

NETWORK STRUCTURES AND THE
DYNAMICS OF TAKEOVER RUMOURS:
AGENT-BASED SIMULATIONS OF
PRE-ANNOUNCEMENT STOCK PRICE
DRIFT

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DECLARATION

I declare that this thesis and the work presented in it are my own. All sources of information have been acknowledged, and any assistance has been credited in the Acknowledgements.

Where parts of this thesis incorporate work produced jointly with others or previously published material, this is clearly indicated at the start of the relevant chapters, and the contributions of all authors are stated. The thesis has been prepared in accordance with the regulations of my institution.

Where applicable, the research described was conducted in accordance with relevant ethical guidelines and approvals. Details of data and code availability (where applicable) are provided within the thesis or appendices.

Stirling, November 2025

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ABSTRACT

Takeover targets often see their stock prices rise sharply before merger or acquisition announcements, mainly because information leaks and related rumours circulate among investors. Although this pattern is well-documented, the underlying process driving such pre-bid increases is still not fully understood[1]. This thesis rebuilds the mechanism from the bottom up: an agent-based market in which an Ignorant–Spreader–Stifler rumour process propagates over a range of networks while heterogeneous value investors and trend followers trade on perceived mispricing and recent returns. Through Monte Carlo simulations, we find a strong link between the magnitude of the run-up and the efficiency of the network topology.

PUBLICATIONS

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CONTENTS

1	INTRODUCTION	1
1.1	Empirical Context: Takeover Events and Market Response	5
1.2	Theoretical Mechanisms: Information Leakage and Rational Anticipation	5
1.3	Methodological Approach: Agent-Based modelling	7
2	LITERATURE REVIEW AND METHODOLOGY	13
2.1	Informed trading and Trend chasing	14
2.1.1	Insider Trading	15
2.1.2	Rational Anticipation	25
2.1.3	Summary	30
2.2	Trading network	36
2.3	Rumour studies background	42
2.3.1	Epidemic spreading model	43
2.3.2	Daley-Kendal Rumour Model	46
2.3.3	Sudbury model	50
2.4	Heterogeneous networks	53
2.5	Agent-based computational models	56
3	RUMOUR AND NETWORK MODEL	61
3.1	Network	61
3.1.1	Comparison to Random Networks	62
3.1.2	Comparison to small-world Networks	64
3.1.3	Modularity	65
3.1.4	Clustering Coefficient	67
3.1.5	Local Efficiency	70
3.1.6	Critical regime (low B_g)	72
3.2	Rumour spread model	74
3.2.1	Baseline Rumour Spreading Results	78
3.2.2	Robustness test	86
3.3	Heterogeneous community size	94
3.4	Summary	102
4	STOCK PRICE MODEL	103
4.1	Introduction	103
4.2	Feasibility of Agent-Based modelling in Pre-Takeover Drift Analysis	103
4.3	Agent behaviours	106
4.4	Agent-Based Model	109
4.4.1	Price Formation Mechanism	109

4.4.2	Trend Follower	112
4.4.3	Value Investor	116
4.4.4	Trend and Value Traders together	121
4.4.5	Takeover Rumours and Intrinsic Value Adjustment in Community Networks	125
4.5	Model Configuration	127
5	STOCK PRICE DYNAMICS FROM INDIVIDUAL BEHAVIOUR	133
5.1	Introduction	133
5.2	Cumulative abnormal return(CAR)	135
5.3	Value investors' and trend followers' net position	136
5.4	Value investors' buy/sell volume	137
5.5	Average mispricing	139
5.6	Buy volume vs. spreader ratio	140
5.7	Forced cover volume	144
5.8	Cross-network CAR	146
5.9	Cross-network comparison of Value investors' and trend followers' net trade	148
5.10	Robustness test against intra-community connectivity	153
6	CONCLUSION	157
6.1	Research motivation	157
6.2	Key results	158
6.3	Strengths and limitations	164
6.4	Future research	166
	BIBLIOGRAPHY	169

LIST OF FIGURES

- Figure 1.1 "Buy on Rumour Sell on News" price pattern [11]: **(I)** excitement and buying during rumour anticipation, **(II)** turning point as rumour being publicly revealed, and **(III)** disappointment and selling afterward. 2
- Figure 2.1 Small-world network 53
- Figure 2.2 A scale-free network of 80 nodes, generated by the B-A scale-free model. Orange nodes represent hubs with degree greater than 6 55
- Figure 3.1 An illustrative network with comparatively higher inter-community connectivity, producing less distinct modular separation between groups. 63
- Figure 3.2 Heat maps of modularity for community-based (left), random (centre), and small-world (right) networks. Each network consists of $N = 6000$ nodes with $N_g = 100$ communities. 66
- Figure 3.3 Heat maps of mean clustering coefficient for community-based (left), random (centre), and small-world (right) networks. Each network consists of $N = 6000$ nodes with $N_g = 100$ communities. For the small-world network $p = \frac{B_g(N_g-1)}{W_g+B_g(N_g-1)}$, $K = \text{round}(N(\frac{W_g}{N_g} + B_g(1 - \frac{1}{N_g})))$, and for a random network $p = W_g * \frac{1}{N_g} + B_g * (1 - \frac{1}{N_g})$. 69
- Figure 3.4 Heat maps of local efficiency for community-based (left), random (centre), and small-world (right) networks. Each network consists of $N = 6000$ nodes with $N_g = 100$ communities. 71
- Figure 3.5 Heat maps of modularity for community (left), random (centre), and small-world (right) networks against B_g ranging from 0 to 0.2 on the x-axis and W_g ranging from 0 to 1 on the y-axis. 72

- Figure 3.6 Heat maps of clustering coefficient for community (left), random (centre), and small-world (right) networks against B_g ranging from 0 to 0.2 on the x-axis and W_g ranging from 0 to 1 on the y-axis. 73
- Figure 3.7 Heat maps of local efficiency for community (left), random (centre), and small-world (right) networks against B_g ranging from 0 to 0.2 on the x-axis and W_g ranging from 0 to 1 on the y-axis. 73
- Figure 3.8 Time evolution of the proportions of ignorant (blue), spreader (red), and stifler (green) agents. The solid lines represent the deterministic model, while the shaded regions indicate the interquantile range between the 40th and 60th percentiles, capturing the variability due to stochasticity in the model. 76
- Figure 3.9 Time evolution of the rumour spreading process illustrating the three agent compartments: ignorants (green), spreaders (red), and stiflers (blue). Four key metrics are extracted from each simulation run: maximum spreader proportion (S_{max}), time to maximum spreader (T_{max}), final stifler proportion (R^*), and time to equilibrium (T_{eq}). These measures summarize the spreading dynamics under each parameter configuration and serve as comparative indicators across network structures and parameter sets. 77
- Figure 3.10 Max spreader proportion (top left), time to max spreader (top right), final stifler proportion (bottom left), and time to final stifler (bottom right) of community (green), random (red) and small-world network (blue) 80
- Figure 3.11 Modularity on random network (red), community network (green) and small-world network (blue). W_g is varied from 0 to 1 while B_g is kept at 0.0005 82
- Figure 3.12 Clustering coefficient on random network (red), community network (green) and small-world network (blue). W_g is varied from 0 to 1 while B_g is kept at 0.0005 82

- Figure 3.13 Local efficiency on random network (red), community network (green) and small-world network (blue). W_g is varied from 0 to 1 while B_g is kept at 0.0005 83
- Figure 3.14 Proportion of informed neighbours for $W_g = 0.25$ (top left), $W_g = 0.50$ (top right), $W_g = 0.75$ (bottom left) and $W_g = 1.00$ (bottom right). The x-axis represents the time from T_0 to end of the process. 84
- Figure 3.15 Rumour spreading dynamics as a function of total population size N under fixed intra-community connectivity $W_g = 0.8$. Red, blue, and green curves correspond to random, small-world, and community networks, respectively. 88
- Figure 3.16 Max spreaders (top-left), time to max spreaders (top-right), final stifler (bottom-left) and time to final stifler (bottom-right) plots of rumour spreading on community networks against intra-probability W_g , with various total number of population (blue- $N = 6000$, orange- $N = 9000$, green- $N = 10000$, red- $N = 12000$ and purple- $N = 18000$) 89
- Figure 3.17 Rumour spreading metrics (maximum spreader proportion (top-left), time to maximum spreaders (top-right), final stifler proportion (bottom-left), and time to final stifler (bottom-right)) as a function of intra-community connection probability W_g for community networks with varying numbers of communities N_g . Each curve corresponds to a different N_g value: blue ($N_g = 30$), orange ($N_g = 50$), green ($N_g = 100$), red ($N_g = 200$), and purple ($N_g = 300$). 91
- Figure 3.18 Distributions of community sizes resulting from varying levels of group assignment disturbance. Each panel shows a histogram of group sizes aggregated over multiple Monte Carlo runs, with disturbance factors of 0.1, 0.2, 0.3, and 0.4 (top-left to bottom-right). 94

- Figure 3.19 Average degree centrality (top-left), clustering coefficient (top-right), modularity (bottom-left), and local efficiency (bottom-right), as a function of the community size disturbance factor. Each point represents the mean value across 20 Monte Carlo simulations, with error bars indicating standard deviation. 95
- Figure 3.20 Max spreader proportion (top left), time to max spreaders (top right), final stifler (bottom left) and time to final stifler (bottom right) against intra-prob W_g for community networks with disturbance factor = 0 (standard network)—green, 0.1—blue; 0.2—orange; 0.3—red; 0.4—purple 97
- Figure 3.21 Max spreader proportion (top left), time to max spreaders (top right), final stifler (bottom left) and time to final stifler (bottom right) for community (green), random (red) and small-world (blue) networks against β . $W_g = 0.8, B_g = 0.005, \beta = (0.1, 10)$ 98
- Figure 3.22 Max spreader proportion (top left), time to max spreader (top right), final stifler (bottom left) and time to final stifler (bottom right) in community network against β from 0 to 1, with $W_g = 0.6$ (blue), 0.7 (orange), 0.8 (green), 0.9 (red), 1.0 (purple) 100
- Figure 4.1 Schematic view of a threshold-based trading strategy Black line in middle is $m_t = 0$ benchmark where price is equal to value; orange lines represent entry threshold $\pm T$ and green lines represent exit threshold $\pm \tau$ 117
- Figure 4.2 Blue line represents the simulated stock price under the influence of value investors whose intrinsic value is reflected by the orange line. The green line indicates the log-normal random walk of price as if value investors were absent. 119
- Figure 4.3 Mispricing against net-trade by value investors 120

- Figure 4.4 Stock price dynamics (blue) under the co-existence of trend followers and value investors. Orange line represents the shared common intrinsic value by all value investors. The green line illustrates the trajectory of the price driven purely by exogenous noise, reflecting how the market would evolve in the absence of both trader types. The rumour is absent. 122
- Figure 4.5 Net position dynamics of value investors (blue) and trend followers (orange) over time. Value investors exhibit intermittent and sharp position changes in response to mispricing, while trend followers adjust positions more smoothly and frequently based on observed momentum. 123
- Figure 5.1 Average cumulative abnormal return on community-based network from day -45 to day 15 relative to takeover announcement, day 0. The rumour is spread from day -45. Shaded area represents the 95% confidence intervals across 50 simulation runs. 135
- Figure 5.2 Average net positions of value investors (blue) and trend followers (orange) in days relative to the announcement (day 0). 137
- Figure 5.3 Average buy and sell volume of value investors over time. The green bars represent aggregate daily purchases, while the red bars capture aggregate sales. Time is measured in days relative to the announcement (Day 0). 138
- Figure 5.4 Average mispricing of all value investors from day -45 to day 0 relative to announcement day. 139
- Figure 5.5 comparison plot of spreader proportion (orange line) and buying volume (green bar). 141

- Figure 5.6 Comparison plot of spreader proportion (orange line) and buying volume (green bar) under various rumour transition rates β . Top panel shows the measures under $\beta = 0.5$, spreading rate being half as much as stifling rate. Bottom panel indicates the relative curves under $\beta = 2$ where spreading is twice as efficient as stifling. 143
- Figure 5.7 Time series of forced cover volume for $\beta = 2$ 144
- Figure 5.8 Average CAR trajectories generated under the random (red), community (green) and small-world (blue) network structures. The red dashed, green solid and blue dotted lines represent the respective average CAR, while the shaded areas indicate the 95% confidence intervals across 50 Monte-Carlo simulation runs. The vertical dashed line at Day 0 denotes the takeover announcement. 146
- Figure 5.9 Value investors' daily trading volume on random (red), community (green) and small-world network (blue) 148
- Figure 5.10 Trend followers' daily trading volume on random (red), community (green) and small-world network (blue) 149
- Figure 5.11 Value investors' average daily buy volume (green bars, left axis) and spreader ratio (orange line, right axis) over time on community (top left); random (top right) and small-world network (bottom left). Bottom right plots the spreader ratio on random (red), community (green) and small-world network (blue) 150
- Figure 5.12 Daily forced cover volume on random (red), community (green) and small-world network (blue) 152
- Figure 5.13 Average run-up on random (red), community (green) and small-world network (blue), against intra-community connection probability W_g on the x-axis. The shaded area indicates 95% confidence intervals across 50 Monte Carlo simulations. 153
- Figure 6.1 Fundamental mechanisms in shaping the runup 160

LIST OF TABLES

Table 3.1	Summary of Model Parameters in Chapter 3	62
Table 3.2	Baseline rumour spreading model parameters used in Section 3.2.1.	79
Table 4.1	Summary of agent types and behavioural as- sumptions	110
Table 4.2	State-dependent Trading Decision Rules	118
Table 4.3	Summary of Model Parameters	129

INTRODUCTION

Traditional financial theories, such as Rational Choice Theory, view market participants as fully rational agents who assess costs and benefits in order to maximise utility, leading to prices that are expected to align with underlying fundamentals [2]. However, real markets often deviate from these idealised assumptions [3]. Traders herd [4], chase momentum [5], and sometimes act on unverified news [6] when information is uneven or fragmentary, leading to transient price deviations from fundamentals. Eugene Fama, one of the pioneers of the efficient market hypothesis (EMH), incorporates such returns anomalies by a semi-strong form of market efficiency where the price would not always be sensitive in reflecting private information [7], with information asymmetry being the main cause of abnormal returns gained by superior information holders such as insiders and institutional traders [8].

For instance, Richard documents a cross-industry event study ranging from the release of Pixar studio's movie [9] to the trade shows of Apple Computer [10] and finds a recurring stock price movement surrounding such events as shown in Figure 1.1 [11]. The positive returns are concentrated in the developing phase of the event, when information asymmetry prevails and only a subset of traders act on early or selectively transmitted signals. Once the information becomes fully public, no informational advantage remains, and the initial optimism gives way to selling pressure as expectations are realised. As a result, it is advisable to buy on the rumour and sell on the news ¹.

Building on this observation, an important question arises as to how and when markets respond to privately held information. In particular, one may ask within what time frame such information becomes reflected in prices, through what channels it spreads among traders, and which participants act as its primary carriers. Ultimately, the key issue is how the gradual diffusion of unverified information, or rumour, translates into observable

¹ While Figure 1.1 illustrates the full “buy the rumor, sell the news” price pattern, the focus of this thesis is primarily on the pre-announcement phase (Stage I) and, to a lesser extent, the announcement phase (Stage II). The post-announcement adjustment (Stage III: disappointment) is not explicitly modelled, as the aim is to investigate how rumor diffusion and anticipatory trading generate the pre-takeover price run-up.

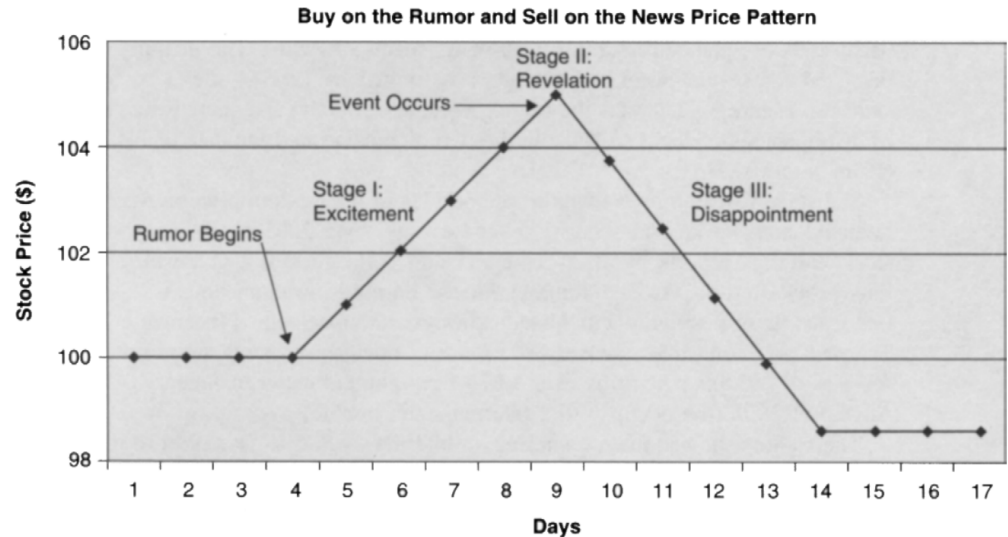


Figure 1.1: "Buy on Rumour Sell on News" price pattern [11]: (I) excitement and buying during rumour anticipation, (II) turning point as rumour being publicly revealed, and (III) disappointment and selling afterward.

price dynamics. In this thesis, a rumour is understood as unverified but potentially price-relevant information that circulates among a subset of market participants before formal public confirmation. It may originate from direct information leakage, indirect professional inference, or speculative interpretation of market signals, but in all cases it is characterised by uncertainty, selective dissemination, and the potential to influence trading behaviour before the underlying event is officially disclosed.

The takeover announcement offers an ideal empirical setting to examine these questions: it conveys information with substantial price impact, involves a wide network of participants exposed to differing degrees of private knowledge, and features a characteristic pre-announcement run-up that reflects the market's collective process of rumour aggregation [12]. Moreover, takeover announcement represents a distinct category among all kinds of financial events due to its unscheduled characteristics since in the realm of scheduled corporate announcements (such as dividends and annual earnings announcements), some traders are found to engage in speculative betting even in the absence of superior information².

² Speculation based on historical performance plays a significant role in shaping investor expectations and market behaviour around scheduled corporate events like dividend announcements or earnings reports. Therefore the trades preceding the scheduled announcement date can be at least in part explained

The empirical finding that trading volume decreases before scheduled announcements suggests that scheduled announcements exhibit less information asymmetry and the increase in trading volume before unscheduled ones indicates a higher speculative level accompanies [14]. Mergers and Acquisitions (M&A) announcements, on the other hand, are not planned and so the public is often unaware of their pending occurrence with little chance to make historical inference [15]. This discrepancy holds significance since the extent to which abnormal trading activities are accounted for by the possession of information is dominant due to the non-scheduled and highly unpredictable nature of the takeover announcement [16].

Furthermore, such price-related information can be defined as a rumour since it could never be confirmed true immediately and there's always a risk of cost if the information is not ultimately materialised [17].

For example, the stock might turn somehow unprofitable when the bidder who sees the target price run-up unexpectedly decides to postpone or cancel a planned bid while trying to learn the cause of the run-up [18]. Alperovych et al. point out the inherent uncertainty embedded in the dissemination and market interpretation of M&A-related rumours [19]. Drawing from a comprehensive global dataset, the authors demonstrate that although rumours frequently precede formal bid announcements, a substantial proportion of them ultimately fail to materialise into concrete acquisition offers. Specifically, their empirical findings indicate that only 43 percent of takeover rumours are followed by an actual bid. This relatively low conversion rate suggests that the majority of such rumours represent speculative episodes rather than accurate forecasts of impending corporate control transactions. The low realisation rate underscores the difficulty of distinguishing between rumours that accurately reflect nascent deal-making activity and those that merely reflect strategic noise or speculative optimism.

For example, Diamond Shamrock cancelled its planned bid for Natomas after Ivan Boesky's insider trading caused Natomas' stock price to rise by more than 20% during February 1983; General Electric (GE), in 1981, also suspended the takeover bid for

as a reflection of a consensus of market sentiment to the firm regarding its recent historical performance, without necessarily having a private information dissemination mechanism involved. See for example Joon Chae, who investigates the dynamics of trading volume before scheduled and unscheduled corporate announcements [13].

Phelps Dodge Corporation, a major mining and manufacturing company after it was revealed that insider trading had taken place. A stock trader, Robert M. Freeman, was implicated in insider trading activities that led to an increase in Phelps Dodge's stock price. This price manipulation made the acquisition financially unfeasible and risky for GE, leading to the abandonment of the planned bid [20].

On the other hand, even in the absence of the risk of an aborted bid, the inherent difficulties in verifying the accuracy of information also make it challenging for investors to assess its credibility accurately considering various possibilities of deliberately rumourmongering. For example, Kenneth, in his seminal work "Rumour Has It: Sensationalism in Financial Media" highlights the media's incentive to publish sensational stories, namely attention-grabbing, speculative news with broad readership appeal to win attention regardless of the reliability: "Media coverage that is skewed toward speculative stories, possibly at the expense of accuracy, could distort investors' beliefs and impact asset.". For concreteness in illustrating the trade-off between attractiveness and truthfulness, Kenneth lists an article that was featured on the front page of the Seattle Times on September 2, 1993, titled "Could GE Buy Boeing? It's Speculation Now, But Not Entirely Far-Fetched." [21]. The article speculated on a potential takeover of Boeing by GE, describing it as a scenario where "fiercely independent Boeing succumbs to an opportunistic corporate raider," with GE's ambitious chairman Jack Welch positioning the company for a major acquisition. Though Welch had not explicitly stated his intentions, the article suggested he coveted Boeing. By focusing on a major local company, Boeing, which would significantly impact the Seattle Times' audience, and using both provocative and exaggerated language akin to that found in a novel, such as "opportunistic raider," "Boeing succumbs," and "Welch covets.", the press's intention to attract readership is clearly demonstrated.

In addition, Kenneth also cited a letter to the editor of the Seattle Times, published a few days later, to provide insight into how this article was received by readers. The letter states, "In my opinion, your paper chose to give this story front-page attention only for the purpose of selling newspaper. Unfortunately, judging by the fact that The Times newspaper box outside the gate where I work was empty when I left work (this is the first time I've not had this occurrence), you succeeded". Ultimately, the rumour did not materialise, as GE never made a bid for Boeing.

1.1 EMPIRICAL CONTEXT: TAKEOVER EVENTS AND MARKET RESPONSE

Being acquired represents a pivotal moment in a company's history, and it has garnered significant attention in financial research. A major insight from empirical studies is that the takeover announcements are regularly accompanied by a dramatic surge in the target company's stock price which exhibits an enticing opportunity for transient traders, who often are privy to the discussions about the takeover well before such information is made public [22]. Among the various factors that contribute to the profitability of anticipating merger and acquisition (M&A) events, the acquisition premium offered by the bidding firm constitutes the principal incentive for speculative trading. The prospect of selling shares at a price substantially above the prevailing market level prompts traders to accumulate positions in potential target firms prior to public disclosure of a bid [23].

This dynamic often leads to increased demand and upward price pressure—sometimes observable even before any official announcement. Importantly, the economic benefit of the premium is not confined to corporate insiders or board members; open-market investors who hold shares at the time of the acquisition are likewise eligible to tender their shares at the offered price, should the deal go through. Consequently, both trading volume and price volatility in target firm stocks tend to rise in the lead-up to, and immediately following, the announcement of a takeover bid [24]. Nonetheless, Brown points out that the expected return during the post-bid markup period, empirically speaking, is unlikely to be statistically significant [25]. This finding is consistent with the market efficiency in reacting to public information since the price would have been adjusted to a consensual value of market sentiment and expectation once the bid offer is publicised. However, during the pre-bid period, a constant abnormal return as well as trading volume is frequently observed with the fundamental causes still remaining ambiguous.

1.2 THEORETICAL MECHANISMS: INFORMATION LEAKAGE AND RATIONAL ANTICIPATION

Two primary mechanisms have been advanced to explain abnormal pre-announcement trading: rational anticipation by market

participants and insider information leakage. The former refers to skilled traders detecting subtle signals—such as unusual trading volumes or large block purchases—and speculating on potential corporate actions like mergers or acquisitions. The latter involves the circulation of confidential information, whether deliberate or accidental, among a network of institutional investors, hedge funds, and other well-connected market actors. Both contribute to pre-takeover price drift, yet distinguishing their effects in real-world data is notoriously challenging.

It's long been controversial whether pre-announcement trading activities indicate information-based trading or rational market anticipation [26]. Is the abnormal trading activity before corporate announcements rooted in materially informed decisions or mere speculation on the basis of the historical performance of the firm [27]? Extant literature presents evidence that supports both hypotheses and the debate is extended to the consideration of market efficiency [28]. The informed trading faction is in favor of the semi-strong form of market efficiency since abnormal return is explained by the possession of private information that the market is not efficient at reflecting. On the other hand, the anticipation theory suggests a strong form of market efficiency in operation since the price run-up is a result of professional traders' superior analysis to the past signals available to all participants such as abnormal trading volume or stock price movement. That is to say, when so-called tape watchers who look closely at the market observe unusual activity in a company's stock with no apparent reason, it can serve as a clue that something significant is happening behind the scenes, often leading to speculation about a probable merger or acquisition (M&A). This point of view is valid since in many cases takeover announcements are preceded by large blocks of share purchases by the acquiring company due to strategic reasons³.

³ There are a variety of reasons behind the bidder's early accumulation of the target firm's share. 1). Reduced costs: By acquiring a substantial stake before announcing a takeover bid, the bidder can purchase shares at the current market price, which is typically lower than the premium price offered in the bid. 2). Increased influence: Owning a significant portion of shares provides the bidder with a stronger position in negotiation with board members of target firm. 3). Demonstration of commitment and discouragement of potential competitors etc. Nonetheless, there are regulatory oversights to protect market integrity and transparency such that a bidder would trigger mandatory disclosure of share ownership once surpassing a certain level (which, in the UK, starts at 3% of the total voting rights and then at each 1% threshold thereafter governed by the Financial Conduct Authority (FCA))

John Pound admits that very few takeover bids for publicly held corporations are true surprises [28]. On the contrary, in the weeks leading up to a bid announcement, rumours spread among Wall Street professionals and through business media, enabling the market to anticipate the possibility of a firm becoming a takeover target. The nature of these rumours often occupies a nebulous zone, straddling the line between fully public (officially disclosed) information and confidential information held by specific market players, especially arbitrageurs. Private information regarding potential takeovers often circulates among institutional traders before public announcements [29]. This spread can be attributed to the networks and relationships that institutional investors maintain within the financial industry [30]. Such traders may receive early hints about M&A activities, allowing them to adjust their portfolios to capitalise on the impending announcements. For example, Eliezer documents the behaviour of hedge funds in the period surrounding merger and acquisition (M&A) announcements and indicates that hedge funds in the aggregate increase their holdings of soon-to-be takeover targets by 7.2% during the quarter prior to the public announcement [31]. Massa and Rehman employ data from quarterly mutual fund and 13F filings⁴ to demonstrate that institutional traders affiliated with entities holding confidential banking and loan renegotiation details engage in profitable trading activities subsequently [32]. Yan Wang examines the correlation between institutional trading and sequential announcements through which concrete price signals are released and finds that institutional traders' proactive trading offers positive predictability in future stock returns, indicating superior and timely information is in their possession [33].

1.3 METHODOLOGICAL APPROACH: AGENT-BASED MODELLING

The persistent pre-announcement trading advantages enjoyed by institutional traders—such as hedge fund managers and

through the Disclosure Guidance and Transparency Rules (DTR). Therefore, the stakebuilding is surely not unlimited.)

⁴ Form 13F filings are quarterly reports required by the U.S. Securities and Exchange Commission (SEC) from institutional investment managers with at least 100 million in assets under management. They disclose detailed equity holdings and are commonly used to track institutional investment activity (SEC, 2023).

bank agents—can be attributed to two principal mechanisms: the selective leakage of insider information and the sophisticated, rational anticipation of potential corporate actions. While the former involves the privileged circulation of confidential details through professional networks, the latter reflects the ability of skilled market participants to infer forthcoming events from subtle market signals and patterns. Both factors exacerbate information disparities and adverse selection, challenging the integrity and fairness of financial markets. Yet, disentangling the respective impacts of information leakage and rational anticipation remains an ongoing challenge, as their effects are often intertwined and mediated by the social and professional networks that link market actors. To address this complexity, our study adopts a modelling approach capable of representing both mechanisms in a unified framework. To rigorously investigate the genesis of pre-takeover price drift, it is essential to employ a modelling framework that can accommodate the intricate heterogeneity and microstructural complexity characteristic of real-world financial markets.

Agent-based modelling (ABM) meets these requirements by enabling the explicit representation of individual market participants—each endowed with distinct information sets, trading heuristics, and adaptive behavioural rules—within a dynamic and interactive environment. This methodological approach is particularly well-suited for the present study, as it allows for the explicit delineation and separate treatment of key agent archetypes: *intrinsic value traders*, who are positioned to receive and act upon private information, and *trend-following agents*, who respond endogenously to emergent market signals. Through this framework, both information leakage and rational anticipation mechanisms can be operationalised at the agent level, rather than subsumed within aggregate statistical models. Such granularity facilitates the tracing of macro-level market phenomena—including the observed pre-takeover drift in target firm stock prices—directly to the micro-level interactions and behavioural heterogeneity among agents. Accordingly, the ABM paradigm affords a robust platform for disentangling the relative contributions of these mechanisms in driving anomalous market outcomes.

Central to our agent-based modelling framework is the mechanism by which value investors acquire and transmit takeover-related rumours. This process is inherently dependent on the structure of the communication network through which pri-

vate information diffuses among institutional traders [34]. In practice, the dissemination of such rumours is shaped not by chance encounters, but by persistent, often opaque, patterns of professional interaction—collegial ties, repeated collaborations, and institutional affiliations—that give rise to tightly knit clusters within the financial community [35]. Recognising that the topology of these networks plays a decisive role in determining who gains early access to market-moving information, our study systematically investigates the impact of different network structures on the dynamics of information flow and the resulting price behaviour. By implementing and comparing a variety of artificial network topologies—including random graphs, small-world networks, and, most importantly, community-based (modular) structures—we are able to assess how features such as clustering, path length, and modularity influence both the spread of rumours among value investors and the emergent patterns of price movement in the lead-up to takeover announcements. In particular, our focus on community-based networks is motivated by empirical evidence suggesting that real-world financial communications are highly cliquish and modular, with information tending to circulate rapidly within groups before leaking out more broadly. Through this approach, we aim to shed light on the extent to which the underlying structure of market participants' relationships amplifies, attenuates, or channels the effects of insider information leakage—thus providing a more nuanced understanding of the mechanisms driving pre-takeover anomalies. The following section presents the design and analytical rationale for the network configurations employed in our simulation framework.

In this study, we develop an agent-based model (ABM) that incorporates heterogeneous trader types—specifically value investors and trend followers—embedded within artificial financial networks characterised by varying levels of modularity and clustering. Our primary objective is to investigate how micro-level rumour propagation mechanisms can collectively give rise to the pre-announcement cumulative abnormal return (CAR)⁵ pattern commonly observed in the context of corporate takeover events. By explicitly modelling the diffusion of takeover-related

⁵ Cumulative Abnormal Return (CAR) is defined as the sum of abnormal returns over a specified event window. The abnormal return is typically calculated as the difference between the observed return of a stock and its expected return under a benchmark model. CAR is widely used in event studies to measure the impact of events such as takeover announcements on stock prices.

rumours among value investors, and allowing trend followers to react to ensuing price signals, we succeed in reproducing the stylised upward drift in CAR prior to the announcement day—an anomaly that has been well-documented across multiple empirical studies.

Importantly, our findings do not purport to establish a definitive causal link between real-world pre-bid stock price movements and the specific microstructure we simulate. Rather, we present a coherent and internally consistent mechanism that is capable of generating such dynamics from the bottom up, without requiring centralised coordination or a priori price setting. In doing so, we provide a concrete illustration of how decentralised information flow—when shaped by the underlying network of trader interactions—can lead to aggregate market behaviour that closely mirrors empirical patterns.

Furthermore, we demonstrate that the structural properties of the network—such as clustering coefficient, modularity, and inter-group connectivity—substantially influence both the intensity and timing of the simulated CAR pattern. In particular, networks with pronounced community structure exhibit a delayed and more gradual drift in comparison to more diffusely connected configurations, suggesting that the topology of trader interactions plays a critical role in shaping the speed and scope of rumour-driven price responses. This contributes to a growing body of literature emphasising the non-trivial effects of market microstructure and agent connectivity on price dynamics, especially in environments characterised by information asymmetry.

