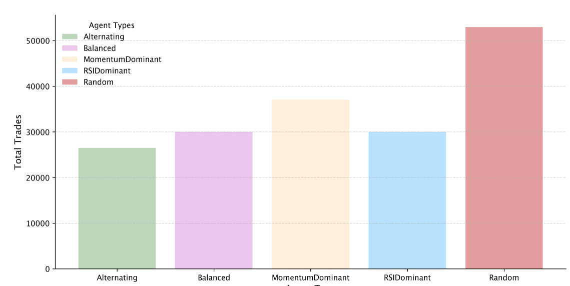

Figure 26: *Total Trades by Agents*

tation of the model are impacted by the gap between simulated and real-world volatility. Real-world volatility is influenced by

Aspect	Simulated Data	Real-World Data
Volatility	Low and controlled due to deterministic rules.	High, with frequent and irregular spikes and drops.
Periodicity	Periodic corrections every 200 days.	No fixed periodicity; driven by market dynamics.
External Shocks	Small randomness introduced via ‘external_market_effect‘.	Large, unpredictable shocks from real-world events.
Recovery Mechanism	Artificial recovery when prices fall below 50% of start price.	No artificial stabilization, market recovery depends on demand.
Investor Behavior	Fixed trader rules (e.g., momentum, RSI).	Dynamic behavior influenced by market sentiment.

Table 6: Comparison of Simulated vs Real-World Log-Returns

numerous external factors, including geopolitical events, regulatory actions, and macroeconomic trends, which are absent in the simulation. For example, research conducted by Bouri et al. (2017) [7] shows how Bitcoins price fluctuations are influenced by institutional support and regulatory clarity influence. Bitcoin has thin markets that amplify the impact of large trades which create drastic price changes.These factors are difficult to replicate in deterministic models, leading to an underestimation of real-world volatility and misrepresentation of market dynamics.There are important ramifications for model validity and application when real-world and simulated volatility diverge The simulation shows a controlled and predictable world, which is very different to this. While the simulation successfully reproduces basic price dynamics and correction mechanisms, it fails to capture the chaotic, high-risk nature of cryptocurrency markets. To better represent real-world conditions, future models should integrate stochastic and behavioral elements, ensuring greater accuracy in volatility representation and price behavior prediction. These refinements would make simulations more applicable for risk management, policy analysis, and educational purposes.

Task 3.3 - Agent Behavioral Impact

In the simulated model, differences in agent behavior, particularly in terms of trading frequency and risk tolerance, significantly influence market volatility. The trading volume chart and other metrics from the simulation demonstrate how agent types contribute differently to market dynamics. Random agents, for example, engage in the highest frequency of trades, introducing substantial noise into the market. This behavior leads to elevated short-term volatility due to their unpredictable and uncoordinated actions, which do not align with strategic market trends. While such behavior is realistic in capturing the presence of noise traders [35], the proportion of Random agents in the simulation may amplify their effect beyond real-world scenarios, where noise traders are balanced by institutional investors and market stabilizers [5]. Momentum-Dominant agents also play a pivotal role in increasing volatility. Their reliance on price trends and reactionary trades to upward or downward movements creates market feedback loops. These agents amplify existing trends, causing sharper price increases or declines [20]. The large maximum drawdowns associated with these agents further indicate their susceptibility to significant losses during market reversals. While this behavior captures the essence of trend-following strategies observed in real markets [9], the simulation could refine their reaction thresholds to better align with empirical trading patterns, such as incorporating varying sensitivity to market noise. Balanced and Alternating agents, with their moderate trading volumes and hybrid strategies, act as stabilizers in the market. They alternate between momentum and mean-reversion strategies, which helps temper extreme price movements. These agents' impact on volatility is realistic, as their balanced approach mirrors the behaviour of diversified traders in financial markets [35]. Similarly, RSI-Dominant agents, which rely on overbought and oversold signals, exhibit low trading volumes and conservative behaviour, adding stability to the market. However, their limited participation may underestimate their potential to mitigate volatility in real-world scenarios, where technical indicators are widely used by retail and institutional traders [9]. The realism of these agent behaviours depends on the specific context of the simulation. While the overall dynamics capture essential market phenomena such as trend amplification and stabilization, some behaviours—particularly the overwhelming influence of Random and Momentum-Dominant agents—may require adjustment to better reflect empirical market conditions. Incorporating more nuanced agent designs, such as adaptive risk thresholds and behavioral diversity, could enhance the model's accuracy in replicating real-world financial markets [20].

