GameStop and the Social-Media Trader: An Agent-Based Model of the Short Squeeze

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Abstract

In January 2021, the stock price of GameStop, iconic American video game retailer presented a meteoric rise, surging more than twenty-fold, in the largest short-squeeze of the 21^{st} century. Retail traders, previously considered unable to influence stock prices, collaborated through Reddit's WallStreetBets forum and coordinated their acquisition of shares in the stock, triggering the squeeze against hedge funds. Current financial market agent-based models (ABMs) can explain various statistical properties of real markets through the interactions between trading agents in the artificial environment. However, the complexity and unprecedented nature of the GameStop event, coupled with the recent retail trading growth, fuelled by commission-free trading, calls for the development of a new model, able to explain how the situation unfolded and observe the financial market anomalies that emerged. In this thesis, we adapt pioneering works in ABM literature, and combine those with an opinion diffusion model through a social network to develop a novel agent class, the retail trader driven by his commitment to a social cause. Furthermore, we create a computational model which accurately replicates hedge fund behaviour throughout the event, supporting previous research on the behaviour of such institutions. These agent classes interact through an artificial market and the resulting ABM provides valuable insights into the behaviour of the market participants, uncovering main factors that drove the price surge. Furthermore, this thesis provides financial regulators and investors with a robust solution that can be tuned to accommodate for other social-media driven short squeezes, guiding future policies or investment decisions under uncertainty.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Vlad Matei*)

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Chapter 1

Introduction

In early 2021, a unique event for the world of finance took place. The price of GameStop (GME), iconic US video game retailer, presented a meteoric rise, from $18.84 per share at the end of 2020, to an all-time high closing price of $347.51, on January 27, 2021 [1].

GameStop was considered a company *"going downhill"*, with shareholders' returns consistently declining year on year [2], and which several analysts had deemed as a *"dying business"*, due to the ongoing digitalisation of the gaming industry, coupled with the impact of the COVID-19 pandemic, which forced the brick-and-mortar retailer to close all stores [3]. However, a minority of retail traders still believed in the company's future outlook, with one trader arguing that the stock was undervalued, and that its loyal customer-base, along with an ongoing digital expansion, make the stock a good investment [4]. He was sharing his beliefs and investments publicly on the social-media forum Reddit/WallStreetBets, a community where users can openly post investment decisions and strategies and receive feedback from their peers [5].

In January 2021, GameStop appointed new directors, one of which had previously ran a successful e-commerce business [6]. This, coupled with users on Reddit observing large short-selling activity of institutional investors on GME triggered the start of a *short-squeeze*. Retail traders acted together as one committed collective, coordinating their actions on Reddit and buying shares in the stock. This drove the share price up, forcing institutional investors to close their positions which further increased the price [7]. The uniqueness of the GameStop event stems from how the surge was driven by retail traders, amateur investors buying securities for personal accounts, which were previously considered *dumb money* by Wall Street professionals [8] and from the key role social media played in how the event unfolded. Reddit users saw their actions as a way of getting back at those that influenced the 2008 financial crash, which resulted in austerity and depressed wages, while large financial institutions were deemed as *Too big to fail*, receiving bailouts from taxpayers' money to keep afloat [9]. The event can be seen as a *David versus Goliath* battle, where the institutions which traditionally dominated the market through virtue of their deep pockets and advanced technology, were witnessing the rise of a new market power, the small retail trader, driven by a desire to make a point, rather than financial gains [10].

Agent-Based Models (ABMs) are models used in simulating the actions and interactions of agents in an artificial environment. Modelled agents act heterogeneously, with behaviour being governed by simple rules taking into account both agent properties and the surrounding environment. Complex phenomena emerges from agent interactions, which can then be analyzed, offering insights into how the said phenomena develops. The large amount of financial data available to researchers, the heterogeneity of trading behaviour, and debates around rationality of market participants ensure financial markets are well suited to Agent-Based Modelling [11].

Recently, retail trading has grown tremendously, accounting for 23% of all US equity trading in 2021, more than doubling compared to 2019 levels [12]. This has been enabled by commission-free brokerage apps, such as Robinhood [13], and accelerated by the COVID-19 pandemic, as the app reached over 22.5 million active users [14].

While current ABMs of financial markets are able to explain some of the statistical properties observed in real-world markets, the uniqueness and complexity of the GameStop event, as well as the recent retail trading boom, call for the development of a new model, capable of replicating the event and capturing the specific interactions between traders on social media, their approach to trading and the reaction of institutional investors.

In developing such a model, the following research questions arise, as introduced in the IPP [15]:

- Can the unique short-squeeze of GamesStop be replicated through an Agent-Based Model, where *retail* and *institutional* investors interact indirectly through their decisions in an artificial market environment?

- Can the collective commitment and the phenomenon of expressive trading, based on non-wealth investment motives, as identified in [16], [10] be recreated through a computational model?

- What were the main driving factors that influenced the short-squeeze?

- How did the interactions between social-media traders develop throughout the event in relation to price evolution, and what was the decision-making process of institutional investors as a response to the price surge?

Answering these research questions, the model developed builds on existing works [17], [18] and provides financial regulators and practitioners with insights into how the event unfolded, explaining the behaviour of retail and institutional traders as well as the market dynamics that led to the exponential price surge. Through providing a robust model that captures the complexity of the social-media driven short squeeze, this thesis offers regulators and finance professionals a basis for future policy making and investment frameworks. Furthermore, the field of computational finance research benefits from this project's contribution, as the agent classes and modelled interactions cover the participating actors of future social-media driven squeezes, subject to parameter estimation for specific cases. It is important to note that, due to time constraints, the main goal of this thesis remains the development of a robust model of the squeeze, capturing the behaviour and interactions of market participants. The potential regulatory or exploratory research described above is out of this project's scope.

The remainder of this thesis is structured as follows. Chapter 2 provides the background required for understanding and evaluating the work performed. It starts through covering a timeline of the short-squeeze, followed by an introduction of emerging literature. The chapter continues through introducing current research on opinion diffusion models and financial market ABMs, observing current limitations, and stating the contributions of this project. In chapter 3, the design of the agents is covered, introducing the variables describing each agent's state, the actions each agent class can conduct and the set of possible interactions with other agents and the environment. Assumptions made during agent design are detailed, with parameter choices justified through references or empirical analysis. The model is validated in Chapter 4, both in terms of the input, as well as output. Validation covers general stylized facts of financial markets, as well as specific GME anomalies and historical price evolution. Chapter 5 introduces a sensitivity analysis, through which it is shown that the model's results are robust to parameter changes. Furthermore, this chapter presents a discussion in terms of the behaviour of each agent class, along with identified limitations. The chapter ends relating the findings to the research questions of the project, stating the insights gained through the analysis of results. Finally, in Chapter 6, the findings are summarised and placed in the larger picture of the changing market environment, along with a discussion of proposed future work.

Chapter 2

Background

To represent the unique event of the GameStop short squeeze through an ABM, elements of network science, financial markets modelling and general trading knowledge are required to be merged. The first section of this chapter covers how the GME event unfolded and introduces emerging literature, from social and financial points of view, which guides the design process of the agent classes present in this dissertation. Opinion diffusion through network science is then introduced, detailing current work and research gaps. Finally, financial markets ABM literature is covered, presenting the elements of previous implementations which provide the starting point of the market developed in this thesis. Clarifications are made on how this project builds on the works presented, filling in identified research gaps.

2.1 GameStop Short Squeeze

2.1.1 What Happened?

In January 2021, the largest short-squeeze of the 21^{st} century took place on the New York Stock Exchange, inflicting financial losses for institutional investors [19]. Retail traders acted together, as one committed collective, influencing the market in a way previously deemed impossible, targeting short-selling[1] behaviour of Wall Street firms.

GME, iconic American high-street video game retailer, had been struggling for years, due to an outdated business model, based on physical stores and not well-suited to the evolving ecosystem of the video game industry, as customers shifted from buying physical copies in stores to directly downloading games [20], [21].

[1] borrowing a stock, only to sell it instantly, esentially betting that the price will decline

The Coronavirus pandemic forced countries worldwide to go into lockdown, closing stores and encouraging online shopping, thus further increasing the issues of the already struggling company. In an article posted on SeekingAlpha,[2] popular crowd-serviced financial markets website, the authors argued how GME was on its way to liquidation, due to negative earnings reports coupled with the changing market environment accelerated by the pandemic [22]. Sentiment regarding GME's future outlook in the face of the overall trends of the gaming industry and COVID restrictions was negative, and the company was considered to be "*heading to the grave*" [23], [24].

Large institutional investors decided to short the stock, expecting GameStop to fail [25]. Shorting a stock means borrowing and selling it immediately, expecting the price to fall, then buying later at a reduced price and returning the stock, thus locking in a profit. This approach presents large risks, as the maximum possible gain is 100% of the investment, provided a stock loses all its value, however, loss potential is unlimited, as the stock can theoretically grow to infinity [26].

The social media platform *Reddit* has several sub-forums where like-minded individuals can meet and discuss. One of these is *Wall Street Bets* (WSB) [5], a community where users are encouraged to share investment strategies and offer/receive feedback on their trades. The subreddit has developed a reputation in the media for the risky trades made by its members, often supported by memes or statements as *YOLO* (You Only Live Once) [27]. Opposing the image painted by the media, [28] analysed the returns of r/WSB over the 2019-2021 period and found that returns of the sub-reddit surpass those of the S&P 500 over the same period, showing how these investors also employ sophisticated analysis when investing.

One user on the forum had a large investment in the stock, as he believed the company had great upside potential. He considered the stock to be undervalued, claiming that the digitisation of the gaming industry will not continue at the rate most people were expecting, and GME can reinvent itself, through an expansion of its digital capabilities, and leveraging its community of 60 million loyal customers [29]. In early 2021, the company appoints 3 new directors, one of which had previously ran a successful e-commerce business, resulting in a stock price increase. This increase, along with Reddit users observing the large short positions held by hedge funds in the stock (over 140% of shares available), triggered the start of a *David vs Goliath* narrative [30], as retail investors coordinated on the forum, to collectively drive the price up, either through simply buying shares or through the purchase of call options (see 2.1.2). The

[2] https://seekingalpha.com/

price of GME went up, which in turn forced institutional investors to close their positions, as they aimed to limit losses, further driving the price up. This feedback loop is also known as a *short-squeeze* [31]. In a controversial decision, commission-free stockbroker Robinhood, the main platform used by retail investors [13], decided to restrict trading on the stock, citing irregularly high volume. Users could only unwind existing positions, while the opening of any long[3] positions was banned [32].

Figure 2.1 presents plots of the closing price, volume and return values. In the bottom right plot, we can observe how a volume increase predates the surge in price. The high stock volatility can be observed during the latter period, which coincides with the moment Robinhood halted any long positions on the stock. The halting of trading is a crucial point of the GME frenzy, and is included in the model, without developing a specific *Robinhood* or broker agent, but as a function of the market environment. This design decision minimises model complexity while still allowing for the observance of emerging behaviour in the aftermath of the key event.

Figure 2.1: GameStop closing, volume, and return over analysed period

[3]purchasing of an asset

2.1.2 Option Trading as An Accelerator

The exponential surge in price observed in Figure 2.1 was fuelled not only by simple acquisition of shares by Reddit users, but also through derivative trading. Call options give the buyer the right (but not the obligation) to buy shares at an agreed strike price within a specific time span, in exchange for paying a premium [33]. When buying options, the counterparty is usually a market maker. In order to hedge their risk when selling the option, the market maker buys slightly more dollar value of the stock than the premium price of the option. Thus, the price paid for buying an option results in an even larger acquisition of shares in the underlying stock [34].

As the stock goes up in price, the market maker needs to adjust his position, and is forced into buying more shares to keep the hedge in place. This effect is known as a *gamma squeeze*, and contributed greatly to the GameStop's meteoric rise [35], [36] (further details in A.5). This implication also drives key agent-design decisions, as presented in Chapter 3.

2.1.3 Emerging Literature

In the aftermath of the event, new research has been conducted in order to shed light on how the situation unfolded.

[7] analysed the event from a social dynamics point of view, characterising the interaction network and user behaviour observed during the event. This analysis revealed how the community of traders could be seen as a network with a robust scale-free property, and how topic dispersion of the most influential users is larger than that of common users. Similarly, [16] analysed Reddit and financial data, and described how the surge in commitment to the *David vs Goliath* cause in the network predated the price surge. In [32], the event is characterised from a legislative point of view, touching on the impact of market-makers in how the situation unfolded, as presented in 2.2.2. [37] analysed the event from the perspective of financial theory, characterising the participants as *naive, fanatical* or *rational short/long term* investors. Using financial intra-day data, [38] revealed how the squeeze led to market abnormality and to the *anti-leverage effect*, displaying direct correlation between stock prices and volatility. Analysing from a social point of view, [39] found sentiment coming from Reddit had a direct impact on the daily returns of GME, supporting the findings of [16].

In summary, current literature offers insights into the development of the short squeeze, both from a social and financial point of view. This thesis contributes to the growing literature, through using these findings as guidance in the design of the proposed ABM, as further explained in Chapter 3.