Overall, this study presents a stochastic model in which information asymmetry and heterogeneous trader behaviour jointly reproduce the pre-takeover price drift observed in real markets. It highlights the explanatory potential of network-based ABMs as tools for exploring complex financial phenomena that are otherwise difficult to capture through traditional representative-agent or equilibrium-based models. Future extensions may incorporate empirical network data or additional behavioural heterogeneity to bridge the gap between theoretical abstraction and real-world market behaviour.

The remainder of this thesis is organised as follows.

Chapter 2 reviews the relevant literature in behavioural finance and rumour spreading, outlining how information asymmetry and trader interactions have been used to explain deviations from market efficiency.

Chapter 3 introduces the rumour-spreading framework used to model the transmission of information among traders. It outlines the Ignorant–Spreader–Stifler (ISR) process and examines how different network structures—random, small-world, and community-based—affect the dynamics of information propagation.

Chapter 4 extends this framework into an agent-based market model that links the information-spreading process to trading behaviour and price formation. Heterogeneous agents—value investors and trend followers—trade based on perceived mispricing and trend signals, producing an endogenous evolution of stock prices under information asymmetry.

Chapter 5 presents the simulation results, focusing on how variations in network topology, spreading parameters, and trader heterogeneity influence the emergence of pre-takeover price drift. The model’s outcomes are compared with empirical evidence from takeover markets to assess its ability to reproduce real-world price anomalies.

Chapter 6 concludes the thesis by summarising the key findings, discussing their implications for understanding market efficiency and information flow, and suggesting directions for future research, including potential empirical validation and model extensions.

The phenomenon of pre-takeover run-up in target firms' stock prices is a well-documented occurrence in financial markets around the world. For instance, Arthur (1981) integrates the daily holding period returns of 194 successfully acquired firms (101 stocks listed on the New York and American Stock Exchanges and 93 stocks traded on the Over-the-Counter Market) between 1975 and 1978 prior to the first public announcement of their proposed merger and finds that the Daily Average Residuals are positive on 26 out of the final 27 days prior to the announcement date as shown [29]. The findings are consistent with what appears to be common knowledge on the street: impending merger announcements are poorly held secrets, and trading on this nonpublic information abounds.

In a similar manner, Michael examines the stock prices as well as the trading volumes of 399 Canadian firms from 1985 to 2002 and further presents a notable increase in both ARs (abnormal returns) and AT (abnormal turnovers) over the days leading up to the takeover announcement, with the rise in AT starting significantly earlier than the increase in ARs, where the abnormal return is referred to as the difference between the actual return of a stock over a specific period and the expected return based on the market's overall performance or the stock's historical performance. The abnormal turnover is referred to as the trading volumes that significantly deviate from the norm, adjusted for the typical trading activity of the firm. Specifically, AT is the measure used to capture unusually high or low trading volumes in the stock of a company in the period leading up to a takeover announcement, which cannot be explained by normal market or firm-specific conditions. More specifically, AT across the sample becomes positive and statistically significant around 37 trading days prior to the actual announcement, accompanied by ARs only during the last five days [36].

Paul Irvine also reveals a statistically significant rise in institutional trading activity and net purchasing ranging from five to twenty days prior to the public disclosure [37]. This increase in abnormal buying persists even when accounting for the tendency of institutions to follow momentum trading strategies. Patrick (2018) undertakes a rigorous examination of insider trad-

ing within the context of takeover announcements, concentrating specifically on the options market [38]. Utilising a comprehensive dataset of 1,859 U.S. takeover transactions, Patrick employs an event study methodology that quantifies abnormal trading volumes and returns in the period immediately preceding takeover announcements by calculating deviations in trading metrics against established market benchmarks—a methodological choice that enables the author to disentangle the influence of takeover-related information from broader market trends. Further, Patrick incorporates regression analysis that controls for confounding factors, such as firm-specific characteristics and prevailing market conditions. The empirical results demonstrate marked increases in options trading volumes, coupled with positive abnormal returns during the pre-announcement phase, indicative of insider trading by individuals likely possessing material non-public information. These findings, which expose the challenges regulatory bodies face in identifying and curbing illicit trading activities, underscore the critical need for enhanced regulatory surveillance within the options market to uphold market integrity and deter trading behaviour that capitalises on privileged information. By linking pre-announcement market fluctuations directly to probable insider trading, Patrick's research contributes a crucial perspective to the literature, highlighting inherent regulatory deficiencies that complicate the detection and prevention of trading practices based on proprietary information.

Yet it's been well demonstrated that share prices of target firms see a pervasive run-up before takeover bid announcements, the reason behind this phenomenon remains rather plausible.

2.1 INFORMED TRADING AND TREND CHASING

Pre-takeover trading activity has been extensively studied in financial research, often revealing pronounced anomalies in trading volumes and price movements preceding public announcements, which have sparked considerable debate concerning the primary underlying drivers of this phenomenon [39]. As Thomas Eyssell and Nasser Arshadi discussed in their seminal work "Insiders, Outsiders, or Trend Chasers?: An Investigation of Pre-Takeover Transactions in the Shares of Target Firms," pre-takeover trading can be attributed to three primary mechanisms: **insider trading**, where individuals with privileged access to non-public information act ahead of the market; **informed trad-**

ing by outsiders, involving sophisticated market participants who infer potential takeovers through complex analysis as well as expert networks; and **trend-chasing behaviour**, characterized by positive feedback trading initiated by investors responding to emerging price trends. Collectively, these mechanisms provide a comprehensive framework to interpret the dynamics of pre-takeover trading surges [27].

Empirical studies present mixed evidence, with support for each mechanism depending on market conditions and specific cases, making it challenging for regulators and academics to differentiate definitively between materially informed trading and rational, yet derivatively informed, anticipation; These hypotheses, therefore, present critical questions regarding fairness, transparency, and efficiency in financial markets, as they all reflect unique but plausible ways in which information can impact trading behaviour and pricing. This section explores these mechanisms in greater detail, examining how each contributes to pre-announcement trading and their implications for regulatory enforcement and market integrity.

2.1.1 Insider Trading

As stated by Congressman Edward, chairman of the House Telecommunications and Finance Committee, "In our current economic environment, corporate takeovers regularly provide a catalyst for insider trading. The magnitude of the stock-price run-ups in many cases points to possible leaks or tips by insiders connected with the transaction." . In a more recent case in 2022, the SEC charged nine individuals, including a former Chief Information Security Officer (CISO) and an investment banker, for insider trading related to acquisition announcements. The CISO, Amit Bhardwaj, and his associates were found to have made over \$5.2 million in illicit profits by trading on non-public information about Lumentum Holdings Inc.'s acquisition plans. These cases illustrate how insider information is shared within networks, leading to significant financial gains for those involved before public announcements are made.

Alperovych, Cumming, and Groh (2016) provide a rigorous empirical investigation into the mechanisms through which M&A-related rumours originate in financial markets [40]. Their research represents one of the most comprehensive studies to date on the subject, utilising a global dataset comprising over 47,000 announced transactions between 1997 and 2013. Unlike

much of the existing literature, which focuses predominantly on the market reaction or consequences of rumours, this study devotes particular attention to the origin and structural characteristics of information leaks preceding official merger announcements.

The authors begin by distinguishing between two primary sources of rumour emergence: unintentional, process-related information diffusion, and strategic, deliberate rumour generation. On the unintentional side, rumours often arise from breakdowns in confidentiality during the preparatory stages of a transaction. M&A processes frequently involve a multiplicity of stakeholders, including investment banks, legal advisors, consultants, and multiple bidding parties. The larger and more complex the deal, the more likely it is that sensitive information may inadvertently be disseminated. This is particularly pronounced in deals involving publicly listed target firms, which tend to attract increased media scrutiny and market speculation, thereby increasing the likelihood of pre-announcement information becoming public through informal or secondary channels.

Empirical patterns in the study support this assertion. The probability of a rumour being associated with a transaction increases significantly when the target company is large in size, older in age, or when multiple acquirers are involved. These characteristics likely correlate with greater visibility, more touchpoints for potential leaks, and increased monitoring by market participants. Moreover, transactions involving public targets are particularly prone to early information diffusion, due to their heightened exposure to investor commentary, media coverage, and regulatory disclosure obligations.

In contrast to accidental leaks, the authors also emphasise that rumours may be generated deliberately as a strategic maneuver. Certain actors—whether they be rival bidders, stakeholders opposed to the deal, activist shareholders, or even one of the negotiating parties—may stand to benefit from the controlled release of confidential information. Competitors might leak news of a potential deal to discourage others from proceeding or to invite regulatory scrutiny. Bidders themselves may disseminate selective information to manipulate market expectations, pressure the selling party into a lower valuation, or accelerate the negotiation process. In such cases, the rumour functions not as a by-product of weak information control, but as a calculated instrument of influence designed to alter the strategic landscape of the transaction.

The study further identifies environmental and institutional factors that influence the prevalence of M&A rumours. Transactions that occur in jurisdictions characterized by strong legal enforcement, high-quality investor protection, and low levels of public-sector corruption are statistically less likely to experience information leaks. Conversely, countries with weaker legal institutions and a less robust regulatory framework display a higher incidence of rumour-driven disclosures. These patterns suggest that the probability of rumour emergence is not merely a function of deal-specific complexity, but is also contingent upon the broader integrity and professionalism of the M&A environment in which the transaction is embedded.

In conclusion, the findings of Alperovych et al. (2016) offer strong empirical support for the proposition that M&A rumours arise from two principal sources: structural vulnerabilities and strategic incentives instead of merely random or incidental events. Structural vulnerabilities encompass inherent features of the deal-making process that increase the likelihood of unintentional information leakage. These include factors such as the complexity and scale of the transaction, the number of parties involved, and the public nature of the target firm, all of which heighten the exposure of sensitive information to the market. On the other hand, strategic incentives refer to the deliberate and tactical dissemination of information by interested parties who seek to influence the outcome of a potential deal. These actors may exploit rumour propagation as a means to manipulate bargaining positions, trigger competing bids, or shape public and investor sentiment. By conceptualising rumour formation through the dual lens of structural and strategic forces, the authors provide a more nuanced and realistic account of how unverified M&A-related information enters the public sphere, thereby enriching our understanding of the dynamics that precede formal takeover announcements.

The information-based insider trading hypothesis posits that certain market participants engage in trading activities based on material, non-public information, which gives them a significant advantage over others. This form of trading is typically illegal, as it involves exploiting private knowledge that is not available to the general public [41]. Regulatory bodies such as the SEC (Securities and Exchange Commission) and the FCA (Financial Conduct Authority) have stringent rules in place to curb insider trading, but detecting and proving such activities remains a significant challenge due to the covert nature of the information

flow and the difficulty in distinguishing it from legitimate market analysis [42]. Despite the legal restrictions, informed trading remains a persistent issue in financial markets, raising questions about the effectiveness of current enforcement mechanisms and the ethical implications of information asymmetry.

Traditionally, this form of trading is associated with “insiders” in the strict sense—such as board members, executives, or other high-level stakeholders with privileged access to corporate developments. However, the scope of insider trading often extends beyond these direct insiders to encompass a broader network that may include family members, close associates, and business partners who, through direct or indirect interactions, gain access to sensitive information.

For instance, Ahern sheds light on how inside information flows through social ties, such as family relationships, friendships, and geographical proximity, eventually impacting stock prices and traders’ gains [43]. By analysing a hand-collected dataset of insider trading cases filed by the SEC and DOJ from 2009 to 2013, the study illustrates how insider trading networks are formed around strong social ties, with 23% being family members, 35% friends, and 35% business associates.

Harrison also carries out empirical evidence supporting the idea of an “epidemic model” of information dissemination [44]. As J. William Robinson, a principal at Georgeson & Co. (a firm specialising in soliciting shareholder proxies for takeover confrontations), describes, “You start with a handful of people, but when you get close to doing something the circle expands pretty quickly. You have to bring in directors, two or three firms of lawyers, investment bankers, public relations people, and financial printers, and everybody’s got a secretary. If the deal is a big one, you might need a syndicate of banks to finance it. Every time you let in another person, the chance of a leak increases geometrically”.

For example, Simonov explore how investment banks, leveraging their insider roles in advising corporate mergers and acquisitions (M&A), engage in strategic trading to capitalise on non-public information. The study investigates how banks with privileged access to confidential details—such as deal timing, target firm identities, anticipated price premiums, and bidder motivations—use this insider knowledge to establish advantageous positions in target stocks before deal announcements, effectively engaging in a form of information leakage [45]. The authors provide detailed empirical evidence demonstrating that advisory

banks frequently accumulate significant stakes in target companies prior to public announcements, positioning themselves to benefit from the expected surge in stock prices following a deal's disclosure. This pre-announcement trading behaviour is shown to yield substantial profits, with advisory banks outperforming standard merger arbitrage benchmarks. Moreover, it also highlights a broader form of internal information dissemination within financial conglomerates, where advisory banks, privy to sensitive M&A deal information, indirectly share insights with their affiliated divisions. Rather than explicitly leaking information to external clients, the study reveals that advisory banks within large conglomerates often align their investment strategies across divisions, such as asset management, enabling these affiliates to capitalise on confidential deal insights.

This intra-firm sharing of information allows conglomerate-affiliated investment managers to take preemptive positions in target firms based on advisory divisions' insider knowledge, effectively bypassing formal information barriers meant to enforce confidentiality, such as "Chinese walls." By leveraging cross-division coordination, these conglomerates benefit as a unified entity from the anticipated stock price appreciation of target firms, resulting from impending M&A deals. This arrangement, though less direct than external information leaks, demonstrates how financial conglomerates can exploit advisory knowledge to enhance profitability across their various divisions, challenging regulatory assumptions about the independence of advisory and investment management functions within the same organization.

Furthermore, Caporale et al. discuss compelling incentives for insiders to amplify volatility, allowing them to exploit their informational advantage, especially during periods of heightened economic uncertainty [46]. The first incentive revolves around profit maximization through market volatility. By selectively leaking information or timing trades to create market ripples, insiders can induce temporary surges in volatility. This volatility amplification is particularly advantageous because it allows insiders to exploit price fluctuations that stem directly from informational asymmetry. With access to private, material knowledge, insiders are positioned to initiate trades before the broader market has adjusted, capturing the profit potential associated with the spread between pre- and post-information prices. This behaviour is especially pronounced in periods of economic uncertainty, where market responses to new informa-

tion are more volatile, enabling insiders to secure returns that are considerably amplified compared to stable market conditions. The second incentive driving insiders toward information manipulation is rooted in the capacity to influence market sentiment and control the timing of information release. Insiders who possess non-public information hold significant sway over market dynamics, particularly if they strategically disseminate this information in ways that benefit their trading objectives. By staggering the flow of private data or selectively leaking partial information, insiders can steer market reactions, creating a fertile ground for profitable trading. This selective disclosure allows insiders to manipulate perceptions of a firm's financial health or anticipated corporate actions, resulting in price shifts that align with their trading goals.

These incentives, cumulatively, highlight the role of insider information manipulation as a powerful mechanism through which insiders exert control over market conditions, leveraging their informational advantage to achieve enhanced returns while introducing inefficiencies and volatility into the broader financial landscape.

This concept of insider trading, or more aptly, "insider information leakage," reflects not only transactions initiated by registered insiders but also those resulting from information cascading through informal networks. Close associates, whether friends, family, or business affiliates, may become privy to impending mergers, acquisitions, or other corporate events via indirect disclosures—whether intentional or inadvertent—by primary insiders. Consequently, these indirectly informed individuals may also engage in anticipatory trading that impacts stock prices in the lead-up to formal announcements. The illicit advantage conferred by this broader insider network is substantial, as such leaks can lead to unusual pre-announcement price and volume shifts that reflect the dissemination of sensitive information beyond the inner corporate circle. In essence, the influence of insider trading is often amplified by a network effect, where information leakage—intentionally or otherwise—spurs a cascading impact on market behaviour, ultimately complicating regulatory efforts to curb unfair trading advantages.

This expanding circle of access highlights the persistent risk of information leakage that characterizes high-stakes corporate maneuvers, where complex negotiations and extensive logistical arrangements bring a growing number of participants into the fold. Consequently, as the circle of those "in the know" widens,

the probability of unintentional leaks rises sharply, resulting in pre-takeover price surges and abnormal trading volumes that reflect the broader dissemination of insider information through indirect channels. The networked nature of insider leakage complicates regulatory oversight, as monitoring informal disclosures across such a vast network of associates and service providers poses significant challenges. Ultimately, insider leakage remains a pervasive factor in pre-takeover market behaviour, where both formal insiders and peripheral participants contribute to the dissemination of privileged information, fueling anticipatory trading activities that impact stock prices long before formal announcements are made.

Eyssell and Arshadi (1993) reveal that a significant proportion of the pre-announcement escalation in trading volume is, in fact, driven by registered insiders, who, benefiting from the comparatively relaxed regulatory framework of the early 1980s, were able to exploit non-public information with limited fear of legal repercussions, thereby inducing abnormal trading volumes preceding takeover announcements [27]. This insight aligns with the findings of Meulbroek (1992), whose work also elucidates a direct correlation between access to insider information and intensified trading activity surrounding consequential corporate events, thus reinforcing the argument for the role of insider knowledge in shaping pre-announcement market behaviour [47].

Mehemet conducts a meticulous investigation into the role of managerial insider trading during periods of market misvaluation that often precede merger and acquisition events. His empirical analysis seeks to determine whether such insider trading behaviours are opportunistic, especially in scenarios where the market demonstrates mispricing of assets. By closely examining the timing and characteristics of insider trading transactions, Mehemet identified patterns that reveal whether managers systematically capitalise on periods of overvaluation or undervaluation in the lead-up to mergers.

To bolster the robustness of his findings, Mehemet employed regression analysis that accounts for an array of market factors, thereby isolating the specific effects of asset misvaluation on insider trading behaviour. This methodological approach enables a more nuanced understanding of the relationship between market misvaluation and strategic trading by insiders. The results strongly indicate that managerial insiders exploit these periods of misvaluation by timing their trades to align with anticipated

merger announcements, positioning themselves advantageously in anticipation of favourable market shifts. Notably, the findings reveal a distinct pattern: insider purchases increase when firms are undervalued, signalling confidence in the firm's prospects, while insider sales become more frequent during periods of overvaluation, suggesting an effort to maximize personal gains before the market adjusts.

Jain employs an event study methodology to analyse the abnormal returns and trading volumes of target firms' stocks, focusing on a sample of merger announcements over a specific period, aiming to detect patterns that could indicate the presence of informed trading by insiders prior to the official announcement [48]. The event study involves examining stock price movements and trading volumes in event windows before, during, and after the merger announcement. By calculating abnormal returns using a market model, the effect of merger-related information from broader market factors is isolated. Regression analysis is then used to further evaluate the determinants of abnormal trading activity, accounting for market, industry, and firm-specific characteristics. The findings reveal substantial evidence of abnormal price run-ups and increased trading volumes prior to merger announcements, which strongly suggests the existence of insider trading. These price and volume changes indicate that market participants may have been acting on privileged information ahead of the merger disclosure. The paper highlights that insiders can significantly influence price dynamics before mergers, complicating regulatory efforts to maintain market integrity. By linking pre-announcement stock price movements directly to insider activities, the study provides valuable insights into the effectiveness of market surveillance and the need for more robust regulatory frameworks to curb illicit trading.

Schwert offers compelling evidence that insider trading contributes significantly to the pre-bid performance of target firms, with legal repercussions confirming the systematic nature of such behaviour [49]. He centers the analysis on the pre-bid stock price runups that often precede public takeover bids, covering a substantial set of takeover bids from 1975 to 1991, and examines how leaks and informed trading shape pre-bid market performance. His evidence indicates that these pre-bid price increases do not merely result from general market optimism but are often prompted by direct information flow from insiders to the market. The study points to specific cases where insider trading

was identified and prosecuted, highlighting the systematic impact of these trades on acquisition pricing. For instance, insider trading cases involving well-known figures like Ivan Boesky and Dennis Levine underscore how pre-bid runups were sometimes driven by individuals who had gained privileged information about pending bids. Boesky, notably active in merger-related insider trading during the 1980s, acquired significant stakes in target companies before public announcements, leveraging information leaked by investment bankers. This activity not only inflated the stock price of target companies before bid announcements but also led to notable legal actions. The SEC's pursuit of Boesky and his associates, including Martin Siegel, illustrates how the spread of confidential information led to clear, prosecutable cases of insider trading, which, as Schwert's data suggest, contributed directly to the pre-bid runups observed in many acquisition scenarios.

It is important to note that in the context of financial markets, the term "rumour" encompasses not only idle speculation but also privileged information that is circulated informally among a subset of market participants prior to public disclosure. Takeover-related private information, while sometimes originates from intentional or unintentional leaks, is typically disseminated as a rumour—its veracity uncertain, its audience selective, and its impact on trading behaviour significant. This characterization is supported by both empirical findings and legal evidence, which document the spread of merger and acquisition intelligence through informal and often modular social networks. Modelling this information as a rumour within our simulation framework thus reflects both the uncertain and networked nature of pre-announcement trading advantages in real-world markets. The private information that precedes takeover announcements in financial markets frequently possesses the core attributes of a rumour: its content is often unverified, selectively disseminated, and subject to manipulation by market participants with differing incentives and investment horizons.

Daniel discusses another aspect of the uncertainty of financial rumour with respect to the trading horizon of the initial rumourmonger [50]. The credibility of a rumour in financial markets is significantly influenced by the investment horizon of the individual spreading it. Investors with a short-term horizon are often inclined to share truthful information to maximize the immediate impact on stock prices. They rely on the price to react quickly to the positive information so they can cash out with

gains within a short period. For instance, an investor might buy a stock at 100, anticipating a rise to 130 due to positive information dissemination, resulting in a profit of 30 per share. In such cases, telling the truth serves the short-term investor's interests, as it ensures the price aligns closely with subsequent information releases, thereby maximizing immediate gains. Thus, short-term investment horizons can foster credible information sharing among investors and accelerate the incorporation of information into market prices.

Conversely, long-term investors may have different incentives that lead them to manipulate stock prices by spreading false information. They can spread negative rumours to artificially deflate the stock price, allowing them to profit from both short and long positions. For example, a long-term investor could start by short selling the stock at 100, expecting the price to drop to 80 based on the false information they disseminate. Once the price falls, they would buy back the stock at 80, then hold it until it eventually returns to its fair value of 150. This strategy allows the investor to gain twice: first from the 20 profit on the short sale, and then an additional 70 profit from the price recovery. This kind of manipulative behaviour leverages the long-term predictability of price corrections once the true information is revealed. By spreading false rumours, long-term investors can first benefit from the market's initial reaction and then from the eventual correction, maximizing their profits over a more extended period.

Ziyang's study further explores the transmission of exaggerated or false information and its intertemporal effects on investor sentiment, emphasising how misleading financial news can shape market behaviours over different time horizons [51]. The research indicates that the dissemination of such information often results in a two-phase reaction among investors. Initially, there is an immediate impact characterized by a rapid surge or drop in stock prices, depending on whether the information is positive or negative. This immediate reaction is largely driven by heightened investor attention, where sensational news captures the focus of both individual and institutional investors, prompting swift buying or selling activity. However, the effects do not stop there. The study also points out that as time progresses, the persistence of uncertainty stemming from the original false information can lead to prolonged volatility in stock prices. The market's process of adjusting to and filtering out exaggerated information often takes time, causing an un-

predictable oscillation in investor sentiment. This can result in stocks experiencing continued swings as market participants reassess the credibility of the information, often after more concrete evidence either validates or refutes the earlier rumours. The interplay between attention-grabbing yet unreliable news and the gradual correction by more informed investors reflects a recurring pattern of uncertainty in financial markets, emphasising the disruptive power of "black mouth" behaviour on both short-term price movements and longer-term investor confidence. This dynamic highlights the non-homogeneous nature of information flow within financial networks.

Ziyang's work effectively contributes to the literature by demonstrating that the spread of such rumours is not a uniform process but rather is influenced by network factors, including investor connectivity and the speed of news dissemination. The study provides evidence that exaggerated news tends to spread more rapidly within certain investor clusters, thereby increasing the clustering effect and reinforcing the community nature of financial information networks. This uneven distribution of information leads to distinct behaviours across different investor segments, which can amplify market inefficiencies and prolong periods of abnormal returns and volatility.

In summary, the essence of private, pre-takeover information in financial markets is that it is not simply a binary of fact or fiction, but a spectrum of uncertainty and intent, mediated and magnified by the networked relationships among market participants. This reality justifies—and indeed necessitates—the modelling of such information as rumour in our study.

2.1.2 Rational Anticipation

The second factor is rational market anticipation by informed outsiders, who, though lacking direct access to confidential information, are adept at predicting and inferring likely takeovers through advanced analysis and indirect information channels. These investors—often highly skilled analysts or institutional traders—rely on a sophisticated combination of market indicators, such as undervalued assets, atypical trading patterns, or strategic positioning, and supplement these with derivative insights. While they do not have direct insider access, informed outsiders effectively create actionable information by piecing together fragmented data and conducting thorough, skill-based analyses of potential takeover targets.

In this context, financial rumours of an impending takeover may arise from both mechanisms. Insiders, whether driven by incentive or inadvertent disclosure, may release sensitive information directly or indirectly, thus sparking early speculation. At the same time, outside traders, particularly those with institutional acumen, might spread their findings through peer-to-peer networks or word of mouth, thereby amplifying rumours as their insights circulate and gain traction in the market. Consequently, these two mechanisms—insider leaks and outsiders' informed anticipation—foster a rich informational environment where takeover expectations are shaped by both implicit signals and calculated, speculative analysis, each reinforcing the other in propagating takeover rumours.

For instance, Pound and Zeckhauser's (1990) study investigates the origins and effects of takeover rumours on stock prices, with a focus on how these rumours emerge and influence market behaviour [28]. They argue that takeover rumours, rather than being random or baseless, often arise from observable market signals and analyses conducted by professional market watchers—referred to as “shark watchers” and arbitrageurs—who scrutinize trading patterns for signs of a potential takeover. These signs frequently include unusual price and volume spikes or the accumulation of substantial stock positions by large investors. The authors suggest that such activities prompt speculation among informed outsiders, who, despite lacking direct insider knowledge, infer the possibility of takeover bids. To analyse this phenomenon, the authors utilise data from the “Heard on the Street” column in *The Wall Street Journal*, a widely read source of takeover speculation, capturing rumours and market responses from 1983 to 1985. They identify that, on average, target firms experience a notable price increase of about 7% in the 20 trading days leading up to the publication of a rumour, indicating that market participants begin pricing in potential takeover outcomes well before official announcements. Interestingly, however, only a minority (43%) of these rumours ultimately culminate in formal takeover bids, and very few materialise within a short period, which suggests that the rumours often stem from informed outsider speculation rather than direct leaks from deal insiders.

The study's findings highlight that while the presence of unusual trading activity often ignites takeover rumours, the publication of these rumours in the press does not reliably lead to excess returns for investors. This observation supports the

hypothesis that the market efficiently incorporates speculative information. The authors conclude that the origination of takeover rumours is primarily speculative, deriving from outsiders' rational interpretation of indirect signals, rather than from insider leaks. Their work thus underscores the role of informed speculation and its ability to shape market expectations, while also illustrating the challenges faced by regulators in distinguishing between informed speculation and illicit information disclosure.

Palepu, King and Padalko support the notion that informed outsiders can identify likely takeover targets by skillfully combining market signals with derivative information content, allowing them to effectively speculate on takeover activity even without explicit insider knowledge. According to this view, skilled investors may observe certain signals, acquire information or undertake analyses that suggest a company is a likely takeover target, such as undervaluation, strategic corporate actions, large block transactions, or industry consolidation trends. These investors then adjust their portfolios accordingly, leading to price movements that reflect rational anticipation of future events rather than the exploitation of insider information [52]. In other words, recent unusual price and volume behaviour of the target's stock itself cast as determining evidence that leads professional investors and speculators (such as so-called shark watchers) to guess or infer that some control-oriented activity is occurring or about to occur, which is compatible with the market's high sensitivity to undisclosed share accumulation patterns and (inferentially) to resource expenditures by market observers to identify changes in large shareholders' actions and intentions [36].

Jarrell and Poulsen (1989) offer a comprehensive analysis of the price and trading volume increases in target firms ahead of tender offers, examining whether these patterns are attributable to insider trading or broader market anticipation [15]. The authors argue that stock price runups are frequently fueled by informed speculation rather than illicit trading, as market participants react to observable signals that often indicate a potential takeover. Notably, they highlight how information cascades—wherein early suspicions or minor signals prompt a chain reaction of responses among investors—play a central role in the spread of takeover rumours. These cascades emerge as professional traders, analysts, and institutional investors, or arbitrageurs, share insights within networks that amplify these suspicions, even without direct insider information. With unan-

anticipated premiums¹ and pre-bid run-up² as two direct measures of the freshness of takeover disclosure, the degree to which a takeover is anticipated is found to be positively correlated to the position in the target at the time of the bid held by the bidder. In other words, a higher percentage of the acquirer's stakebuilding leads to a more suspicious exposure of ongoing takeover, based on which the more outsiders engage in speculative betting, resulting in a more massive pre-bid run-up as well as a poorer portion of unanticipated premiums.

The study suggests that arbitrageurs, who often act as key players in takeover speculation, analyse market signals such as unusual price movements, significant stock accumulations by potential bidders, and changes in trading volumes [3]. Such activity serves as a form of implicit communication, indicating to the market that a takeover may be imminent. These traders rely on both public disclosures, like mandatory 13D filings that reveal substantial holdings by new investors, and more informal sources, such as strategic conversations within financial networks. Through these channels, arbitrageurs essentially act as conduits for information flow, using their analyses to create an environment of heightened anticipation that can spread quickly across the market. The speculative nature of this activity gives rise to information cascades, where investors, witnessing the actions and interest of sophisticated traders, may assume these signals are based on privileged or superior information, thus reinforcing the speculative frenzy around the target firm.

Furthermore, Jarrell and Poulsen argue that this cascading effect does not solely arise from formal, public information. Rumours often propagate through informal channels and professional discussions, where insights from one party can quickly

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- 1 Unanticipated premiums refers to the portion of the price increase in the target company's stock that is not anticipated by the market before the public announcement of a tender offer, which is essentially the difference between the stock price immediately after the announcement and the price before the announcement, adjusted for any market movements that could have been predicted based on information available before the bid.
 - 2 Pre-bid run-up describes the increase in the target company's stock price occurring in the period leading up to the tender offer announcement, which reflects how much of the eventual takeover premium (the total price increase from before the runup period to after the tender offer is fully absorbed by the market) is anticipated by investors and thus incorporated into the stock price before the official announcement. In short, the higher the degree of market anticipation, the lower the level of unanticipated premiums and vice versa. Similarly, a higher anticipation leads to a higher stock price run-up before the official news because investors are buying in expectation of that news.

influence broader investor sentiment. These insights are exchanged within professional circles, generating momentum that reaches the broader market through analyst reports, financial commentary, and even media speculation. The anticipation surrounding a potential bid gains legitimacy and spreads as arbitrageurs and analysts circulate their informed suspicions, effectively bridging the gap between legal speculation and rumour. As a result, the market's response—visible through price runups and trading volume spikes—often mirrors the behaviour one might expect if insider trading were occurring, although in reality, it may be driven by skill-based anticipation and inferential analysis.

Jarrell and Poulsen's findings challenge the notion that pre-bid trading activity is inherently illicit, suggesting instead that a significant portion of these price runups result from cascading speculative behaviours grounded in observable, legally available data. This environment enables takeover rumours to gain traction rapidly, highlighting how professional speculators, through their interactions and indirect communication, can create a ripple effect that shapes market expectations. Their work thus underscores the need for careful differentiation between legitimate informed speculation and illegal trading practices, especially when assessing the origins of takeover rumours and pre-bid stock behaviour [3].

Frederick reveals markedly positive institutional order flow during the pre-rumour phase followed by significantly negative order flow after the announcement, indicating that this trading pattern is not the result of institutional momentum buying [53]. The findings remain robust even after adjusting for information that is publicly accessible and when benchmarked against a control group of firms selected based on their likelihood of being takeover targets. Therefore, the data suggests that institutional traders are likely acting on private information in their transactions involving companies rumoured to be takeover targets, rather than demonstrating a proficiency in collecting and acting on public information.

Massa and Rehman employ data from quarterly mutual fund and 13F filings to demonstrate that institutional traders affiliated with entities holding confidential banking and loan renegotiation details engage in profitable trading activities subsequently [32]. Under the anticipation hypothesis, rational market participants analyse publicly available information—such as unusual trading volumes, changes in ownership, strategic restructuring,

and other corporate activities—to infer the likelihood of an impending takeover. When aggregated, these inferences generate trading activity that elevates the target firm's stock price, reflecting the market's anticipation of a potential acquisition. This behaviour is consistent with the semi-strong form of market efficiency, where prices are assumed to incorporate all publicly available information. However, the inherent ambiguity arising from overlapping informational channels makes it challenging to clearly differentiate purely informed speculation from trading influenced by leaked insider information, thereby obscuring the true drivers behind pre-takeover price dynamics.