Task 4 - Propose a New Agent Class

Task 4.1 - New Agent Design

The Contrarian Trader class was created using principles of mean-reversion trading. Mean-reversion assumes that asset prices fluctuate around their historical averages, with deviations to indicate contrarian trading opportunities. Avellaneda and Stoikov's *High-Frequency Trading in a Limit Order Book* [1], and Bouchaud et al.'s *Trades, Quotes, and Prices: Financial Markets Under the Microscope* [6], show that the agent uses volatility awareness and reference price calculations to help stabilize market behavior. Behavioral finance research, including Kahneman and Tversky's *Prospect Theory* [28] and De Bondt and Thaler's *Does the Stock Market Overreact?* [18],backs up the theory that market players overreact to information, which makes mean-reversion tactics profitable. The design of the Contrarian Trader follows the four steps for agent design.

The objective of the contrarian trader is to spot and take advantage of market overreactions by purchasing cheap and selling high when volatility is at its highest. Two important metrics—rolling volatility and price variation from a reference price—are used to inform its decisions. Volatility is calculated as the standard deviation of log returns:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2}, \quad r_i = \ln\left(\frac{P_i}{P_{i-1}}\right),$$

where P_i represents the price on day i. The reference price, P_{ref}, is defined as the 30-day rolling mean:

$$P_{\text{ref}} = \frac{1}{n}\sum_{i=1}^{n} P_i,$$

and price deviation is computed as:

$$\Delta p = \frac{P_t - P_{\text{ref}}}{P_{\text{ref}}},$$

where P_t is the current price. Entry occurs when the price deviation exceeds a reversal threshold ($|\Delta p| > 5\%$) and volatility surpasses a predefined threshold ($\sigma > 2\%$). Specifically, the agent buys when the current price is below P_{ref}, anticipating a reversion to the mean, and sells when the price rises above P_{ref}. The `position_open` flag, which indicates whether the agent has Bitcoin, and the price_history=attribute, which saves recent prices for trend and volatility analysis, are used to manage the Contrarian Trader's data and status. The agent's decision logic is implemented in the make_decision method. EWhen the price falls much below the reference price during periods of extreme volatility, an entry is made; when the deviation falls back to within half of the entry threshold or when the volatility levels off, an exit is made. The agent interacts with the market by opening and closing positions. When buying, it converts GBP into Bitcoin, and when selling, it converts Bitcoin back to GBP. This interaction ensures that trades remain within the agent's financial constraints, avoiding artificial market conditions. Unlike momentum-driven strategies, such as RSI, which amplify trends, the Contrarian Trader acts contrarian, countering extreme market movements and stabilizing the market. This aligns with Menkveld's *High-Frequency Trading and the New-Market Makers* [38], which highlights the stabilizing role of liquidity-providing agents during volatile periods. Agent proportions were dynamically reallocated to incorporate the Contrarian Trader into the agent the environment. Specifically, 10% of RandomTraders were replaced with Contrarian Traders, reflecting findings from Farmer and Joshi's *The Price Dynamics of Common Trading Strategies* [21] on balancing agent types in simulations. Without sacrificing ecosystem diversity, this reallocation guarantees that the Contrarian Trader may maintain its stabilizing effect. The Contrarian Trader successfully manages extreme market conditions by using volatility and price deviation as decision measures and following mean-reversion principles, which promotes market stability and profitability.

Task 4.2 - Market Impact Analysis

The Contrarian Trader's introduction into the simulated market has had a major impact on price stability, market dynamics, and wealth generation. A comparative analysis of Bitcoin price movements with and without the Contrarian Trader highlights its stabilizing role. In the plot without the Contrarian Trader, Bitcoin prices exhibit an almost exponential growth pattern, reaching over 11,000 GBP by day 1750. In the plot with the Contrarian Trader, prices peak below 7,000 GBP and maintain a more stable trajectory, preventing extreme volatility and unsustainable growth. This shows how contrarian strategies correct mean-reversion effects to promote growth, at the same time avoid having an unmanageable volatility [1]. The Contrarian Trader used volatility thresholds and selectively opposing price aberrations to assist the market reflect growth patterns that more closely resembled actual market activity.