2.2 ABMs of Financial Markets

Historically, economic theory has proven successful in explaining financial equilibrium, however, the models developed are fitted to historical data and assume a perfect world, where agents behave rationally [40]. This is not satisfactory when aiming to understand the micro processes that lead to price formation in a stock market. Real-world market participants behave heterogeneously and display irrationality, contradicting the main assumption of econometric models [41]. Modelling stock markets through a bottom-up approach, with large number of agents whose behaviours are governed by relatively simple rules provides the opportunity of understanding the micro processes that lead to the emergent macro phenomena [42]. Agent-based computational finance models view markets as interacting groups of agents which are boundedly-rational, being able to adapt strategies to reflect personal beliefs and market conditions [11]. Figure 2.2 presents the general framework observed in literature, where agent interactions (micro processes) are driven by simple behaviour rules. Their interactions affect price formation through the market. In turn, price updates influence agent behaviours. The emergent macro phenomena can be analysed as a result of these interactions.

In recent years, ABMs have increased significantly in popularity and are being used in guiding financial policy decision-making by regulators, central bankers and stock exchanges [43], [44]. Standard economic models were not able to prevent nor explain key events, such as the financial crisis of 2008, and ABMs uncover key insights into what contributed to these events, guiding future policies [45], [40]. In [46] the effectiveness of regulatory policies was analysed through an agent-based financial market, most notably a trading halt, which takes place when prices move at rates deemed too high. The model is relevant to the proposed project, as trading was halted during the GameStop event, which caused price to plummet (see 2.1.1).

The work of Lux and Marchesi, a pioneering financial market ABM [47] divides the pool of agents into two types. A *fundamentalist* class, which respects the efficient market hypothesis [48], believing that prices follow the fundamental value of an asset, and a *chartist* class, which ignores fundamentals and aims to identify price trends when making investing decision. Agents can switch between the two classes, as they observe profit differences between using each of the approaches. Price changes in the model

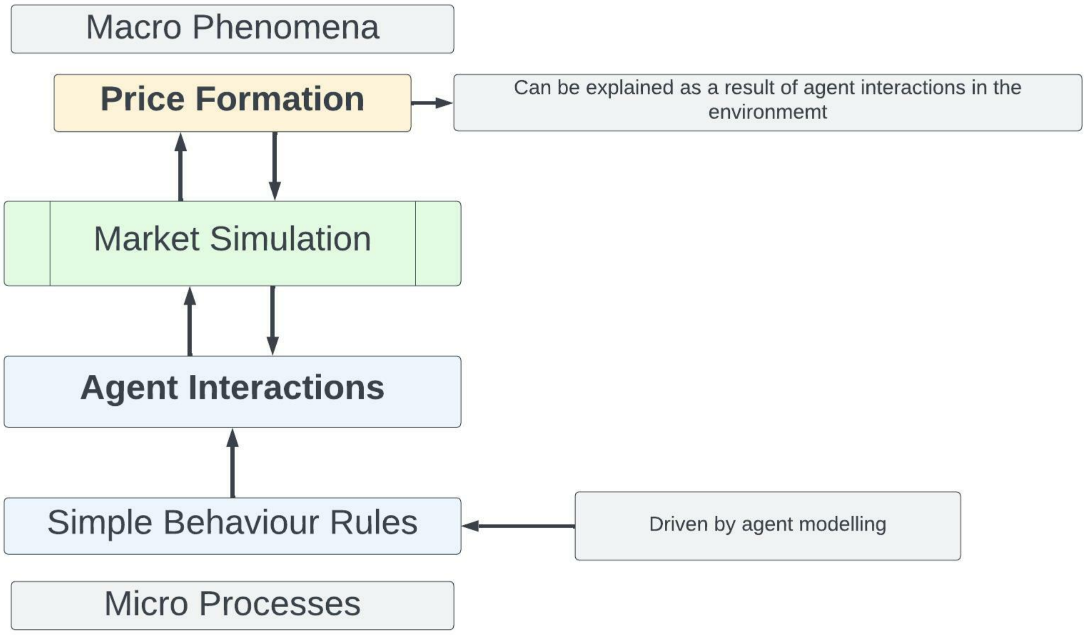

Figure 2.2: General Financial Market ABM Framework

are endogenous and come as a direct result of market demand-supply imbalances.

[49] introduce a model where agents can be characterised into 3 classes, adding a *noise trader* class to the fundamentalist and chartist approaches. Subsequent works build on this model, using the three trading classes in their simulations [50], [18], [51]. All models are able to reproduce the complex phenomena observed in real-life markets and extract insights into how specific features of market design, such as ratio between the different trader types or the distribution of trader characteristics can affect market liquidity and price formation. Building on the pioneering works presented, models have been created to analyse specific real-market events. [52] and [53] have built ABMs analysing the Flash Crash of 2010, when prices of leading US stock indices fell drastically and rebounded within several minutes. Validated by the report of the U.S Securities and Exchange Commission [54], the findings can drive future policies regarding automated trading. ABMs of market dynamics can be linked with opinion dynamics works, as presented in 2.3, to understand how sentiment and opinion diffusion through a social network impact price formation [55].

The proposed project builds on background work presented in this chapter, creating a market model of the GameStop saga. Pioneering financial market ABMs ([17], [18]) are adapted to model event participants, building on information presented in Section 2.1. Furthermore, the project links previous work on opinion diffusion models [56],

[57] expanding existing implementations, to explain the unique social behaviour observed amongst retail traders. Formulas used in designing the agents' decision-making are presented in Chapter 3, referencing relevant works.

2.3 Opinion Diffusion

Network science represents an emerging interdisciplinary field which aims to increase understanding of the architecture and behaviour of real-world networks [58]. Representing the main actors and relationships between them as nodes and links, allows researchers to study complex systems and observe the emerging behaviour through the topological structure of the network [59]. A pioneering work in this area, [60] develops a model that can accurately reproduce the scale-free power-law distribution of node connectivities observed in real-world large networks. The model expands continuously through the addition of new nodes, which, rather than connecting randomly to existing nodes, do so in a *preferential attachment way*, meaning that they will preferentially link with nodes with high degree values. This property can also be observed during the GameStop saga, in the network of Reddit users, as further described in Section 3.1.

In opinion diffusion models, interacting agents adapt their opinion based on a predefined threshold value. If the difference in opinions is too high, then the agents will neglect the opinion of others. However, if the difference is below the threshold, agents adapt their opinion based on that of the agent they came in contact with. Similarly, in a real-world network, if a member of a social group holds one opinion, while the majority holds a contradictory opinion, the said member is likely to update his [61].

Binary diffusion models, where agents in the network can hold one of two opinions have been successfully employed in literature to describe *herd behaviour* [62], which, in financial markets, is characterised as the tendency of investors to copy the behaviour of others [63], [64], [65]. Despite its successes, a binary diffusion model can be considered limiting in the context of modelling the GameStop event. Users on social media act heterogeneously, and the overall sentiment can not be accurately represented through a binary model, as more granularity is required. As discussed in 2.2.1, the initial group of users that led the event influenced the actions of other users, however, their commitment can not be considered equal to that of users only joining the cause as it was gaining traction.

In [56], a bounded confidence model of continuous opinion dynamics is presented. This work introduces a model where out of N agents, each with opinion x_i, two are randomly chosen at each step. Based on the pre-defined threshold value, the agents either continue without discussing, or adjust their opinions according to the below equations:

$$x_i = x_i + \mu \cdot (x_j - x_i) \tag{2.1}$$

$$x_j = x_j + \mu \cdot (x_i - x_j) \tag{2.2}$$

, where x_i and x_j are the opinions of agents i and j respectively, and μ is a convergence parameter, which scales how fast the agents reach consensus.

[66] implemented the confidence model presented above, and compared the results of simple case of mixing introduced by [56] to mixing within a scale-free network. A key finding also driving the design of this project was how nodes with largest connectivity appeared to be most influential in the network. In subsequent research, [67] introduced a bounded confidence model including extremists, or very convinced individuals with opinions close to the upper/lower bounds. Results show the highest shifts to extreme for all agents are more likely to form when several agents are already certain.

A drawback of the models presented above is the interaction process between agents. Although population values are large, pairs of agents are randomly chosen at each step for opinion updating. In a social network as the one modelled for this project, agents are influenced by the general opinion of all nodes they interact with as part of their network, rather than only one of the individuals in their network.

The approach proposed in this dissertation differs from those presented above, using a temporal scale-free network, presenting a number of certain extremists from the start. Rather than modelling agent interactions as a *random* communication structure, the agents take into consideration all neighbouring opinions, when deciding whether to update their own. Finally, to accurately model the complexity of human behaviour and beliefs, the threshold value for opinion updating is chosen from a uniformly sampled distribution of values, rather than a pre-defined unique value.

Chapter 3

Model Design

This chapter introduces the design of the agent classes in the model. Firstly, analysis of empirical data retrieved from activity on *r/WSB* as the short-squeeze developed and GME price data retrieved from Yahoo Finance [68] is introduced, guiding several subsequent design decisions. Following this, the Reddit agent class is presented, along with the Institutional Investor and the Market Environment developed.

During model design, complexity was kept low, to avoid the risk of over-fitting. As [69] note, for a good design, acquiring knowledge of the underlying mechanisms affecting prices is more important than replicating the exact results of a financial market. Overly complex ABMs are criticised in literature due to intractable results [70].

3.1 Empirical Data Analysis

As part of data gathering, two data sets were retrieved, one extracted from the YFinance API, for the GME ticker with volume and price information over December-February period, and a second one, extracted from Kaggle, with all posts and comments data in the r/WSB community throughout the short-squeeze [71].

When conducting the analysis, the aim was to test initial assumptions regarding the event, developed throughout background research, thus guiding the design of the agent models. Hypotheses were tested as presented below:

H1: The network of Reddit users can be modelled as a scale-free network

Real-world networks are believed to be scale-free, which implies their degree distribution follows a power-law: $P(k) \sim k^{-\gamma}$, where $P(k)$ is the probability of observing a node with degree k and γ is a scaling parameter, typically in the 2-3 range [72]. This explains the emergence of hubs in a network, or nodes connected to a large number of other nodes.

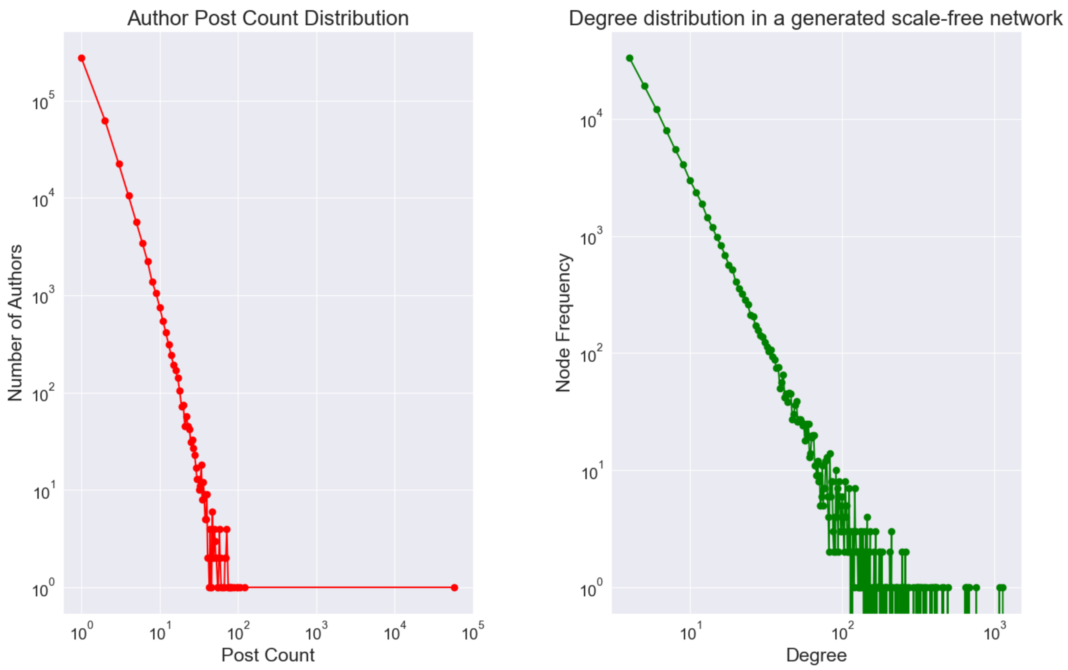

Figure 3.1: r/WSB author-post count distribution (LEFT) vs generated scale-free network degree distribution

Figure 3.1 presents the log-scale plot of author-post count distribution observed on Reddit, against the degree distribution of an artificial scale-free network generated through the NetworkX[1] package. Only a handful of users are responsible for large numbers of posts, while most users present a post count between 1-10. The right-hand side of the figure presents the degree distribution in a generated scale-free network with 10^5 nodes, and high-similarity can be observed between the two plots. Furthermore, [7] identified a group of users as being *Influential*, as did [16], which state how a handful of initial committed users led to the growth of the collective identity of the forum. These users are reflected in Figure 3.1 through the nodes with high post counts.