While the anticipation hypothesis provides a plausible explanation for pre-takeover price drifts, the influence of information leakage often complicates this view. If private, material information leaks out during takeover negotiations—whether intentionally or accidentally—those with access to such privileged knowledge may engage in trading. This trading activity generates observable signals like unusual price movements or trading volumes that other market participants may interpret as a legitimate response to public information. Thus, what appears to be a rational market reaction under semi-strong efficiency might actually be a result of private information entering the market through unauthorized channels, blurring the boundary with the strong form of market efficiency.

This convergence of rational anticipation and information leakage creates ambiguity in the market. Under the Efficient Market Hypothesis, strong-form efficiency implies that all information—both public and private—would be reflected in the stock price. In practice, however, the emergence of rumours and trading activity caused by leaks presents a scenario where insider information indirectly influences the price, which makes it difficult to ascertain whether the pre-takeover price drift results from legitimate public analysis (semi-strong efficiency) or privately leaked information that has found its way into the market (approaching strong efficiency). Consequently, insider leaks often masquerade as rational market analysis, and distinguishing between the two mechanisms becomes a complex task, clouding the understanding of true market efficiency.

2.1.3 *Summary*

In summary, the mechanisms driving pre-takeover price drift can be attributed to two primary pathways: insider leakage and

rational anticipation. Insider leakage entails the direct or indirect release of sensitive, non-public information from those within the organization or closely connected parties, enabling a select group of market participants to engage in informed trading before any official announcement. This form of leakage, whether intentional or inadvertent, results in a selective distribution of privileged knowledge, leading to observable trading patterns that signal an impending takeover. In contrast, rational anticipation arises not from direct access to insider information but from external analysts and traders who infer potential takeover activity based on a range of publicly available indicators. These indicators may include strategic corporate maneuvers, unusual stock price or volume movements, and other market signals that suggest a possible M&A event. Additionally, rational anticipation is often amplified through the informal sharing of analysis and insights among professionals. Skilled analysts, institutional investors, and market observers frequently communicate their inferences, further spreading anticipatory signals within professional circles and creating an informal network of shared insights. Through peer-to-peer discussions, industry conferences, and financial media, these analyses circulate, generating a collective anticipation that effectively mirrors the spread of insider rumours.

The boundary between insider leakage and rational anticipation in financial markets is often fluid, creating challenges in distinguishing between legally permissible speculation and illegal information sharing. Real-world trading behaviour frequently exhibits characteristics of both mechanisms, with market participants leveraging both direct insider knowledge and sophisticated public analysis. In cases of insider leakage, information is explicitly sourced from individuals within or connected to a firm, leading to trading actions based on undisclosed, material data—an act that is clearly illegal under regulatory frameworks. However, rational anticipation operates differently, with skilled analysts and traders deducing likely corporate actions, such as takeovers, from a combination of public signals and inferred insights. This anticipatory approach may involve collaboration and the informal sharing of analyses among professionals, further blurring the line between insider-driven advantage and expert-informed speculation. The difficulty in defining the boundary between these mechanisms is compounded by the fact that both insider leakage and rational anticipation ultimately revolve around the spread of potentially sensitive information within

the market. In practical terms, the shared features of insider and anticipatory trading behaviour lead to similar market effects, such as price drifts or unusual trading volumes, that reflect the spread of information—be it leaked or inferred—much like a rumour within a networked trading environment.

Given these overlapping characteristics, defining such anticipatory insights as “rumours” is a suitable approach, particularly when considering aspects of trustworthiness and risk management. Rumours inherently lack official confirmation, carrying a level of uncertainty that distinguishes them from verified information. For insider leakage, the rumour originates from an internal source, but until formal disclosure, it remains unverified, and thus carries elements of speculative risk. Similarly, rational anticipation results in information that, while grounded in professional expertise, remains speculative, since it is based on public indicators combined with interpretive assumptions. This uncertainty underscores the suitability of treating both insider leaks and speculative inferences as rumours, as it signals the need for cautious interpretation and a recognition of the potential for error.

From a trustworthiness perspective, categorizing anticipatory information as a rumour alerts investors to the conditional reliability of the information. Insiders’ private knowledge may be accurate, but until confirmed, it is unverifiable, while analysts’ anticipatory insights may be sound yet inherently speculative, given the assumptions underpinning their conclusions. This classification as a rumour encourages market participants to evaluate the credibility of sources critically and to exercise caution before making decisions based solely on unverified signals.

In terms of risk management, defining this type of information as a rumour also highlights the heightened volatility and uncertainty it can introduce into trading strategies. Acting on rumours, especially in rumour-sensitive contexts like anticipated takeovers, exposes investors to potential financial risk if the anticipated event does not materialise or differs from expectations. By treating insider leaks and anticipatory signals as rumours, investors are encouraged to employ protective strategies—such as diversifying portfolios, setting stop-loss limits, or hedging positions—to mitigate the potential impact of volatile rumour-driven price movements. This approach aligns with best practices in risk management, as it emphasises the speculative nature of rumour-based information and prompts traders to

manage exposure carefully in the face of unpredictable market reactions.

In conclusion, the overlapping nature of insider leakage and rational anticipation, coupled with the suitability of defining anticipatory insights as rumours, provides a framework for understanding how unverified information circulates in financial markets. This perspective enables market participants to navigate the complexities of trustworthiness and risk with a disciplined approach, acknowledging both the speculative potential of rumours and the safeguards necessary to manage the associated risks effectively.

Despite the differences in how insider leakage and rational anticipation operate, both mechanisms fundamentally involve the dissemination of takeover-related information before any public confirmation. This shared characteristic underscores the fact that pre-takeover trading activity often behaves like the spread of a financial rumour—whether derived from insider sources or inferred from strategic analysis. Consequently, the influence of these pre-announcement insights is not limited to isolated trading actions; rather, the propagation of such information through interconnected networks of traders and analysts amplifies its market impact.

Given this similarity, it becomes imperative to examine not just individual trading decisions but the network structures that facilitate this flow of information. In financial markets, information rarely spreads linearly; instead, it travels through a complex web of relationships among participants, where connections and clustering can significantly influence how quickly and broadly a rumour is disseminated. The topology of these networks—comprising tightly knit groups, brokerage affiliations, and institutional connections—determines both the speed and reach of rumour diffusion, shaping the pre-takeover trading landscape. As both insider leakage and rational anticipation rely on such networked dissemination, understanding the network's structural properties becomes crucial for capturing the full scope of how takeover information impacts the market.

By integrating an analysis of the spreading topology, we can achieve a more nuanced view of pre-takeover price dynamics. Examining how information percolates through small-world and cliquish network structures, for example, allows us to model the likely patterns of information contagion. This approach not only enriches our understanding of informed trading mechanisms but also underscores the potential for network-driven accel-

erations in price adjustments prior to public announcements. As we transition to the following discussion on financial networks, this focus on spreading topology offers a foundation for understanding how the interconnected architecture of market participants underpins the informational cascades that characterize pre-takeover trading activity.

Oriented to simulate the spread of stock-related rumours in the marketplace, Jos Van Bommel employs a modified Kyle (1985) model that incorporates private information diffusion through strategic rumourmongering [54]. The study posits that these "rumourmongers," often smaller investors with limited trading capacity, share imprecise yet informative signals with followers to amplify the impact of their information on stock prices. The model operates through a mechanism where the informed investor, after trading based on private information, disseminates a binary rumour (bullish or bearish) to a network of followers. These followers, acting on the rumour, collectively influence the market price, often causing it to overshoot the security's true value. This overshooting allows the original rumourmonger to execute a second, profitable trade by reversing their position once they anticipate the market correction.

His contagion framework is based on a networked pattern of rumour diffusion, where a primary informed investor, or "rumourmonger," initiates the spread of a private signal to a set number of traders, referred to as followers, in each trading period (or auction). It is postulated that the initial rumourmonger spread the private information to a fixed number(m) of his followers at each auction, who would keep on spreading to another set of m traders at the next auction thereby creating an exponential cascade of rumour diffusion. Upon receiving the rumour, each trader is assumed to buy in the same capacity so that the aggregate demand would build up the price to overshoot the true value, where the initial rumourmonger shall benefit from reversing her position and selling all her holding stocks. This contagion model, therefore, depicts rumour spread as a sequential, branching process where each wave of traders passes the information forward, leading to rapid market-wide dissemination. This approach bridges the domains of behavioural finance and rumour diffusion by offering a mathematical portrayal of information-driven trading cascades in financial markets.

Nevertheless, there exhibits key limitations due to its foundational assumptions, which hinder its applicability to real-

world scenarios. Although the model simulates the mechanics of rumour-driven price distortions, several critical aspects of real-world network interactions and trader behaviour are oversimplified or excluded. Firstly, the model assumes a mutually exclusive network structure where each follower in the diffusion process passes the rumour to a unique and non-overlapping set of new followers. In reality, financial networks are far more interconnected; followers' connections often overlap, meaning that information could be repeatedly shared within certain groups while missing other network segments entirely. This overlap is typical in real-world social and trading networks, where information circulates through established clusters and connections rather than following a strict, tree-like progression. Consequently, the model's assumption of a perfectly branching diffusion process limits its ability to capture the uneven and often redundant paths through which rumours actually spread in financial markets.

Additionally, the model presumes that each follower remains continuously active in the spreading process without factoring in potential disengagement. In practice, traders' engagement with a rumour can fluctuate based on a range of factors, including perceived credibility, changing market conditions, or personal risk tolerance. Some participants may halt their trading activity mid-process, opting to exit the rumour-based strategy before the rumour has fully diffused, while others might amplify their efforts under certain conditions. Bommel's model does not allow for such variability in participant behaviour, as all followers are assumed to respond uniformly and consistently until the rumour reaches full market penetration. This limitation restricts the model's ability to reflect the sporadic and sometimes cyclical nature of rumour-driven trading patterns observed in reality.

These assumptions—mutual exclusivity in follower networks and continuous engagement by all participants—render the model somewhat theoretical, limiting its utility in depicting realistic rumour dynamics. To enhance the model's robustness, incorporating a small-world network structure, where information dissemination allows for both local clustering and occasional long-range connections, would provide a more accurate representation of financial networks. Moreover, enabling a state-transition mechanism where followers can dynamically enter or exit the rumour-spreading process based on external conditions or internal strategy adjustments would introduce a layer of behavioural realism. By addressing these aspects, future mod-

els could achieve a more nuanced portrayal of how rumours influence price dynamics in complex, interconnected markets.

2.2 TRADING NETWORK

The phenomenon of pre-takeover drift, characterized by a noticeable increase in share prices prior to official merger announcements is widely understood to stem from the spread of insider information, speculation, and anticipatory trading by those who gain early access to confidential details. The existence of these early price signals highlights the significant role that information dissemination plays within the financial system and the complex interplay between informed and uninformed participants.

Understanding the origins and causes of this phenomenon, particularly the ways in which rumours and private information affect market behaviours, has been a major focus of research in finance and economics. While much of the analysis centers on identifying the presence of pre-takeover drifts and understanding their causes, it is equally crucial to examine the underlying structures and mechanisms that allow such information to spread effectively. The flow of information is not random; rather, it is facilitated and influenced by the network structure within which market participants operate. The connections between traders, analysts, institutional investors, and other stakeholders form intricate networks that govern the efficiency and reach of information sharing. These networks, consisting of tightly connected clusters and strategic bridge nodes, can either enhance or inhibit the flow of valuable insights, contributing to observable market effects such as abnormal trading volumes and price movements before major corporate events.

In this context, the structure of trading networks plays a vital role in shaping how information propagates through the marketplace. Social ties, shared affiliations, and direct relationships contribute to the formation of community structures within financial networks. This section aims to review the literature on the underlying network structures that facilitate the spread of information among market participants. By examining concepts such as network centrality, clustering, and the strategic positioning of key players, we gain deeper insights into how the relational architecture of these networks affects trading behaviour and market outcomes. The following reviews highlight the non-homogeneous nature of information transmission in financial networks, demonstrating that information does not

spread uniformly across a random mix of participants. Instead, financial information networks display a high level of clustering and modularity, indicating the presence of community-type structures. Understanding these dynamics can shed light on why certain participants are better positioned to capitalise on early information, while others remain on the periphery, reacting only after information has become more widely distributed.

In the realm of accounting and finance, Social Network Analysis (SNA) has emerged as a powerful tool to explore the relational ties and interactions between firms, individuals, and key financial actors. Pietro surveys the expanding body of research on SNA, reviewing 162 articles published between 2000 and 2021, and provides a road map to guide future advancements in this field [55]. He presents a comprehensive empirical illustration of key SNA concepts, utilising real-world financial networks to demonstrate the prevalence of community structures. A variety of proxies—such as analyst ties, auditor ties, and director links—are applied to measure and analyse these networks, aiming to uncover their impact on firm outcomes and market behaviour [56]. The key finding is these corporate networks are not random but display characteristics of dense intra-community connections and sparse inter-community linkages, which are crucial for understanding information flow and strategic behaviour within financial systems.

The methodology is constructing empirical networks by identifying entities such as firms, auditors, and analysts as nodes, and the relationships or interactions between them (e.g., shared directors, common auditors, or overlapping analyst coverage) as edges. This approach allows them to model real-world financial and corporate networks that mirror market participants' complex and interdependent nature. For instance, real-world data from BoardEx is applied to build a network of S&P 500 companies based on board interlocks in 2018 with nodes representing firms and edges indicating shared directors. Directors who serve on multiple boards facilitate the formation of tightly-knit communities, leading to a high clustering coefficient, a defining feature of community networks. These intra-community connections are critical for the dissemination of governance practices, strategic decisions, and information within these clusters. While the intra-community connections are dense, the inter-community links are relatively sparse, reflecting the modular structure of these networks. For example, in auditor networks, firms audited by the same company may be closely linked, but there are fewer

connections to firms audited by different companies, resulting in a clear separation between different audit communities. This pattern is indicative of modular networks, where entities within the same module are densely connected, while connections between different modules are limited.

Johan and Han introduce the concept of the Empirical Investor Network (EIN), which serves as a proxy for the market's information network to understand the relationship between investors' network centrality, profits, and the timing of trades [57]. The study suggests that the EIN reflects decentralised information diffusion, likely occurring through informal channels such as word-of-mouth and Internet forums, rather than through centralised media channels due to the latency of trades. This network is constructed using detailed account-level trading data from the Istanbul Stock Exchange (ISE) for the year 2005, specifically focusing on investors who trade in the same direction within short time frames, such as within an hour. The author underscores the importance of centrality within this network, with eigenvector centrality being used to assess how well-connected investors are and how quickly they receive information compared to others. A positive relationship between an investor's centrality in the network and their returns is concluded: Central investors, who receive information earlier, can make more profitable trades. Specifically, a one-standard deviation increase in centrality correlates with a 0.7% to 1.8% increase in returns over a 30-day period: central investors not only receive information earlier but also tend to trade sooner than their peripheral counterparts, particularly around significant information events. This timing advantage contributes to their higher returns, underscoring the benefits of being centrally positioned within the network. Therefore, the author argues that information does not spread uniformly or solely through public channels but instead diffuses through a decentralised, network-based process among investors.

Kenneth documents a unique hand-collected dataset from SEC and DOJ cases between 2009 and 2013 to explore the mechanisms of information dissemination within insider trading networks [43]. A similar result is drawn: the closeness and centrality within these networks critically determine the extent and profitability of insider trading. Central traders in these networks earn significantly higher returns, up to 35% over 21 days, highlighting the value of the information advantage gained through social connections. On the other hand, the returns for later

recipients decrease, indicating a dilution of the informational advantage over time. One key contribution of the paper is its detailed documentation of the structure and dynamics of insider trading networks. It shows that these networks are not densely connected but rather resemble a tree structure with information spreading outward from cliques to cliques. As the information diffuses, the relationships between tippers and tippees become more distant, shifting from close family and colleagues in the same institution to cross-organization business associates. The hierarchical nature of information flow, where higher-ups (such as corporate insiders) share information with subordinates (such as analysts or fund managers), ensures that the most critical and potentially profitable information reaches those who are in a position to trade on it quickly. As information trickles down through the hierarchy, it becomes more widely disseminated but also less exclusive, possibly reducing its value as more individuals act on it.

Similar to Ahern's findings on the centrality of traders within insider trading networks, study conducted by Oleksandr on the information spreads through online networks also reveals parallel structural mechanisms [58]. Motivated to capture the pattern of interpersonal exchange of opinion considering the strategic positioning phenomenon frequently observed on online platforms such as Facebook, where a small fraction of agents can significantly influence the overall network by disseminating information quickly and widely due to their centrality and connections, Oleksandr formulates a segmented artificial network which is divided into tightly-knit cliques with bridge nodes that connect different segments representing the presence of central agents referred to as "opinion leaders". These strategic positions enable central figures to access timely information, creating an advantageous information cascade.

Cherifi et al. discuss several community detection algorithms and provide evidence of community structures of information flow within marketplaces. These methods effectively identify clusters of densely connected nodes (firms or entities) that interact more frequently with each other than with the rest of the network. This clustering aligns with real-world scenarios where companies often form alliances, supply chains, or strategic partnerships within specific groups, leading to dense intra-community connections.

For instance, by applying modularity-based methods, high modularity scores in networks that represent trade relationships

or business collaborations are observed, which indicates that companies within a community are tightly linked, suggesting a preference for intra-group interactions. Another key aspect of marketplace structure revealed by community detection is the presence of sparse inter-community connections, or "structural holes," which indicate limited interactions between different clusters. These sparse connections suggest that while firms are strongly connected within their own communities, they have fewer interactions across different groups. This behaviour is often observed in trade networks, where firms may focus on local or regional partners, limiting broader engagement. However, entities that serve as bridges between communities play a strategic role in facilitating information and resource flow across the network, acting as brokers between different market segments. By identifying these bridge nodes, community detection helps highlight companies or entities that possess strategic positions in the marketplace. These firms can leverage their position to access diverse information, negotiate better terms, or introduce innovations across different communities, enhancing their competitive edge. This structure mirrors real-world business ecosystems where key players act as intermediaries, connecting various industry clusters and enabling collaboration across sectors.

Davis's seminal work on the inter-corporate network also presents supportive evidence for not only the clustered structure of financial networks but also the pairwise direct communication between interlocked directors, rather than mere imitation of similar firms, which drives the spread of information [59]. The author conducts a case study on the poison pill³, a defensive strategy used by a company's board of directors to prevent or discourage hostile takeover attempts, to analyse how the diffusion of new strategic innovations or practices among Fortune 500 firms during the 1980s. The paper highlights the role of the inter-corporate network, particularly the influence of interlocking directorates, in the diffusion of the poison pill strategy. The timing of the adoption of the poison pill strategy in the sampled firms is in line with the centrality of the firms which refers to the extent to which a firm is connected to other firms through shared directors known as interlocks: Firms that are more cen-

³ The poison pill was first introduced in the 1980s, officially known as a shareholder rights plan. A poison pill allows existing shareholders to purchase additional shares at a discount, diluting the value of shares held by a potential acquirer and making the takeover more expensive and less attractive.

tral in this network are more likely to adopt such defensive strategies early.

Moreover, to reject alternative possible explanations of applications on poison pills, Davis specifically tested the hypothesis that firms would adopt poison pills if many others in their industry had already done so. However, the results showed no significant effect of industry-level adoption, undermining the structural equivalence model's prediction that firms imitate their industry peers. Thus, the author posits that cohesion models align more closely with the social structural mechanism driving the diffusion process rather than structural equivalence. In addition, the structure of interlocking directorates in the corporate world resembles the cliquey structure of social networks, with dense connections within groups and looser ties across them, emphasising the role of central actors in maintaining cohesion and disseminating innovations. The role of interlocking directors as bridging nodes parallels the function of individuals in social networks who connect different social circles, facilitating the flow of information across diverse groups.

Burt's seminal work on the network structure of social capital introduces two primary mechanisms: structural holes and network closure, which also provide insights into the community structure of social networks in the marketplace [60]. Network closure refers to a dense, cohesive network where nodes (individuals or organizations) are tightly connected. In such a structure, all members are aware of each other's interactions, which facilitates trust, coordination, and efficient communication. Burt (2000) argues that closure fosters a secure environment for the exchange of information and the enforcement of norms, as it enables effective sanctions against those who deviate from group expectations. This type of network is often associated with strong social capital within communities because it encourages cooperation and shared norms, thus reflecting the high clustering observed in many real-world social networks. In the context of the marketplace, network closure can be seen in tightly-knit clusters of firms or individuals who regularly engage with each other, forming strong, repeated interactions. For example, sectors where long-term relationships and trust are critical—such as finance, supply chains, or collaborative industries—tend to exhibit high network closure. This cohesive structure ensures stable, predictable exchanges, but it may also limit exposure to new ideas or innovations that lie outside the immediate network. Contrary to network closure, structural holes represent gaps be-

tween otherwise disconnected communities or networks. Burt's research highlights that actors who occupy these structural holes serve as brokers, connecting different clusters and facilitating the flow of information across network boundaries. These brokers benefit from early access to diverse, non-redundant information, providing them with a competitive advantage and greater flexibility in navigating market dynamics. Together, the concepts of network closure and structural holes provide a comprehensive framework for understanding the community structure of social networks within the marketplace. Network closure explains how dense, cohesive networks can build trust and maintain stability within communities, while structural holes illustrate how sparse inter-community structures enable the flow of new information and innovation between different groups. The interplay between these two structures is crucial for market dynamics, as it determines the balance between stability and adaptability, collaboration and competition.

Anas and Oleksandr also provide a detailed exploration of how the structural aspects of social networks, particularly in terms of community clustering and bridging, affect the efficiency of information dissemination, mirroring real-world social network behaviours [19]. They highlight the importance of understanding the community structure of social networks—identifying bridge nodes for sparse inter-community links and leveraging opinion leaders for dense, intra-community connections—to design effective information dissemination strategies.

2.3 RUMOUR STUDIES BACKGROUND

The investigation of rumour spreading is driven by the desire to understand how information, often of uncertain or unverified nature, disseminates within social networks and how it can influence public opinion, behaviour, and decision-making [61]. Rumours, by their very nature, thrive in environments characterized by ambiguity and social tension, making them powerful drivers of both collective anxiety and collective action. In recent years, researchers have employed a range of modelling approaches to elucidate the underlying mechanisms and factors that govern the spread of rumours, with the deterministic models and stochastic models standing as the two most influential and primary modelling paradigms.

The initial work in the field of information spreading is by Daley and Kendall rumour model who proposed a mathematical

model for the spread of rumour in their 1964 paper titled "Epidemics and Rumours". This model draws a compelling parallel between the mechanisms underlying the spread of infectious diseases and rumours within a population. Their model uses well understood methodologies from the study of disease to the field of social communication [62].

2.3.1 Epidemic spreading model

The classic epidemic model, often referred to as the SIR (Susceptible-Infectious-Recovered) model, is characterised by the following set of ordinary differential equations:

$$\frac{dS}{dt} = -\eta SI \quad (2.1)$$

$$\frac{dI}{dt} = \eta SI - \gamma I \quad (2.2)$$

$$\frac{dR}{dt} = \gamma I \quad (2.3)$$

where:

- $S(t)$: Number of susceptible individuals at time t .
- $I(t)$: Number of infectious individuals at time t .
- $R(t)$: Number of recovered (and immune) individuals at time t .
- η is the transmission rate (the rate at which susceptible individuals become infected upon contact with an infectious individual).
- γ is the recovery rate (the rate at which infectious individuals recover and move to the recovered compartment).

The basic reproduction number, denoted as R_0 , is regarded as one of the most fundamental parameters in epidemiology, as it measures how far/fast a disease can spread in a completely S population [63]. This parameter is crucial in determining whether an epidemic will expand within a population or eventually fade away. Specifically, R_0 is defined as the average number of secondary cases generated by a single infectious individual in a fully susceptible population. This value is critical in assessing

the potential for a disease to spread, with an R_0 greater than 1 indicating the likelihood of an outbreak, whereas an R_0 less than 1 suggests that the disease will gradually die out.

The derivation of R_0 typically focuses on the initial phase of the epidemic, when the majority of the population is susceptible and the number of infected individuals is relatively small. During this early stage, it can be assumed that the number of susceptible individuals S is approximately equal to the total population size N , as only a negligible proportion has become infected. This assumption allows for a simplified mathematical treatment of the epidemic dynamics, which provides insights into the behaviour of the disease transmission during its nascent phase. The concept of R_0 is also central to public health strategies aimed at controlling infectious diseases. When R_0 is precisely estimated, it offers guidance on the level of intervention required to prevent further spread. For example, vaccination campaigns aim to reduce the susceptible fraction of the population to a level where the effective reproduction number R drops below 1, ensuring that the transmission chain is interrupted and the disease cannot sustain itself within the community.

In epidemiological modelling, R_0 also plays a key role in the development and calibration of mathematical models, such as the **SIR (Susceptible-Infectious-Recovered)** model. In these compartmental models, the reproduction number is influenced by several factors, including the transmission rate (η), the contact rate between individuals, and the average infectious period ($1/\gamma$). Mathematically, R_0 is often expressed as:

$$R_0 = \frac{\eta N}{\gamma}.$$

The interpretation of R_0 through this formula highlights how reducing either the transmission rate or the duration of infectiousness can be effective in mitigating the spread of an infectious disease.

Overall, the basic reproduction number R_0 encapsulates fundamental aspects of infectious disease dynamics and plays an instrumental role in epidemiological studies and public health policy-making. Its value not only determines the potential for an outbreak but also provides a benchmark for evaluating the effectiveness of control measures, guiding responses to emerging infectious threats, and preparing for future epidemics.

The equation for $I(t)$ becomes:

$$\frac{dI}{dt} = \eta SI - \gamma I \approx \eta NI - \gamma I. \quad (2.4)$$

Factoring out I gives:

$$\frac{dI}{dt} = I(\eta N - \gamma). \quad (2.5)$$

For the number of infectious individuals to increase ($\frac{dI}{dt} > 0$), the following condition must hold:

$$\eta N - \gamma > 0. \quad (2.6)$$

Dividing both sides by γ , we get:

$$R_0 = \frac{\eta N}{\gamma} > 1. \quad (2.7)$$

Interpretation of R_0

The stability of disease free equilibrium is determined by the eigenvalues of the Jacobian matrix:

$$J_{DEF} = \begin{pmatrix} \frac{\partial \dot{S}}{\partial S} & \frac{\partial \dot{S}}{\partial I} & \frac{\partial \dot{S}}{\partial R} \\ \frac{\partial \dot{I}}{\partial S} & \frac{\partial \dot{I}}{\partial I} & \frac{\partial \dot{I}}{\partial R} \\ \frac{\partial \dot{R}}{\partial S} & \frac{\partial \dot{R}}{\partial I} & \frac{\partial \dot{R}}{\partial R} \end{pmatrix} \Big|_{\{N,0,0\}} = \begin{pmatrix} 0 & -\eta & 0 \\ 0 & \eta - \gamma & 0 \\ 0 & \gamma & 0 \end{pmatrix}.$$

With the eigenvalues equal to 0 of multiplicity 2 and $\eta - \gamma$ of multiplicity 1.

According to the Hartman-Grobman theorem [64], the stability of the disease-free equilibrium depends on the sign of the eigenvalues:

- If $\eta - \gamma < 0$, which corresponds to $R_0 < 1$, then the disease-free equilibrium is stable.
- If $\eta - \gamma > 0$, which corresponds to $R_0 > 1$, then the disease-free equilibrium is unstable.

Thus, the disease-free equilibrium is stable if $R_0 < 1$ and unstable if $R_0 > 1$.

2.3.2 Daley-Kendal Rumour Model

In a similar manner, Daley and Kendall formulated an analogue to simulate the spread of rumour, by conceptualising a closed, homogeneously mixing population of size $S = N + 1$ and dividing it into three mutually exclusive and exhaustive categories:

Ignorants (I): Individuals who have not heard the rumour.

Spreaders (S): Individuals who have heard the rumour and are actively spreading it.

Stiflers (R): Individuals who have heard the rumour but have stopped spreading it, either due to disbelief, lack of interest, or because the rumour has reached a saturation point where it is no longer deemed 'news'.

The theoretical mechanism of the rumour spreading process can be generalised as follows: a person who's aware of the rumour will go on telling it until a time comes when they find it no longer new and interesting after running into a certain amount of individuals who are also aware of the rumour. Initially, the population consists of N ignorants and one spreader, with no stiflers. The transitions between these states occur as follows:

1. **Ignorant to Spreader:** An ignorant becomes a spreader upon contact with a spreader, occurring at a rate proportional to IS .

2. **Spreader to Stifler (via another Spreader):** When a spreader meets another spreader, both become stiflers at a rate proportional to $\frac{S(S-1)}{2}$ ⁴.

3. **Spreader to Stifler (via a Stifler):** When a spreader meets a stifler, the spreader becomes a stifler at a rate proportional to SR .

The system's dynamics can be described by a set of transition probabilities within a small time interval dt :

$$P\{(I, S, R) \rightarrow (I - 1, S + 1, R)\} = IS dt$$

$$P\{(I, S, R) \rightarrow (I, S - 2, R + 2)\} = \frac{S(S - 1)}{2} dt$$

$$P\{(I, S, R) \rightarrow (I, S - 1, R + 1)\} = SR dt.$$

⁴ The term $\frac{S(S-1)}{2}$ represents the number of distinct unordered pairs that can be formed among S spreaders. The factor $(S - 1)$ reflects that each spreader can interact with all other spreaders except itself (i.e., self-interactions are excluded), while division by 2 avoids double counting of pairs.

The transitions occur until there are no spreaders left, at which point the process terminates.

The Deterministic Analogue

The deterministic analogue of the stochastic model can be described using differential equations. Let $I(t)$, $S(t)$, and $R(t)$ represent the number of ignorants, spreaders, and stiflers at time t , respectively. The differential equations governing the deterministic model are:

$$\begin{aligned}\frac{dI}{dt} &= -IS \\ \frac{dS}{dt} &= IS - \frac{S(S-1)}{2} - SR \\ \frac{dR}{dt} &= \frac{S(S-1)}{2} + SR.\end{aligned}$$

These equations reflect the continuous-time changes in the population states due to interactions between ignorants, spreaders, and stiflers.

Daley and Kendall used the concept of a "first integral" to find a conserved quantity during the deterministic motion. They derived the function:

$$\Phi(I, S) = 2I + S + N \log \left(\frac{N}{I} \right).$$

This function remains constant throughout the process. Given the initial conditions $I(0) = N$ and $S(0) = 1$, the value of Φ is $2N + 1$.

From this, they determined that the ultimate fraction of the population that learns the rumour is approximately 0.8, independent of the total population size. This fraction is derived from solving the equation for the extinction point where $S = 0$.

Despite commonalities with the epidemiology model in the propagation structure, the distinct recovery rule causes fundamental differences in the rumour-free equilibrium. In contrast to the self-decay process in the disease spreading model, the stifling mechanism in the rumour spreading process highlights a contact-based transition. That is to say, the spreaders shall become stifled only as a result of encountering those who are already aware of the rumour whereas in the epidemiology model,

the infected individual decays spontaneously such that the removal is a linear function of the overall number of infected. This deviation in the transition mechanism leads to a disparity in the stability at disease free equilibrium. As Daley and Kendall conclude, "The salient feature of the mechanism of rumour-propagation considered here is the absence of any threshold effect; the fraction of the population which ultimately learns the rumour is approximately independent of the population size".

Monte Carlo Simulations and Diffusion Approximation

To validate the theoretical results, Daley and Kendall conducted Monte Carlo simulations, which involved simulating the random walk of the rumour spread process. The simulations confirmed the theoretical predictions, showing that the extinction distribution is bimodal, with one mode near the value corresponding to a minor outbreak and the other near the major outbreak value. They also used a diffusion approximation to describe the behaviour of the stochastic process more accurately. By treating the small jumps of the stochastic process as a continuous diffusion, they derived expressions for the mean and variance of the number of individuals who never heard the rumour.

Despite commonalities with the epidemiology model in the propagation structure, the distinct recovery rule causes fundamental differences in the rumour-free equilibrium. In contrast to the self-decay process in the disease spreading model, the stifling mechanism in the rumour spreading process highlights a contact-based transition. That is to say, the spreaders shall become stifled only as a result of encountering those who are already aware of the rumour whereas in the epidemiology model, the infected individual decays spontaneously such that the removal is a linear function of the overall number of infected. This deviation in the transition mechanism leads to a disparity in the stability at disease free equilibrium. As Daley and Kendall conclude, "The salient feature of the mechanism of rumour-propagation considered here is the absence of any threshold effect; the fraction of the population which ultimately learns the rumour is approximately independent of the population size".