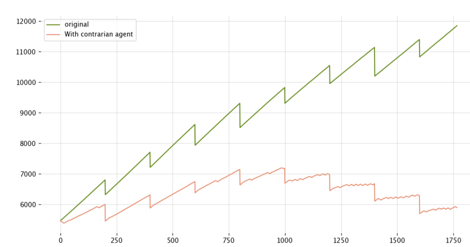

Figure 27: *Comparision of price movements with and without Contratian Traders*

The rolling volatility charts and log returns show how the Contrarian Trader affects market conditions.A more controlled and stable price movement results from the introduction of the Contrarian Trader, which lessens the strength of spikes. However, the Contrarian Trader doesn't eliminate volatility entirely; instead, it redistributes it more evenly across time, helping maintain a realistic and active market. This effect is made apparent by the rolling volatility graphs. Volatility occasionally and sharply jumps in markets without the Contrarian Trader, indicating instability that may cause market behavior to be disrupted. In contrast, the presence of the Contrarian Trader reduces the size of these spikes, creating a more balanced trading environment.The rolling volatility graph reveals a slight increase in baseline volatility, showing how the Contrarian Trader adds a layer of controlled fluctuations to a market that might otherwise be overly static. By doing so, the Contrarian Trader injects just enough activity to keep the market dynamic and healthy. This approach is rooted in mean-reversion strategies, like those highlighted by **(author?)** [1] and **(author?)** [23], which focus on addressing extreme price swings while maintaining market liquidity.The Contrarian Trader helps markets self-correct in a natural way, avoiding the pitfalls of speculative excess. The graph demonstrates how this agent dampens sharp spikes in volatility while slightly elevating the baseline to prevent stagnation and ensure market vitality. This behavior aligns closely with the role of liquidity-providing agents, as explored by **(author?)** [38], who emphasize their importance in stabilizing fast-moving trading environments. By introducing measured price corrections, the Contrarian Trader fosters a well-balanced market, where price changes are not erratic but instead reflect real trading conditions and genuine market activity.

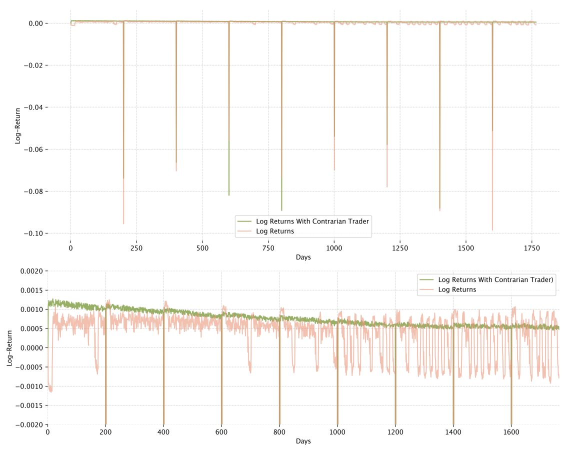

Figure 28: *Comparision of rolling volatility movements with and without Contrarian Traders*

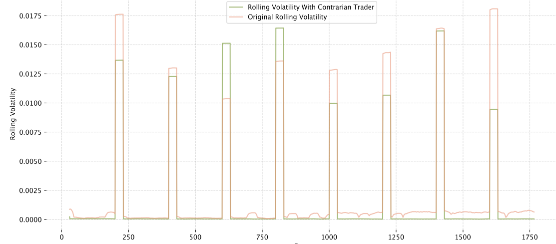

Figure 29: *Comparision of price log returns with and without Contrarian Traders*