H2: Evolution of community sentiment drives the short-squeeze

We observe the evolution pattern of GME closing price, market volume and daily posts count on Reddit, in a rescaled plot as presented in Figure 3.2. A volume surge predates the price surge, however, it is interesting to note how the number of posts lags behind price movements as the price increases, however decays faster than the

[1] https://networkx.org/

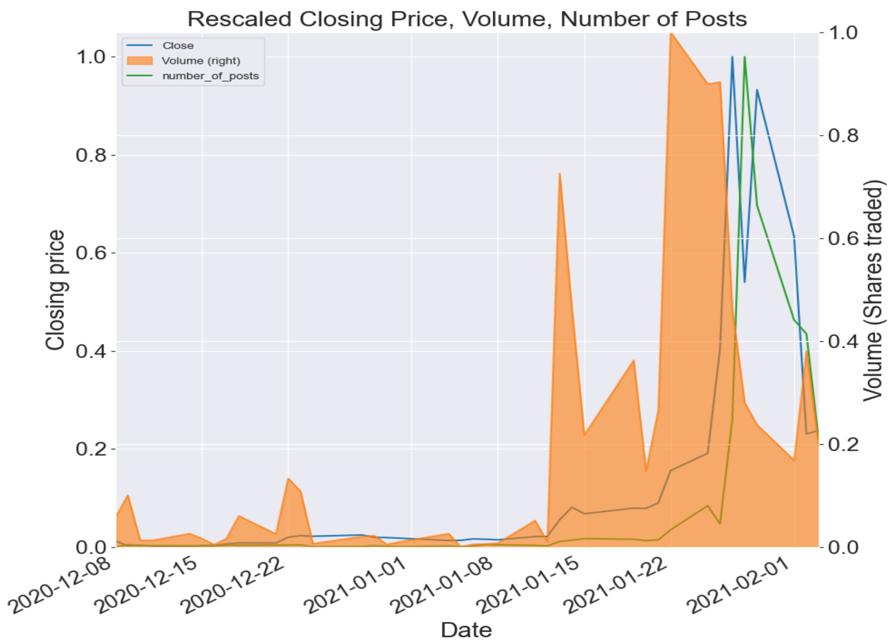

Figure 3.2: Rescaled GME Price, Volume and r/WSB post numbers

price following the halting of trading. Although this could be seen as contradicting the findings of [16], which state that a commitment surge predates any surge in price, it is important to consider the following. Firstly, Lucchini et al. quantify commitment based on the information within the post, not simply through the post. Secondly, the re-scaling of the plot loses important information. An increase in commitment of the network can lead to a much higher increase in price, mainly due to the option-trading behaviour of Reddit users, which acted as an accelerator for the price increase, as presented in 2.2.2. The crash better reflects how commitment sentiment influenced price changes. Finally, [16] note how the initial spike was ”followed by a surge in commitment”, validating this analysis’ findings.

3.2 Reddit Trading Agent

Guided by background research findings, Reddit agents were separated into ***Influential*** and ***Regular*** [16], [7]. The regular class introduces further heterogeneity through separating into investors with long-term and short-term market views, which, in turn, affects their market behaviour [37]. Direct interactions between agents are represented through a temporal, scale-free network, where regular agents with low initial commitment interact with each other and with influential, fully-committed agents, leading to network commitment spread.

3.2.1 Agent Description

The Influential agent is representative of the fully-committed agents from the beginnings of the GameStop saga, which played a key role in influencing the Reddit community. At the start of simulation, a scale-free network is generated, and the 5 nodes with the highest degree are assigned as *Influential* agents. This agent's commitment to the cause does not change at any point throughout the simulation. In terms of demand in the stock, the influential agent does not take into consideration price trends and can be seen as a *fundamentalist*, with perceived fundamental value of the asset several orders of magnitude higher than the original GME price. This assumption is based on the findings of [39] and the testimony of Keith Gill, the owner of the initial sizable GME investment [29]. Five was the chosen number of influential nodes following model calibration and empirical analysis.

The regular trader reflects the general user on WSB, which followed the updates of the community and whose decisions in the market were largely influenced by his commitment to the social cause of the Reddit group. These agents can be seen as *chartists/fundamentalists*, similar to those observed in works as [18] or [73], during the initial surge in price. Prior to being fully committed to the cause, they calculate an expected price based on their preferred market-approach. Once their commitment to the cause increases, their decisions are no longer based on financial analysis, and are solely driven by their strong beliefs regarding GME. As [74] observed, the halting of trading clearly killed the community's momentum and was a main reason for the stock's decline. Basing on market data, we have assumed that the investor with a long-term view, once momentum is killed, will act based on his perceived fundamental value of the asset, which is more in line with the general media sentiment, until his commitment rebuilds. Similarly, short-term investors continue acting as chartists and base decisions on market price trends. This leads to a market where investors drive the price towards its fundamental value, with indications of future spikes based on commitment spread.

3.2.2 Agent Parameters - Influential Trader

Parameter	Description	Value	Source
Investor Type	Influences the market behaviour	Influential	[37]
Demand	Demand in the traded asset	1	Imposed
δ	Commitment to the social cause of the GME squeeze	1	Imposed
Neighbour_ids	This agent's neighbours in the network	Defined during simulation	[16]
β	Scaling factor in terms of expected GME price	Sampled from uniform distribution [500, 1000]	[39], [29]

Table 3.1: Parameters of the Influential Reddit Trader

3.2.3 Agent Parameters - Regular Trader

Parameter	Description	Value	Source
Investor Type	Influences the agent's market behaviour	Short/Long-term] with $p = 0.5$	[37]
Demand	An investor's demand in the traded asset	0	Imposed
δ	An agent's commitment to the social cause of the GME squeeze	Sampled from uniform distribution [0.3, 0.5]	Imposed
Neighbour_ids	The neighbouring nodes this agent comes in contact with throughout the simulation	Defined at simulation start	[16]
P_f	Fundamental price of long-term investor	Sampled from [1, 16]	[23], [22]

β	Scaling parameter all regular investors use in calculating their expected price through a chartist/fundamentalist formula	Sampled from uniform distribution [-1, 1]	[73]
γ	Threshold parameter of difference in opinion which triggers update	Sampled uniform distribution [0.3, 0.5]	[56]

Table 3.2: Parameters of the Regular Reddit Trader

3.2.4 Actions the Agent Can Perform

Influential Trader

This agent does not perform any actions throughout the simulation, other then linearly increasing his demand, whenever selected to participate in the market, through the volume function (see 3.4.2). His main role is driving the evolution of the commitment throughout the network, as his personal demand does not impact the price in a significant way. This assumption is based on market volume empirical data. Although the initial investment of committed users was sizable from a personal point of view and positively influenced WSB users, as percentage of the overall market volume it was insignificant.

Regular Reddit Trader

This agent makes market-decisions based on endogenous and exogenous parameters. In terms of external parameters, the agent considers average commitment across the network, and ongoing price evolution. For internal parameters, the agent considers his own commitment to the social cause, the weighting factor assigned to his price expectation, and his trading strategy, dictated by the investor type parameter.

As presented in Algorithm 1, a highly-committed agent, once the average commitment across the network also reaches high levels, will decide to buy options. As [37] note, option trading is similar to a ”pre-programmed trading strategy”, where the investors buys more and more shares. The 100 scaling factor reflects the contract size of an option in financial markets. Otherwise, a committed agent will set his demand as a function of his commitment, thus increasing demand solely based on commitment,

Algorithm 1 An agent's decision making process

Data: Commitment, avg_network_commitment, current_price, price_history, noise_value, commitment_scaler

if *commitment* $>$ *0.6 AND avg_network_commitment* $>$ *0.625* **then**
    demand = 100 * commitment
else if *commitment* $>$ *0.5* **then**
    demand = commitment_scaler * commitment
else if *0.25* $<$ *commitment* $<$ 0.5 **then**
    if *E(price)* $<$ *current_price* **then**
        demand -= commitment_scaler * commitment
    else
        demand = commitment_scaler * commitment
else if *commitment* $<$ 0.25 **then**
    $demand = -(demand * commitment)$ ▷ Sell-off under the trading halt
end

without regards to financial analysis. An agent which is still not committed to the cause entirely will take a more general market-approach, calculating his expected price. This is performed either through a fundamentalist approach (3.1) for long-term agents, or momentum-based approach (3.2, 3.3) for short-term investors [73]. In the trading halt scenario, *"momentum is killed"*, triggering a large market sell-off, [74] and thus agents update their demand as a negative function of current demand and commitment, again disregarding financial analysis. The trading halt mechanism implemented is further described in 3.4.2.

With the aim of keeping model complexity low and to avoid over-fitting empirical data, agent demand is set as a function of commitment, rather than a pre-defined fixed value. This approach correlates with the findings of [16], as increased commitment predates the price surge, and allows for retail trader market-behaviour to develop in relation to the social interactions.

$$E(x) = P_t + \beta(self.P_f - P_t) + noise\_term \tag{3.1}$$

$$E(x) = P_t + \beta(P_t - p_{M_t}) + noise\_term \tag{3.2}$$

$$p_{M_t} = \frac{1}{M}\sum_{i=0}^{M-1} price_{t-i} \tag{3.3}$$

p_{M_t} reflects the rolling average of prices, set as a window of 15 for all agents based on empirical findings in previous works. Similarly, the noise term added to both equations is sampled from a random uniform distribution [-1, 1], ensuring heterogeneity in agent price movement expectations, as observed in real markets.

3.2.5 Interaction with Other Agents

Agents interact directly with each other in the network, and indirectly with institutional investors, through their investments. In modelling commitment spread, a bounded and continuous opinion diffusion model has been implemented. The *commitment* variable takes values between 0 and 1, and an agent decides whether to update his own commitment based on the threshold parameter, γ, as presented in Table 3.2.

The model implemented is an adaptation of the work observed in [56] and [67]. Extremists are introduced, represented by the Influential Traders, starting with a commitment of 1. Furthermore, differently from previous works, the average opinion of neighbours is used in the update function, rather than that of a single agent. This approach more closely replicates the social media context this project is focusing on. Furthermore, previous works update the opinions of both agents in an exchange, thus reaching a consensus. In our model, only the agent with a lower commitment value updates his beliefs towards the higher value, as presented in Equation 3.4, where $\bar{\delta}_{neighbours}$ is the average of all neighbouring opinions, simulating the growth of community identity and δ_i is the commitment of an agent i. In [56], at each time step two agents are randomy chosen for interaction. In our model, the opinion profile of the population gets updated $\tau = \frac{N\_agents}{2} * t$ times, where N_agents is the total number of agents, and t is the number of trading days simulated. The rationale for this decision is that social media users closely follow updates on a daily basis, and a large part of the population will be constantly re-assessing their beliefs.

$$\delta_i = \bar{\delta}_{neighbours} + \mu \times |\bar{\delta}_{neighbours} - \delta_i| \tag{3.4}$$

μ represents the scaling factor which determines the rate of convergence towards the average opinion of neighbours. This is a calibrated parameter, defined as 0.17 in the final model. The Appendix (A.2) presents examples of the calibration process.

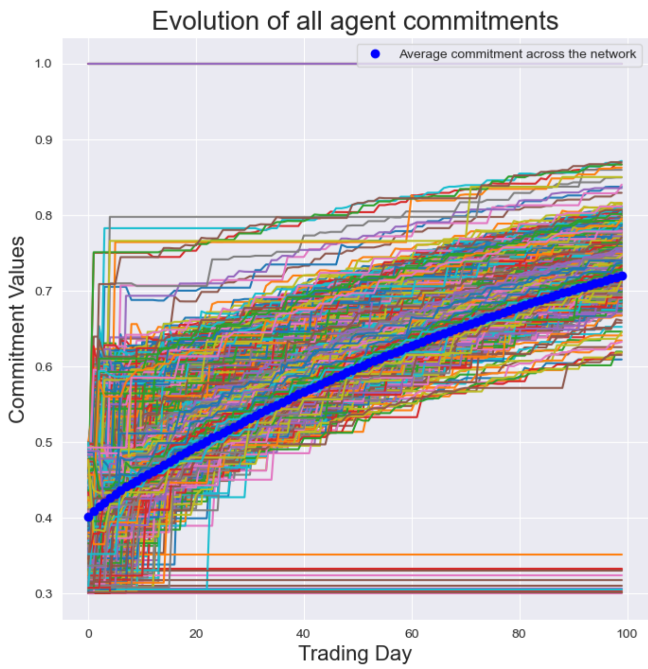

Figure 3.3: Commitment diffusion in the modelled social network

Figure 3.3 presents the outcome of the opinion diffusion model proposed above under 100 trading days, alongside the continuous average (blue). Interactions between agents lead to the general average opinion shifting towards that of the Influential users. Opinion heterogeneity can be observed, as although most opinions follow a similar upscale trajectory, exact values vary. Furthermore, two extremists groups emerge. A minority of agents present low commitment values, and, as the average commitment of the network steadily increases, they isolate themselves from other members. To further analyse the diffusion process, the trading timeline was split into 5 equal periods. Figure 3.4 presents the temporal evolution of the network, where only nodes (agents) with a commitment higher than 0.6 are plotted, with node-size proportional to the number of neighbours. At simulation start, only the 5 Influential users are fully committed. The following 2 periods depict growth at a slow rate, in the number of committed individuals, with influential users being key in the network. The final 2 periods present tremendous growth, with the latter one showing a well-connected network, where influential agents have almost "lost" their status, as most users are highly committed. The 0.6 threshold was selected as it represents the trigger value for option trading.