The Daley-Kendall model provides a simple framework for understanding the spread of rumours within a population. By combining stochastic processes with differential equations, Daley and Kendall capture the dynamics of rumour propagation. While the Daley-Kendall model provides a foundational un-

derstanding of rumour dynamics, subsequent research has introduced several variations and extensions to better capture the complexities of real-world information spread. These modified models incorporate additional parameters and mechanisms, allowing for more nuanced representations of how rumours propagate through diverse social networks.

The Maki-Thompson Model

One prominent variation is the Maki-Thompson model, which extends the original Daley-Kendall framework considering distinct state transition rates as shown below [65]:



with corresponding differential equation as follows:

$$\begin{cases} \frac{dI(t)}{dt} = -\alpha I(t)S(t) \\ \frac{dS(t)}{dt} = \alpha I(t)S(t) - \theta S(t)(S(t) + R(t)) \\ \frac{dR(t)}{dt} = \theta S(t)(S(t) + R(t)) \end{cases} . \quad (2.9)$$

so that ignorant(I) individuals become spreaders(S) at a spreading rate α and spreaders progress to stiflers(R) at a unique rate θ as the stifling rate.

Equilibrium Point

The rumour-free equilibrium is characterized by having no spreaders or stiflers at time T_0 :

$$(I(0), S(0), R(0)) = (N, 0, 0).$$

The system of equations can be written in vector form:

$$\mathbf{f}(I, S, R) = \begin{pmatrix} -\alpha IS \\ \alpha IS - \theta S(S + R) \\ \theta S(S + R) \end{pmatrix}.$$

The Jacobian matrix J is the matrix of first-order partial derivatives of the system:

$$J_{(N,0,0)} = \begin{pmatrix} \frac{\partial f_1}{\partial I} & \frac{\partial f_1}{\partial S} & \frac{\partial f_1}{\partial R} \\ \frac{\partial f_2}{\partial I} & \frac{\partial f_2}{\partial S} & \frac{\partial f_2}{\partial R} \\ \frac{\partial f_3}{\partial I} & \frac{\partial f_3}{\partial S} & \frac{\partial f_3}{\partial R} \end{pmatrix}_{(N,0,0)} = \begin{pmatrix} 0 & -\alpha N & 0 \\ 0 & \alpha N & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

where the eigenvalues are given by 0 with multiplicity 2 and αN with multiplicity 1. Since there exists one positive eigenvalue αN , the rumour-free equilibrium is strictly unstable. This indicates that any perturbation in spreaders from 0 will result in an outbreak of rumour through the population regardless of valuation of spreading or stifling rate. Thus, it is apparent that any threshold for the rumour to propagate is in the absence for the compartmental model.

2.3.3 Sudbury model

A key problem of interest – how broad can the rumour spread, what is the ultimate fraction of stifler R^* in other words, has been rigorously analysed by Sudbury [66] using a discrete-time stochastic approach. Sudbury provides a rigorous mathematical treatment to determine the proportion of the population that never hears a rumour. The key result is that this proportion converges to approximately 0.203 as the population size tends to infinity.

The model assumes a population divided into three categories: Susceptible (S), those who have not heard the rumour; Infective (I), those who have heard and wish to spread it; and Removed (R), those who have heard the rumour but no longer wish to spread it. The rumour spreads according to the following rules: if an infective contacts a susceptible, the susceptible becomes infective. If an infective contacts another infective or a removed individual, the infective loses interest and becomes removed. Other interactions have no effect.

The process is analysed in discrete time steps called epochs, with each epoch representing an event that changes the population state. At each epoch, the key variables are s_k , i_k , and r_k , representing the number of susceptibles, infectives, and removed individuals, respectively. The transition probabilities are determined based on the current state of the population. The process ends when there are no infectives left ($i = 0$).

Sudbury uses a martingale approach to derive key equations governing the rumour spread. One of the main results is that the sum of infectives, twice the susceptibles, and removed individuals remains constant throughout the process. By applying martingales and Chebyshev's inequality, Sudbury shows that the expected number of susceptibles at the end of the process ($E[s_T]$) equals the initial number of susceptibles (s_0). The variance of s_T is also derived, and as the population size grows, the proportion of the population that never hears the rumour converges to approximately 20.3%.

$$\frac{dR}{dI} = -\frac{\alpha}{\theta} * \frac{S+R}{I} = -\frac{\alpha}{\theta} * \frac{N-I}{I}. \quad (2.10)$$

$$(2.11)$$

Rearranging gives:

Adapting initial conditions where $R_0 = 0, I_0 \approx N = 1$, we obtain:

$$c = -\frac{\theta}{\alpha}R - N \log I + I = 1. \quad (2.12)$$

With $\int_0^\infty S(t)dt = R^* = \lim_{t \rightarrow \infty} R_t$, we have $I^* + R^* = N$. So by rewriting I^* as $N - R^*$, the transcendental equation that contains only one variable R can be obtained.

$$-\left(\frac{\theta}{\alpha} + 1\right)R^* - \log(1 - R^*) + 1 = 1 \quad (2.13)$$

$$-\left(\frac{\theta}{\alpha} + 1\right)R^* = \log(1 - R^*). \quad (2.14)$$

Rearranging one gets:

$$R^* = 1 - e^{\gamma R^*}, \quad (2.15)$$

where $\gamma = -1 - \frac{\theta}{\alpha}$.

Despite a simple ODE system introduced, Maki and Thompson have laid the foundation for successive researchers to work on, for instance

1). Laijun Zhao [67], enlightened by the self-removal transition of the infected individuals in the epidemic case, further improved the rumour model by introducing the forgetting mechanism in the process, allowing spreaders to become stifled without necessarily making contact with whoever aware of the rumour and hence formulate the differential equations as follow:

$$\frac{dI(t)}{dt} = -\lambda I(t)S(t) \quad (2.16)$$

$$\frac{dS(t)}{dt} = \lambda I(t)S(t) - \alpha S(t)(S(t) + R(t)) - \delta S(t) \quad (2.17)$$

$$\frac{dR(t)}{dt} = \alpha S(t)(S(t) + R(t)) + \delta S(t), \quad (2.18)$$

where δ represents the forgetting rate for a spreader to self decay into stifled. And it's been proved that the forgetting mechanism may weaken the influence of rumour as expected.

2). Qian [68] proposed a new type of model characterized by 'independent spreaders', allowing the ignorant to spontaneously become a spreader, reflecting the fact that individuals can get the rumour from other channels rather than just from their neighbours within the network:

$$\frac{dI(t)}{dt} = -\lambda I(t)S(t) - \delta I(t) \quad (2.19)$$

$$\frac{dS(t)}{dt} = \lambda I(t)S(t) - \alpha S(t)(S(t) + R(t)) + \delta I(t) \quad (2.20)$$

$$\frac{dR(t)}{dt} = \alpha S(t)(S(t) + R(t)), \quad (2.21)$$

where $\delta I(t)$ is the density of independent spreaders at each time step. Results indicate a monotone increasing relationship between δ and global spreading speed.

3). Hu [69], focusing on the spreader-ignorant contact case, stated that an ignorant shall jump directly to a stifler when

meeting with a spreader, corresponding the fact of an instant disagreement on hearing the rumour, and built the improved model accordingly as follow:

$$\frac{dI(t)}{dt} = -\alpha I(t)S(t) \quad (2.22)$$

$$\frac{dS(t)}{dt} = (1 - \gamma)\alpha I(t)S(t) - \mu S(t)(S(t) + R(t)) \quad (2.23)$$

$$\frac{dR(t)}{dt} = \gamma\alpha I(t)S(t) + \mu S(t)(S(t) + R(t)), \quad (2.24)$$

where α and μ represent the spreading and stifling rate, respectively and γ is the rate of witnessing a "wise man" among the ignorant who would immediately deny the rumour thereby turning stifled.

2.4 HETEROGENEOUS NETWORKS

The ODE methodology presents a good theoretical model to mathematically interpret the spreading pattern of a rumour [70, 71]. However, the homogeneity assumption on topology has

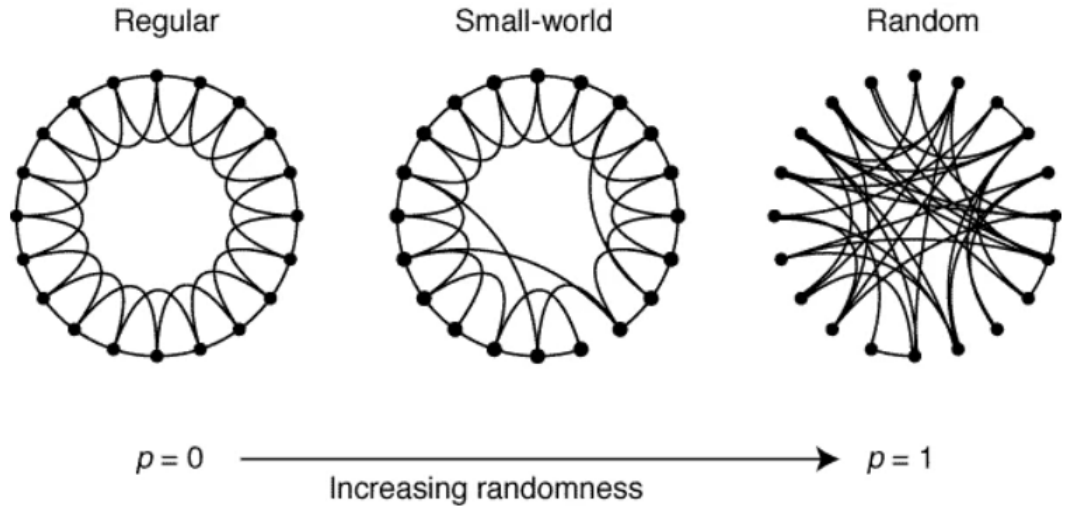


Figure 2.1: Small-world network

made it inadequate to simulate a real-world phenomenon, which has become greatly diversified with the emergence of Social Networking Services (SNS) [72], multiplex networks [73], mobile social networks [74] for instance. Thus, works on constructing complex networking models have been of increasing necessity in recent decades [75–77], among which the most famous one

is the Small-World network, as shown in figure 2.1, introduced by Duncan Watts and Steven Strogatz [78] featuring that one can be connected to any person in the network by just a few others, known as “six degrees of separation” [79]. The network is designed based on a rewiring mechanism, such that any node still has a majority of connections within their neighbour and only a minority of contacts to distant nodes [70]. When p is 0, the graph is regular such that all the nodes are connected only with their nearest neighbours and as p grows, the graph becomes increasingly disordered until at $p = 1$, the system is rewired into a fully random network [80].

The major property SW network presents can be summarised as a high clustering coefficient and low distances which has been shown to improve the performance of many dynamical processes as compared to regular lattices [81].

His studies suggested that on small-world networks with varying network randomness, the model exhibits a critical transition between a regime where the rumour “dies” in a small neighbourhood of its origin and a regime where it spreads over a finite fraction of the whole population [82]. Application of Watts and Strogatz small-world network model has been widely applied over a variety of industries such as cyber security, disease control [83], transport optimization [84], etc, among which we are particularly interested in rumour prevention in the stock market system.

To capture the uneven nature of real-world connectivity, Barabási and Albert presented a scale-free network characterised by a power-law distribution of the number of connections (degree) that each node has [85]. They argued that in many systems—from social networks to financial markets—some individuals or entities could hold far more connections and influence than others. The model reflects this heterogeneity in social exposure and influence, where a few highly connected “hub” nodes play a dominant role in linking the network, while most nodes remain only locally connected as shown in Figure 2.2. This structure mirrors how people, firms, or information sources in reality attract attention or links in proportion to their visibility or reputation—those already well connected tend to become even more so. In this way, the scale-free model represents the inequality of connection and influence that shapes how information, rumours, or trends spread through complex systems.

However, Broido and Clauset (2019) re-examined the scale-free network, using a dataset of over a thousand empirical networks

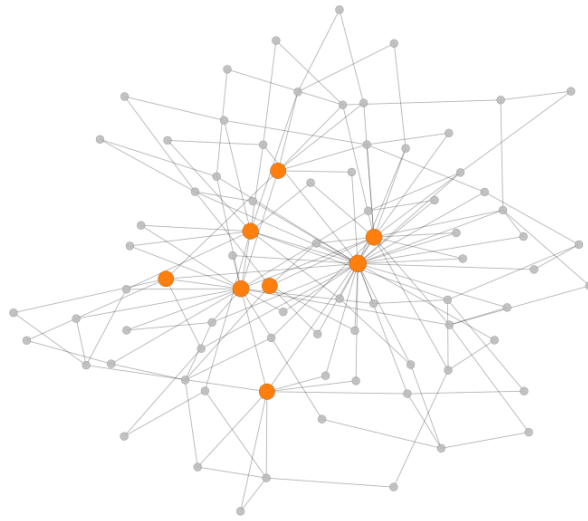


Figure 2.2: A scale-free network of 80 nodes, generated by the B-A scale-free model. Orange nodes represent hubs with degree greater than 6

from various domains and showed that scale-free networks are far less common than expected [86]. Through statistical tests of scale-free property, only a small fraction (around 4%) of networks showing strong significance for a power-law fit. Most only display heavy-tail but non-power-law distribution in degree centrality. These findings suggest that the scale-free framework, while influential, may not capture the full complexity of real communication networks. In many cases, connections are not simply hierarchical or hub-driven but instead organised into clusters or groups of densely connected nodes. This observation leads naturally to the study of community or modular networks, which better reflect the layered and group-based nature of social and informational interactions.

Research on community or modular networks emerged from the observation that real-world systems—especially social and communication networks—exhibit a high degree of clustering and modularity. Girvan and Newman formalised the concept of modularity, proposing algorithms to identify groups of nodes that are densely connected internally but sparsely connected externally [87, 88]. Their work established modularity as a key measure of network structure and provided a framework for studying how information, influence, or contagion spreads within and across groups.

2.5 AGENT-BASED COMPUTATIONAL MODELS

According to Iori and Porter, traditional economic approaches operate under the assumption that markets are inherently stable and that agents act with perfect rationality, which often fails to account for the complex dynamics observed in real-world financial systems [89]. ABM was developed to address these limitations, by allowing for heterogeneous agents who exhibit bounded rationality⁵ and adaptive learning capabilities, thus providing a more realistic representation of market behaviour.

Originating in complex systems research, ABM departs from traditional equilibrium-based models by explicitly modelling individual agents and their interactions. Early works such as Arthur [90] and Lux [91] demonstrated how ABM can reproduce key financial stylised facts, including clustered volatility, heavy-tailed return distributions, and non-Gaussian price fluctuations. More recent studies, including [92] and [93], further developed ABM frameworks to incorporate different trader types, such as value investors and trend followers, leading to realistic market dynamics.

To explore the complexities associated with rumour propagation and its subsequent impact on financial markets, the application of an ABM approach is particularly advantageous. ABM is a computational methodology that simulates systems composed of interacting, autonomous agents, each governed by individual decision-making rules. These agents can represent different entities within a financial system—such as institutional investors, retail traders, or intermediaries—allowing the model to reflect the diverse strategies and behaviours present in real markets. Unlike traditional models based on the assumption of rational representative agents, ABM embraces heterogeneity and individual-level adaptation, thereby enabling a richer and more realistic understanding of market behaviour.

A key benefit of ABM is its ability to capture emergent phenomena that arise from the decentralised interactions of agents. Financial markets are inherently complex systems characterized by feedback loops, non-linearities, and adaptive behaviours. The spread of rumours is one such phenomenon where agents react

⁵ Bounded rationality refers to the idea that agents make decisions under cognitive and informational constraints, rather than with full rational optimisation. Instead of maximising utility perfectly, individuals rely on simplified rules or heuristics due to limited information, time, and computational capacity (Simon, 1955).

not only to fundamental economic indicators but also to information that may be unverified or even intentionally misleading. In these situations, understanding how local interactions and information exchanges between agents contribute to broader market dynamics becomes crucial. ABM allows for this exploration by enabling each agent to respond uniquely to incoming information, considering factors such as risk tolerance, timing of information acquisition, and expectations about future market movements. As a result, ABM can effectively model how rumours propagate, how agents choose to act upon them, and how these individual decisions collectively influence stock prices and market volatility. Moreover, ABM effectively represents the dynamic and constantly evolving nature of financial markets, which are typically characterized by non-equilibrium conditions. Unlike classical models that often seek a steady-state equilibrium, ABM recognises that markets are continuously evolving, shaped by new information, strategic behaviour, and interactions among participants. This is especially relevant when analysing rumour-driven trading, where price adjustments can be erratic and market sentiment can oscillate between euphoria and panic. The stochastic nature of agent interactions in ABM means that it can reproduce phenomena such as herd behaviour, where agents mimic the actions of others, leading to contagion effects that amplify the impact of rumours. Such dynamics are particularly challenging to capture using traditional analytical models but are intrinsic to ABM's framework. Another significant advantage of ABM is its capacity to represent adaptive behaviour. Agents in an ABM can learn and change their strategies over time, responding to both their past experiences and to evolving market conditions. This feature is particularly useful for modelling scenarios in which agents adjust their responses to rumours—either by developing more sophisticated methods for validating information or by reacting more cautiously to market movements. Through the lens of ABM, the spread of financial rumours can be analysed not only in terms of the initial market impact but also in terms of how agents adapt to misinformation over time, potentially mitigating or exacerbating its effects.

In the context of this study, ABM allows to simulate a financial network where nodes represent individual market participants and edges represent the channels through which information flows. This networked structure is critical for modelling how rumours spread—whether through tightly connected communities or through influential "hub" agents who can amplify in-

formation widely. By incorporating stochastic elements and behavioural rules that guide trading actions upon receiving information, ABM can offer insights into the underlying mechanisms through which rumours induce market bubbles or crashes. It also facilitates an understanding of how different types of networks—ranging from highly clustered community networks to sparse, random structures—affect the propagation speed and impact of rumours on market volatility. In summary, ABM provides a flexible and powerful framework for analysing financial systems characterized by heterogeneity, non-linearity, and adaptation. Its capacity to simulate the spread of information and the resultant trading behaviours of individual agents makes it particularly well-suited for examining the role of rumours in financial markets. By focusing on agent-level interactions and emergent market phenomena, ABM enhances our understanding of how seemingly localised behaviours can lead to widespread market effects, thereby offering a deeper insight into the stochastic and complex nature of financial systems.

Instead of assuming mathematical optimization by agents in equilibrium, ABMs postulate that agents with bounded rationality adapt to market forces. Various approaches have been adopted to model agent behaviour in financial ABMs, ranging from passive automatons with no cognitive function to active data-gathering decision-makers with advanced learning capabilities. These agents are not only heterogeneous and interactive but also adaptive, with different circumstances and histories. Modelling economic markets from the ground up with numerous interacting agents is emerging as a promising research methodology, poised to significantly influence our understanding of interactions in economic models. An expanding body of literature is already focusing on modelling financial interactions from the agent's perspective, utilising computational tools extensively to surpass the limitations of traditional analytical methods.

Frankel and Froot (1982) are deemed the pioneers in proposing an agent-based model that distinctly accounted for various types of traders [94]. They recognise that traditional models, which typically rely on the assumption of rational expectations and equilibrium conditions, are insufficient to fully capture the intricacies of exchange rate determination, particularly when agents display diverse motivations and decision-making processes. To address this limitation, they introduce an approach that effectively incorporates the differing expectations and adap-

tive behaviours of these market participants. Chartists⁶, who base their trading decisions on past trends and technical analysis, often exacerbate short-term price movements and contribute to heightened volatility. Fundamentalists, in contrast, anchor their actions on macroeconomic fundamentals such as interest rate differentials and intrinsic economic value, thereby exerting a stabilising influence on exchange rates over the long term. The need for a model capable of incorporating these distinct agent behaviours prompted the use of ABM. By focusing on how individual agents, with diverse strategies and expectations, interact in a dynamic financial environment, the agent-based approach enables a more realistic representation of the foreign exchange market. Specifically, ABM is introduced as a means to capture the emergent properties of exchange rate movements that arise from the interaction between chartists and fundamentalists, including phenomena such as overshooting, speculative bubbles, and periods of rapid correction.

Fundamentalists form their expectations based on economic fundamentals, such as interest rates, inflation rates, and gathered information. They believe that the intrinsic value of a currency is determined by these underlying economic factors, and they trade based on deviations from this perceived intrinsic value. If the market price deviates significantly from what fundamentalists consider the "true" value, they will buy or sell the currency accordingly, expecting the price to eventually revert to its fundamental value.

Chartists, on the other hand, base their expectations and trading decisions on past price movements and trends. They use technical analysis tools, such as moving averages, momentum indicators, and chart patterns, to predict future price movements. Chartists believe that historical price data can reveal trends that will continue in the short to medium term, and they trade accordingly to capitalise on these trends.

⁶ In financial modelling, "Chartists" (also known as technical traders) are agents who base their decisions on past price movements and trends, often using price charts to identify patterns. In contrast, "Fundamentalists" are traders who base their decisions on the intrinsic value of an asset, derived from economic and financial fundamentals such as earnings or dividends. This distinction is well-established in the literature on heterogeneous agent models of financial markets (e.g., Lux, 1995; Chiarella, 1992).

RUMOUR AND NETWORK MODEL

Our motivation is to understand how information, for example a rumour, spreads through a network of individuals employed in several institutions where information can flow easily within the organisation and less so between organisations. For example, traders can share information with colleagues within their department but rely on fewer personal contacts with traders in other institutions. In this idealised scenario, we envisage two types of connections; within-group connections (for those that are within the same institution and where there are low barriers to the flow of information and so it can spread at a relatively fast rate) and between-group connections (where there are fewer connections between individuals in different institutions/groups and so information flows at a slower rate). We then simulate the spread of the rumour on this community-based network and compare the dynamics to those in a random network and a small-world network, which serve as reference models.

To improve clarity and ensure consistency in notation, the key parameters used throughout the rumour-spreading model are summarised in Table 3.1.

Unless otherwise stated, simulations are conducted by systematically varying the intra-community connectivity parameter W_g and the spreading probability β , while holding all other parameters fixed.

3.1 NETWORK

To capture the structural features of real-world social communities, we construct a network of N nodes representing trading agents. The network is partitioned into N_g communities. Connectivity in this context refers to the likelihood of links forming between agents, and is operationally related to the degree of each node (i.e., the number of connections an agent has). We distinguish between intra-community connectivity, denoted by W_g , which governs the probability of connections between agents within the same community, and inter-community connectivity, denoted by B_g , which governs the probability of connections between agents in different communities. Both W_g and B_g are parameterised between 0 and 1 and we interpret them as the

Table 3.1: Summary of Model Parameters in Chapter 3

Description	Symbol	Value / Range
<i>Network Structure Parameters</i>		
Number of nodes	N	6000
Number of communities	N_g	100
Intra-community connection probability	W_g	$[0, 1]$
Inter-community connection probability	B_g	$[0, 1]$
Rewiring probability (small-world)	p	$[0, 1]$
<i>Rumour Spreading Parameters</i>		
Spreading probability	α	$[0, 1]$
Stifling probability	θ	$[0, 1]$

probability that individuals or nodes within a network are connected to other nodes within the same group or community and between nodes in different groups or communities. Thus the communities are built up from N_g random-networks which are randomly connected with each other.

We create the community-based network in the following manner: We assign the N nodes in the network to one of the N_g communities. For each pair of nodes in the network, if they are in the same community/group we connect them with a probability W_g and if they are in a different group we connect them with a probability B_g . We naturally assume that $W_g > B_g$ in our idealised scenario but do not enforce this in our network building algorithm or in our analysis. Figure 3.1 illustrates an example of a community network with several sub-communities, each labelled with different colour. It is obvious that local connections are more frequent compared to cross-community ones.

To characterise this network, we measure the level of clustering in terms of W_g and B_g using three quantitative measures modularity, clustering coefficient and local efficiency which are then compared against an Erdos-Renyi random network and a Watts-Strogatz small-world network.

3.1.1 Comparison to Random Networks

To ensure a meaningful comparison between different network topologies, we calibrate the parameters of the random and small-world (SW) networks such that their key structural characteristics are aligned with those of the community network. For

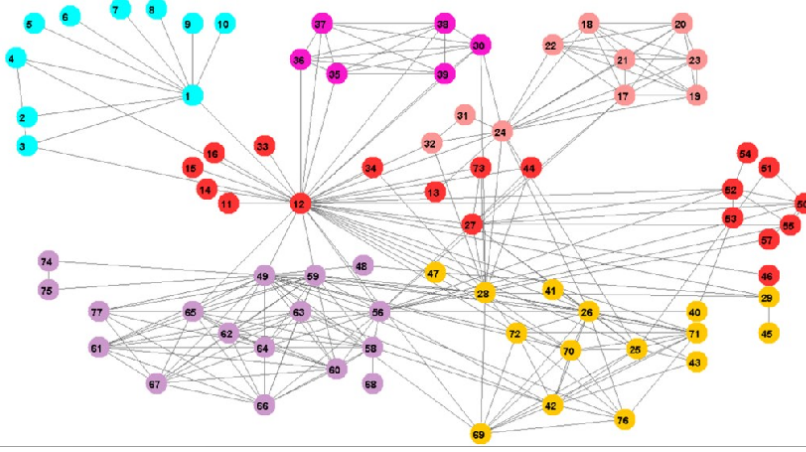


Figure 3.1: An illustrative network with comparatively higher inter-community connectivity, producing less distinct modular separation between groups.

the random network, this is achieved by matching the average degree (i.e., the average number of links per node), ensuring a comparable overall level of connectivity. For the small-world network, both the number of nearest neighbours and the number of rewired (long-range) connections are selected to reflect a balance between local clustering and global connectivity, consistent with the structure observed in the community network. This approach allows us to isolate the effect of network topology on rumour diffusion, rather than differences arising from overall connection density. In community network, each node's expected number of edges (its centrality) can be expressed as:

$$C = \frac{W_g N}{N_g} + B_g \left(N - \frac{N}{N_g} \right), \quad (3.1)$$

where $W_g \frac{N}{N_g}$ refers to the number of contacts made within its cluster while $B_g \left(N - \frac{N}{N_g} \right)$ represents the number of connections to the outsiders.

Normalisation gives the expected degree centrality (the number of links incident upon a node) for each node in community based network as

$$\langle C \rangle = \frac{W_g}{N_g} + B_g \left(1 - \frac{1}{N_g} \right). \quad (3.2)$$

An Erdos-Renyi random network has two parameters: the number of nodes, N , and the probability of an edge occurring be-

tween any two nodes, p_{random} . As $p_{random} \rightarrow 1$ the network becomes complete, i.e. all nodes are connected to all others, at which point the network will have its maximum clustering coefficient. To ensure comparability across network types, the parameters of the random and small-world networks are chosen to match key structural properties of the community network. In particular, the random network is calibrated to have the same average degree, while the small-world network is constructed with comparable local and long-range connectivity. This ensures that differences in rumour diffusion arise from network topology rather than overall connectivity. The probability p_{random} can be expressed in terms of W_g, B_g as

$$p_{random} = W_g \frac{1}{N_g} + B_g \left(1 - \frac{1}{N_g}\right), \quad (3.3)$$

where N_g is the number of communities in the network. This allows us to directly compare the clustering of community based networks with random ones.

3.1.2 Comparison to small-world Networks

Random networks like the ones we have been analysing do not, typically, have local clustering since the probability of two nodes being connected is constant, random, and independent. Another important network that is used to model information spread is the small-world network. The Watts-Strogatz algorithm for creating small-world networks consists of two parameters, the mean degree K of each node, and rewiring rate, p , so let us now express these in terms of W_g and B_g .

The Watts-Strogatz algorithm is characterised by 2 parameters; K , the number of nearest-neighbours a node is connected to, and p , the probability that a neighbouring node is re-wired to another node. The probability that 2 nodes are within the same community is approximately $K(1 - p)$ and the probability that 2 nodes are in different communities is Kp . The community network parameters W_g and B_g represent the intra-group (within-community) and inter-group (between-community) connection probabilities, respectively. These can be mapped onto the small-world parameters K and p by equating the probabilities of local and global connections. The probability of two nodes being connected within the same group in a community

network is $W_g(\frac{N}{N_g} - 1)$, where N is the total number of nodes, and N_g is the number of groups. In a small-world network, this corresponds to $K(1 - p)$.

The probability of two nodes being connected in different groups in a community network is $B_g(N - \frac{N}{N_g})$, which corresponds to the fraction of rewired connections in a small-world network Kp .

Setting both neighbouring and outside connections in two networks equal, we have

$$\begin{cases} W_g(\frac{N}{N_g} - 1) = K(1 - p) \\ B_g(N - \frac{N}{N_g}) = Kp \end{cases} . \quad (3.4)$$

Rearranging gives

$$\begin{cases} K = N \left(W_g(\frac{1}{N_g} - \frac{1}{N}) + B_g(1 - \frac{1}{N_g}) \right) \\ p = \frac{B_g(N - \frac{N}{N_g})}{W_g(\frac{N}{N_g} - 1) + B_g(N - \frac{N}{N_g})} \end{cases} . \quad (3.5)$$

3.1.3 Modularity

Modularity describes how well a network can be separated into groups of nodes that are more closely connected to each other than to the rest of the network. Specifically, modularity measures the fraction of edges within communities, adjusted by the fraction expected in a random network with the same degree distribution. Mathematically, modularity Q is defined as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j),$$

where:

- A_{ij} is the adjacency matrix of the network, with $A_{ij} = 1$ if there is an edge between nodes i and j , and $A_{ij} = 0$ otherwise.
- k_i and k_j represent the degrees of nodes i and j , respectively.
- m denotes the total number of edges in the network.

- c_i and c_j are the communities to which nodes i and j belong.
- $\delta(c_i, c_j)$ is the Kronecker delta, which equals 1 if $c_i = c_j$ (nodes i and j are in the same community) and 0 otherwise.

The modularity value Q lies in the range $[-1, 1]$, where higher values indicate stronger community structures. Networks with high modularity exhibit dense intra-community connections and sparse inter-community links, characteristics often observed in real-world systems such as social, biological, and information networks.

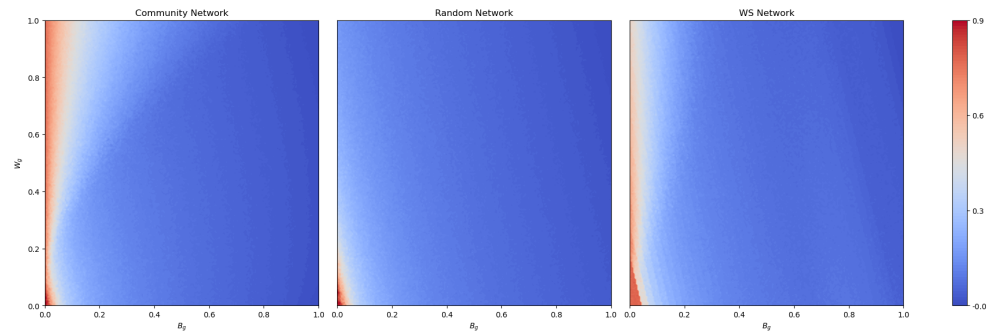


Figure 3.2: Heat maps of modularity for community-based (left), random (centre), and small-world (right) networks. Each network consists of $N = 6000$ nodes with $N_g = 100$ communities.

Fig 3.2 compares the modularity of three network models — Community Network, Random Network, and Small-World Network — under varying levels of intra-group (W_g) and inter-group (B_g) connectivity applying above cross-networks parametric transition. Modularity, as a measure of community structure, quantifies the extent to which nodes within the same group are densely connected while connections between groups remain sparse. The modularity of the Community Network is the highest among the three network types, particularly in regions where W_g is large, and B_g is small. These conditions foster strong intra-community links while minimizing inter-community mixing, resulting in well-defined, isolated community structures. At $B_g = 0$, there are no inter-group connections in Community Networks, and the chance of inter-group connections in Random and Small-World Networks is also negligible.

Without inter-group connections, the separation between communities remains intact, resulting in higher modularity, as the

network is effectively divided into distinct clusters or isolated nodes

As B_g increases, the modularity declines significantly, reflecting the erosion of community boundaries due to the increased influence of inter-group connections. This behaviour aligns with the explicit design of Community Networks to maximize local clustering within groups.

The Random Network exhibits uniformly low modularity across all values of W_g and B_g . This outcome is expected, given the network's random nature, which lacks any deliberate clustering or structural features that promote community formation. The consistent modularity values further affirm that the random placement of edges results in a homogeneous network, with no strong distinction between intra- and inter-group connectivity.

The Small-World Network demonstrates modularity levels that fall between those of the Community and Random Networks. At high W_g and low B_g , the modularity is strong, despite of relatively lower sensitivity to W_g compared to that of the community network. However, the rewiring probability (p) introduces randomness through long-range connections, which weakens the overall community structure. Consequently, the modularity values for the Small-World Network are consistently lower than those of the Community Network, particularly as W_g increases.