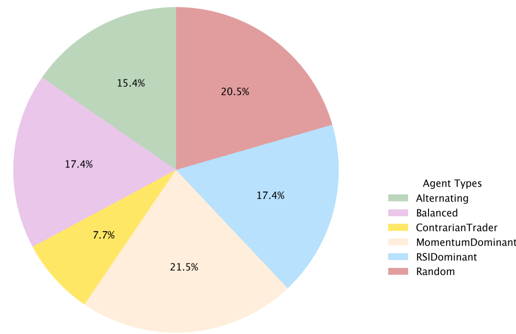

Figure 30: *Wealth Distribution by Agent Type*

The introduction of the Contrarian Trader into the simulated market has had an impact on wealth accumulation, market dynamics, and agent interactions. Without the Contrarian Trader, Random Traders dominated wealth accumulation, and captured **30.2%** of the total market wealth. It held around and **£10 million** in the monthly wealth graph. Their performance is driven by their capacity to take advantage of unpredictable price and volatility surges. The introduction of the Contrarian Trader, Random Traders' share drops to **20.5%** This change is partly due to the reallocation of **10%** of Random Traders to Contrarian Traders and partly due to the Contrarian Trader's role in curbing volatility and encouraging stability. Momentum Dominant agents, who thrive in environments with moderate trends, held the most market wealth having around**21.5%** of the wealth and surpassing **£10 million**. This shows their ability to

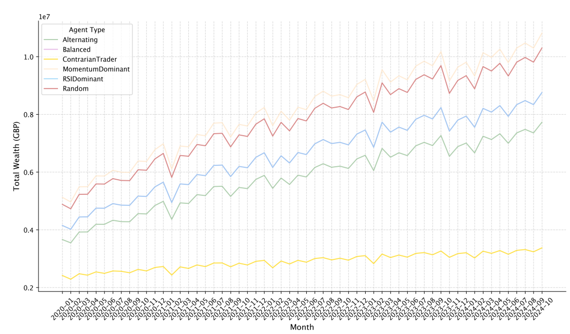

Figure 31: *Monthly Wealth Distribution by Agent Type*

adapt to price movements. Other agents, such as RSI Dominant, Balanced, and Alternating agents, also benefit, with their shares increasing due to the more balanced market conditions. The Contrarian Traderhas **7.7%** of the wealth, around **£4 million**. This wealth redistribution is evident in the monthly wealth graph, where the gap between agent types narrows, reflecting a more equitable market environment. The Contrarian Trader is consistent with mean-reversion strategy theory by reducing speculative dominance and adding controlled volatility [1] and the role of liquidity providers in promoting market stability [38]. The overall impact of the Contrarian Trader demonstrates its ability to successfully establish a dynamic yet stable market the environment, where wealth distribution reflects realistic and balanced trading opportunities, even though some of the observed changes can be attributed to the reallocation of agent proportions.

Task 4.3 - Performance Discussion

The ContrarianTraders exhibit steady, conservative wealth growth. In contrast to Random Traders' higher but more erratic wealth trajectories, their technique minimizes large drawdowns, which is a defining feature of their risk-averse approach. Random Traders, while capable of achieving substantial short-term gains, exhibit erratic behavior due to their lack of coordinated strategy, leading to elevated wealth fluctuations. By comparison, Chartists, particularly Balanced and Alternating agents, show intermediate performance, acting as stabilizing forces within the market. Contrarian Traders outperform Random Traders in volatile conditions by counteracting prevailing trends and effectively dampening extreme price movements, aligning with the principles of mean reversion seen in real-world contrarian trading strategies [26, 19]. Despite these advantages, Contrarian Traders may underperform during strongly trending markets, where momentum-driven strategies dominate, reflecting a key limitation in their approach. Their ability to counteract market overreactions mirrors empirical observations of value investors and market stabilizers [32, 2]. However, their impact in the simulation could be overestimated if their representation is disproportionate to real-world market dynamics. Further refinement of their parameters to incorporate adaptive thresholds based on volatility or sentiment indicators could enhance their realism and effectiveness, aligning their simulated behavior more closely with empirical data [4]. Overall, ContrarianTraders demonstrate potential as stabilizing agents in simulated markets, balancing risk and return effectively.