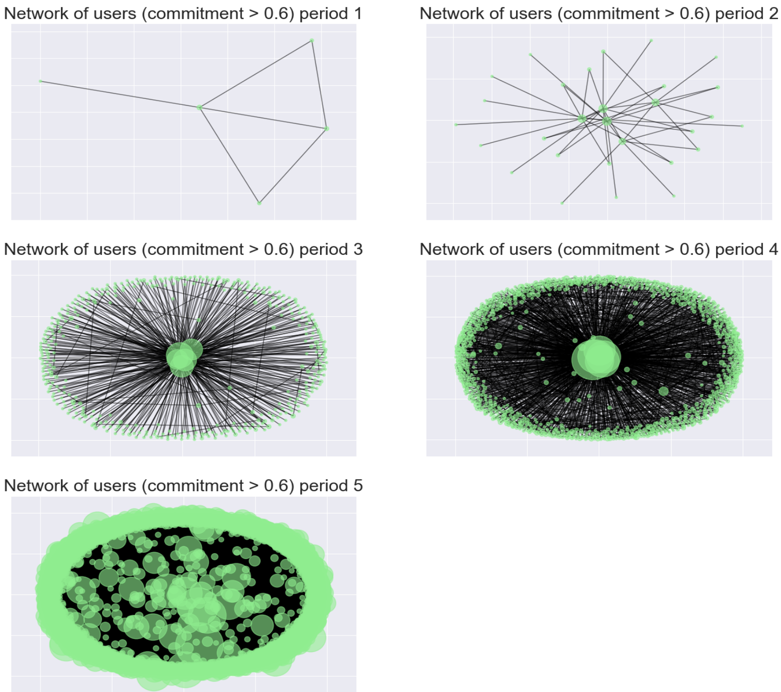

Figure 3.4: Temporal evolution of the agent network (agents with $commitment > 0.6$)

3.3 Institutional Investors

3.3.1 Agent Description

This agent class is modelled to reflect the behaviour of institutional investors throughout the event. Each agent starts with negative demand, reflecting the short positions of these investors. Decision-making behaviour of this class is modelled through Prospect theory, an influential theory of risk-based decision-making, which allows to model the decision of this agent class through one function. Heterogeneity of decisions is introduced through variation in the noise term, influencing expected returns of each agent, and variation in the risk-attitude of agents.

When faced with unprecedented uncertainty through the rallying of social media users, institutional investors could not behave fully rationally, and, depending on each fund's risk-attitude, they decided at different times when to switch behaviour and close positions, taking losses, despite their fundamental beliefs with regards to GameStop's value. The pioneering work of [75], [76] provides the framework for the model, and the findings of [77] reinforce our assumption: a hedge fund's investment strategy is directly linked to its risk-aversion, and the value function of prospect theory can describe how managers evaluate possible approaches. Assumptions made in parameter setting reflect the speculative-nature of hedge funds [78], as risk-behaviour is sampled from a probability distribution weighted towards risk-loving agents. Furthermore, when evaluating potential gains and losses, probabilities are skewed towards potential gain, encouraging profit-maximisation behaviour.

3.3.2 Agent Parameters

Parameter	Description	Value	Source
Risk_loving	An agent's risk-attitude	Sampled from [False, True] with P = [0.33, 0.67]	Imposed
Demand	The agent's demand in the asset	-100	Imposed
p_f	The fund's perceived fundamental price of the stock	1	[31], [26]
α	Used in the agent's value function calculation - lower value assigned to risk-averse funds	[0.5, 2]	[79], [80]
β	Used in the agent's value function calculation	1	[80]
p_{gain}	Weight assigned to perceived gain value function	0.8	Imposed
p_{loss}	Weight assigned to perceived loss value function	0.2	Imposed
g_1	Weight of the fundamentalist component in the price expectation for	[1, 2]	[18]
g_2	Weight of the chartist component in the price expectation formula	[2.55, 0.9]	[18]

Table 3.3: Parameters of the Institutional Investor Agent

3.3.3 Actions the Agent Can Perform

In the simulation, at each step, $\frac{N}{2}$ institutional investors make a decision, assessing current market conditions and endogenous parameters. This choice results in these agents trading relatively frequently. In periods of market turmoil, research has shown higher speeds and lower accuracy to better reflect empirical hedge fund returns [81].

In terms of decision-making, the process can be split into two phases. First stage is *prospect construction*, where agents calculate their perceived gains and losses as the difference between the current asset price and their expected price. Agents calculate expected price through formulas 3.5 and 3.6, where g_1 and g_2 are weight terms for fundamentalist and chartist respectively, p_t is price at time t, p_m represents price trend and ε is a noise parameter. When calculating perceived gains (x_{gain}), the fundamentalist term is assigned a greater weight, while the opposite is true for perceived loss, thus ensuring the model is in line with the decision of representing funds as *fundamentalists*.

$$E[r_{t+1}] = \frac{1}{g_1 + g_2 + n} \times [g_1 \times ln(\frac{p_f}{p_t}) + g_2 \times p_m + \varepsilon] \tag{3.5}$$

$$x_{gain/loss} = E[p_{t+1}] = p_t \times e^{E[r_{t+1}]} \tag{3.6}$$

Price trend is calculated as the average return over the last t trading days: $p_m = \frac{1}{t}\sum_{i=1}^{t} ln\frac{t-i}{t-i-1}$, where t has been set as 10 for all agents.

Following expected price calculation, agents perform the second phase, *prospect evaluation*, calculating the utility functions of perceived gains and losses as:

$$V(loss) = \lambda \times (x_{loss}^{\alpha}) \tag{3.7}$$

$$V(gain) = p_{gain} \times (x_{gain}^{\alpha}) - (1 - p_{gain}) \times \lambda \times x_{loss}^{\beta})) \tag{3.8}$$

where λ has been set as 2.25 initially based on [75], and further calibrated to 1.75 for the proposed model. Once the two utility functions are calculated, an agent compares their values. If $V(gain) > V(loss)$, the agent aims for profit maximisation, and thus further decreases demand in the asset, representing short-selling behaviour. However, if the opposite is true, the agent opts for the sure loss option, closing its positions.

The design decision to allow for continued short-selling for this agent provides benefits that are twofold. It limits complexity, and also models the leverage used by these sophisticated investors in real-markets, as they rely on it to enhance returns [82], [83].

3.3.4 Interaction with Other Agents and the Environment

Institutional investors do not interact directly with each other. The only exogenous parameters taken into account are price movements, as they influence the agent's perceived loss calculations. Each agent interacts indirectly with other institutional investors, as well as Reddit traders, through their market actions. Agents' demand updates influence market movements, and thus, indirectly affect other agents' behaviour.

3.4 Market Environment

The final agent class of the proposed model is represented by the market environment, where traders interact indirectly. Price in the market is updated based on excess demand from both sets of agents. After each update, agents observe the new price and re-evaluate positions, creating a feedback loop which leads to price formation in the model. A noise term is also introduced, reflecting stochastic stock-price behaviour [17], [73]. As is the case in real markets, the price in the simulation is not allowed to fall below 0. If price is low, and the excess demand multiplied by noise would result in a negative price, the value gets set to 0.

3.4.1 Environment Parameters

Parameter	**Description**	**Value**	**Source**
Initial Price	Price of the asset at simulation start	16	[68]
ED	Excess agent demand	$ED_{reddit\_agents} + ED_{inst\_investors}$	[73]
τ	Noise-term for price updating	1.09	Calibrated [73]
P_t	Asset price at each simulation step	$\max(0, P_{t-1} + \tau * ED)$	[73]
θ	Scaling value of average commitment in volume calculation	1.5	Calibrated

Date	Parameter storing the current day in the simulation	All week days	Imposed
$N_{redditagents}$	Number of Reddit traders	10000	Empirical data / Calibration
$N_{institutional}$	Number of institutional investors	200	Empirical data / Calibration
$N_{trading\_days}$	Number of trading days simulated	100	Imposed
Volume threshold	Percentage of total agents participating in the market for trading to be halted	97%	Calibrated [84]

Table 3.4: Parameters of the Market Environment

3.4.2 Market Environment Code Structure

Figure 3.5 below presents the flowchart of the proposed market environment. After parameter and agent initialization, retail traders start interacting, according to the methods introduced in section 3.2, and update their commitment. Volume of participating agents is calculated as a linearly-increasing function of average commitment. A probability dictionary with keys as agent ids and values selected from a uniform distribution between 0 and 1 is created and a , $threshold = average\_commitment * \theta + noise\_term$ is caclulated, where θ is the commimtent scaler is defined. Agents with probability lower than the threshold participate in the market, and hence update their demands heterogeneously. Once volume is updated, the value is checked against the threshold parameter. If market volume is higher than the threshold, then trading is halted, otherwise a new price is calculated as a function of excess demand and added noise. In the trading halt process, agents with commitment lower than 0.65 have it updated to a value sampled from a uniform distribution (0.1, 0.2), reflecting the killing of momentum [74].

After each current day update, the value is compared to total days to be simulated. If higher, the simulation stops. Otherwise, we observe whether current trading day represents a weekend day. In this case, only commitments are updated, as agents continue interacting, without market updates, until current day becomes a week day, point when the market reopens. The day parameter, and the resulting market weekend closing allow for the development of commitment throughout the network, without direct influence on agent demand, which leads to the emergence of the *weekend effect*, further discussed in Chapter 4.

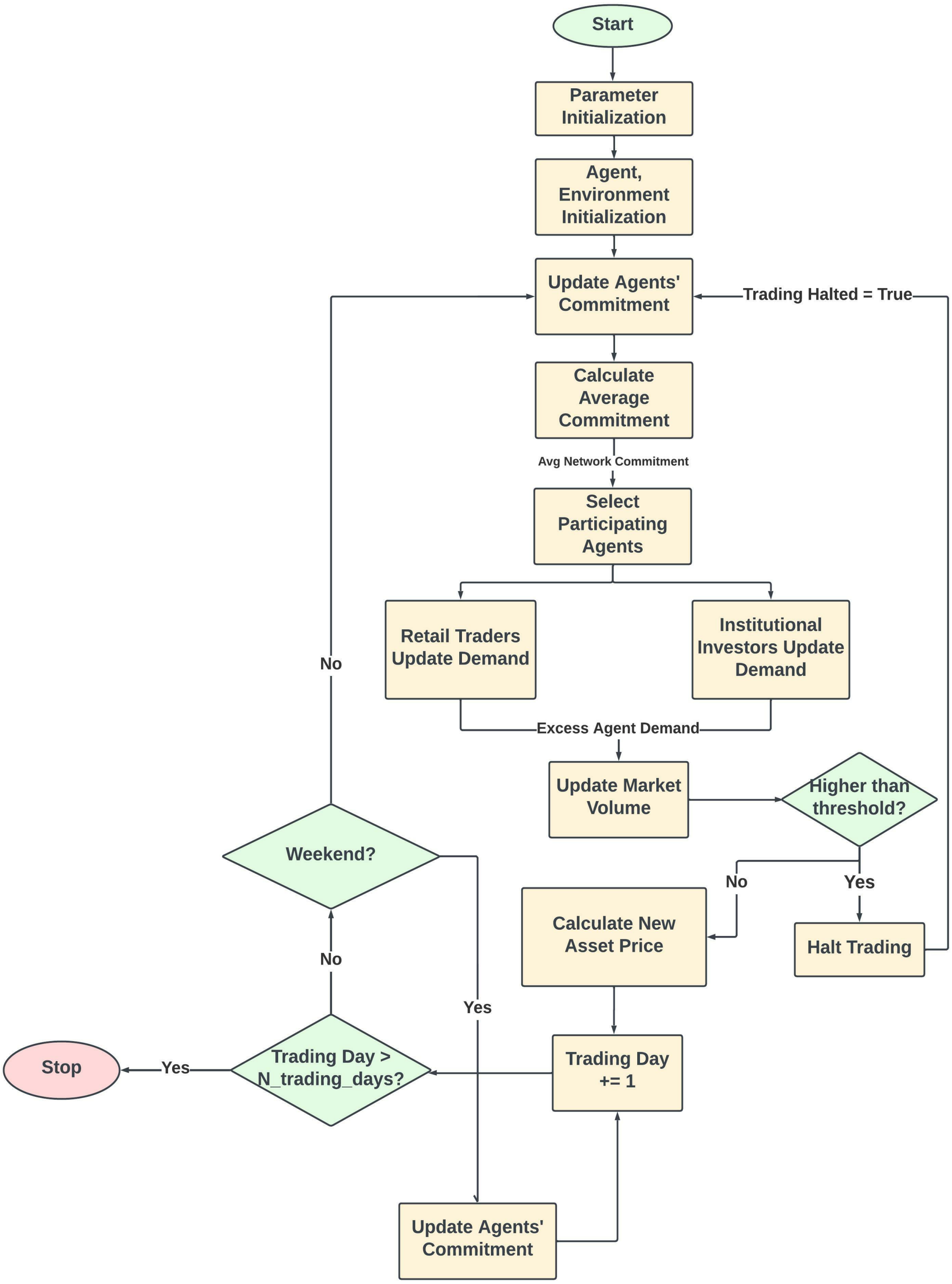

Figure 3.5: Code Structure of the Simulated Market Environment

Chapter 4

Model Validation

The validation process assesses how well the developed system represents the real world system it is reproducing. Validation currently represents a main challenge in agent-based modelling, due to the complexity of the models and the heterogeneous nature of the agents [85]. To deal with the complex models and streamline the validation process, it can be split into: *input validation* and *output validation*. Following output validation, models can be assessed as either useful, if they exhibit some of the observed historical patterns, accurate, if results present only historical patterns, or complete, when they exhibit all patterns observed in real world.