In the region where both W_g and B_g approach zero, all three network models — Community Network, Random Network, and Small-World Network — exhibit relatively high modularity. This behaviour may appear counterintuitive, this is because modularity measures the fraction of edges that fall within communities relative to a null model, but in sparsely connected networks, the few existing edges are likely to fall within the same small clusters, inflating modularity scores.

3.1.4 Clustering Coefficient

In this study, we employ the clustering coefficient as a key metric to quantify the level of local clustering within networks. The clustering coefficient measures the tendency of nodes in a network to form tightly connected groups, or cliques. Mathe-

matically, the local clustering coefficient for a node i is defined as:

$$C_i = \frac{2T_i}{k_i(k_i - 1)}, \quad (3.6)$$

where:

- T_i is the number of triangles (closed triplets) involving node i ,
- k_i is the degree of node i , and
- $k_i(k_i - 1)/2$ is the maximum possible number of triangles for a node with degree k_i .

The global clustering coefficient, used throughout this chapter, is the average of C_i over all nodes in the network:

$$C = \frac{1}{N} \sum_{i=1}^N C_i, \quad (3.7)$$

where N is the total number of nodes. A higher clustering coefficient indicates a greater prevalence of tightly-knit groups within the network.

We adopt the clustering coefficient as it provides a direct measure of the local cliqueness of a network, complementing global metrics such as modularity. The clustering coefficient is particularly relevant for understanding how network structure fosters local interactions, such as those within communities. In this content:

- For **Community Networks**, we expect high clustering coefficients due to their explicit design, which emphasises dense intra-group connections.
- For **Random Networks**, clustering coefficients are anticipated to remain low, reflecting the randomness of connections and lack of inherent clustering.
- For **Small-World Networks**, we expect intermediate values, as these networks balance local clustering with long-range connections.

The clustering coefficient enables us to evaluate the extent to which local clustering persists under varying intra-group (W_g)

and inter-group (B_g) connection probabilities. This makes it a vital metric for comparing the structural properties of networks and understanding the interplay between randomness, clustering, and community formation. Figure 3.3 depicts the local clus-

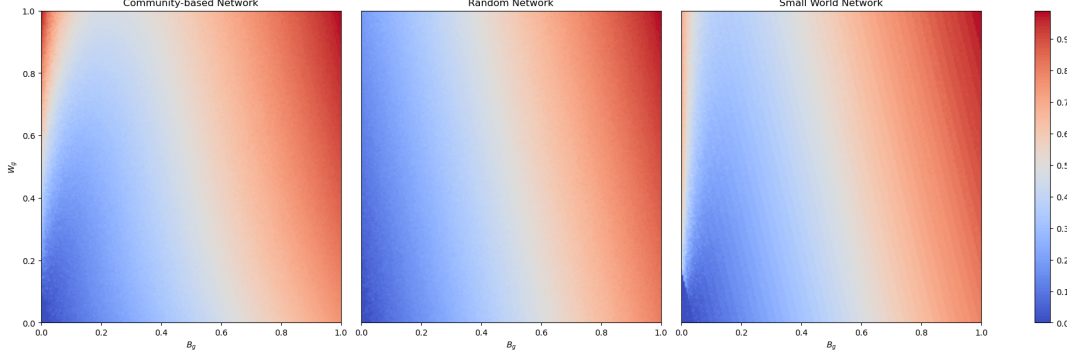


Figure 3.3: Heat maps of mean clustering coefficient for community-based (left), random (centre), and small-world (right) networks. Each network consists of $N = 6000$ nodes with $N_g = 100$ communities. For the small-world network $p = \frac{B_g(N_g-1)}{W_g+B_g(N_g-1)}$, $K = \text{round}(N(\frac{W_g}{N_g} + B_g(1 - \frac{1}{N_g})))$, and for a random network $p = W_g * \frac{1}{N_g} + B_g * (1 - \frac{1}{N_g})$.

tering tendencies for Community Network, Random Network, and Small-World Network, under varying intra-group (W_g) and inter-group (B_g) connection probabilities. In the Community Network, the clustering coefficient is highest in the region where W_g is large and B_g is small. This outcome is expected, as strong intra-group connectivity fosters dense local clusters within communities, while minimal inter-group connectivity ensures these communities remain well-isolated. As B_g increases, the introduction of inter-group connections weakens this isolation, leading to a gradual reduction in the clustering coefficient. Similarly, as W_g decreases, the lack of intra-group connections diminishes the network's ability to sustain strong local clustering. This behaviour demonstrates the critical role of W_g and B_g in shaping the local structural properties of Community Networks. For the random network, the clustering coefficient exhibits a smooth and monotonic increase as both intra- and inter-community connection probabilities (W_g and B_g) rise. This pattern reflects the fact that, in an Erdős–Rényi structure, clustering emerges primarily as a by-product of overall edge density rather than any explicit local organization. Consequently, the contour plot shows a gradual transition from low to high clustering values—from the lower-left region (sparse connectivity) to the upper-right

region (dense connectivity)—without the distinct non-linear peak observed in the community or small-world networks. In other words, while the random network does develop higher clustering under dense connectivity, it lacks the turning-point behaviour associated with the high- W_g , low- B_g regime where local cliquishness dominates.

In the small-world network, the clustering coefficient exhibits a clear local clustering pattern along the low- B_g region, increasing steadily with rising W_g . At relatively low W_g , the small-world network displays higher clustering than the community network because its construction links each node to nearby neighbours on a ring lattice, naturally forming local triangles even under sparse connectivity. As W_g increases, however, the community network surpasses it in clustering magnitude, as dense intra-group random connections generate a larger number of closed triplets. This crossover behaviour—where the small-world network initially dominates at low W_g but is overtaken by the community network at high W_g —arises directly from their respective formation logics: proximity-based wiring in the small-world network versus probabilistic intra-group connectivity in the community network.

3.1.5 Local Efficiency

We also employ local efficiency as a complementary metric to assess the robustness and resilience of local connectivity within networks. While the clustering coefficient quantifies the prevalence of tightly connected groups (or cliques) by measuring the likelihood that a node's neighbours are also connected to each other, local efficiency extends this concept by evaluating how efficiently information can propagate within a node's local neighbourhood, even in the absence of the node itself. Mathematically, the local efficiency of a node i is defined as:

$$E_i = \frac{1}{k_i(k_i - 1)} \sum_{j,k \in \mathcal{N}_i} \frac{1}{d_{jk}},$$

where:

- $\mathcal{N}_i$ represents the set of neighbours of node i ,
- d_{jk} is the shortest path distance between neighbours j and k within the subgraph excluding node i ,
- k_i is the degree of node i and

- $k_i(k_i - 1)$ normalises the sum by the number of possible connections among the neighbours.

The global local efficiency of the network is then obtained by averaging E_i over all nodes:

$$E_{\text{local}} = \frac{1}{N} \sum_{i=1}^N E_i.$$

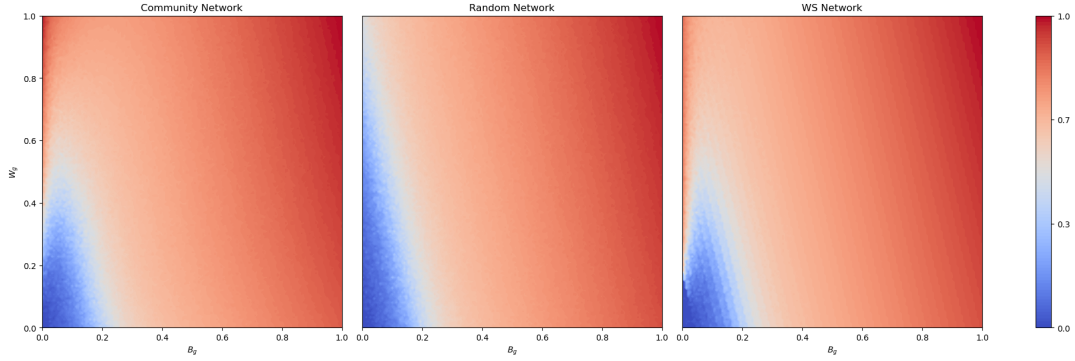


Figure 3.4: Heat maps of local efficiency for community-based (left), random (centre), and small-world (right) networks. Each network consists of $N = 6000$ nodes with $N_g = 100$ communities.

Figure 3.4 presents the local efficiency against intra and inter connectivity for the three networks. Similar to clustering coefficient, local efficiency sees an overall increasing trend from $(0,0)$ to $(1,1)$. The local efficiency sees an overall positive correlation against network connectivity. Similar to 3.2 and 3.3, the most significant differences among the three networks appear in the left-hand side of the heatmap, where B_g is low. In this region, local efficiency increases most significantly in the community network, moderately in the small-world network, and least sensitively in the random network.

To conclude, the adopted network measures display a consistent pattern across the three network types. While all networks exhibit broadly similar trends on the Heat maps, clear differences appear in the low B_g region, where inter-group connectivity is weak and intra-group connectivity remains strong. In this regime, the community network consistently achieves the highest clustering coefficient and modularity, indicating a strong tendency for nodes to form tightly knit subgroups. The small-world network shows moderate clustering, while the random network remains largely unstructured, reflecting its homogeneous link

distribution. These results confirm that the community network most effectively captures the clustered organisation typical of real social systems, but only when inter-community connections are limited. As cross-community links increase, the structural differences between the three networks diminish, leading to a convergence in clustering behaviour.

3.1.6 Critical regime (low B_g)

To further examine the structural characteristics of the constructed community network, a more focused analysis is conducted over the regime where inter-group connectivity remains low. In this regime, the influence of intra-group connectivity becomes dominant, allowing the underlying structural features of each network type to manifest more clearly. Accordingly, the parameter space is restricted to B_g in $[0, 0.2]$, while W_g continues to vary over its full range. This targeted examination enables a clearer visual and quantitative comparison of how each network responds to variations in intra-group connectivity under limited cross-group interaction. By isolating this critical region, the analysis aims to highlight the extent to which each network topology captures clustered, or “clique-like,” structures, which are central to the modelling framework adopted in this study.

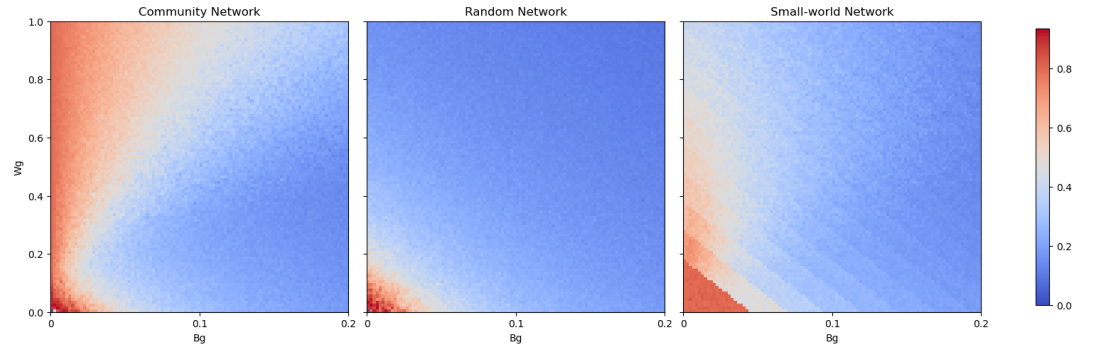


Figure 3.5: Heat maps of modularity for community (left), random (centre), and small-world (right) networks against B_g ranging from 0 to 0.2 on the x-axis and W_g ranging from 0 to 1 on the y-axis.

Figures 3.5, 3.6, and 3.7 present the behaviour of modularity, clustering coefficient, and local efficiency, respectively, for the random network over the restricted parameter range $B_g \in (0, 0.2)$; $W_g \in (0, 1)$, corresponding to figures 3.2, 3.3 and 3.4, respectively. Across all three measures, random network

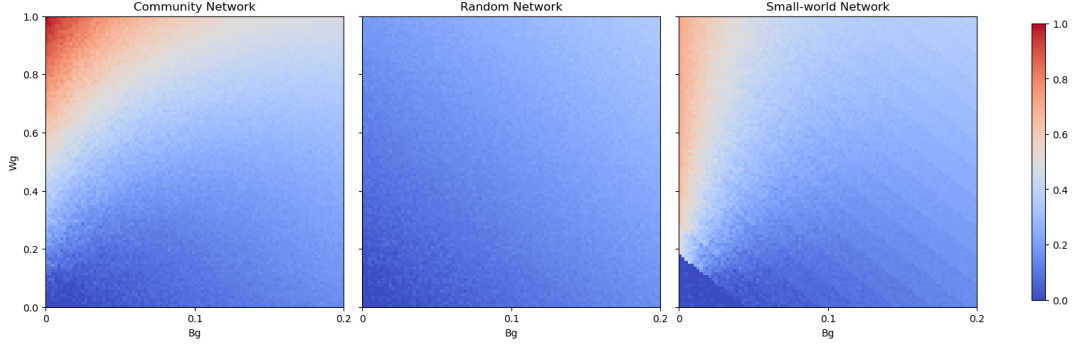


Figure 3.6: Heat maps of clustering coefficient for community (left), random (centre), and small-world (right) networks against B_g ranging from 0 to 0.2 on the x-axis and W_g ranging from 0 to 1 on the y-axis.

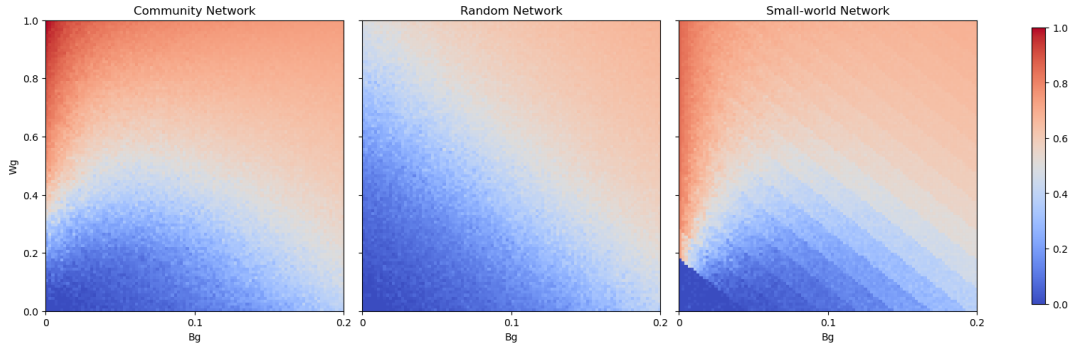


Figure 3.7: Heat maps of local efficiency for community (left), random (centre), and small-world (right) networks against B_g ranging from 0 to 0.2 on the x-axis and W_g ranging from 0 to 1 on the y-axis.

displays a consistent and smooth gradient, with values increasing steadily from the lower-left region towards the upper-right region. This pattern indicates a largely monotonic relationship between the network metrics and the underlying connection probabilities.

In contrast to the random network, both the small-world and community networks exhibit clear deviations from the monotonic patterns. While an overall increasing trend with respect to W_g and B_g is still present, the evolution of all three measures is no longer uniform. Instead, noticeable curvature and localised variations emerge across the parameter space, particularly in the region characterised by high W_g and low B_g . These deviations can be attributed to the heterogeneous structure inherent in both network types. Unlike the random network, connections in the small-world and community networks are not formed inde-

pendently; rather, they are influenced by underlying structural constraints that favour local connectivity. As a result, increases in intra-group connection probability do not translate into purely global density effects, but instead amplify local clustering and structural organisation. This leads to nonlinear responses in clustering coefficient, modularity, and local efficiency, reflecting the increasing importance of local connectivity patterns as the network becomes more internally cohesive.

Although both networks display such behaviour, the extent of these deviations differs markedly. The small-world network, while incorporating local clustering through its construction, exhibits only moderate departures from monotonicity. In contrast, the community network demonstrates much more pronounced variations, particularly within the low B_g , high W_g regime. This indicates that the structural effects associated with densely connected groups are significantly stronger in the community network, giving rise to sharper transitions and more distinct patterns across all three measures.

3.2 RUMOUR SPREAD MODEL

We implement the rumour-spreading process using a Python-based simulation framework. The model begins with the construction of a network consisting of nodes and edges, where each node represents a trading agent and each edge denotes a pairwise communication link between two connected agents. The overall structure of the network is defined by two key parameters: W_g , the probability of intra-group connectivity, and B_g , the probability of inter-group connectivity.

Once the network is generated, each node is assigned an initial state from the Ignorant–Spreader–Stifler (ISR) model. Ignorant nodes are unaware of the rumour, while spreaders actively transmit it to their neighbours, and stiflers represent agents who have heard the rumour but no longer participate in spreading.

The evolution of these states proceeds in discrete time steps, where each time step is interpreted as one trading day. At each time step, the simulation iterates through nodes sequentially, and interactions are evaluated over connected pairs of agents. State transitions occur probabilistically based on the current states of interacting agents and their network connections. This

implementation follows the probabilistic structure implied by the mean-field ISR model in equation 3.8, but is realised as a sequence of discrete stochastic events. The update scheme is asynchronous, as node states are updated sequentially rather than simultaneously, allowing intermediate state changes within a time step to influence subsequent interactions.

The initial conditions of the model are specified such that one node is assigned to the spreader state ($S(0) = 1$), while the remaining $N - 1$ nodes are initialised as ignorant ($I(0) = N - 1$), and no nodes are initially stiflers ($R(0) = 0$). This configuration reflects the realistic assumption that market rumours typically originate from a single source, such as an insider, a journalist, or an informed analyst, before disseminating through the network. The initial spreader is selected uniformly at random from the population, without restricting it to a particular community. Although this assumption provides a simplified starting point, it may influence the early-stage dynamics of the spreading process, particularly in community-structured networks, where the location of the initial spreader can affect the speed and extent of diffusion across groups.

$$\begin{cases} I + S \xrightarrow{\alpha} S + S \\ S + S \xrightarrow{\theta} S + R \\ S + R \xrightarrow{\theta} R + R \end{cases}, \quad (3.8)$$

where α is the spreading rate, representing the probability of a spreader turning an ignorant into a spreader per unit time; θ is the stifling rate, denoting the probability of a spreader turning to stifter compartment upon making contacts with stiflers or other spreaders.

The rumour-spreading process in this study is implemented through a stochastic simulation, in which randomness plays a central role in determining how information is transmitted between agents. Each interaction is governed by probabilistic rules rather than fixed outcomes. While this design allows the model to mimic the uncertainty and heterogeneity inherent in real communication behaviour, it also introduces the question of reliability: to what extent can a stochastic realisation accurately represent the underlying dynamics of the spreading system? To address this concern, we first verify that the stochastic model behaves consistently with its deterministic counterpart. Specifically,

we compare the compartmental time series of the stochastic simulation with those generated by the deterministic mean-field model.

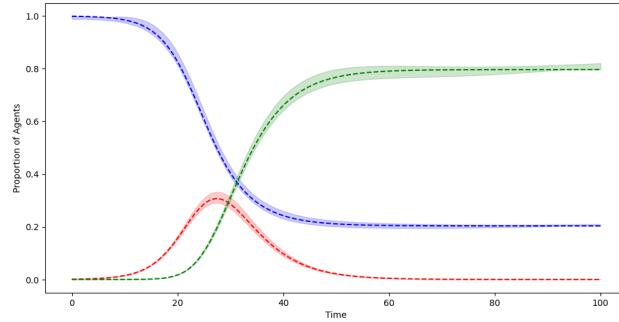


Figure 3.8: Time evolution of the proportions of ignorant (blue), spreader (red), and stifler (green) agents. The solid lines represent the deterministic model, while the shaded regions indicate the interquartile range between the 40th and 60th percentiles, capturing the variability due to stochasticity in the model.

Considering the inherent variability and randomness within the stochastic model, multiple simulation runs are performed with the results are aggregated across multiple simulation runs, with variability illustrated using the interquartile range between the 40th and 60th percentiles.

As illustrated in Figure 3.8, the trajectories align closely, and the variation across repeated runs remains within a tolerable range. This validation demonstrates that the stochastic model captures the essential dynamics of the spreading process while maintaining acceptable levels of randomness, providing a reliable basis for subsequent analyses.

In order to understand how different network structures shape the dynamics of rumour propagation, we design a series of simulations that systematically vary key model parameters. In particular, we adjust the level of intra-group connectivity and the rumour transmission rate to examine how these factors influence the spreading process across different network types.

We conduct a systematic parameter analysis to examine the robustness of the model dynamics. By varying the values of W_g and β , where β represents the ratio between spreading rate and stifling rate, over a defined range, we investigate how structural differences in network topology—such as clustering coefficient and modularity—affect the propagation of information.

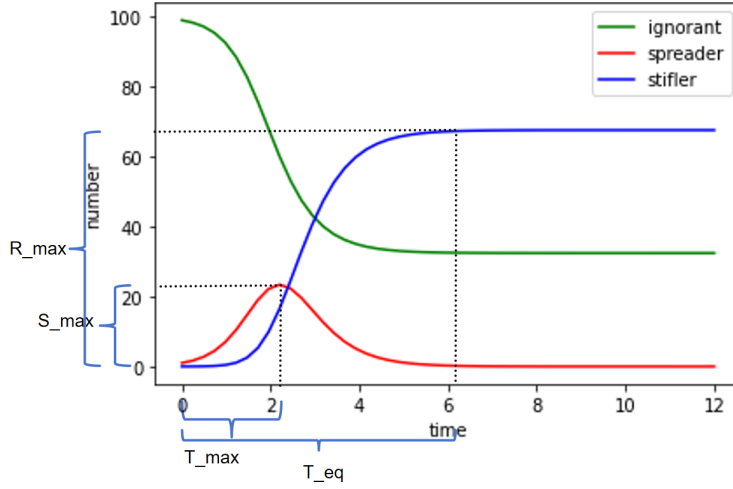


Figure 3.9: Time evolution of the rumour spreading process illustrating the three agent compartments: ignorants (green), spreaders (red), and stiflers (blue). Four key metrics are extracted from each simulation run: maximum spreader proportion (S_{max}), time to maximum spreader (T_{max}), final stifler proportion (R^*), and time to equilibrium (T_{eq}). These measures summarize the spreading dynamics under each parameter configuration and serve as comparative indicators across network structures and parameter sets.

For each parameter configuration, multiple stochastic simulation runs are performed, and the reported results correspond to averages across these runs. This Monte Carlo averaging allows us to account for the inherent randomness in the model and obtain stable estimates of the system behaviour.

Additionally, considering the expanded complexity introduced by performing multiple simulations across varying parameter values, we condense the time-series data from simulations into four representative metrics that provide a snapshot of the spreading dynamics: max spreader, time to max spreader, final stifler, and time to final stifler, in order to streamline the analysis and maintain clarity. By extracting these four measures, we reduce the dimensionality of the data while preserving its most essential features. These metrics provide a concise yet informative summary of the dynamics, capturing both the intensity (e.g., peak spreader proportion, final stifler proportion) and timing (e.g., time to peak and equilibrium) of the spreading process:

1) Maximum rumour intensity (S_{max})

The maximum rumour size records the highest proportion

spreader reaches along the process.

2) Time of reaching maximum rumour size (T_{max})

The time to reach a maximum rumour size indicates the time for spreader curve to change monotony from increasing to decreasing.

3) Final rumour coverage (R^*)

The final rumour coverage rate is reflected by the proportion of stiflers at equilibrium state, which also has positive correlation to rumour spreading effectiveness.

4) Time to reach equilibrium state (T_{eq})

The time to equilibrium refers to the time step at which the stochastic rumour-spreading process reaches a state with zero spreaders remaining in the network.

In summary, it is sufficient to represent the graph with above numerical measures taken at each stationary point of the curves whose monotony between each measure is all simple. We begin by examining how the spreading process is influenced by the intra-group connectivity probability (W_g).

3.2.1 Baseline Rumour Spreading Results

This subsection presents the baseline simulation results obtained under a standard parameter setup. The purpose is to illustrate the typical rumour-spreading dynamics across the three network structures—community, small-world, and random—before performing robustness analyses in subsequent sections.

We pick $N = 6000$, $N_g = 100$, $B_g = 0.0005$, $\alpha = 0.001/\text{day}$ and $\theta = 0.001/\text{day}$, with the independent variable intra connectivity W_g uniformly incremented from 0 to 1. The choice to parameterise the network in this way is based on the structural differences these parameters induce in various network types as shown above in 3.2 and 3.3. That is to say, the region where B_g is low displays the most pronounced differences between community-based networks and the two reference networks, which suggests a unique sensitivity of community-based network to changes in W_g while B_g is low. Thus, to emphasise how various topologies affect the spread of rumour, we adopt this region that isolates the effects of community modularity and clustering on spreading dynamics.

The baseline parameter values are chosen to represent a stylised but plausible financial communication network. We assume that approximately $N = 6000$ traders are actively interested in the stock and are organised into $N_g = 100$ com-

munities, corresponding to institutions or closely connected professional groups. This gives an average community size of $n = N/N_g = 60$ traders. Since one simulation time step corresponds to one trading day, an individual trader has, on average, $W_g(n - 1)$ opportunities for within-community communication per day. As W_g varies from 0 to 1, this corresponds to between 0 and 59 intra-community contacts per day. In contrast, with $B_g = 0.0005$, the expected number of inter-community contacts is

$$B_g N \left(1 - \frac{1}{N_g}\right) \approx 3$$

per day. Consequently, under the strongest intra-community connectivity ($W_g = 1$), the model represents a trader communicating with approximately 59 colleagues within the same institution but only around three traders from other institutions each day. This reflects the strong tendency for financial information to circulate primarily within established professional networks before spreading more widely.

The corresponding parametrisation is as shown in Table 3.2.

Table 3.2: Baseline rumour spreading model parameters used in Section 3.2.1.

Parameter	Value	Description
N	6000	Total number of agents
N_g	100	Number of communities
W_g	$0 \rightarrow 1$	Intra-community connection probability (varied)
B_g	0.0005	Inter-community connection probability
α	0.001/day	Spreading rate
θ	0.001/day	Stifling rate
Initial spreaders	1	Number of initially informed agents
Monte Carlo runs	50	Independent simulation runs per parameter set

Figure 3.10 shows the change of four rumour spreading metrics in random (red), community (green) and small-world network (blue) to intra-connectivity W_g . **Max Spreaders** All three networks begin with an increasing curve in the number of maximum spreaders as intra-community connectivity, W_g increases.

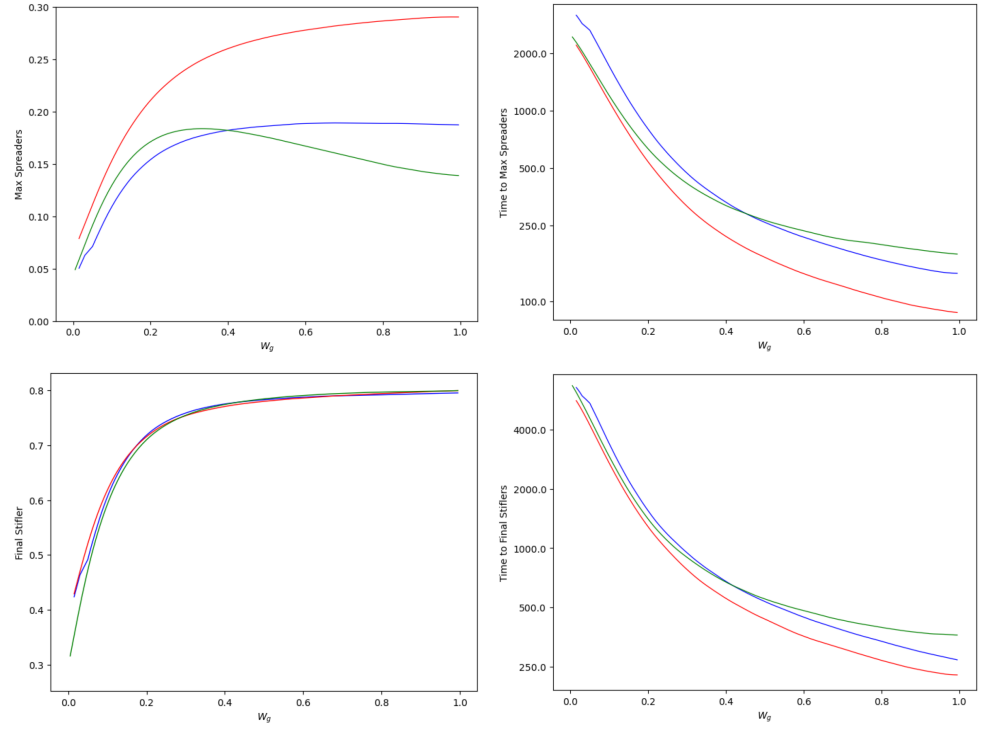


Figure 3.10: Max spreader proportion (top left), time to max spreader (top right), final stifler proportion (bottom left), and time to final stifler (bottom right) of community (green), random (red) and small-world network (blue)

This behaviour is expected, as a higher W_g reduces the number of isolated nodes, allowing for greater interaction between connected agents and thereby intensifying the spread of the rumour. However, as W_g grows beyond approximately 0.2, three types of networks exhibit distinct responses to the increasing level of clustering. The random network maintains a steady upward trend that eventually levels off at the highest level. The small-world network initially follows an increasing trend similar to the random network but levels off at a much lower value. The community network shows a decreasing curve following the initial upward trend.

Time to Max Spreaders The top right plot depicts the time required to reach the maximum number of spreaders as a function of intra-community connectivity W_g . All three types of networks exhibit a decreasing trend which is intuitive since higher overall connectivity leads to a faster propagation of information on the network. However, the trajectories of the three networks reveal distinct patterns. The random network consistently maintains the lowest time to max spreaders across the entire range of

W_g while the small-world and community networks display an intersecting behaviour around $W_g = 0.4$. For lower W_g values, random network takes longer time to reach max spreader proportion and vice versa for higher W_g values.

Final Stiflers The bottom left plot presents the proportion of final stiflers against intra-community connectivity W_g , which reflects the proportion of population that has once heard the rumour. All three networks display a consistent exponential-like pattern with subtle differences across the W_g range. This suggests that the final proportion of stiflers is largely independent of the network type under the conditions modelled, with no pronounced distinctions between the behaviours of the three networks.

Time to Final Stiflers The final plot illustrates the time required for all nodes to reach the stifler state as a function of intra-community connectivity W_g . All three networks demonstrate a clear decreasing trend, with random network staying the lowest over the domain. Moreover, the community and small-world network intersect, at a similar level around $W_g \approx 0.4$.

The above plots reveal both commonalities and distinctions in their behaviour across three types of networks. While the overall final rumour coverage is remarkably consistent across all three networks, the underlying spreading dynamics differ significantly. The random network always exhibits the fastest spreading and the highest rumour intensity across all values of W_g . The community and small-world networks demonstrate an intersecting behaviour in both transmission speed and intensity measures. When W_g is high, the community network experiences a longer time to reach the maximum spreader proportion and equilibrium, as well as a lower maximum spreader proportion than the small-world network, and vice versa for lower W_g values. This intersection occurs around $W_g = 0.4$, representing a crossover point where topological properties begin to differentially influence spreading efficiency.

These findings highlight the dual influence of network structure on information dissemination: while structural differences minimally affect the ultimate coverage, they have a pronounced impact on the pathway to saturation, shaping the speed and peak intensity of spreading. To explain these trends, we detail the following key structural metrics: the clustering coefficient, modularity and local efficiency along the same parameter space

used for the spreading dynamics which is W_g from 0 to 1 with B_g fixed at 0.0005.