The maximum drawdown chart points out the risk profiles of

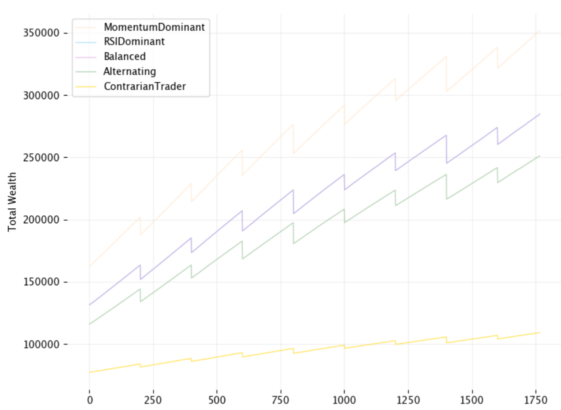

Figure 32: *Total Wealth of Chartists*

the traders, particularly the Contrarian Traders, in comparison to Chartists and Random Traders. Contrarian traders have the lowest maximum drawdowns which puts emphases on their

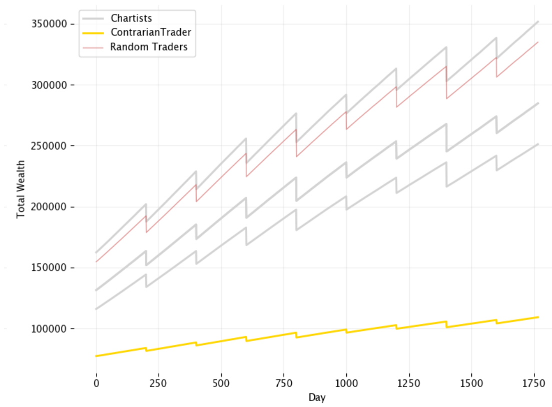

Figure 33: *Total Wealth of Chartists vs Random Traders*

risk management strategies. This is due to the mean-reversion approach, which minimizes exposure to market downturns by actively counteracting extreme price trends. MomentumDominant agents face higher drawdowns as they rely on trend follow strategies which make them susceptible to market reversals. Alternating and Balanced agents, display moderate drawdowns, which reflects their balanced strategies . Random Traders, on the other hand, exhibit the highest maximum drawdowns as they are vulnerable to extreme market fluctuations due to uncoordinated and stochastic trading behaviors. These observations highlight the effectiveness of ContrarianTraders in stabilizing markets and reducing systemic risk, a characteristic that could be analogous to the role of risk-averse institutional investors in real-world markets [26, 32]. However, the overly conservative stance of ContrarianTraders may limit their profitability during prolonged market trends, suggesting a need for adaptive strategies that incorporate elements of trend-following to enhance their versatility. Further refinement of the simulation to reflect the varying proportions and interactions of these agents in real financial markets could enhance its predictive validity [4]. The calculation of win rates for various agent

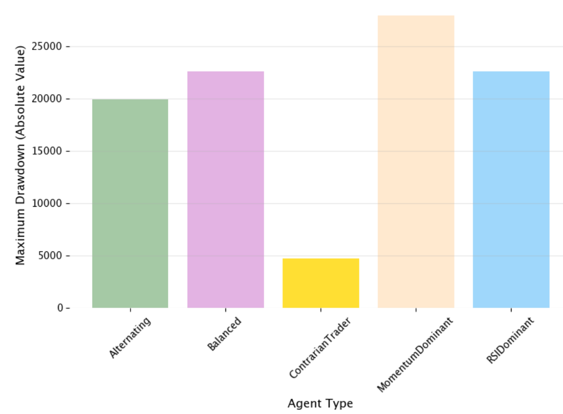

Figure 34: *Maximum Dropdown Rate of Chartists*

types offers important information about how well different strategies work in the simulated market setting. Contrarian