In the following chapter, the methodologies used in the validation stages of the ABM developed for this dissertation are introduced, along with an assessment of the proposed model in terms of the three categories introduced above.

4.1 Input Validation

Input validation represents the process through which the assumptions and starting parameters of the model are evaluated, in relation to the real world system [86]. To ensure system validity, our market environment is initialized with a price history, extracted from empirical GME price data. This allows any technical analysis performed by both agent groups to be an accurate representation of what would have happened in real world during the early stages of the simulation. Where empirical data could not be directly used as input to the model, it has been used as guidance in identifying the right parameter values. For instance, in Table 3.3, parameter p_f represents an institutional investor's perceived fundamental price of the asset, and the value set in the model has been derived from a report published by one of the funds most affected during the squeeze [87]. Similarly, assumptions as the ratio between retail traders and institutional investors have been validated through a critical analysis of available market information, as cited in the Design Chapter. Finally, parameters within the models, such as the convergence rate of the opinion diffusion model, were set through calibration, observing the outcome produced by different parameter values and identifying the most accurate reflection of desired behaviour in relation to historical observations.

4.2 Output Validation

To assess the validity of the financial market developed, model returns are examined against empirical data the model is aiming to reproduce and against statistical regularities observed in financial markets, also known as stylized facts. These facts have emerged from the analysis of different markets and instruments by researchers, and the identification of common properties among them [88]. Furthermore, the unprecedented nature of the GameStop squeeze has resulted in specific properties, unique to the event, against which our model will also be assessed.

Due to heterogeneity introduced by sampling agent parameters from distributions, simulation results are slightly different each run, therefore tests carried below are performed on 200 simulations, with prices averaged across the resulting time-series array. The simulated asset price at time t is given by $p_t = \frac{1}{200}\sum_{i=0}^{i=200} p_{t\,i}$, where i represents the iteration. Log returns are calculated from the resulting time-series.

4.2.1 Insignificant Autocorrelation of Squared Returns

A common property of price returns is insignificant autocorrelation, except for very short time intervals. This property reflects market efficiency, as previous prices can not be seen as an indication of future price movements. Figure 4.1 shows the autocorrelation function for returns in the simulated market environment and for GME empirical data. Both plots present a similar tail-end, with the correlation values slowly decaying towards 0, as expected. The initial period, shows higher variance in the correlation values for GME empirical data, although both sets of values are well within the 95% confidence interval. The lower auto-correlation in our simulation can be explained through the price formation process. Price updates according to excess demand, and each agent's demand is a function of its commitment to the cause. As commitment spreads in the network linearly, demand is slowly increasing, and thus price follows,

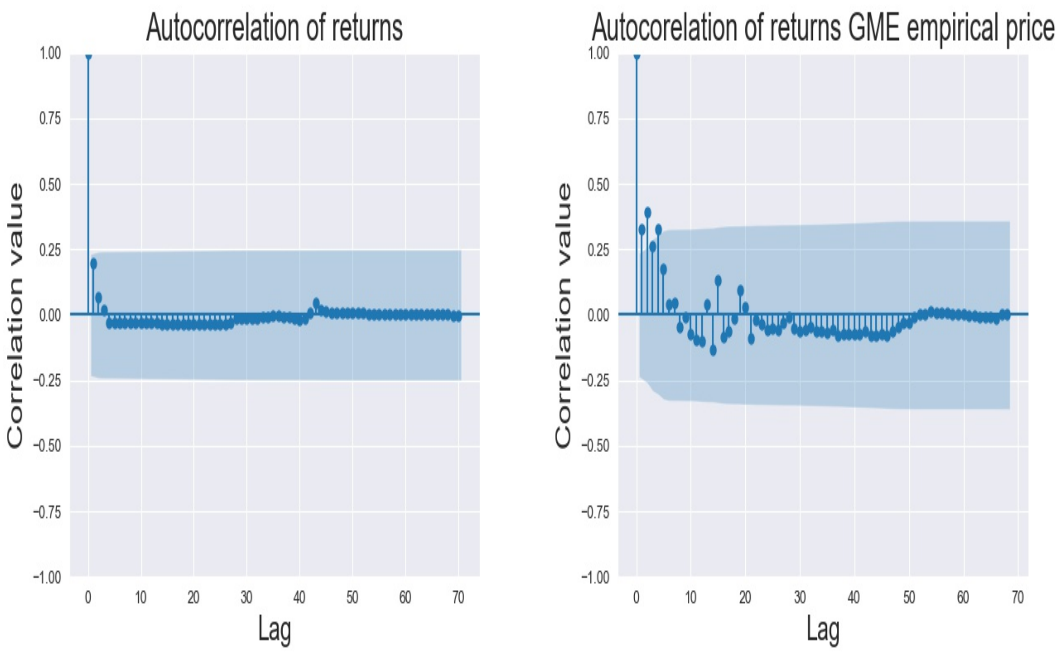

Figure 4.1: Returns autocorrelation in simulated (LEFT) and empirical data (RIGHT)

bar the initial period where negative demand from institutional investors outweighs retail traders' demand. As the price increases, correlation with the initial value slowly decreases. The higher volatility in GME empirical price results in the increased initial correlation, however, as the price spikes in both the simulation and real-world, return autocorrelation values start mirroring each other.

4.2.2 Heavy Tail in Returns Distribution

A second statistical property consistently observed across different markets and assets is the heavy tail in returns, implying how asset returns can not be accurately characterised through a normal distribution.

Figure 4.2 confirms this stylized fact, present across both simulation values and empirical GME data. The red line depicts the form of a normal distribution through the data, and both plots show heavy tails, as returns deviate from what would be expected with such a distribution.

4.2.3 Observed Price Evolution and Weekend Effect

Besides the general stylized facts of financial markets, it is important to observe and contrast the price evolution observed in the simulation against empirical data. Figure

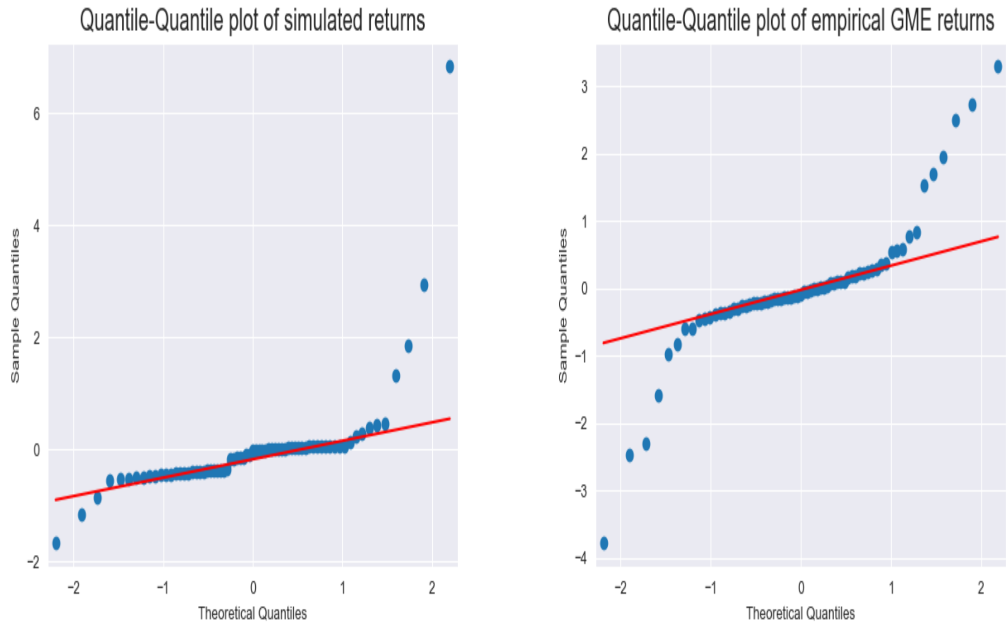

Figure 4.2: Quantile-Quantile returns distribution in simulated (LEFT) and empirical data (RIGHT)

4.3 presents the comparison, and it can be seen how the price, initially driven down and held at relatively low values by the actions of institutional investors and the low market action of Reddit traders, increases exponentially once network commitment spreads and more traders partake in option trading. However, this also results in the trading halt being applied, as volume threshold is surpassed. The trading halt affects the commitment of the agents, which, as explained in Chapter 3, revert to applying analysis, according to their investment strategies. The downward slope slowly decreases as trading days increase, due to the social interactions between agents, which are rebuilding their commitment to the cause.

A distinguishing property of the market developed for this project is the inclusion of the date variable and the subsequent closure of trading at weekend time. Retail traders continue social interactions during this period, however neither them nor institutional investors can update demand. The weekend effect in financial literature refers to market returns being lower on a Monday than those of the prior Friday [89]. Researchers have explored this anomaly, and reasons identified relate to the trading behaviour of individual investors being impacted by external factors, non-related to pricing data. Furthermore, studies have consistently identified strong positive correlation between Friday and Monday returns [90]. Analysing the proposed model, returns

Log Returns

Week	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**	**7-8**
Friday	-0.0455	0.1244	0.0138	0.0056	0.0381	0.035	0.031
Monday	0.0092	0.118	0.0078	0.0344	0.0392	0.0346	0.0306
Week	**8-9**	**9-10**	**10-11**	**11-12**	**12-13**	**13-14**	**14-15**
Friday	0.0279	0.3508	-0.0353	-0.0326	-0.0384	-0.0451	-0.0553
Monday	0.0275	0.2616	-0.0336	-0.0332	-0.0393	-0.0474	-0.0571

Table 4.1: Analysis of Monday/Friday returns throughout simulation

Returns Correlation Values

	Monday	Friday
Monday	1	0.97826
Friday	0.97826	1

Table 4.2: Correlation of Monday/Friday returns

following the weekend are affected by the social interactions of agents, an external factor not related to price data. Analysing the data from a Monday-Friday perspective, a reverse weekend effect is observed, which can be attributed to the commitment of agents spreading throughout the network, resulting in herding behaviour. The strong correlation between the two time-series can be observed in Table 4.2

Figure 4.3: Simulation price evolution against empirical data

4.2.4 Anti-leverage effect

So far, we have focused on validating the model against stylized facts of financial markets. However, emerging literature studying the event identified specific market anomalies against which the model can also be validated. The leverage effect, characterised by negative correlation between asset volatility and returns [88], was not present. During the squeeze, volatility and price increased simultaneously, in what can be seen as an *anti-leverage effect* and a novel way of reporting market anomalies [38].

Figure A.4 plots price volatility against log returns. Volatility at each trading day has been calculated through looping over price entries, computing the mean and variance up to each point, and extracting variance square root. The initial simulation period, where negative hedge fund demand is keeping the price low results in close to 0 volatility values. However, prior to the exponential price surge, volatility increases. Furthermore, as returns decrease again, volatility stays high for a short period. Towards simulation end, as traders are mostly acting based on their trading beliefs, while commitment is rebuilding, returns stabilise and volatility follows. The results presented here further validate our model, depicting the abnormal events observed in real-life.

4.2.5 Model Assessment

Following validation, the proposed ABM can be classified as being complete.

The model presents stylized facts of financial markets, such as the absence of autocorrelation in returns, and the slow decay to zero, as also observed in GME's historical price. Returns' distribution presents heavy tails when compared to a normal distribution. As social interactions between agents are a key part of the model, the weekend effect has been analysed. Irrational market behaviour is observed, with prices influenced by external factors. Regarding the event modelled, results depict the irregular price surge observed in the stock, followed by a downward trend attributed to a market sell-off and retail traders losing momentum. Simulated price does not perfectly fit historical price, however, this is not the objective of the model, as doing so would result in an overfit model. Real world is always more complex than any stylized model, and the GME case is no different. The model can be considered complete, as it exhibits all observed price evolution patterns. It also separates itself from previous models as it replicates well social interactions between the new group of amateur traders, switching between financial analysis or socially-expressive trading, which was not seen in previous literature.