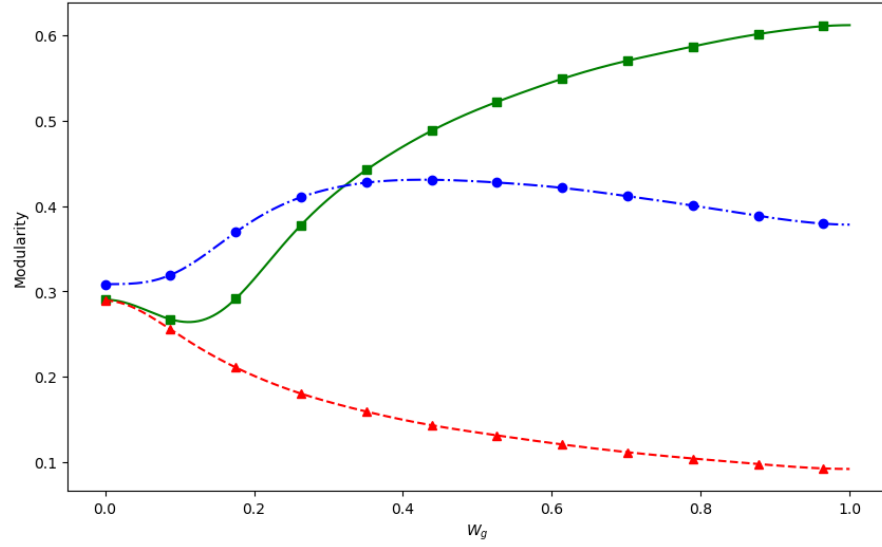


Figure 3.11: Modularity on random network (red), community network (green) and small-world network (blue). W_g is varied from 0 to 1 while B_g is kept at 0.0005

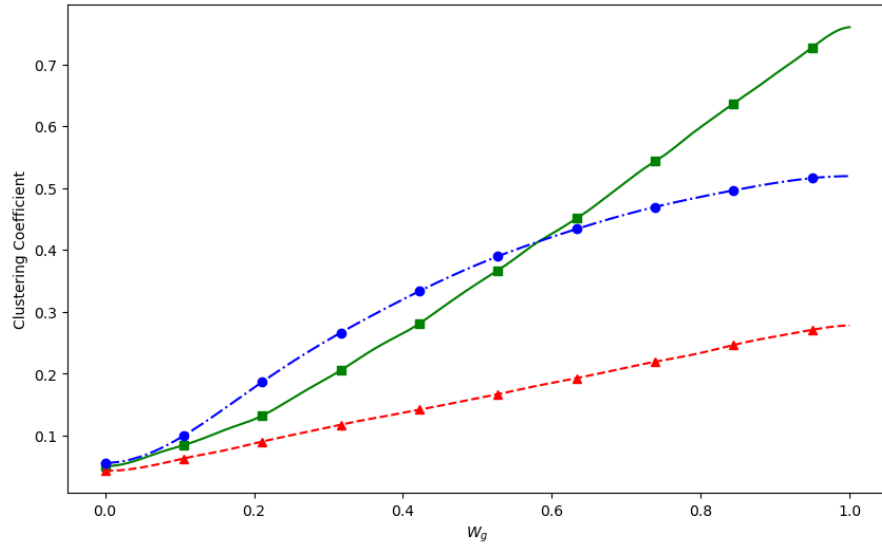


Figure 3.12: Clustering coefficient on random network (red), community network (green) and small-world network (blue). W_g is varied from 0 to 1 while B_g is kept at 0.0005

Figure 3.11, 3.12 and 3.13 present the modularity, clustering coefficient and local efficiency of the three experimental networks over the parameter space, which are the cross-sections along $W_g = 0.0005$ of 3.2, 3.3 and 3.4 respectively. The trend

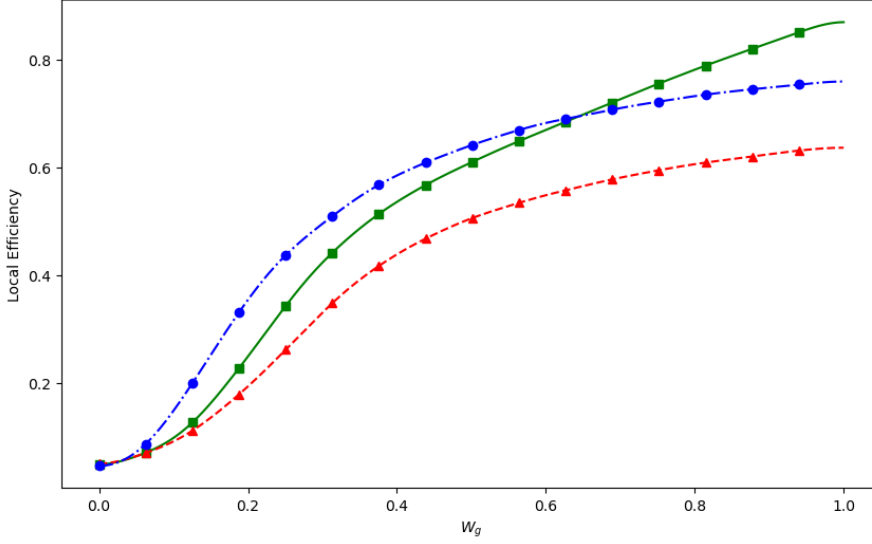


Figure 3.13: Local efficiency on random network (red), community network (green) and small-world network (blue). W_g is varied from 0 to 1 while B_g is kept at 0.0005

is consistent with observations in the above rumour metrics: random network shows the lowest curve while the community and small-world ones intersect. Thus, it can be inferred that the transmission speed and rumour intensity are negatively correlated with the clustering level. This could be attributed to the stifling mechanism as shown in equation 3.8. Unlike the infected individuals in the epidemic model, who decay to recovered compartment spontaneously, spreaders in the rumour spreading model are to be inactivated to stifler compartment only as a result of making contacts to other spreaders or stiflers. In this case, the structural difference would lead to a difference of spreaders' stifling efficiency across different types of networks even under unified degree centrality.

In other words, a closely connected local cluster potentially increases the likelihood for a spreader to encounter other spreaders or stiflers, thereby reducing its lifespan, which results in a lower rumour intensity in both community and small-world networks compared to the random network as shown in 3.10. To validate this hypothesis, we examine the proportion of informed neighbours—comprising stiflers and other spreaders—for each spreader in the three networks.

Figure 3.14 compares the average proportion of each spreader's informed neighbours in random (red), community (green) and small-world (blue) networks under various W_g values. The horizontal axis represents the time-space during the spreading

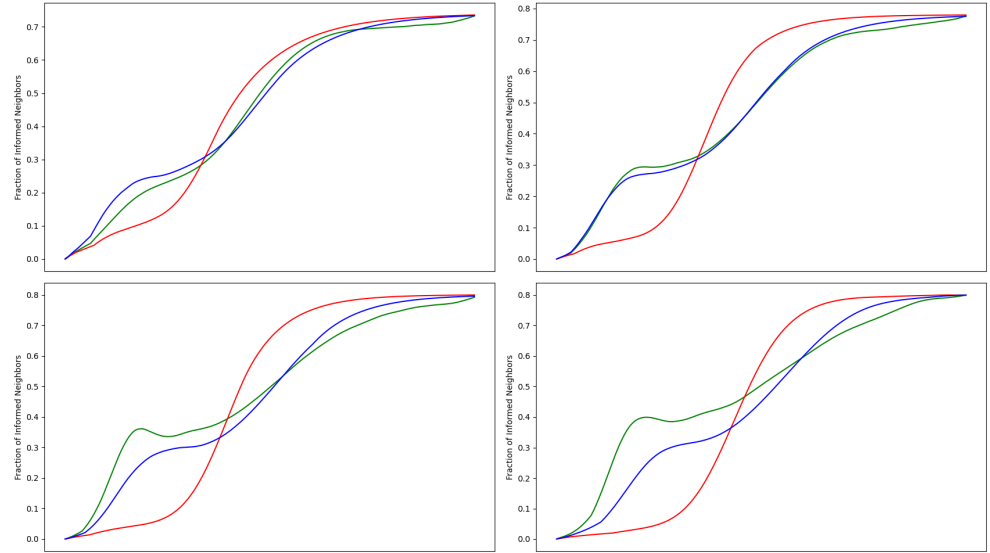


Figure 3.14: Proportion of informed neighbours for $W_g = 0.25$ (top left), $W_g = 0.50$ (top right), $W_g = 0.75$ (bottom left) and $W_g = 1.00$ (bottom right). The x-axis represents the time from T_0 to end of the process.

process, with $(0,0)$ representing T_0 and the final point representing the time to equilibrium state. Note that as shown in bottom right plot of Figure 3.10, differences exist in the time to reach equilibrium state in each stochastic simulation. To facilitate cross-network analysis, interpolation is applied to align the timelines. In this way, each line could be viewed as normalised trajectories that provide a unified perspective over three types of networks for comparing purposes. The higher the value, the more easily the spreader gets stifled.

Despite the observed differences in the trajectories of informed neighbours, all three networks converge to a similar final level of informed individuals. This finding aligns with previous results that the final fraction of informed individuals remains unaffected by the underlying network structure as shown in figure 3.10. The y-value to which each line levels off is also consistent with the deterministic model. In the early phase of spreading, community and small-world networks show substantially higher proportions of informed neighbours compared to the random network for each W_g plot, which is aligned with the hypothesis that clustered network incurs a local saturation effect on spreaders. The relative behaviour in the proportion of informed neighbours between community and small-world networks also offers compelling explanatory power for the observed trends in spreading dynamics. Specifically, the patterns of lower maxi-

maximum spreader proportions and the intersection points between small-world and community networks, which are also evident in other metrics such as time to maximum spreaders and time to equilibrium, can be attributed to differences in clustering levels. This analysis underscores the degree of clustering as a critical factor influencing the spreading dynamics across the networks."

At low W_g value, 0.25 for example, the informed neighbour of small-world network is higher than community; at middle W_g value, 0.5 (top-right), the trajectories of the small-world and community networks converge, indicating comparable clustering levels. For high W_g values, the community network surpasses the small-world network. Thus, higher clustering coefficient leads to a higher ratio of spreaders' informed neighbour, which results in shorter lifespan.

To conclude, we analysed the spreading pattern of rumour on community-based, random and small-world networks through four representative metrics: the maximum spreader proportion, the time to reach this maximum, the final stifler proportion, and the time to reach the final stifler state. The results suggest that networks with stronger clustering structures tend to exhibit slower and less intense rumour diffusion. In particular, in the low B_g , high W_g regime—where the community network displays pronounced modular structure—rumour spreading is both delayed and reduced in magnitude.

Since the clustering coefficient was previously shown to increase monotonically with the intra-community connection probability W_g (Section 3.1.4), the observed increase in both the time to peak spreading and the time to equilibrium as W_g increases is consistent with the interpretation that more highly clustered networks slow the propagation of rumours. Although this association is inferred through the common dependence on W_g , rather than demonstrated directly by plotting spreading metrics against the clustering coefficient, the simulation results consistently support the view that stronger local clustering confines information within tightly connected communities before it diffuses more broadly across the network. Consequently, greater clustering is associated with slower rumour diffusion and a more gradual progression towards equilibrium.

This effect can be understood in terms of repeated interactions within tightly connected communities, which limit the exposure of spreaders to new ignorant agents and thereby reduce the overall efficiency of transmission across the network. While this

relationship is observed consistently across the network types considered, it should be interpreted as a qualitative trend rather than a formally established statistical correlation.

It should also be noted that these results are obtained under a fixed set of transition parameters. This raises the question of robustness, which is addressed in the following sections by varying key model parameters, including the number of communities (N_g) and the total population size (N).

3.2.2 Robustness test

In the preceding analysis, we characterise the community-based network as a collection of sub-groups, with W_g and B_g regulating intra-community and inter-community connections, respectively. We examine the rumour spreading dynamic on different phases of W_g/B_g plane. To contextualise its structural properties, we compare it against a random network and a small-world network. Our findings indicate that the community network exhibits a superior clustering coefficient in the high W_g -low B_g regime relative to the reference networks. Additionally, we observe that in this critical regime, introduction of community structure significantly alters the spreading process: both the intensity and the speed of rumour diffusion are notably reduced. Therefore it can be inferred that network modularity, by localising information flows within tightly-knit clusters, inhibits widespread rumour contagion. However, before generalising this conclusion, it is essential to test its robustness under varying model parameters. Having established the standard model behaviour under a fixed population size, we now extend the analysis and examine the generalisability of the above findings.

Size of population A critical question in modelling rumour spreading is how network size impacts dynamics. As networks grow, structural features such as clustering may interact differently with spreading processes. To probe this dimension, we now analyse how varying the total population size (N) alters the propagation dynamic. This analysis explores whether the patterns observed in the standard model—particularly the slower and less intense spreading in community networks—remain consistent as network scale changes. For this analysis, we simulate community networks with N ranging from 6,000 to 18,000 nodes. As in the standard model, we track four core metrics:

- max spreaders: the maximum proportion of nodes simultaneously in the spreader state.

- time to max spreaders: the time step at which the peak number of spreaders occurs.
- final stifler: the final fraction of nodes in stifler state.
- time to final stifler: the total time until the rumour has effectively ceased spreading.

To assess the robustness of our initial conclusions, we extend our analysis to examine whether the relative dynamics among the three network types—random, small-world, and community—are preserved as the total population size N increases. While the earlier findings established that community networks exhibit lower spreading intensity and slower propagation relative to the other topologies under standard parameters, it remains an open question whether these network-specific characteristics persist across different scales. In other words, we test whether the community network continues to exhibit slower and less intense spreading compared to random and small-world networks when scaled up to larger sizes. To this end, we fix the intra-community and inter-community connection probabilities at $W_g = 0.8$ and $B_g = 0.005$, respectively. Then we evaluate how each of the four key metrics varies with increasing network size across the three network structures. Our objective is to determine whether the hierarchy of spreading behaviours—where community networks consistently manifest lower peak spreader proportions and longer diffusion times compared to random and small-world networks—remains stable under larger network sizes.

Figure 3.15 reveals consistent and stable relative behaviours across network types as total population size N is scaled. Specifically, the top-left panel indicates that the maximum spreader proportion increases systematically with N for all network types, maintaining the established hierarchy: random networks consistently sustain the highest peak spreading intensities, followed by small-world and community networks. This result underscores the persistent capacity of community structures to moderate rumour propagation intensity even at larger scales.

Examining the temporal dynamics further reinforces this finding. The top-right panel illustrates that the time to reach the maximum spreader state declines with increasing N , reflecting accelerated initial rumour diffusion in larger populations due to greater availability of spreading nodes. Nonetheless, community networks remain the slowest to reach their spreading peak, whereas random networks propagate rumours most rapidly.

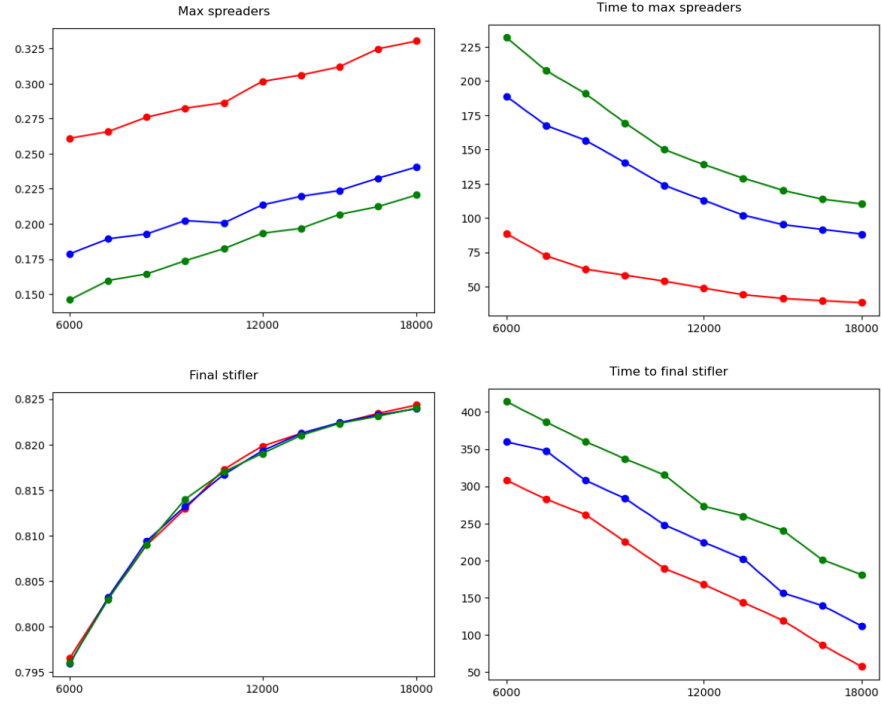


Figure 3.15: Rumour spreading dynamics as a function of total population size N under fixed intra-community connectivity $Wg = 0.8$. Red, blue, and green curves correspond to random, small-world, and community networks, respectively.

The bottom-left panel indicates that the final stifier proportion, representing the ultimate extent of rumour coverage, increases slightly and converges across all network types as N increases. Notably, the curves closely overlap at higher values of N , suggesting that while community structures substantially delay and moderate rumour intensity, they do not inhibit eventual widespread rumour saturation in large networks. Finally, the bottom-right panel demonstrates a consistent decrease in the total duration of the rumour diffusion process with increasing N . Despite this general reduction, community networks consistently exhibit the longest diffusion times, further validating the inherent slowing effect of modular community topologies.

Collectively, these findings robustly affirm our original hypothesis: network modularity, characteristic of community-based topologies, significantly dampens rumour spreading intensity and slows diffusion relative to random and small-world configurations, irrespective of network scale.

Having established the robustness of the relative spreading dynamics across different network topologies in Figure 3.15, we now further investigate the internal consistency of rumour

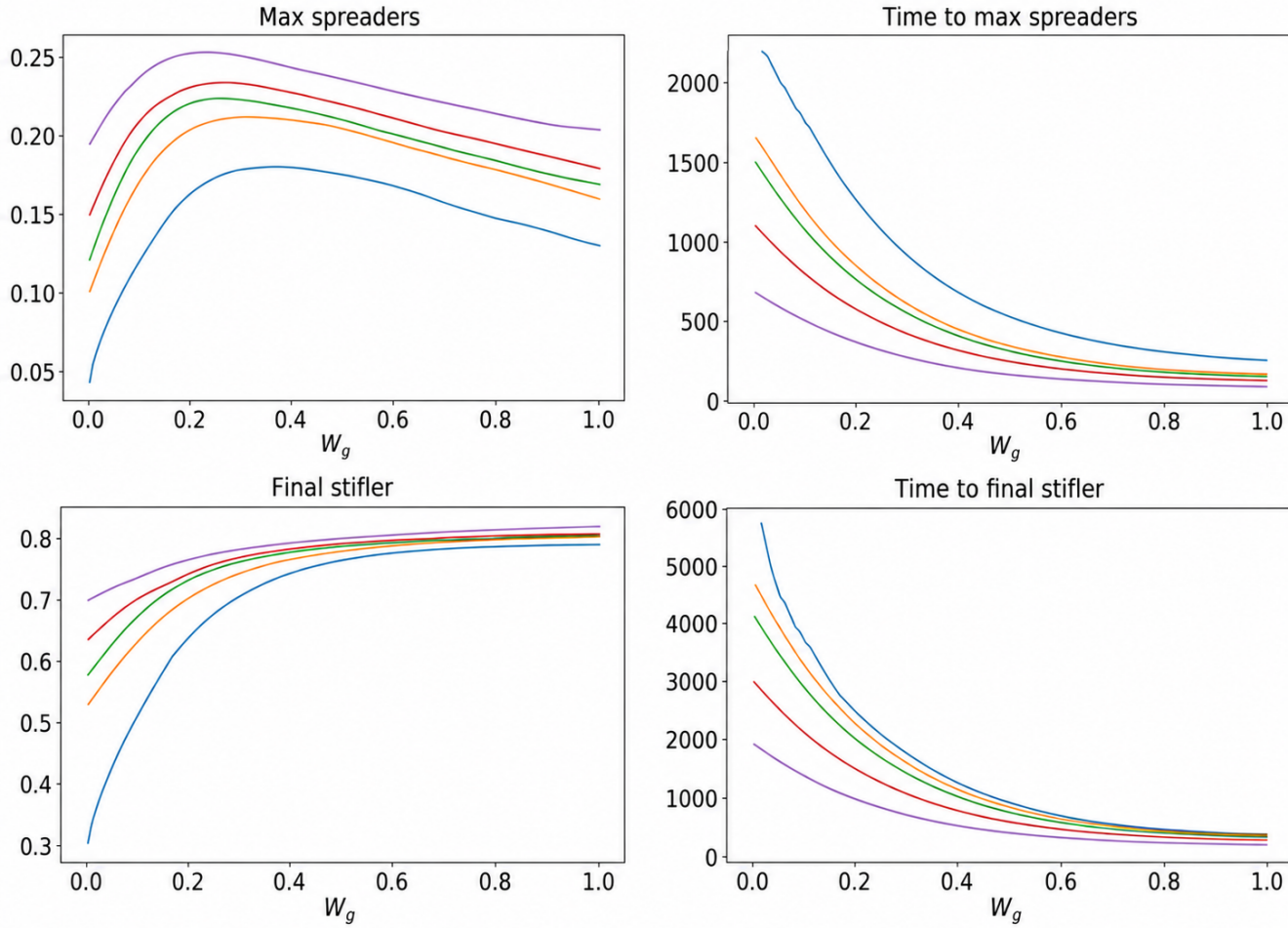


Figure 3.16: Max spreaders (top-left), time to max spreaders (top-right), final stifler (bottom-left) and time to final stifler (bottom-right) plots of rumour spreading on community networks against intra-probability W_g , with various total number of population (blue- $N = 6000$, orange- $N = 9000$, green- $N = 10000$, red- $N = 12000$ and purple- $N = 18000$)

propagation patterns within community networks as the total population size (N) is varied. Figure 3.16 explores whether the trajectories of rumour spreading metrics previously identified in the standard parametrisation persist under varying total population sizes (N) within community networks. Specifically, we track four key metrics against intra-community connectivity (W_g), progressively scaling the network from smaller $N = 6000$, blue) to larger sizes ($N = 18000$, purple).

As shown in the top-left panel, the maximum spreader proportion consistently exhibits a non-monotonic relationship with intra-community connectivity, initially increasing and subse-

quently decreasing beyond an optimal connectivity threshold (approximately $W_g = 0.3$ to $W_g = 0.4$), with this characteristic curve preserved across all network scales. Likewise, the temporal metrics—time to maximum spreaders (top-right) and time to final stiflers (bottom-right)—uniformly decrease as intra-community connectivity strengthens, demonstrating a robust inverse relationship independent of network size.

Lastly, the final stifter proportion (bottom-left) demonstrates a saturating trend, rapidly increasing at low intra-community connectivities and plateauing at higher values, a pattern which remains stable and consistent across all tested network scales. Additionally, the results presented in each panel of Figure 3.16 reveal that the relative ordering of the curves corresponding to different population sizes (N) remains consistent across all intra-community connection probabilities (W_g). Specifically, larger networks systematically exhibit higher peak values in maximum spreader proportion, lower times to reach peak spreader states, marginally higher final stifter proportions, and shorter overall rumour diffusion times. Importantly, this monotonic ordering with respect to network scale (N) persists uniformly across all connectivity levels, underscoring the robustness and internal consistency of rumour spreading behaviours as the network scales.

These findings further affirm that the impact of network size scaling on the rumour spreading process is both predictable and consistent, enhancing confidence in the scalability of our earlier conclusions regarding the fundamental dynamics associated with community network structures.

Number of communities Another fundamental feature of community networks is their internal organization—specifically, how the population is partitioned into subgroups. In this subsection, we turn our attention to the effect of varying the number of communities (N_g) on rumour propagation dynamics. By increasing N_g while keeping the total network size fixed, we systematically alter the granularity of the network’s modular structure, resulting in smaller, more fragmented communities. This allows us to explore how the degree of segmentation within the network influences both the efficiency and extent of information spread. Through comparative analysis of key spreading metrics across different values of N_g , we assess the persistence and generalisability of the previously observed patterns under increased community fragmentation. The results in Figure 3.17 display the effects of varying the number of communities (N_g) on key

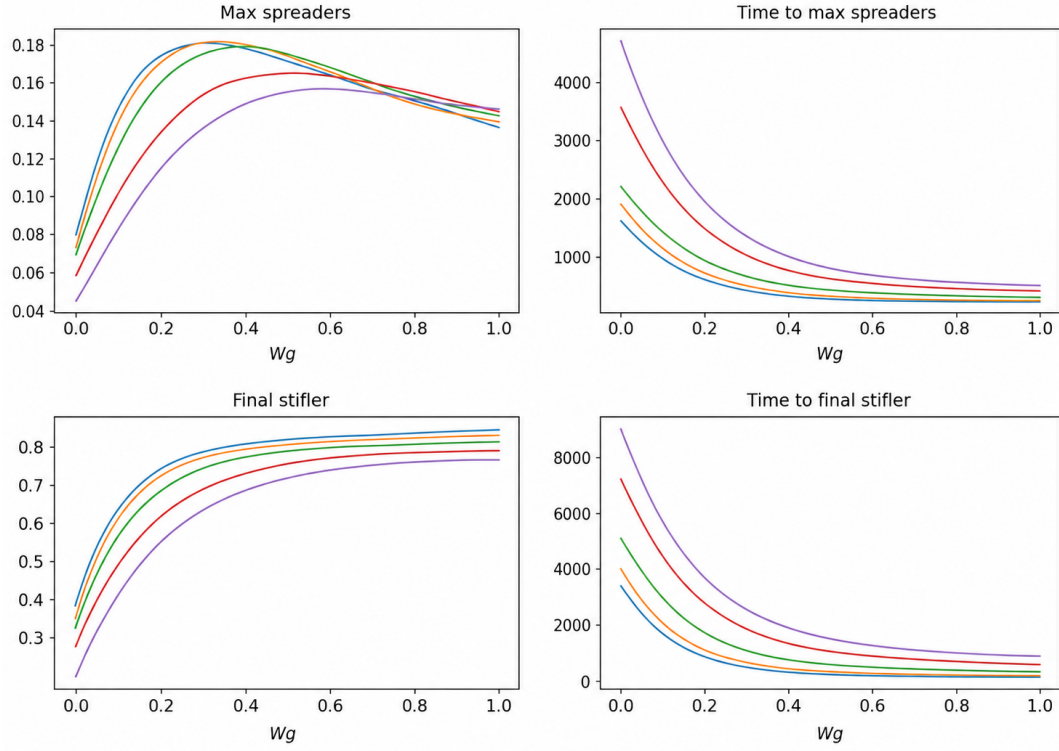


Figure 3.17: Rumour spreading metrics (maximum spreader proportion (top-left), time to maximum spreaders (top-right), final stifler proportion (bottom-left), and time to final stifler (bottom-right)) as a function of intra-community connection probability W_g for community networks with varying numbers of communities N_g . Each curve corresponds to a different N_g value: blue ($N_g = 30$), orange ($N_g = 50$), green ($N_g = 100$), red ($N_g = 200$), and purple ($N_g = 300$).

rumour spreading metrics, plotted against intra-community connection probability (W_g). In the top-left panel, the maximum spreader proportion for all values of N_g shows a characteristic non-monotonic trend, rising to a peak at intermediate W_g values and then gradually declining as W_g increases further. The top-right panel demonstrates that the time to reach maximum spreaders decreases rapidly with increasing W_g , with higher N_g consistently associated with longer times across the entire range. The bottom-left panel shows the final stifler proportion, which increases sharply at low W_g and then saturates at higher values, with higher N_g leading to lower final stifler levels throughout. In the bottom-right panel, the time to final stiflers also decreases monotonically with W_g and increases systematically with N_g .

Specifically, networks with a greater number of communities consistently require a longer time both to reach the maximum number of spreaders and to achieve the final stifler state, across all values of intra-community connectivity W_g . This systematic increase in propagation times with higher N_g can be explained by examining the dependence of node centrality C on the number of communities. Recall that the expected degree centrality in a community network is given by 3.1,

$$C = \frac{W_g N}{N_g} + B_g \left(N - \frac{N}{N_g} \right), \quad (3.9)$$

where W_g and B_g denote the intra- and inter-community connection probabilities, respectively. Taking the derivative of C with respect to N_g , we obtain

$$\frac{dC}{dN_g} = -\frac{N(W_g - B_g)}{N_g^2}, \quad (3.10)$$

Since $W_g > B_g$ in all our experiments, the derivative is negative, indicating that increasing N_g leads to a sharp decrease in expected node centrality. This reduction in local connectivity means information must traverse more boundaries and sparser bridges between communities, thus directly causing the prolonged spreading and equilibration times observed in networks with higher N_g .

On the other hand, the maximum spreader proportion plot reveals a distinctly non-monotonic behaviour for all values of number of communities. At low W_g , when intra-community connectivity is minimal, the differences between curves for varying numbers of communities are modest, with fewer, larger

communities exhibiting higher peak spreading levels. As W_g increases, the maximum spreader proportion for each configuration rises to a peak at intermediate connectivity, indicating that enhanced cohesion within communities initially facilitates more effective rumour propagation. However, as W_g approaches unity, the trend not only reverses, but also indicate various gradient of decline: networks with fewer, larger communities experience a pronounced decline in the maximum spreader proportion, whereas this reduction is much less marked for networks with many smaller communities, resulting in a reversed ordering among curves at $W_g = 1$ compared to at $W_g = 0$.

The negative correlation between the magnitude of decrease in max spreader proportion and number of communities N_g reflects the fact that in highly modular networks, strong intra-community ties create local “trapping” effects, accelerating rumour saturation within individual communities but impeding its transmission between groups due to the persistent sparsity of inter-community links. As a result, the potential for simultaneous spreading across the entire network diminishes sharply in the presence of large, well-connected communities, whereas in more fragmented networks, the impact of increasing intra-community connectivity is comparatively lowered, resulting in a flatter, less pronounced non-monotonic profile.

In conclusion, the results above demonstrate that all four core rumour spreading metrics exhibit consistent qualitative patterns across a range of community numbers (N_g), confirming the robustness of the observed dynamics to changes in network modularity. Specifically, as N_g increases, we observe systematic and predictable effects: propagation times (both to peak spreading and to equilibrium) increase, while maximum spreader and final stifler proportions decrease and become less sensitive to intra-community connectivity. The non-monotonic behaviour and ordering reversal in the maximum spreader proportion, together with the diminished magnitude of decline for high N_g , highlight the interplay between local saturation and global inhibition inherent to modular networks. Collectively, these findings reinforce the conclusion that the internal fragmentation of community networks fundamentally shapes the tempo and reach of rumour propagation by modulating node centrality, clustering, and the effectiveness of inter-community transmission pathways.

3.3 HETEROGENEOUS COMMUNITY SIZE

While previous analyses were conducted under the simplifying assumption of uniformly sized communities, it remains an open question how robust those findings are to variations in community size—a feature ubiquitous in real-world networks. To address this, we systematically introduce heterogeneity into the group size distribution by randomly reassigning a fraction of nodes to different communities, thereby disturbing the initial uniform structure. By examining the resulting distributions of group sizes across varying disturbance levels, we aim to test the stability and generalisability of the patterns identified in the standard model. This approach enables us to assess whether the qualitative behaviours previously observed—such as the effects of modularity on rumour dynamics—persist in the presence of realistic, heterogeneous community sizes.

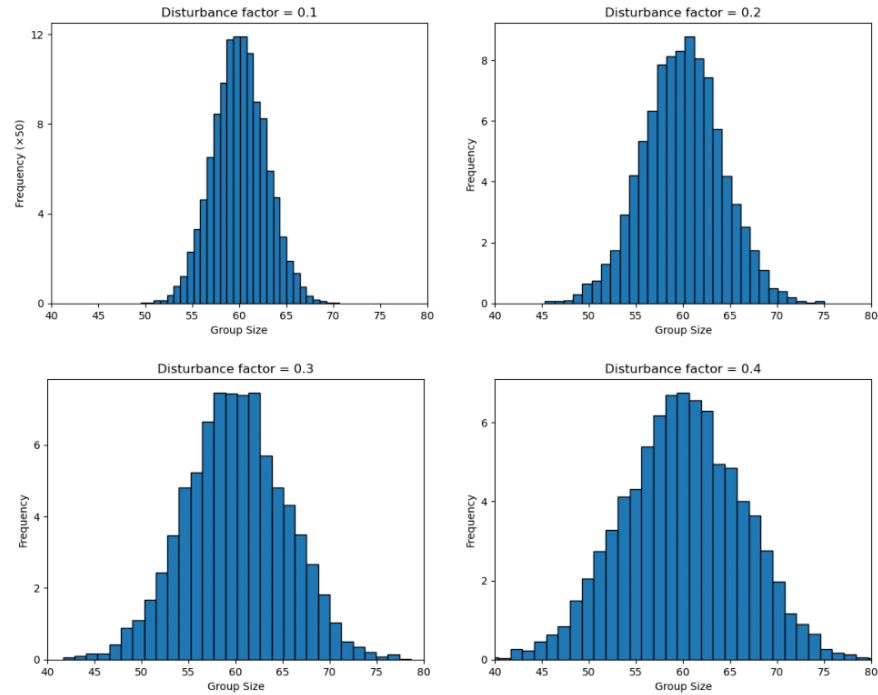


Figure 3.18: Distributions of community sizes resulting from varying levels of group assignment disturbance. Each panel shows a histogram of group sizes aggregated over multiple Monte Carlo runs, with disturbance factors of 0.1, 0.2, 0.3, and 0.4 (top-left to bottom-right).

To rigorously quantify the extent of community size heterogeneity induced by the disturbance procedure, Figure 3.18 displays the empirical distributions of community sizes corre-

sponding to several disturbance factor values. In the baseline configuration, the network is initialised with a perfectly uniform group size distribution. Progressive increases in the disturbance factor result in systematic broadening and increased variance of the distribution of group sizes, reflecting a controlled departure from homogeneity toward greater heterogeneity in community size.

These results validate the effectiveness of the implemented random reassignment algorithm in generating ensembles of networks with tunable group size with the expected distribution, thereby establishing a suitable experimental framework for subsequent robustness analyses of network structural metrics and dynamical processes under realistic, heterogeneous conditions.