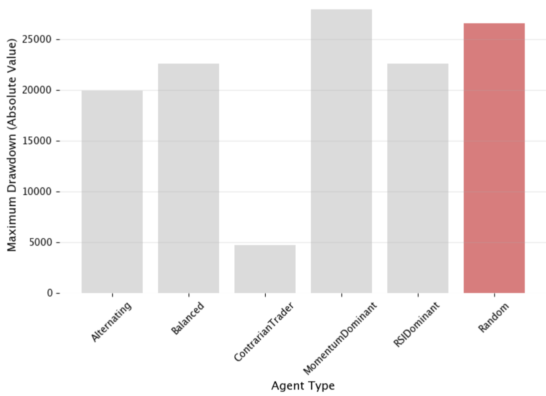

Figure 35: *Maximum Dropdown Rate of Chartists vs Random Traders*

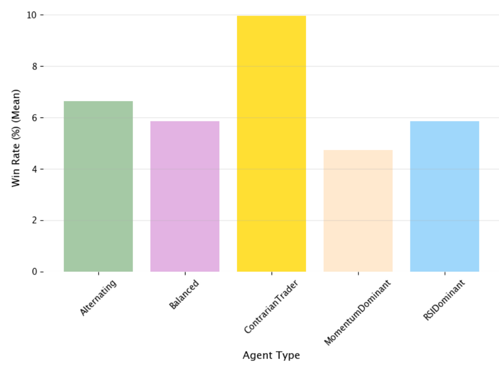

Figure 36: *Win Rate of Chartists*

traders have the highest win rate, and outperformed the other agents which proved the effectiveness of the mean reversion starefies to capitalize on price anomalies in volatile markers. By focusing on counter-trend movements, ContrarianTraders minimize the risks of speculative bubbles and mainted consistent performance by focusing on counter trend movements . Their strategy also reflects real-world trading behaviors, where risk-averse institutional investors often prioritize capital preservation while exploiting market inefficiencies [26]. Alternating and Balanced agents, had moderate win rates. They can adjust to changing market conditions due to their hybrid tactics, which find a compromise between mean-reversion and momentum techniques. RSI-Dominant agents also achieve modest win rates due to their reliance on technical indicators like oversold and overbought signals. Momentum-Dominant agents achieve lower win rates due to market reversals when trends abruptly change direction. Random Traders have the lowest win rates due to their uncoordinated and stochastic trading behavior. Their lack of strategic decision-making limits their success and introduces noise into the market. These results demonstrate how reliable ContrarianTraders are at preserving a high win rate while reducing risks, which makes them especially useful in volatile markets. However, the requirement for extensive market knowledge and quick computing power to recognize and respond to trends in real time may limit their practicality [32]. The win

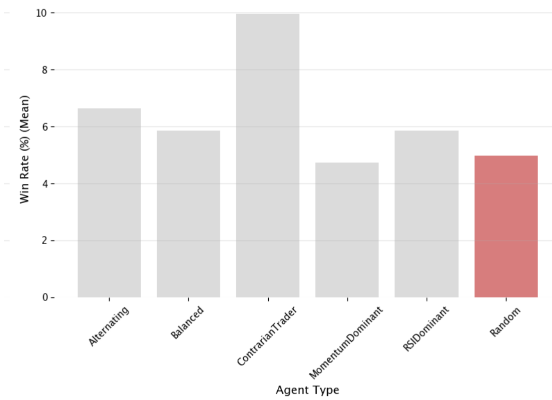

Figure 37: *Win Rate of Chartists vs Random Traders*

rates of momentum-based and RSI-based methods could be further increased by fine-tuning their reaction thresholds to better match actual financial market observations.

Task 5 - Summary

The simulation offered a thorough examination of various trading strategies, illustrating how they affect market stability and dynamics. Random traders became the wealthiest people, accumulating substantial wealth since they were always involved in the market, but their unstructured strategy also made them the most vulnerable to drawdowns and volatility. Momentum-Dominant chartists were very good at spotting trends, which contributed substantial wealth but also made them more vulnerable to market reversals. Balanced agents stood out as consistent performers, effectively minimizing risks while getting the best win rates. RSI-Dominant and Alternating agents took a more conservative approach and preferred stability over high returns. The Contrarian Trader which was introduced later into the simulation was effective in volatile conditions and stabilised extreme market fluctuations through mean-reversion strategies. They achieved lower total wealth compared to Random Traders, but they reduced drawdowns and had higher win rates, which proved their risk-averse nature and ability to stabilize the market. Their performance in trending markets was limited, emphasizing the need for adaptive strategies that integrate trend-following elements. Several limitations affected the model's accuracy. Real-world financial markets are turbulent and speculative, and the predictability of market mechanisms was unable to reflect these features. External shocks, behavioral diversity, and stochastic elements were missing which impacted the model's ability to reflect real-world dynamics. Future improvements should focus on integrating these factors, refining agent behavior, and improving parameter sensitivity to recreat real world market conditions. These adjustments would enforce a more realistic and applicable framework for analyzing trading strategies.

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