Chapter 5

Sensitivity Analysis and Discussion

5.1 Sensitivity Analysis

Sensitivity analysis represents the process of studying the impact of different model parameters on model output [85], offering insights into the dynamics of the ABM under various parameter settings. The technique used here was one-factor-at-a-time (OFAT), which consists of selecting base parameter values, and iteratively varying the value of one parameter while keeping the others as base values [91]. As the model developed is not simply a financial market ABM, but a short-squeeze model, using OFAT as the starting point, specific parameters in the model influencing the exponential price surge are also analysed, quantifying their impact on the squeeze. The root-mean-square-error (RMSE) between simulated and historical GME price was calculated to evaluate performance. Peak and lowest price points were also observed.

5.1.1 One-factor-at-a-time

In performing OFAT sensitivity analysis, parameters were set as presented in Table A.1. For agent numbers, a large sample set was used, to uncover the ideal ratio that best replicates the short squeeze. For institutional investor fundamental price, higher values were observed (1-50), as a higher fundamental price influences the prospect evaluation stage. Commitment and opinion scalers impact sentiment spread and volume calculations, while ”volume threshold” dictates when trading is halted in the market. To ensure all simulations present meaningful results, value ranges did not deviate greatly from base values. For instance, an opinion scaler > 2 would lead to a too-quick, unrealistic spread. Model parameters set according to literature, such α or β

of the *institutional investor*, were not included in the OFAT analysis, nor in parameter estimation, to avoid overfitting risks for the model.

Analysis results depict the robustness of the proposed model to parameter variations. Observing RMSEs, the maximum is 163.27, with a standard deviation of 21.24. The low interquantile range, which covers the spread of the middle 50% of values, further shows how parameter variations do not greatly impact model output, with a value of 20.61. The highest RMSE corresponds to the highest peak price, occurring when volume threshold is set to maximum value. As trading is halted only when volume equals all agents in the simulation, agents greatly increase demand, thus resulting in a high peak. When volume threshold is low, price does not reach high values. At 64%, the maximum price is 13.27, and minimum reaches 3.91. Commitment does not spread fully, and agents do not reach the point of disregarding analysis. Lowest price point occurs when the number of retail agents is low (1571). Although commitment has time to properly spread, the ratio between agent types is not high enough for retail demand to drive price away from its fundamental value. When market volume peaks, the halting of trading process affects the agents' commitment and results in negative demand from both trading groups, thus driving price values towards 0.

Observation	**Min**	**Max**	**Mean**	**Standard Deviation**	**Interquantile Range**
RMSE	23.17	163.27	58.49	21.24	20.61
Peak price	16.35	628.52	278.93	95.78	121.21
Low price	0.00	14.12	6.70	4.85	10.47

Table 5.1: Sensitivity analysis observations

5.1.2 What Impacts the Exponential Surge?

Price is a function of excess demand of all agents, and demand is directly influenced by agent commitment, thus the μ parameter, affecting rate of opinion spread, and θ, which scales average network commitment when computing market volume were chosen for subsequent analysis. μ and θ were sampled linearly from 0.1-0.9 and 0.5-2 respectively, with 30 samples. Simulations were ran in a nested loop, resulting in 900 runs. As the surge was the point of analysis, RMSE was calculated considering the first 52 price entries, as this represented the historical data point when the stock started declining. The surface plot below presents strong correlation between price evolution and the rate of opinion spread. A fast rate of opinion spread results in higher peak prices. However, higher rates result in peaks that deviate too much from empirical data. Although not as influential, commitment scaling increases also affect peak prices. Higher scaling results in higher volumes, further increasing prices. Model robustness and flexibility can be observed, as all parameter combinations lead to the exponential social-media driven surge, and the base values proposed provide a low RMSE. The high yellow peaks can be attributed to noise coming from the sampling of random agent parameters leading to prices surging to values around 500, however, the overall area generally presents similar RMSE values, depicting the robustness of the model. A local minima is present between μ values of 0.1 and 0.2, with RMSE variations depending on θ.

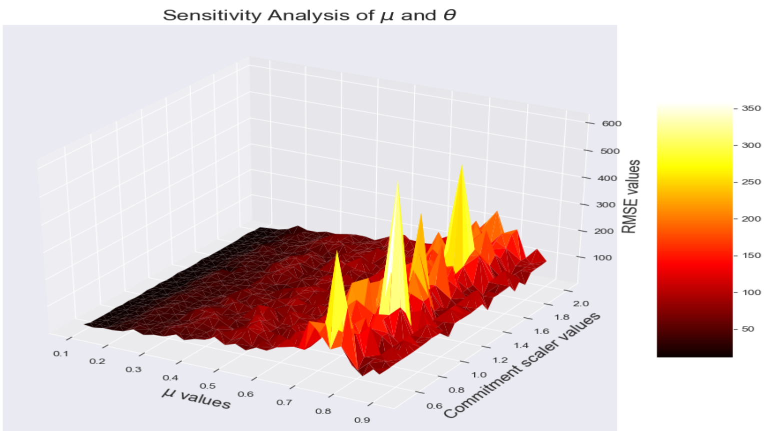

Figure 5.1: Surface plot for μ and θ sensitivity analysis with RMSE objective function

5.2 Reddit Agent Behaviour

In analysing the behaviour of retail traders in the model, action can be split in two periods: *pre-halting* and *post-halting*. Pre-halting, retail traders present expressive trading behaviour [10]. As the sense of community spreads through the social network, investors are using the traded asset as a way of expressing their beliefs, disregarding financial calculations, driven by a desire to make a point, rather than a profit. It is shown that investors with simple behavioural rules for decisions, based on non-wealth investment motives, rather than profit maximisation goals, have the ability to drive market prices away from fundamental values. Referring back to Figure 4.3, post halting presents a clear downward trend, due to agents losing commitment to their cause. As the community continues interacting through the same diffusion model of the pre-halting period, momentum is shifting again, reflected through the steepness decrease of the gradient. The period following the halt depicts a market where investors mostly employ financial analysis for decision-making. Retail traders with a fundamental-approach drive the price down towards its perceived fundamental value, however, as momentum rebuilds in the community and more agents revert to non-wealth investment motives, traders with low commitment but which approach the market based on technical analysis also see profit-potential, thus increasing their demand. If the simulation continues, this results in a brief equilibrium period, until commitment reaches levels where agents disregard financial calculations again.

A possible limitation stems from the trading halt process. Price updates according to excess agent demand and if all agents were to set their demand 0 (sell all owned shares), price would not decrease, as updated price would equal current price. To solve this issue, our model sets a new agent demand as a negative value of current demand divided by inverse commitment. The benefits of this approach are twofold. Firstly, agent demand remains a function of current demand, which has naturally emerged from the interactions up to that point, and updated commitment, validated by empirical data. Secondly, it allows for the development of the downward trend, and gives rise to observations regarding agent behaviour in the post-halt market.

5.3 Institutional Investor Behaviour

Institutional investors play an important role in keeping stock price relatively low in the early simulation stages, as they fundamentally perceive GameStop as a dying company, and continue decreasing their demand in the asset. As figure 5.1 presents, in the space of a few trading days, most funds, depending on their risk-behaviour, decide at slightly different times to close their short positions and accept a sure loss. This point correlates with the moment commitment is spread throughout the network and agents are collectively buying shares/options, disregarding financial analysis. However, around simulation end, as the asset is heading towards its fundamental value, more risk-loving funds decide to short the stock again, as their perceived gain outweighs perceived loss, indicated by the reversal trend of the two lines. It is important to note how this emergent behaviour was also observed in the real-world event, as

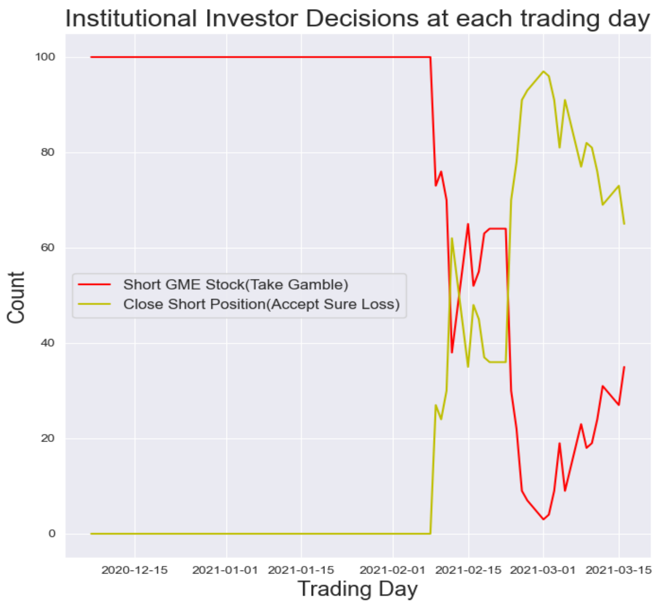

Figure 5.2: Decisions of Institutional Investor agents throughout one simulation

short interest in GameStop did not disappear after the social media rally [92], further validating the model developed.

Regarding limitations, the complexity-tractability trade-off has led to modelling demand uniquely for all agents. Heterogeneity in agent behaviour is observable from the different moments when agents either decide to short the stock or close their position, guided by their endogenous parameters. In real-markets, on top of varying risk-aversions, funds will present different values of assets under management, resulting in different market impact and a wealth parameter for this agent may better replicate real-world.

5.4 Insights Gained

To analyse this projects' contributions and the insights gained through the analysis of results, we will refer back to the research questions posed in Chapter 1.

1. Can the unique short-squeeze be replicated through an ABM, modelling *retail* and *institutional* agents and creating an artificial market environment?

2. Can the collective commitment and the phenomenon of expressive trading be recreated accurately through a computational model?

The model developed replicates all historical patterns observed in the evolution of GME price throughout the analysed period. The agents designed interact both directly and indirectly through the market environment. The direct interactions between retail traders lead to the overall commitment increase in the network, which, in turn, leads to greater involvement in the market. The phenomenon of expressive trading has been modelled successfully, as agents disregard financial analysis and rely solely on their commitment to the overall cause once their personal commitment rises above 0.5. The implementation of option trading, to the best of our knowledge, has not been previously present in literature, and, as seen in the simulation, replicates well the empirically observed *gamma-squeeze*. Furthermore, the halting of trading has been modelled as a killer of momentum, and, based on the proposed design, results in retail traders returning to their preferred trading strategy, with heterogeneous price expectation calculations based on endogenous parameters, following a sell-off. The post-halt market presents non-committed fundamentalists driving the price down, along with non-committed chartists betting on the continued decline of the stock.

3. What were the main factors influencing the short-squeeze?
4. How did interactions develop between social media users and how did large institutional investors react to the price evolution?

Observing agent micro interactions, the main influence on the short-squeeze is the commitment in the network of social-media users. If we were to keep the same model, but stop agents from interacting, prices would hover around the fundamental value, with bubbles unlikely to form due to institutional investors shorting the stock. On the other hand, as seen in 5.3.2, if the rate of commitment spread is too rapid, prices reach peaks that deviate from empirical data. Initially, as average commitment is low, when two agents interact, their commitment difference is either too high and the agents stop the interaction, or both values are low, and, despite interacting, the value reached is still not high. As simulation steps increase, the average commitment increases, and influential users are able to truly impact the community. Responding to social media agents, institutional investors initially stick to their fundamentals and short the stock, as their beliefs reflect GME as a dying company. However, as their decisions are modelled with prospect theory, as prices exponentially increase, most funds perceive expected losses to be greater than gains, opting out of their positions. As momentum is killed, and price driven towards its fundamental value, funds, depending on risk-aversion, decide again that perceived gains from shorting the stock outweigh losses.

Chapter 6

Conclusions and Future Work

The focus of this thesis has been the development of a robust Agent-Based Model, capable of replicating the unique GameStop short squeeze event observed in early 2021. To this end, the project was split into the development of a social network capturing the interactions observed between users on social media throughout the event, and the development of a financial market, where retail trading agents and institutional investor agents can affect prices through their excess demand in the traded asset. The growth of the community identity on social media was modelled through an adaptation of previous opinion diffusion models [56], [67]. Similarly, previous financial market ABMs ([47], [93], [73]) have been adapted to accommodate for the novel class of traders emerging as a result of the GameStop frenzy, amateur investors switching between financial-analysis based trading, and expressive trading [10], which occurs when enough investors are committed to the same cause, and act together as one force, driven by non-wealth investment motives. As such, the results of this thesis present an ABM where heterogeneous agents interact indirectly with each other through the defined market environment. Combining empirical price evolution data with general stylized financial market facts, both model input and output have been validated. Furthermore, the robustness of the proposed model's results has been shown through sensitivity analysis. On top of representing the unique social interactions observed and linking these to a decision-making model in the market, this research brings novelty through the modelling of option-trading and through the inclusion of market weekend closure, which allows for the emergence of irrational phenomena as observed in real markets. Finally, simple behavioural rules governed by prospect theory are shown to accurately replicate the real-life behaviour observed in hedge funds, offering a new computational model to support previous empirical research [77], [82].