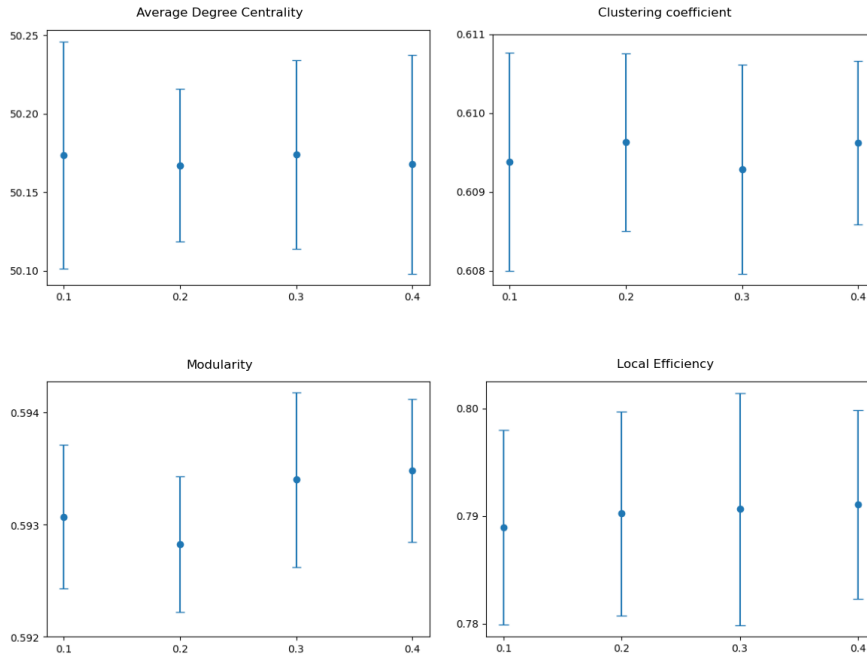


Figure 3.19: Average degree centrality (top-left), clustering coefficient (top-right), modularity (bottom-left), and local efficiency (bottom-right), as a function of the community size disturbance factor. Each point represents the mean value across 20 Monte Carlo simulations, with error bars indicating standard deviation.

Figure 3.19 presents the quantitative response of four canonical network structural metrics—average degree centrality, clustering coefficient, modularity, and local efficiency—to increasing levels of group size disturbance. Despite the substantial broadening of the group size distribution induced by higher disturbance factors, all four metrics remain notably stable across the range

of tested values. The mean values of each metric show no systematic trend and all observed fluctuations are contained within the statistical variability of the Monte Carlo sampling.

This invariance indicates that, for the edge-generation protocol used—where community assignments are first disturbed and then edges are constructed according to the resultant heterogeneous group structure—the fundamental topological properties of the network are largely robust to moderate levels of community size heterogeneity. Both local properties (average degree and clustering coefficient) and global measures (modularity and local efficiency) maintain their characteristic values, suggesting that neither the cohesion of local neighbourhoods nor the broader modular organization and efficiency of the network are significantly compromised by deviations from uniform community size.

Collectively, these findings provide strong evidence that key topological characteristics of the network are robust to controlled, post hoc variations in group size distribution. This structural resilience reinforces the generalisability of earlier results obtained under uniform community assignments, and justifies the extension of previously observed dynamical behaviours to more realistic, heterogeneous contexts.

Figure 3.20 displays the four principal rumour spreading metrics—maximum spreader proportion, time to maximum spreaders, final stifter proportion, and time to final stiflers—as functions of intra-community connection probability, across networks generated with a range of community size disturbance factors. Remarkably, the curves corresponding to different disturbance levels are nearly indistinguishable in all panels, indicating a high degree of robustness in the spreading dynamics with respect to heterogeneity in community size.

This pronounced overlap demonstrates that, even when substantial variability is introduced into the group size distribution, the global features of rumour propagation—including the overall speed, intensity, and eventual coverage—remain virtually unchanged. The observed invariance across all disturbance levels suggests that the qualitative patterns identified in the standard, homogeneous case persist even under realistic levels of group size heterogeneity. These findings provide compelling evidence that the collective behaviour of rumour spreading in community networks is predominantly governed by higher-level structural properties, and is insensitive to moderate deviations from uniform community size.

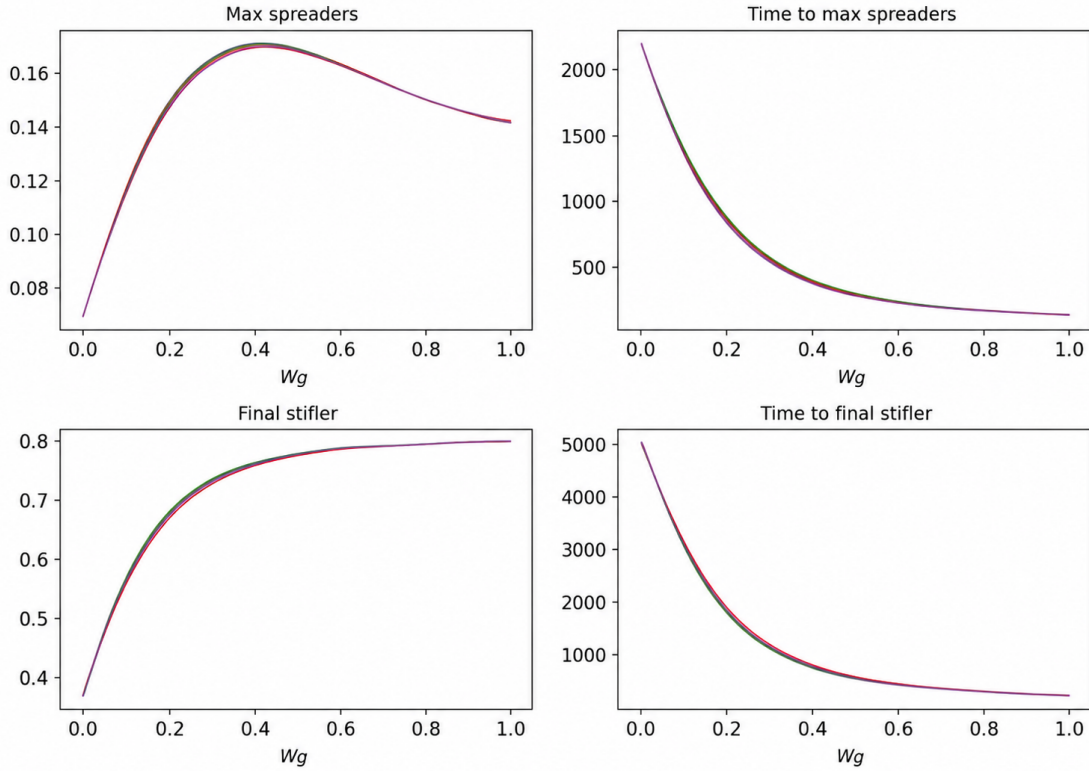


Figure 3.20: Max spreader proportion (top left), time to max spreaders (top right), final stifler (bottom left) and time to final stifler (bottom right) against intra-prob W_g for community networks with disturbance factor = 0 (standard network)—green, 0.1—blue; 0.2—orange; 0.3—red; 0.4—purple

Transition rate The role of intrinsic process rates in shaping rumour dynamics is a central question in information diffusion research. In this context, the spreading-stifling ratio (β) acts as a critical control parameter for the temporal and spatial characteristics of propagation. By explicitly tuning β , we are able to probe the sensitivity of observed network effects and ascertain whether the moderation of rumour intensity and speed in community structures is a robust phenomenon or contingent on specific parameter regimes. To investigate the parameter dependence of our earlier results, we systematically vary the spreading-stifling ratio, β , and examine the corresponding effects on the main rumour dynamics metrics. This allows us to determine whether the qualitative behaviours identified in community networks—such as the moderation of peak intensity and delay in rumour saturation—are intrinsic features of network modularity or are specific to certain parameter settings. Through this analysis, we seek to

provide a more comprehensive understanding of the stability and generalisability of our findings across a broad spectrum of process dynamics.

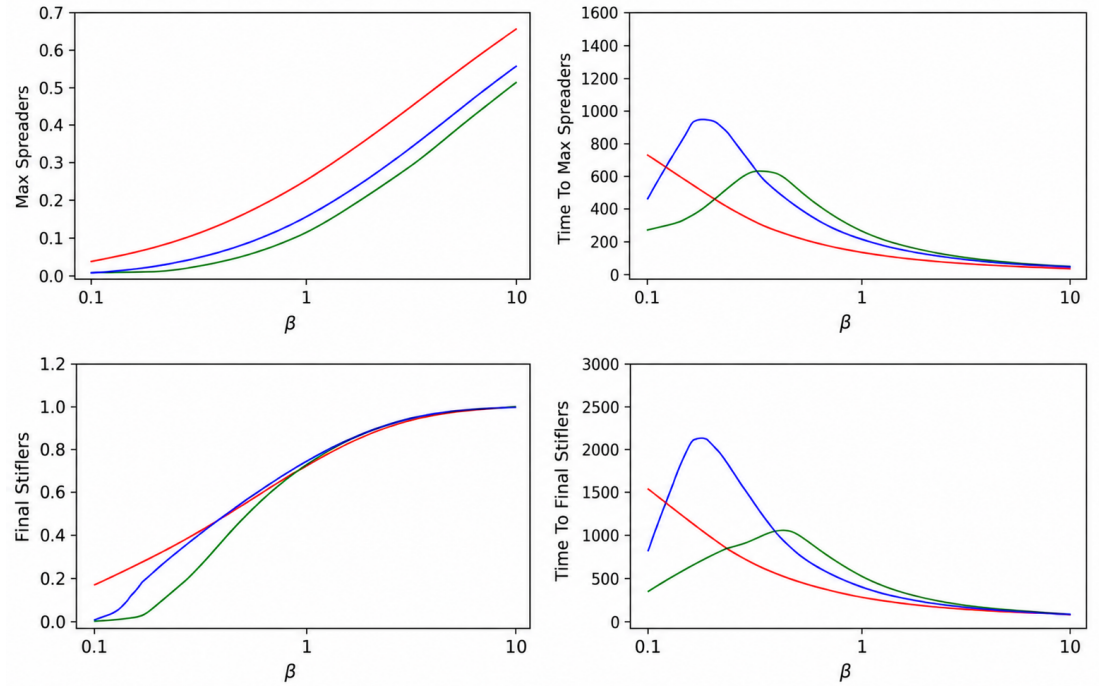


Figure 3.21: Max spreader proportion (top left), time to max spreaders (top right), final stifler (bottom left) and time to final stifler (bottom right) for community (green), random (red) and small-world (blue) networks against β . $W_g = 0.8, B_g = 0.005, \beta = (0.1, 10)$

Figure 3.21 shows the four rumour metrics (max spreader proportion (top left), time to max spreader (top right), final stifler ratio (bottom left) and time to equilibrium (bottom right)) against ratio of spreading and stifling rates, β , from 0.1 to 10. At $\beta = 1$, it is clear that community network (green) has the lowest max spreader proportion and longest time to both max spreader and time to final stifler; random network (red) exhibits the highest rumour intensity and spreading speed; small-world network (blue) lying between community and random network. Also, the final coverage of rumour over the three networks is consistent. These relative observations are expected according to 3.10. However, these trends do not always hold across the β domain in every metric. For instance, in both the time to max spreader and time to final stifler metrics, the differences among the three networks diminish as β increases, eventually converging at high β values. However, at low β , the community

and small-world networks exhibit a distinct non-monotonic trend. Initially, both networks start at lower values compared to the random network, but then display an increasing pattern, whereas the random network follows a strictly decreasing curve.

Additionally, despite the overall converging tendency as β increases, the final stifler proportion demonstrates notable differences across the three networks in the lower β regime, which is inconsistent with their relative behaviour observed at $\beta = 1$. Notably, the community network exhibits an apparent threshold behaviour in the final stifler metric at low β , which can be attributed to a local saturation effect. Specifically, in networks with high clustering, rumour propagation is constrained within localised communities, leading to rapid stifling before the rumour can diffuse to other clusters. This mechanism explains the observed non-monotonic trajectories in time to max spreader and time to final stifler for the community and small-world networks.

The underlying process can be interpreted as follows: for a given spreader, the presence of a high fraction of informed neighbours within a densely clustered local community increases the likelihood of transitioning into the stifler state before the rumour can escape to other communities. This effect is particularly pronounced in the low β regime, where the spreading rate is significantly lower than the stifling rate. As a result, the overall lifespan of the rumour spreading process is compressed in this regime. If the local saturation effect were absent, the three networks would have exhibited a relative positioning in the low β regime that is consistent with their behaviour in the mid-range β regime.

Furthermore, the reduction in time to max spreader and time to final stifler is more pronounced in the community network than in the small-world network. This can be attributed to the higher degree of clustering in the community network, as reflected in Figure 3.12, 3.11 and 3.13. Thus, we hypothesize that in networks characterised by high clustering and strong community structures—such as the community-based networks investigated in this study—the spread of rumours is significantly constrained by a local inhibitive effect at low values of the transmission-to-stifling ratio, β . Specifically, when the spreading rate is relatively low compared to the stifling rate (low β), spreaders are rapidly converted into stiflers within their local clusters due to repeated interactions with already informed neighbours. This mechanism leads to the premature saturation

of rumour diffusion within local communities, inhibiting the propagation of the rumour to other parts of the network. As β increases, the spreading force overcomes this local inhibition, facilitating the transmission of rumours beyond community boundaries and triggering a critical transition from localised diffusion to global spreading. We propose that the severity of this local inhibitive effect is positively correlated with the degree of clustering in the network. Consequently, the community-based network exhibits a more pronounced threshold behaviour compared to random and small-world networks. Therefore, in the subsequent analysis, we investigate whether this pattern persists across varying levels of clustering by systematically adjusting the network parameter W_g , which controls the intra-community connectivity. This enables us to evaluate the relationship between clustering strength and the severity of the local inhibitive effect.

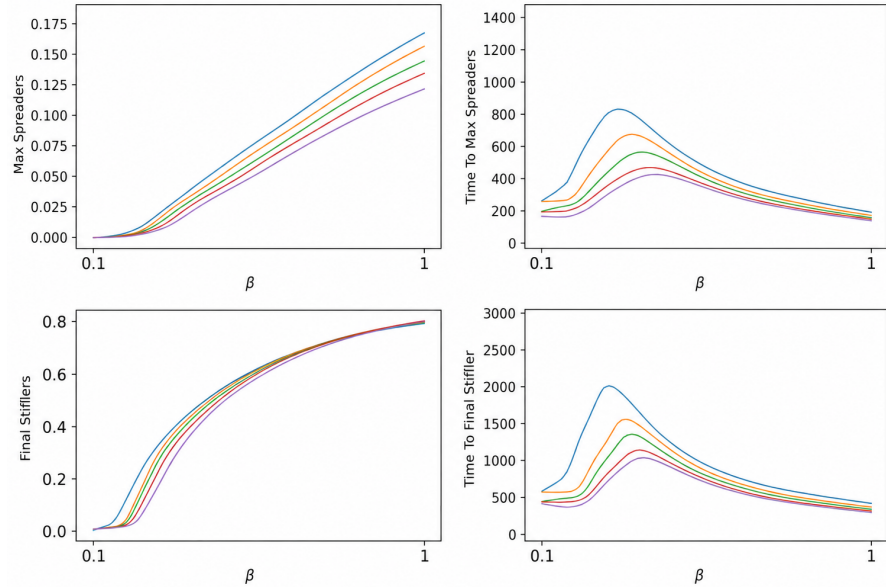


Figure 3.22: Max spreader proportion (top left), time to max spreader (top right), final stifler (bottom left) and time to final stifler (bottom right) in community network against β from 0 to 1, with $W_g = 0.6$ (blue), 0.7 (orange), 0.8 (green), 0.9 (red), 1.0 (purple)

Figure 3.22 presents the 4 rumour metrics—maximum spreader proportion, time to maximum spreaders, final stifler proportion, and time to final stiflers—as functions of the transmission-to-stifling rate ratio (β), while varying the intra-community connectivity parameter (0.6 (blue), 0.7 (orange), 0.8 (green), 0.9 (red), 1.0

(purple)). The analysis is conducted solely on the community network, as previous results have demonstrated that threshold behaviour is most pronounced in this network type.

Across all four metrics, the curves exhibit a transition behaviour in the low β range, particularly at higher values of W_g . This threshold behaviour aligns with the previously identified local saturation effect, where high clustering leads to early rumour suppression before it propagates beyond local groups.

For all values of W_g , the maximum spreader proportion increases monotonically with β , consistent with higher transmission rates favouring rumour propagation. Also, the curves exhibit a prolonged low plateau at lower β values before rising, with the length of the plateau increasing as W_g increases. This suggests that in networks with higher clustering, the rumour struggles for a longer range of β values to break through the local saturation effect and initiate widespread diffusion. This restricts the peak fraction of spreaders in highly clustered networks.

Time to max spreader and time to final stifler present consistent pattern: they increase initially as β rises, reaching a peak and then decline as β continues to grow, with the difference between each W_g value sees a converging trend. Notably, the turning point shifts to higher β values as W_g increases. This shift implies that in more clustered networks, the rumour remains trapped within local communities for a wider range of β , further delaying the transition from localised containment to global dissemination.

In the final stiflers metric, a similar delay is evident. Networks with higher W_g require higher β values to achieve comparable levels of stifler saturation, reinforcing the notion that strong local clustering inhibits rumour propagation until a sufficiently high transmission rate is achieved.

These observations point to a positive relationship between the degree of clustering and the magnitude of threshold behaviour. The fact that higher clustering levels consistently correspond to:

- Longer plateau regions at low β
- Higher turning points on the β axis for peak spreading and stifling dynamics
- Greater resistance to rumour spread at low transmission rates

The results strongly support the interpretation that the threshold phenomenon arises from the local saturation effect induced by high clustering. In highly clustered networks, spreaders are more likely to be surrounded by informed neighbours, increasing the probability of becoming stiflers before the rumour can escape the local community. This dynamic effectively suppresses early-stage diffusion, creating a threshold that must be overcome by increasing β (enhancing the relative strength of spreading over stifling).

3.4 SUMMARY

In this chapter, we developed and examined the stochastic rumour-spreading model across three network structures—community, small-world, and random networks. We began by characterising their topological properties through network metrics such as the clustering coefficient and local efficiency. The results confirmed that community networks exhibit the highest degree of local cohesiveness under the high W_g low B_g regime.

We then implemented a series of simulations to analyse how the network topology influences the rumour dynamics under baseline parameterisation. Specifically, we evaluated four key rumour metrics: the maximum spreader proportion, time to maximum spreader, final stifier proportion, and time to equilibrium. The results showed that network structure plays a decisive role in shaping both the speed and extent of information propagation. We identified a clear threshold phenomenon driven by local saturation effects, where spreaders in densely connected communities tend to encounter informed neighbours early and transition into stiflers before the rumour escapes their local group. We further tested the robustness of these findings by varying critical parameters such as the population size N and intra-community connectivity W_g . The results demonstrated that the observed trends—particularly the threshold behaviour—remain stable across different scales and structural intensities. This consistency reinforces the generality of the model's conclusions regarding the negative relationship between clustering and diffusion efficiency.

STOCK PRICE MODEL

4.1 INTRODUCTION

This chapter develops the stock price formation mechanism that integrates the rumour-spreading dynamics introduced in the previous chapter with an agent-based financial market model. The primary objective is to examine how the diffusion of takeover-related information influences trading behaviour and, consequently, the evolution of stock prices prior to public announcement.

To achieve this, we construct a market framework consisting of heterogeneous agents, including value investors and trend-following traders, whose decisions are driven by both fundamental beliefs and observed price dynamics. In particular, the model incorporates the effect of rumour acquisition on agents' perceived intrinsic value of the asset, linking the information diffusion process directly to trading activity.

The key research questions addressed in this chapter are as follows: (i) how does rumour propagation affect individual trading decisions; (ii) how do interactions between heterogeneous agents translate into aggregate market behaviour; and (iii) how does this mechanism generate price dynamics consistent with the pre-takeover drift observed in empirical studies.

The remainder of this chapter is structured as follows. Section 4.2 introduces the behavioural assumptions of different agent types. Section 4.3 presents the trading rules and demand functions. Section 4.4 develops the price formation mechanism. Section 4.5 describes the parametrisation and simulation setup. Together, these components form a unified framework linking network-based information diffusion to endogenous stock price dynamics.

4.2 FEASIBILITY OF AGENT-BASED MODELLING IN PRE-TAKEOVER DRIFT ANALYSIS

As demonstrated in empirical studies, mainstream research attributes pre-takeover stock price anomalies to two primary

factors: insider leakage and rational market anticipation [48]. Insider leakage occurs when privileged information about a forthcoming takeover is selectively disseminated among certain market participants, influencing their trading behaviour ahead of the official announcement [17]. Rational anticipation, on the other hand, arises when uninformed traders infer the likelihood of a takeover by observing unusual trading activity and price trends, adjusting their strategies accordingly [41].

Despite broad consensus on the relevance of these two mechanisms, quantifying their individual contributions remains a significant empirical challenge. The practical difficulty in distinguishing trades driven by insider leakage from those motivated by rational anticipation complicates any direct attribution in real-world data [39, 42]. Consequently, the extent to which pre-takeover drift is caused by each mechanism remains in a nebulous zone, is imprecisely estimated, and is often not rigorously separated in empirical analyses. However, it is well-established that both mechanisms collectively shape the observed pre-event price behaviour [28]. Given this complexity, it is crucial to adopt a modelling approach that robustly integrates both mechanisms rather than isolating one at the expense of the other. Traditional empirical methodologies that focus solely on either information asymmetry (insider leakage) or trend-following behaviour (anticipation) risk oversimplifying the dynamics at play. A more comprehensive framework that explicitly accounts for the co-existence and interplay of these forces is essential for a more realistic and analytically sound representation of pre-takeover drift.

To address these challenges, we employ an agent-based model, a methodological approach particularly well-suited for capturing heterogeneous trading behaviours, information diffusion, and emergent price dynamics. The pre-takeover price drift phenomenon is characterised by abnormal stock price behaviour preceding a takeover announcement. Empirical studies suggest that this drift is primarily driven by two key mechanisms: insider leakage and rational market anticipation. These mechanisms involve complex interactions among heterogeneous market participants, leading to deviations from standard equilibrium-based financial models. Agent-based modelling (ABM) provides a natural and effective framework for replicating these dynamics. The feasibility of ABM in studying pre-takeover drift is supported by the following commonalities:

- **Non-Gaussian Return Distributions:** Empirical studies on pre-takeover price movements reveal deviations from normal return distributions, often characterised by heavy tails, clustered volatility, and excess kurtosis. These statistical properties indicate the presence of nonlinear dependencies and emergent behaviours in financial markets. ABM was originally introduced to explain such anomalies, particularly non-normal short-term price fluctuations and correlated volatility, which traditional equilibrium-based models struggle to capture [90]. Therefore, ABM is well-suited for addressing these irregularities, as it inherently generates non-normal short-term price fluctuations and correlated volatility patterns through agent-level decision-making and market interactions [89]. The presence of extreme return events and volatility clustering in both pre-takeover markets and ABM simulations underscores their common foundation in decentralised, dynamic market structures.
- **Emergent Price Formation:** Traditional financial models often assume equilibrium pricing, but pre-takeover drift represents a disequilibrium process where price adjustments occur gradually as information spreads. From a microeconomic perspective, markets are composed of decentralised decision-makers, each responding to available information and interacting through price mechanisms. ABM aligns naturally with this framework by explicitly modelling individual agent behaviours and their interactions. This allows us to observe how a collection of small-scale trading decisions aggregate into large-scale price trends, demonstrating an emergent market dynamic that would be difficult to capture using traditional top-down approaches.
- **Heterogeneous Trading Strategies:** Pre-takeover drift emerges as a result of different types of traders acting on distinct motivations—some investors act on leaked information, while others react to price movements and trading volumes. This heterogeneity in trading behaviour leads to non-uniform price dynamics, where different agents contribute to the gradual adjustment of stock prices before the official takeover announcement. ABM explicitly captures this heterogeneity by classifying agents into distinct behavioural types, principally value investors and trend

followers, each with unique decision-making processes. Value investors, who base their trades on fundamental valuation, adjust their intrinsic value assessments as they incorporate newly acquired (often privileged) information about the takeover target. On the other hand, trend followers rely on market signals rather than fundamental insights, trading inferentially based on price momentum, observed volume spikes, and large institutional trades. Their behaviour aligns with rational anticipation, as they attempt to capitalise on emerging patterns that suggest an impending acquisition without direct knowledge of the event.

- **Information-Driven Market Dynamics:** The takeover process involves a high degree of information asymmetry, where some market participants gain early access to deal-related information while others infer it from trading patterns. The decentralised nature of agent interactions aligns well with the fragmented and asymmetric dissemination of takeover-related information in financial markets. ABM is well-suited for modelling information diffusion, as it allows agents to dynamically update their beliefs based on their network connections and trading observations. This mimics the way real-world traders react to both direct and indirect takeover signals.

In summary, by incorporating heterogeneous trading behaviours, information flow, and emergent price dynamics, ABM can effectively reconstructs the pre-takeover drift phenomenon.

4.3 AGENT BEHAVIOURS

Agents are classified into two distinct types according to their behavioural strategies: Value Investors (Fundamentalists) who adjust their behaviour according to the perceived mispricing of the stock; Trend Followers (Chartists), who do not assess fundamental value but rather react to past price movements.

We use value investors as a proxy for the information leakage mechanism in pre-takeover market dynamics because their trading behaviour reflects the structured dissemination of private information. Insider trading does not occur in isolation but rather functions as a contagion process, where private knowledge of an impending acquisition gradually spreads beyond the original insiders [46]. While legally defined insiders—such as

corporate executives and board members—are the primary holders of non-public information, this privileged knowledge rarely remains confined within a small group [95]. Instead, whether actively transmitted or passively diffused, it flows toward other financially sophisticated participants, including institutional investors, hedge funds, and strategic traders. These secondary recipients, while not insiders themselves, gain access to selectively leaked information through informal channels, such as shared board memberships, investment banking relationships, legal advisory roles, and industry affiliations [95]. Value investors, particularly those operating at an institutional level, align closely with this category of informed traders, as their decision-making process is fundamentally driven by assessing intrinsic value based on both publicly available financial data and privileged insights obtained through these indirect connections. Unlike traders who act purely on historical price trends, value investors do not infer takeover probabilities from observable market movements; rather, they respond to direct yet selectively distributed information that influences their valuation models. A key characteristic of value investing is that intrinsic value is not arbitrarily estimated but carefully assessed through professional financial analysis, industry research, and strategic intelligence. This assessment extends beyond standard public disclosures—such as earnings reports and macroeconomic indicators—to incorporate privileged insights obtained through social and professional networks. Institutional investors, hedge fund managers, and other sophisticated market participants often maintain informational advantages through their ties to board members, investment bankers, legal advisors, and industry executives, enabling them to anticipate market-moving events such as takeovers before they become publicly known.

As insider knowledge trickles outward, value investors become key facilitators of pre-takeover price drift, reflecting the broader dissemination of non-public information through interconnected financial networks. Their reliance on privileged information as a core component of their valuation strategy underscores the suitability of using value investors as a representative factor for insider leakage in agent-based modelling. Unlike purely reactive traders, they actively participate in the market-wide incorporation of material private information, reinforcing the role of asymmetric knowledge in shaping pre-takeover stock price dynamics.

On the other hand, we use trend followers as a proxy for the rational anticipation mechanism in pre-takeover market dynamics because their trading behaviour aligns with anticipatory strategies that rely on observed price movements rather than material information. Rational anticipation refers to the market phenomenon where traders, despite lacking direct access to privileged information, act on probabilistic inference—interpreting sudden price surges, large block transactions, or elevated volume as subtle indicators of an impending takeover. Trend followers make trading decisions based on price trends, often buying when prices rise and selling when they fall. They are particularly responsive to upward momentum and unusual trading activity, which they interpret as potential signals of continued price movement. This form of behaviour closely mirrors the reaction patterns seen in rational anticipators. Both groups initiate trades in response to abnormal price and volume dynamics, often doing so at an early stage of the market adjustment process. In this way, trend followers and rational anticipators share a common trigger: the recognition of emerging trends based on past market data. It is this shared reliance on historical price behaviour that motivates the use of trend followers as a proxy for rational anticipators in our model.

Although the underlying rationale behind their actions may differ, their presence in the market contributes similarly to the amplification of price momentum prior to takeover announcements. While this behavioural overlap justifies the use of trend followers as a proxy for rational anticipators in our model, it is important to recognize the conceptual distinction between the two. Rational anticipators are typically characterised by their strategic and probabilistic reasoning. They attempt to infer potential corporate events, such as takeovers, by analysing a broad range of indirect market signals—large institutional trades, sector-wide consolidation patterns, or sustained undervaluation. Their trading reflects a calculated interpretation of market conditions and is grounded in speculative assessment rather than fixed heuristics.

Trend followers, in contrast, do not engage in such interpretive analysis. Their decisions are based on mechanical rules that track past price movements, assuming that positive momentum will continue regardless of the underlying cause. They do not evaluate whether a stock is undervalued or if a takeover is imminent; they simply respond to patterns in the price data itself. This conceptual gap underscores that while the two groups may

behave similarly in practice, their actions arise from fundamentally different decision-making processes. Given this distinction, the decision to model rational anticipators using trend-following agents reflects a pragmatic simplification rather than a conceptual equivalence. While trend followers do not replicate the reasoning processes of rational speculators, their sensitivity to abnormal price patterns makes them suitable for capturing the market's anticipatory response to early trading signals. This modelling approach allows for the generation of price momentum in response to initial signals—whether informed or speculative—without requiring agents to explicitly form beliefs about potential takeovers. As such, the use of trend-following agents offers a tractable means of incorporating anticipatory behaviour into the model, while remaining consistent with observed trading patterns during pre-takeover periods.

Thus, just as rational anticipation describes the process by which uninformed traders respond to market-generated signals, trend followers systematically align their strategies with emerging price patterns. Their role in magnifying momentum effects and reinforcing price drift underscores their suitability as a proxy for modelling rational anticipation in an agent-based framework.

For clarity, the key characteristics of the two agent types are summarised in the table below.

As a result, in this model, the information diffusion network is constructed exclusively among value investors. This assumption reflects the role of value investors as information-sensitive agents who acquire and share takeover-related rumours through their interactions. Trend followers are not included in the network, as their trading decisions are driven solely by observed market trends and do not depend on the rumour diffusion process.

4.4 AGENT-BASED MODEL

4.4.1 *Price Formation Mechanism*

We model stock price dynamics as an outcome of aggregate trading activity generated by heterogeneous agents. At each time step, agents submit buy or sell orders based on their individual strategies, resulting in an imbalance between demand and supply. This imbalance, referred to as net order or excess demand, drives price adjustments in the market. Intuitively, when aggregate demand exceeds supply, the price increases, whereas

Table 4.1: Summary of agent types and behavioural assumptions

Feature	Value Investors (Fundamentalists)	Trend Followers (Chartists)
Decision basis	Intrinsic value and perceived mispricing	Past price movements and trends
Information source	Public information and indirectly acquired private information	Observable market data (price and volume)
Role in model	Proxy for information leakage (insider-driven dynamics)	Proxy for rational anticipation (market-based inference)
Trading behaviour	Buy undervalued assets, sell overvalued assets	Buy when prices rise, sell when prices fall
Reaction trigger	Changes in perceived fundamental value	Emerging price trends and momentum
Information type	Direct or indirectly transmitted information	Inferred signals from market activity
Decision process	Analytical and valuation-driven	Rule-based and reactive
Effect on price dynamics	Gradual incorporation of private information	Amplification of price momentum

an excess of sell orders leads to a price decline.

This framework captures the fundamental mechanism of price formation in financial markets, where prices respond endogenously to the collective behaviour of interacting agents. In the following, we formalise this mechanism by linking individual trading decisions to aggregate order flow and, subsequently, to price dynamics.

Each agent i holds a position $x_t^{(i)}$ at time t , representing the quantity of the asset held by the agent. Trading activity is characterised by changes in these positions over time. The net order submitted by agent i at time t , denoted by $\omega_t^{(i)}$, is defined as the change in position between two consecutive time steps:

$$\omega_t^{(i)} = x_t^{(i)} - x_{t-1}^{(i)}.$$

A positive value of $\omega_t^{(i)}$ corresponds to a buy order, while a negative value represents a sell order. The aggregate net order in the market, denoted by Q_t , is obtained by summing individual orders across all agents:

$$Q_t = \sum_i \omega_t^{(i)}.$$

This aggregate net order captures the overall imbalance between demand and supply in the market and serves as the key driver of price dynamics.