The recent growth of retail trading, fuelled by commission-free trading platforms and accelerated by the COVID-19 pandemic has changed the markets. Institutional investors, which used to dominate through sheer trading volume and advanced technology, are now forced to consider the behaviour and sentiment of this new group of unpredictable amateur investors, which aren't solely driven by profits. As markets are undergoing transformations, regulations must change as well, and the model proposed as part of this thesis can be employed by regulators to understand the behaviours of market participants and guide future policy making. Parameters have been calibrated to fit the GameStop saga, however, slight changes can be made to portray future social-media driven trading events. Computational researchers, institutional and amateur investors alike can use this model to deepen their understanding of how the event unfolded, or accommodate for future similar events, which are bound to re-occur. At the time of writing, a new rally is occurring in a heavily shorted-stock, with WSB users coordinating again in similar fashion to the event modelled in the project [94], [95].

6.1 Future Work Proposals

There are a number of ways to expand the current ABM. Firstly, future works could focus on the market price update mechanism. Under the current implementation, if the price has reached high values, and demand suddenly drops to 0, the price would simply continue trading at the same high value. This represents a limitation, as it does not reflect how price evolves in real markets, and thus an implementation where percentage changes in demand affect price would better reflect markets. Secondly, accommodating more general squeeze scenarios, future works could implement a third agent class, representative of high-frequency trading firms, whose behaviour is modelled through techniques as reinforcement learning or genetic learning algorithms. Previous literature works have successfully developed markets where fundamentalist and chartist agents behaving according to rules as those employed in this thesis, indirectly interact with reinforcement learning agents, paving the way for future research [96].

A final suggestion revolves around option trading. Although novel, the current implementation is still crude. More complexity was not feasible under the time constraints and research goals, however, as the model has been validated and tested for robustness, and the behaviour of the agent groups has been explored, future works could include a market maker, replicating the hedging behaviour of such agents in real markets. Further discussion along with a proof of concept is present in Appendix A.5.

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Appendix A

Supplementary Materials

A.1 Commitment Diffusion Under the Trading Halt

Contrasting Figure 3.4 in the main body of the thesis, Figure A.1 depicts how the trading halt applied to the simulation impacts agent commitment. As opposed to the case where there is no halt and the network evolves to the point where the majority of agents have a commitment higher than 0.6, we can see a network at period 5 that resembles the one at period 3. Influential users play a key role in the network, being connected to the majority of other users. Interactions between users are slowly rebuilding network commitment, however at period 5, a good number of agents are basing their trading decisions on financial calculations, as opposed to period 5 without the halt, where agents are driven by their commitment to the cause, rather than profit maximisation goals.

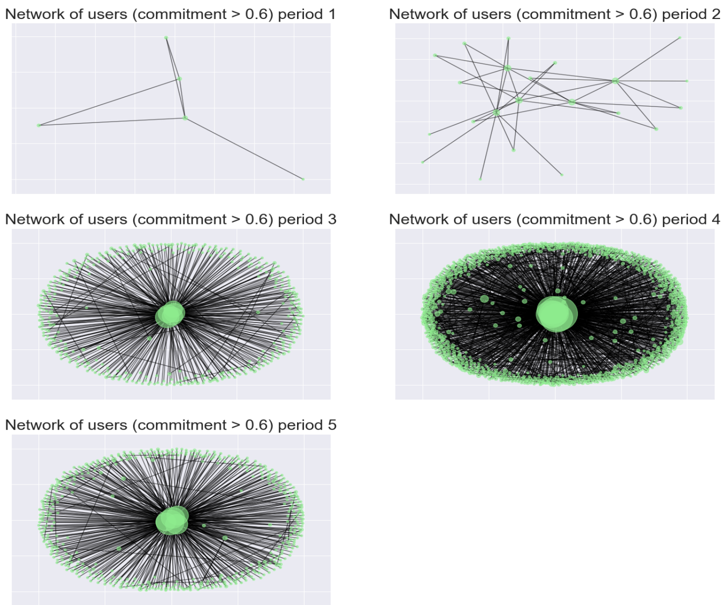

Figure A.1: Temporal evolution of the scale-free network when considering only agents with commitment > 0.6 under the trading halt

A.2 Parameter Estimation

In this section of the Appendix, the parameter estimation process for several model parameters is presented. In order to estimate and identify correct values, several simulations were ran for the parameters, with values ranging within a fixed set, and with a defined number of samples extracted within the set range. This was performed using Python's *numpy* library and *linspace* function.

A.2.1 μ parameter

When estimating the μ parameter, which represents the convergence rate with which agents update their opinion, it was important to find an estimate which would fit the exponential surge observed in the historical price. Observing the plot below, where the rescaled price evolution is represented by the scattered crosses, we can see that high μ values result in a commitment evolution that can be considered too fast, reaching the maximum value of 1 much earlier than the price surge. In the model, to replicate how opinion spread on social media, commitment had to slowly build up in the network up to the point where price surged. Observing the plots and the legend, values ranging from [0.14-0.38] are all reasonable choices. The value chosen for μ subsequently affects the commitment threshold where agents decide to start trading based on non-wealth investment motives, as the two values need to be correlated.

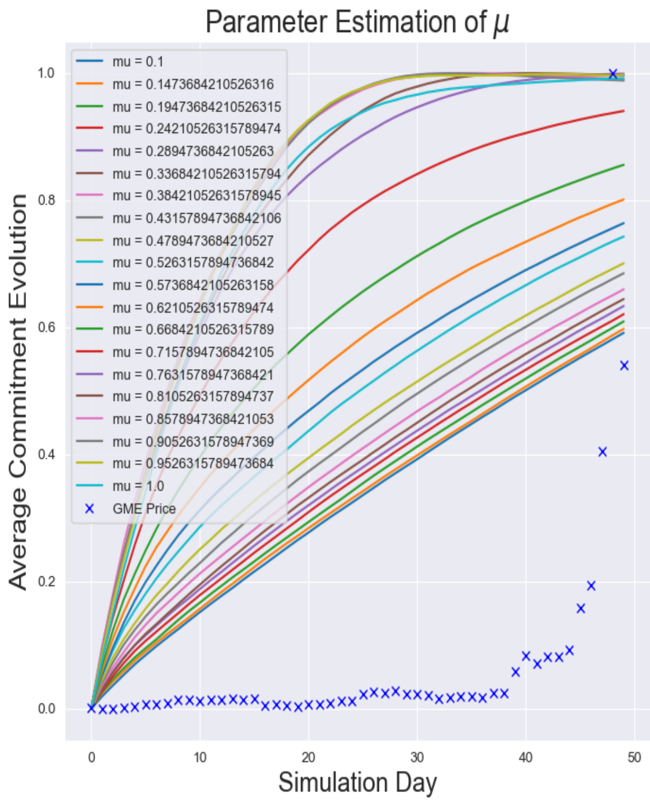

Figure A.2: Parameter estimation process for convergence rate of diffusion model

A.2.2 λ parameter

For λ, which influences the prospect evaluation of institutional investors, where the agents decide whether to short the stock or they consider that the better option is to close their position and accept losses. In the plot of figure A.2, λ was tested on the [1-2.5] range with 10 samples extracted. As can be seen, higher values (2-2.5), result in high sensitivity of funds to the increase in price, which, in turn, sees them close their positions relatively early, and never open them again even as trading is halted and price plummets. On the other hand, low values (1-1.3) sees them never close positions, even as the price grows exponentially. The most accurate representation of the behaviour

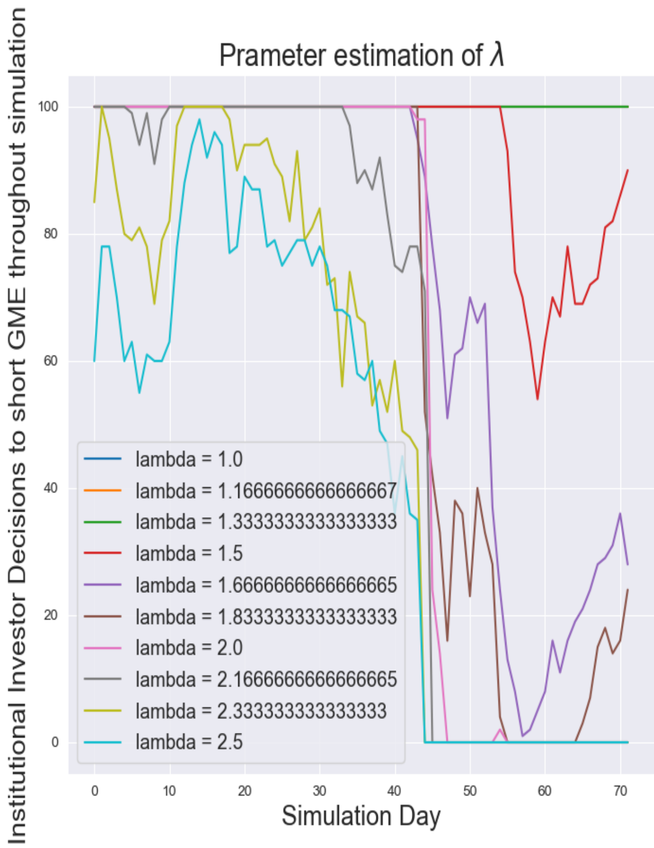

Figure A.3: Parameter estimation process for λ parameter under 10 samples

portrayed in real-markets stems from λ values within the (1-6-1.833) range. Further calibration has resulted in $\lambda = 1.75$ as the proposed base value in the model.

A.3 Model Validation - Anti-leverage Effect

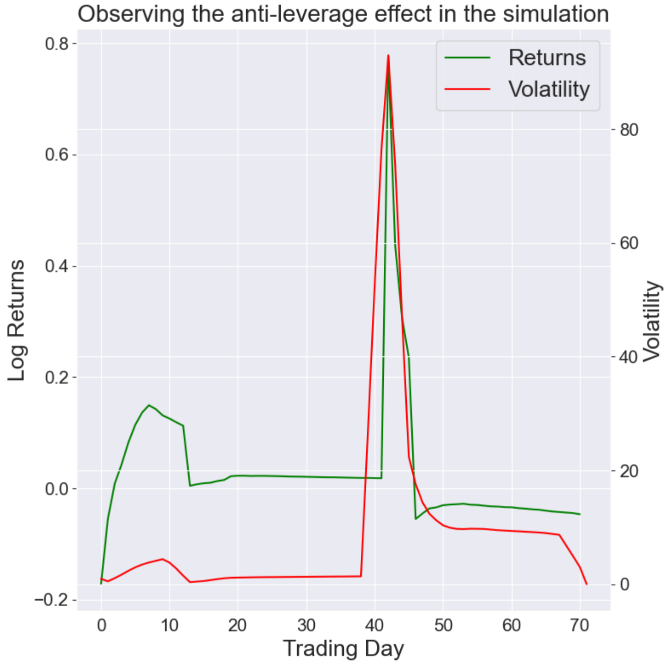

Figure A.4: Observing the anti-leverage effect across all simulation runs

A.4 Sensitivity Analysis

Parameter	**Value Range**	**Samples**	**Base Value**
$N_{redditagents}$	1000-15000	50	10000
$N_{institutional}$	100-2000	50	200
P_f - institutional investors	1-50	11	1
Commitment scaler (θ)	0.1-5	50	1.5
Volume_threshold	0.6-1	12	0.97
Opinion scaler (μ)	0.1-2	20	0.17

Table A.1: Parameter variations in OFAT sensitivity analysis

A.5 Market Maker Proposed Design

As introduced in the main body of the thesis, market-makers played a crucial role in the unfolding of the GameStop event, and will always be involved in similar future events. When a retail traders buys an option contract, or share on the Robinhood platform, the other side of the trade will be represented by a market-maker [97]. When the institution sells the option, it opens itself to potential risk. In most cases, options will expire worthless, and thus the market-maker will be gathering profit from the premium the trader had spent for the purchase of the contract. However, in cases where the call gets exercised, the institution would have to provide the shares at the agreed strike price, incurring sizable losses, if the position was not covered and the shares would have to be bought at current price.

Market-makers employ sophisticated hedging techniques when entering such trades, guarding against risks. These techniques revolve around the calculations of *delta*, *gamma* and *vega*, referred to as the *Greeks* in financial literature [98].

Delta (Δ) refers to the rate of change in the option price compared to the price of the underlying asset. **Gamma** (Γ), a second Greek, measures the change in delta in relation to price changes in the underlying asset.

Delta hedging represents a technique through which traders can hedge their risk when option-trading. If we imagine that the delta of a call option on an asset is 0.5 and a market-maker has sold 10 call options, a hedge against this would require the acquisition of $0.5 \times (10 \times 100) = 500$ shares. Traders aim to keep delta-neutral positions, by buying/selling enough shares in the underlying. However, it is important to keep in mind that the Δ of a stock constantly changes, and thus the value must be closely monitored and the hedge requires periodical rebalancing.

Observing the plot below, when the stock price moves close to the strike price of an option, gamma increases rapidly. High values of gamma result in delta being very sensitive to the price of the underlying, and increasing quickly as well. Increases in Δ force the market-maker to adjust its position in order to remain Δ-neutral. As shown above, this forces the acquisition of shares in the stock, increasing the price of a share, and subsequently triggering a feedback loop.

The following functions were used in the calculation of Gamma in the plot presented below:

$$\Gamma = \frac{N'(d_1)}{S\sigma\sqrt{T}} \tag{A.1}$$

$$d_1 = \frac{ln(\frac{S}{K}) + (r + \frac{\sigma^2}{2})(T-t)}{\sigma\sqrt{(T-t)}} \quad \text{(A.2)}$$

where $N'(x)$ represents the probability density function for a standard normal distribution, S is the asset price, K the strike price of the option, σ the volatility of the traded asset, T is the time-to-maturity and r the risk-free interest rate. The values in the plot below were selected to resemble GameStop's trading price and performance prior to the squeeze. The d_1 parameters arises from the Black-Scholes-Merton option pricing formula [99].

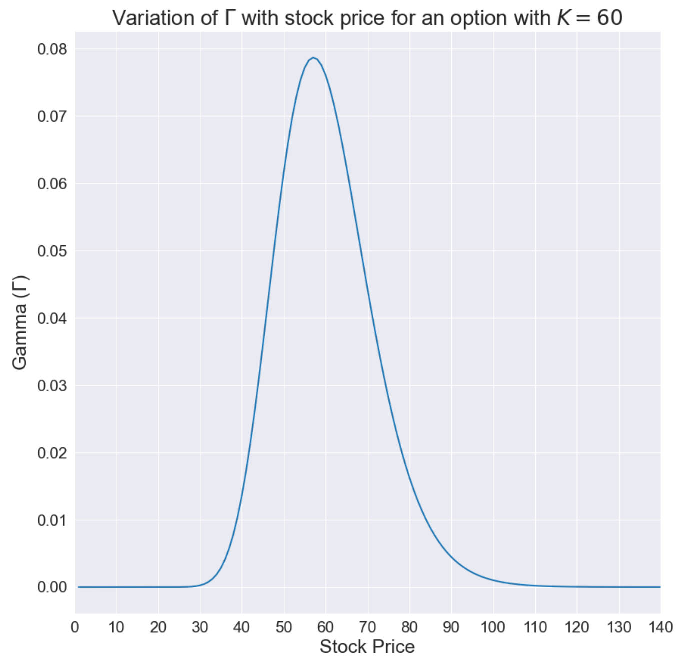

Figure A.5: Variation of Γ with stock price for an option

The analysis above introduces the role of a market-maker, along with an explanation of the hedging process which requires the agent to buy shares in relation to price movements. For a proposed design, there are two alternatives route future works could explore.

1. One Market-Maker agent, providing option contracts and facilitating the acquisition/selling of share for the agents in the simulation, which is dynamically hedging its positions.

2. Multiple Market-Making agents, competing against one another for deal flow.

A.5.1 One Market-Maker Agent Proof of Concept

A.5.1.1 Agent Parameters

In the context of one market-maker agent, previous research in literature can be incorporated to explore the behaviour of such an agent in the face of the unprecedented social-media driven surge.

The agent could incorporate a risk-tolerance parameter, characterising the agent's behaviour. A more risk-averse market-maker would re-adjust its positions constantly, minimising the potential loss in wealth if prices continue increasing [100].

Tables below present the proposed models of a market-maker and the option class proof of concept implementations.

The market-maker presents the risk-tolerance parameter, which is sampled from an array *[0, 0.25, 0.5, 0.75, 1]* with equal probabilities. The agent then also has a dictionary, in order to keep track of all options sold. The option class is a simple model, based on the financial derivative. The strike price is modelled to be slightly above current price, and time to maturity date is randomly sampled from *[5, 10, 15, 20* days, all with equal probabilities.

Parameter	**Description**	**Value**	**Source**
Risk tolerance	The agent's risk-tolerance	Equal probability sampling from [0-1] with step-size 0.25	[100]
Options_sold_dict	Dictionary keeping track of all options sold by market-maker agent	Key: Id / Value: Option object	Imposed

Table A.2: Parameters of the Market-Maker Agent

Parameter	Description	Value	Source
Id	Option id to keep track of all options sold	Id of agent buying the option	Imposed
K	Strike price of an option	$p_t + \tau * p_t$	[101]
expiry_date	Date of expiration of option sold	Current_date + T	[101]
τ	Noise parameter is strike price calculation	Sampled from uniform distribution [0.05, 0.1]	[101]
T	Days to maturity	Sampled from [5, 10, 15, 20] with equal probabilities	[101]
Option_type	Type of the option being sold	Put/Call	[102]
Δ	The degree of exposure of an option to changes in the price of the underlying asset	$N(d1)$ - see A.2	[98]

Table A.3: Option class parameters

A.5.1.2 Actions the agent can perform

In the simulation, the market-maker can perform the following actions:

- Sell an option: When a retail trading agent, based on his commitment value, decides he wants to acquire a GME option, the market-maker initializes an Option object, storing it in the *options sold* dictionary, with key equal to the agent's id
- Calculate Delta: Employing Δ calculation according to the Black-Scholes model [99]
- Hedge position: As soon as an option is sold, the agent calculates the Δ of the said option, and buys shares in the underlying stock accordingly

- Hedge all positions: At each step in the simulation, a Boolean variable, *will_hedge* is sampled from a [*False, True*] array with probabilities *p=[1-risk_tolerance, risk_tolerance].* Based on the value of the variable, the market-maker either recalculates the delta of the options he has sold, observing the difference and re balancing his portfolio to remain delta-neutral, or chooses to ignore price updates and keeps the initial hedge. It is important to note that the σ and $T-t$ parameter, representing volatility and time to expiry of the option, get updated as well during the re-hedging process.

Figure A.6 displays the observed price behaviour in the proof of concept implementation, under varying risk tolerance for the market-maker agent. It can be seen how risk tolerant market-makers (bottom row), result in prices that increase up to 200 and slightly over. This happens as the agent only calculates the delta of the option and hedges against it when it's sold (for risk-tolerance=1) or re-hedges his positions with small probability 0.25 at each step (for risk-tolerance=0.75). For market-makers with less risk-tolerance, prices still follow the same exponential growth pattern, however the values reach much higher peaks (around 800). As prices greatly diverge from the option strike price, so does the option's delta, thus resulting in the market-maker having to acquire large number of shares to keep his position delta-neutral.

A final suggestion for a single market-maker could be observing the use of Reinforcement Learning for dynamic hedging [96], [103]. Previous works have shown how this type of intelligent agent can provide satisfactory performance, improving on standard financial hedging techniques and accomplishing this without the user providing information as volatility, Greek calculations or option strike price. These works have explored normal market conditions, generally with zero-intelligence traders. Observing the behaviour of such an agent in the unusual short-squeeze market is a fascinating research avenue. However, the normal market conditions of previous works also provide a possible limitation. The short-squeeze model has the goal of simulating market dynamics in this specific case, and a *perfect* RL agent may not be reflective of the participants in the event. The works cited above create an artificial market and develop agent models with the goal of solving the pricing and hedging of financial products through a RL approach, a different area to the ABM developed in this project, which aims to observe the emergent phenomena in the market as a result of agent interactions.

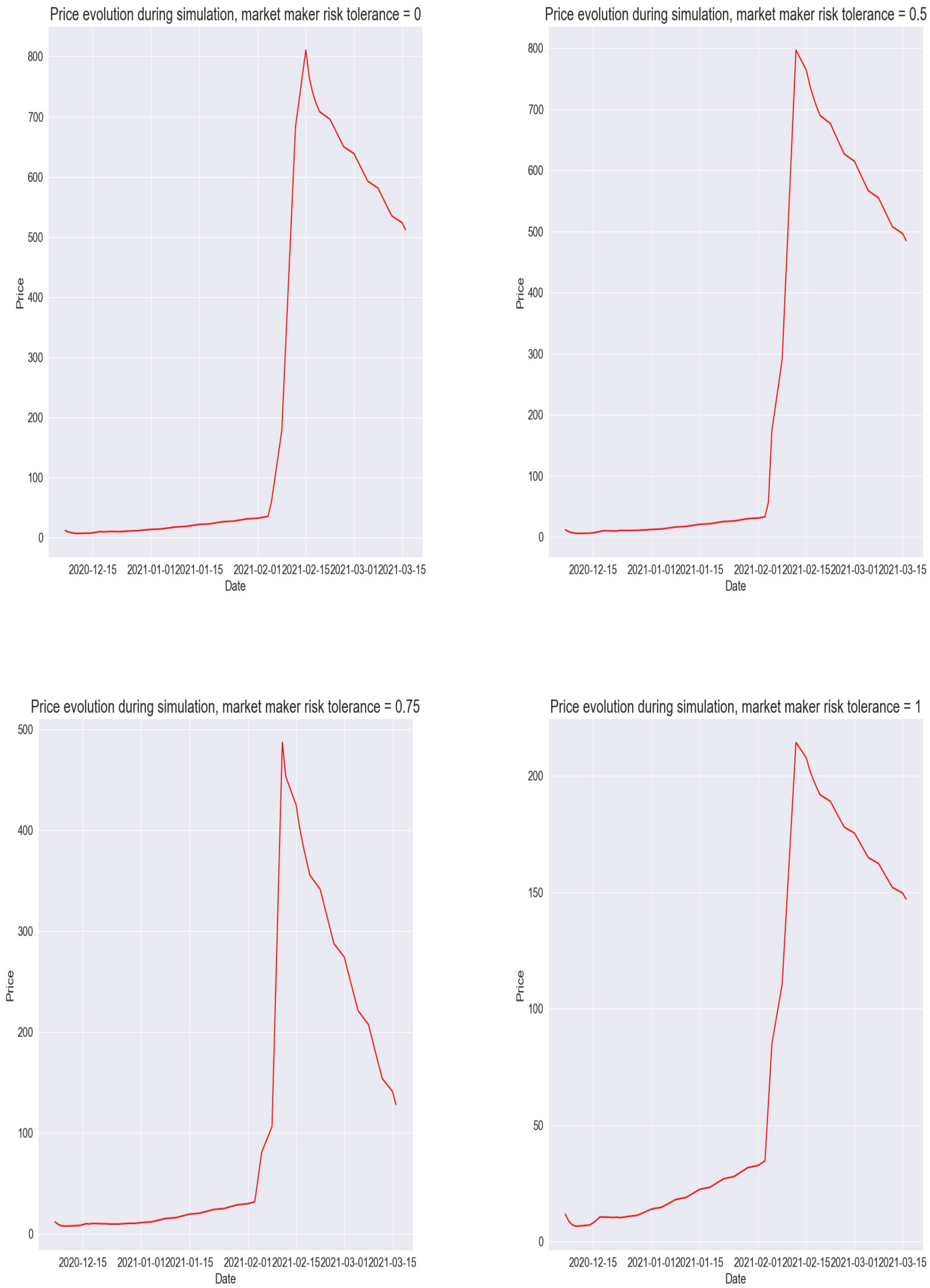

Figure A.6: Exponential price-surge in the market when employing market-maker class with varying risk-tolerances

A.5.2 Multiple Market-Maker Agents

In the context of multiple market-maker agents, we propose a similar design for the agent. However, the differences would arise from the *risk tolerance* parameter being adaptable. As market-makers observe their own profits and losses and those of competing agents, they update their own market-strategy. As agents compete for trade flow, investors can be expected to profit from the resulting increase in market transaction and share acquisition [104].

As was the case for a single market agent, the differences between the markets assumed in previous research and that of a social-media driven short-squeeze can be expected to develop remarkable behaviour. The trade-off between capturing deal-flow and risk in the face of exponential price increases will present a scenario untested in previous works and which might reveal interesting decision-making from the agents involved, subject to their endogenous parameters. As agents are learning and adapting their own risk tolerances, they may be caught out by the exponential rise and become reluctant to provide liquidity. However, as the trading halt applies and prices plummet towards the fundamental stock value, the rate at which agents adapt their approach would be very interesting to observe.

A.5.3 Final Points

It is important to note that the above points simply represent a potential future research avenue. The work presented was not part of the initial project goals and the provided proof of concept covers a general hedging approach observed in market-makers. As mentioned, the study of more sophisticated techniques such as RL can also represent possible research paths.

For a social-media driven short-squeeze model, where the goal was exploring the social interactions that led to the exponential increase, the behaviours of retail agents following the trading halt and the approaches taken by institutional investors, implementing a market-maker only provides added complexity with little to no benefit. However, following validation and sensitivity analysis, once the model is proven robust and the emerging behaviours are well understood, it can be used as a base for exploring market-maker behaviour in the face of this unprecedented short-squeeze. This new research path would fall under *Market Microstructure* research.