Price impact function The relationship between aggregate net order and price adjustment is modelled through a price impact function. Specifically, the price at time t is assumed to evolve as a function of the previous price and the net order imbalance:

$$P_t = P_{t-1} \cdot \exp(f(Q_t)),$$

where $f(Q_t)$ is a general function describing how excess demand affects price changes. This formulation reflects the idea that prices respond to the imbalance between buy and sell orders, with the functional form $f(\cdot)$ capturing the sensitivity of price to aggregate trading activity. In what follows, we specify a particular functional form for $f(Q_t)$ to obtain a tractable representation of price dynamics.

To obtain a tractable specification, we assume a linear price impact function of the form

$$f(Q_t) = \gamma Q_t,$$

where $\gamma > 0$ measures the sensitivity of the price to aggregate net order. Under this assumption, the price dynamics become

$$P_t = P_{t-1} \exp(\gamma Q_t).$$

Taking logarithms on both sides yields

$$\log P_t - \log P_{t-1} = \gamma Q_t.$$

Thus, the logarithmic rate of change in price is proportional to the aggregate net order submitted by market participants. To incorporate exogenous market fluctuations unrelated to agent interactions, we further add a stochastic noise term ϵ_t , so that the return equation becomes

$$r_t = \log P_t - \log P_{t-1} = \gamma Q_t + \epsilon_t.$$

This form provides a simple price formation rule in which excess demand generated by heterogeneous agents is translated directly into log-price changes.

Net order flow In the present model, aggregate net order arises from the combined activity of value investors and trend followers. Let $\omega_{i,t}^V$ denote the net order submitted by value investor i at time t , and let $\omega_{j,t}^T$ denote the net order submitted by trend follower j at time t . The total net order in the market is then given by

$$Q_t = \sum_{i=1}^{N_V} \omega_{i,t}^V + \sum_{j=1}^{N_T} \omega_{j,t}^T,$$

where N_V and N_T denote the numbers of value investors and trend followers, respectively.

This decomposition makes explicit that price dynamics in the model are driven by the interaction of two distinct behavioural mechanisms. Value investors contribute orders based on perceived mispricing relative to intrinsic value, while trend followers contribute orders based on observed price momentum. The aggregate market outcome therefore reflects the joint effect of information-driven trading and trend-based trading.

4.4.2 Trend Follower

In our agent-based model, traders are broadly categorised into two groups: *Value Investors*, who rely on assessments of intrinsic

value and fundamental analysis, and *Trend Followers*, who base their trading decisions on observed price movements and market momentum. Trend followers represent the mechanism of rational anticipation, whereby traders react to evolving market conditions and emerging trends without necessarily possessing privileged information.

Trend followers are a well-documented class of market participants whose trading behaviour is characterised by positive feedback [27]. They tend to buy assets when prices are rising and sell when prices are falling, reinforcing existing trends. This behaviour is often referred to as momentum trading or chartist behaviour, in contrast to fundamental analysis. The rationale behind trend-following strategies lies in the belief that past price movements provide predictive signals for future prices. In essence, trend followers assume that "the trend is your friend"—if prices have been moving in one direction, they are likely to continue moving in that direction, at least in the short to medium term.

In the context of pre-takeover price dynamics, trend followers play an essential role in amplifying and accelerating price movements triggered by initial informed trading or rumour spreading. As value investors adjust their trading behaviour in response to private information regarding a potential acquisition, the resulting price changes create observable market signals—such as increasing prices and elevated trading volumes. Trend followers respond to these signals, initiating trades that further drive the price in the same direction.

This positive feedback loop can lead to a self-reinforcing cycle:

1. Price increases attract trend followers.
2. Trend follower demand pushes the price higher.
3. Rising prices attract additional trend followers and momentum traders.

This process results in:

- **Amplified price trends**, contributing to the pre-takeover drift.
- **Volatility clustering**, as trend followers may overreact to perceived trends.
- **Increased trading volume**, particularly in periods preceding public takeover announcements.

Trend followers open positions when they detect a trend over their time horizon Θ_i . The strength of their response is proportional to the magnitude of the price change over that period. Empirical and theoretical studies, including Farmer and Joshi [96], demonstrate that the presence of trend followers has profound implications for market dynamics:

- Trend followers amplify low-frequency noise, causing prices to exhibit persistent trends.
- They contribute to positive short-term autocorrelation in returns.
- In periods of high participation, trend-following behaviour can induce excess volatility and even price instability.

In pre-takeover scenarios, the interplay between value investors—acting on privileged information—and trend followers—reacting to price signals—creates a distinctive price pattern. The initial drift, often based on insider trading or informed speculation, is amplified by trend-following traders who drive the price away from its fundamental value, contributing to the pre-takeover price run-up commonly observed in empirical studies. To conclude, trend followers serve as an important amplification mechanism in our model. By reacting to observable price patterns rather than intrinsic value, they reinforce market trends and contribute to the emergence of abnormal price behaviour. Their role is particularly significant in pre-takeover market conditions, where price momentum can signal impending corporate actions to uninformed market participants, triggering widespread speculative trading. Having established the behavioural rules governing trend followers in our model, we now turn to their implications for market dynamics. Specifically, we examine how the trading activity of trend followers influences price volatility and return characteristics over time.

To reflect the diversity commonly observed among technical traders in financial markets, the trend followers in the model are heterogeneous in several key behavioural parameters:

- **Trend Thresholds:** Each trend follower is assigned an individual threshold level, representing the minimum price movement required to trigger a response. These thresholds are randomly drawn from a uniform distribution over a specified range, ensuring that some agents are more sensitive to minor price movements, while others act only in response to more substantial trends.

- **Sensitivity Parameters:** Once a trend signal exceeds the individual agent's threshold, the degree to which they amplify their position, is governed by a personalised sensitivity coefficient. Agents with higher sensitivity magnify their positions more aggressively in response to trends, while those with lower sensitivity adjust their positions more cautiously. These sensitivity parameters are also randomly assigned from a predefined distribution.
- **Time Horizons (Θ_j):** Each trend follower evaluates price trends over different historical time windows, representing varying investment horizons. The model assigns each agent a Θ value, determining how many previous time steps are considered when calculating recent price changes. This heterogeneity leads to a richer dynamic in which short-term and long-term trend followers coexist, responding to different features of the price path.

The resulting demand from each trend follower at any given time is a function of the observed price change over their specific time window, adjusted for their individual threshold and amplified by their personalised sensitivity parameter. This behaviour can be formalised as:

$$\omega_t^{(j)} = \begin{cases} C_{\text{trend}} \cdot \left(e^{s_j \cdot (|\Delta p_j(t)| - \tau_j)} - 1 \right) \cdot \text{sign}(\Delta p_j(t)), & \text{if } |\Delta p_j(t)| > \tau_j \\ 0, & \text{otherwise} \end{cases}.$$

- $\omega_t^{(j)}$ is the position of trend follower j at time t .
- s_j is the sensitivity parameter for agent j .
- τ_j is the individual trend threshold for agent j .
- $\Delta p_j(t) = \log P_t - \log P_{t-\Theta_j}$ is the price change over the agent's look-back period Θ_j .
- C_{trend} is a scaling factor common to all trend followers.

By incorporating heterogeneity in key behavioural parameters—such as sensitivity to price trends and individual thresholds for trend activation—the model reflects a more empirically grounded distribution of trend-following behaviour observed in financial markets. This layered response dynamic introduces richer feedback effects into the price formation process, where early movers can amplify nascent price movements and later

responders may reinforce or counteract those trends depending on broader market conditions. Such diversity in agent behaviour not only enhances the realism of the model but also allows for a nuanced exploration of how micro-level trading rules translate into macro-level price patterns.

4.4.3 Value Investor

Value investors operate under the fundamental assumption that market prices do not always reflect the intrinsic value of an asset. Their strategy is built on the premise that, over time, prices will revert to their true value as market participants correct mispricing [94]. To interpret this trading behaviour in an agent-based framework, we adopt a state-dependent threshold-based strategy, where an investor's decision to trade is triggered by pre-defined mispricing thresholds. In brief, traders have heterogeneous thresholds for entering and exiting positions. This ensures a limited trading frequency, where a position is entered only when the mispricing is sufficiently large and exited when it becomes small enough to justify overcoming transaction costs. Mathematically, we define the mispricing at time t as:

$$m_t = \log P_t - \log v_t, \quad (4.1)$$

where:

- P_t represents the observed market price at time t .
- v_t represents the investor's perceived intrinsic value at time t .

A value investor follows a position-adjustment rule based on entry and exit thresholds:

- If the trader is currently in no position and the mispricing exceeds an upper threshold T , he/she initiates a short position (selling the asset).
- If the trader is currently in no position and the mispricing falls below a lower threshold $-T$, he/she enters a long position (buying the asset).
- If the trader is in a short position and the mispricing returns within a smaller exit threshold τ , he/she exits the short position.

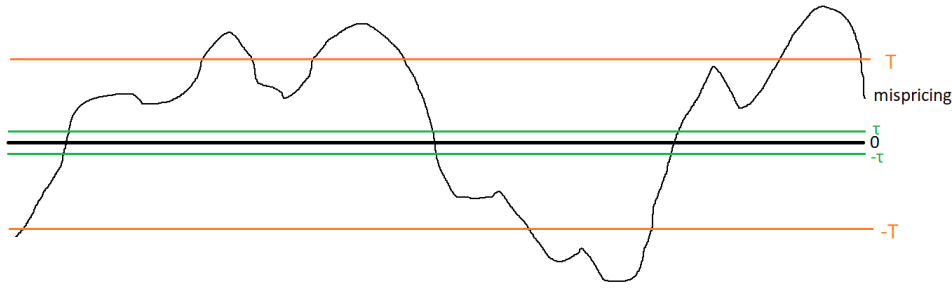


Figure 4.1: Schematic view of a threshold-based trading strategy Black line in middle is $m_t = 0$ benchmark where price is equal to value; orange lines represent entry threshold $\pm T$ and green lines represent exit threshold $\pm \tau$

- And if the trader is in a long position and the mispricing returns within a smaller exit threshold $-\tau$, he/she exits the long position.

As shown in Figure 4.1, the curved black line represents the deviation of the market price from its fundamental value over time. The horizontal black line represents the benchmark, 0, level where price and value are perfectly aligned, meaning no mispricing. When the mispricing line moves above zero, it indicates overvaluation (i.e., the price is higher than the perceived intrinsic value). When it exceeds the entry threshold T , the fundamentalist with no current position can enter a short position and hold it until it drops below τ , at which point they can exit the short position, in anticipation of a market correction to the intrinsic value over time. Similarly, when the mispricing moves below zero, it suggests an undervaluation. Therefore, the fundamentalist shall go long when it's below $-T$ and then exit the long position once the mispricing is reduced to $-\tau$.

In reality, different traders may have varying entry and exit thresholds due to factors such as individual risk management strategies and capital constraints. Thus, instead of assuming identical decision rules across all participants, incorporating heterogeneity in these thresholds better reflects the diversity of trader behaviour.

To account for varying levels of risk tolerance, we model T and τ as values drawn from uniform distribution $(T_{min}, T_{max}), (\tau_{min}, \tau_{max})$, respectively. Risk-neutral traders, who are willing to take on greater uncertainty to maximize profit potential, may set higher T values, waiting for larger mispricing before acting. On the other hand, they may opt for lower (or even negative) τ values, holding positions longer under the belief that the price will eventually revert to its perceived intrinsic value. Conversely, risk-averse traders, who prioritize minimising exposure to uncertainty, may adopt lower T values, entering trades earlier to avoid excessive deviations. They are also likely to choose higher τ values, closing positions sooner to mitigate risk, even if it means sacrificing potential returns.

We set the order size x_t to be an increasing function of $T - \tau$ to account for the transaction costs, postulating that traders managing larger portfolios (i.e., with higher capital) have larger transaction costs, thereby requiring higher mispricing to justify trading. Without loss of generality, we assume a linear relationship¹ between $x_t^{(i)}$ and $T^{(i)} - \tau^{(i)}$ for each trader i such that $x_t^{(i)} = c(T^{(i)} - \tau^{(i)})$

	Mispricing	Action		Δx_t
$x_{t-1}^{(i)} = 0$	$-T^{(i)} \leq m_t \leq T^{(i)}$	Stay unpositioned	$x_t^{(i)} = 0$	0
$x_{t-1}^{(i)} = 0$	$m_t > T^{(i)}$	Enter short position (sell)	$x_t^{(i)} = -c(T^{(i)} - \tau^{(i)})$	$-c(T^{(i)} - \tau^{(i)})$
$x_{t-1}^{(i)} = 0$	$m_t < -T^{(i)}$	Enter long position (buy)	$x_t^{(i)} = +c(T^{(i)} - \tau^{(i)})$	$+c(T^{(i)} - \tau^{(i)})$
$x_{t-1}^{(i)} < 0$	$m_t > \tau^{(i)}$	Hold position	$x_t^{(i)} = x_{t-1}^{(i)}$	0
$x_{t-1}^{(i)} < 0$	$m_t \leq \tau^{(i)}$	Exit short position (buy back)	$x_t^{(i)} = 0$	$+c(T^{(i)} - \tau^{(i)})$
$x_{t-1}^{(i)} > 0$	$m_t < -\tau^{(i)}$	Hold position	$x_t^{(i)} = x_{t-1}^{(i)}$	0
$x_{t-1}^{(i)} > 0$	$m_t \geq -\tau^{(i)}$	Exit long position (sell)	$x_t^{(i)} = 0$	$-c(T^{(i)} - \tau^{(i)})$

Table 4.2: State-dependent Trading Decision Rules

The total net demand D_t at time t is determined by summing the individual order sizes across all value investors:

$$D_t = \sum_{i=1}^N \Delta x_t^{(i)} = \sum_{i=1}^N (x_t^{(i)} - x_{t-1}^{(i)}),$$

where:

¹ A linear mapping is adopted because it is the simplest monotonic response consistent with standard fundamental-demand formulations in heterogeneous-agent models

- $x_t^{(i)}$ is the individual position of trader i at time t .
- N is the total number of value investors.

The market price is then updated based on the excess demand D_t , incorporating a liquidity-adjusted price impact function:

$$P_{t+1} = P_t + \lambda D_t + \epsilon_t \quad (4.2)$$

where:

- λ is the market liquidity parameter, governing how sensitively prices react to net demand.
- $\epsilon_t \sim \mathcal{N}(0, \sigma_p)$ is a Gaussian noise term.

The simulated stock price dynamic is as shown in figure 4.2.

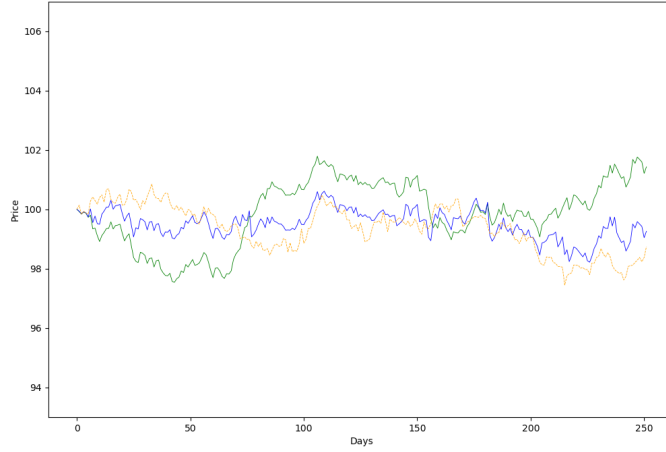


Figure 4.2: Blue line represents the simulated stock price under the influence of value investors whose intrinsic value is reflected by the orange line. The green line indicates the log-normal random walk of price as if value investors were absent.

We let there be $N = 6000$ value investors, whose shared intrinsic value (v) follows a log-normal random walk starting at $v_0 = 100$:

$$v_{t+1} = v_t \cdot e^{\eta_t},$$

where $\eta_t \sim \mathcal{N}(0, \sigma_v)$ is a Gaussian noise term, with the standard deviation equals to that of noise term in the stock price $\sigma_v = \sigma_p = 0.003$. The entry and exit threshold are as follow:

$$T^{(i)} \sim U(0.003, 0.05), \quad \tau^{(i)} \sim U(-0.001, 0.001)$$

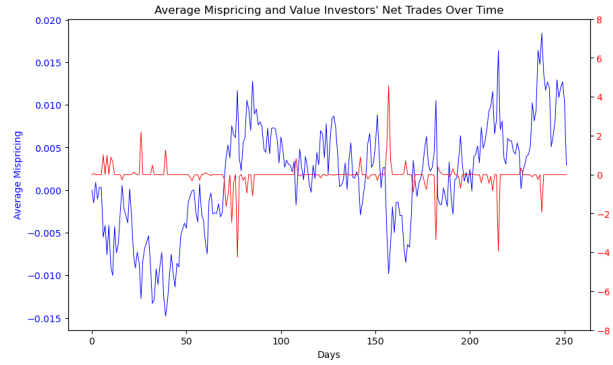


Figure 4.3: Mispricing against net-trade by value investors

Figure 4.2 illustrates the simulated stock price dynamics under the influence of value investors' trading. The blue line represents the market price trajectory, which starts at 100 and evolves as value investors respond to mispricing signals. The orange line depicts the intrinsic value, which follows a stochastic process while the green line shows the price trajectory in the absence of value investor trading, where only the exogenous noise component from 4.2 is present.

The market price always fluctuates between the intrinsic value and the noise-driven price path. When the price deviates from intrinsic value, value investors intervene by trading, pushing it back toward fundamental valuation. However, due to the presence of noise, the price does not fully align with intrinsic value but remains bounded between fundamental value and pure randomness.

Figure 4.3 compares the mispricing (blue) and value investors trading position (red) over the time space. It is obvious that large trading volumes tend to be present when the absolute value of mispricing is high and when mispricing switches sign. It's straightforward to understand: when the mispricing surpasses the entry threshold, value investors trade in the opposite direction (long when it's undervalued and short when it's overvalued); and when the mispricing being reduced close to zero, within the exit threshold, traders in a position exit it to gain profit. The rest of the time sees little trading activity, indicating a holding or unpositioned behaviour when no threshold is triggered.

4.4.4 *Trend and Value Traders together*

We extend the model by introducing a market model populated by both value investors and trend followers and analyse how value investors and trend followers coexist. Trend followers in the model adopt a non-linear strategy to respond to recent trends in price dynamics. Specifically, their trading behaviour is governed by a hyperbolic tangent tanh function of recent price changes. This non-linear response ensures that trend followers are less sensitive to small and potentially noisy fluctuations, avoiding frequent position adjustments that might otherwise arise from insignificant price movements. Only when the absolute change in price over a specified time window exceeds a pre-defined threshold do trend followers take a position, and the magnitude of their response increases with the strength of the observed trend. The sensitivity parameter amplifies their reaction to these trends, allowing them to exert greater influence on market prices during periods of significant momentum.

Value investors, by contrast, trade based on the discrepancy between the market price and their individually perceived intrinsic value of the asset. Each value investor evaluates the mispricing at every time step and determines whether it exceeds their personal entry threshold, prompting them to initiate a position. The entry and exit thresholds for value investors are heterogeneous and randomly assigned at the beginning of the simulation. This heterogeneity reflects differences in risk tolerance, trading strategies, and investment horizons across agents. As a result, some value investors are more sensitive to mispricing and take positions earlier, while others require larger deviations from their perceived intrinsic value before acting. If the market price falls sufficiently below their intrinsic value, a value investor enters a long position; conversely, if the price is deemed excessively high, they initiate a short position. Exit decisions are based on whether the mispricing narrows to within a specified exit threshold. In the current setup, the intrinsic value for each agent evolves independently according to a stochastic process, and no external information or rumour diffusion is present.

Figure 4.4 depicts the evolution of the asset price over time, alongside the intrinsic value and the price path driven solely by exogenous noise with no rumour planted. These price fluctuations emerge endogenously from the interaction between two structurally opposed trading forces: stabilising value investors

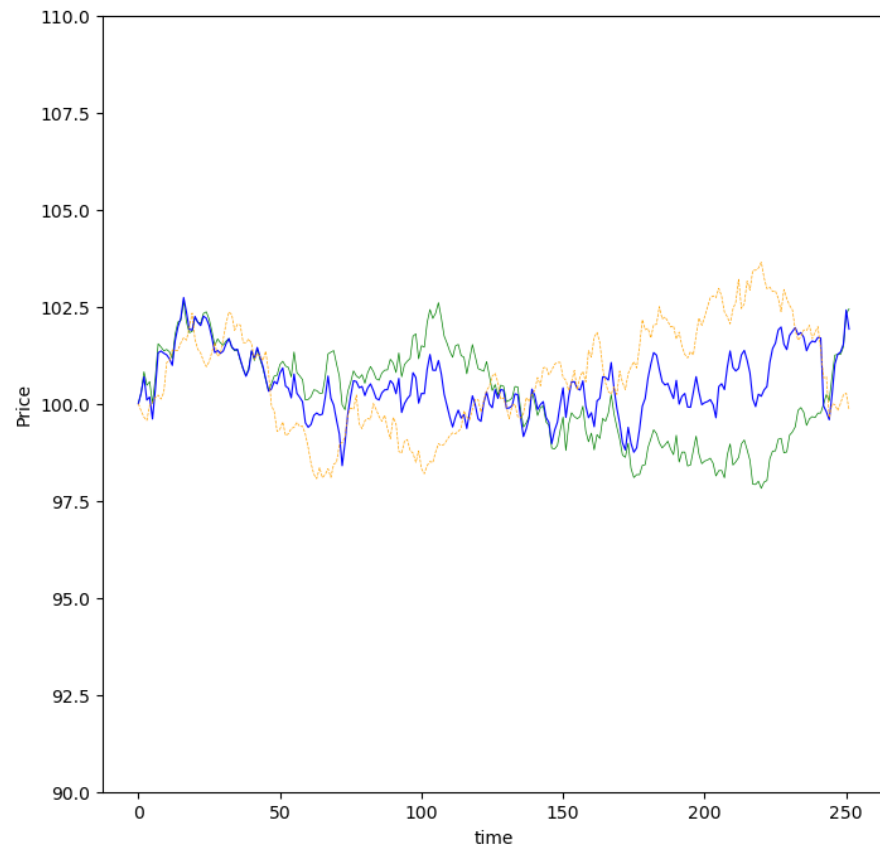


Figure 4.4: Stock price dynamics (blue) under the coexistence of trend followers and value investors. Orange line represents the shared common intrinsic value by all value investors. The green line illustrates the trajectory of the price driven purely by exogenous noise, reflecting how the market would evolve in the absence of both trader types. The rumour is absent.

and destabilising trend followers. When the asset price drifts upward due to random noise or a cluster of coincidental buy decisions, trend followers interpret the movement as a trend signal and initiate or scale up their positions accordingly. This behaviour acts as a positive feedback loop, reinforcing the price rise and pushing it further away from the intrinsic value. This delayed correction is what creates short bursts of persistent price movements, even in the absence of new information. As the mispricing widens, value investors—each operating under heterogeneous sensitivity thresholds—begin entering short positions in increasing numbers. Their mean-reverting behaviour introduces downward counter-pressure, which gradually overcomes the trend followers' influence. This dynamic eventually initiates a reversal, after which the same pattern often plays out

in the opposite direction. In effect, the price exhibits persistent oscillations around the fundamental value, a direct outcome of the alternating dominance between momentum-based and value-based strategies. The resulting pattern is a tug-of-war between these two groups, with trend followers contributing to temporary overreactions and value investors applying corrective forces over time. While the intrinsic value follows a relatively smooth stochastic path, the market price deviates in a manner that reflects not just noise, but the amplified structure of strategic feedback embedded in the agent population.

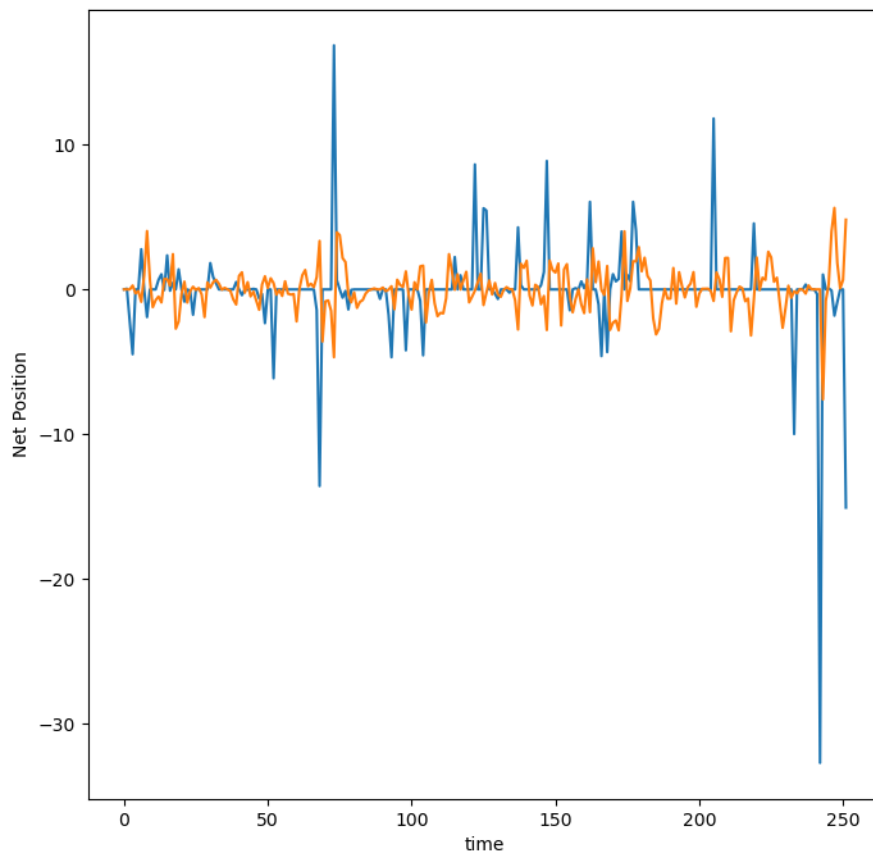


Figure 4.5: Net position dynamics of value investors (blue) and trend followers (orange) over time. Value investors exhibit intermittent and sharp position changes in response to mispricing, while trend followers adjust positions more smoothly and frequently based on observed momentum.

Figure 4.5 illustrates the aggregate net positions over time for the two trader types: value investors (blue) and trend followers (orange). This plot offers a window into the underlying mechanics driving the observed price dynamics. While the market price

reflects the result of all trading activity, the position trajectories reveal how and when each group engages with the market.

The behaviour of value investors is notably sporadic and state-dependent, characterised by intermittent but sharp position changes. These shifts occur when the mispricing between market price and intrinsic value breaches individual entry thresholds. Due to threshold heterogeneity, this response is staggered across the population, resulting in clusters of collective trading pressure that are neither smooth nor regular. Once engaged, these investors quickly reduce or liquidate positions once mispricing corrects or risk limits (e.g., forced covering) are triggered. This explains the sudden spikes and reversals in their net position curve—short-lived bursts of corrective pressure in response to growing deviations from fundamental value.

In contrast, the trend followers exhibit a more continuous and responsive trading pattern. Their net positions fluctuate more smoothly, reflecting their ongoing sensitivity to rolling price changes. The diversity in their look-back windows (Θ_i) means that some respond to short-term momentum while others react to longer-term trends. This leads to a relatively persistent but adaptive engagement with price movements. Rather than waiting for a large mispricing, they continuously adjust positions in line with perceived directional momentum, leading to the observed frequency and amplitude in their position curve.

Crucially, the plot reveals persistent episodes of conflicting pressure, where the two trader types respond to the same price movement in opposite strategic directions. For example, during phases where the asset price trends upward beyond its intrinsic value, value investors begin to accumulate short positions, interpreting the market as overvalued. Simultaneously, trend followers interpret the same price momentum as a continuation signal, increasing their long exposure. This divergence of interpretation leads to a situation where aggregate demand is pulled in two directions—not by noise, but by the intrinsic logic of the agents' strategies. These opposing forces do not neutralise each other in a smooth or instantaneous manner. Instead, their conflict plays out over several time steps, resulting in transitional dynamics that drive the price away from or back toward equilibrium. The system does not settle immediately because of the asymmetry in response timing and mechanism: trend followers typically react earlier and more continuously, often initiating positions as soon as directional signals emerge, while value investors are more selective, waiting for a sufficient build-up of mispricing before

acting. This structural lag creates a delay between trend amplification and mean-reversion, giving rise to self-limiting cycles of overshooting followed by correction. Taken together, the net positions plot provides direct evidence of the strategic friction embedded in the system. It highlights that market volatility and reversals are not simply outcomes of external shocks, but rather the result of internal market mechanics—specifically, the alternation between amplification (momentum) and restoration (value correction).

4.4.5 *Takeover Rumours and Intrinsic Value Adjustment in Community Networks*

We now extend the model by introducing a takeover-related rumour, which is postulated to propagate exclusively among value investors. This choice is grounded in the behavioural distinction between the two trader types: value investors are characterised as information-seeking agents who actively assess the fundamental value of the asset. In contrast, trend followers rely solely on observed price patterns and are assumed to remain uninformed of underlying fundamental news.

The nature of a takeover rumour typically conveys that the asset is trading below its true value, with the expectation that an acquisition would lead to a price adjustment reflecting a takeover premium. Thus, upon receiving the rumour, value investors will revise their intrinsic value estimates upward to incorporate this anticipated revaluation. This adjustment introduces asymmetry in the belief structure across the population and initiates a second layer of dynamics: the diffusion of information through the network and its impact on aggregate trading behaviour.

To simulate the dissemination of the takeover rumour, we implement a stochastic spreading process over an artificial network, where each node represents a trading agent and each edge represents a pairwise channel for information exchange. To reflect the clustered nature of real-world social and professional networks—such as analyst circles, institutional desks, and private investor communities—we adopt the community-based network characterised by tightly knit sub-communities with high intra-group connectivity and sparse inter-group connections. This design captures the empirical observation that information tends to circulate rapidly within groups before diffusing more slowly across community boundaries. We postulate that the rumour

propagates through informal contact among agents, consistent with how unverified or selectively disclosed information might spread in real financial environments. In particular, we adopt a variant of the classic Ignorant–Spreader–Stifler (ISR) model, commonly used in rumour dynamics, where agents transition between different belief states depending on their exposure to the rumour through connected peers.

To operationalise the impact of rumour acquisition on agent behaviour, we implement a mechanism whereby value investors revise their individual estimates of the asset's intrinsic value upon exposure to the takeover rumour. In this setup, each value investor is initially endowed with a belief anchored to a stochastic baseline fundamental value process. When an investor transitions into the "spreader" state within the rumour model, their belief is updated to reflect the rumoured takeover valuation — modelled as a fixed premium over the original fundamental value. This update persists while the agent remains influenced by the rumour. Crucially, the belief revision is not static across all agents: it may be abandoned after a stochastic duration if the rumour fails to materialise into public confirmation. This heterogeneity in belief updating timelines captures the real-world uncertainty and decay associated with unverified information.

$$v_t^{(i)} = \begin{cases} v_t, & \text{for ignorant investor,} \\ (1 + \delta_v)v_t, & \text{for spreader investor,} \end{cases} \quad (4.3)$$

where δ_v represents a mispricing coefficient indicating that the rumour implies a higher fundamental value than the original value due to a potential takeover announcement. Since in most takeover cases the price is expected to rise, we naturally assume δ_v is always positive. For example, if $\delta_v = 0.2$ and $v = 100$ at some time $t = 3$, then on day 3, value investors who have already become a spreader will trade with new intrinsic value at 120, while those who remain ignorant trade with $v = 100$.

Furthermore, once the rumour is publicly confirmed (simulated as a takeover announcement), the model assumes all agents synchronise their beliefs to the known bid value, representing full information revelation. This transition is implemented by introducing an exogenous event at a pre-specified time step T_m , which instantaneously resets each agent's perceived intrinsic value to the announced takeover price. From this point onward,

trading behaviour reflects the new consensus valuation rather than private rumour-based beliefs.

In operational terms, this announcement acts as a global signal that overrides individual heterogeneity in rumour states. For value investors, any ongoing influence from the spreading process is terminated, and their positions are re-evaluated based on the newly revealed price. To reflect an efficient market reaction to public information, the model enforces that the asset price jumps directly to the announced bid price on the day of the takeover announcement. This instantaneous adjustment represents the market's rapid incorporation of the publicly disclosed takeover valuation, consistent with standard assumptions in event studies and market efficiency literature.

Unlike conventional agent-based value-investor models, where intrinsic value evolves independently of information diffusion, the present framework explicitly links an agent's perceived intrinsic value to its state within the rumour-spreading process. Consequently, valuation updates are no longer exogenous but arise endogenously from the propagation of takeover information across the communication network. This coupling constitutes the central methodological contribution of the proposed model, providing the mechanism through which network-based information diffusion directly influences trading behaviour and, ultimately, stock price dynamics.

4.5 MODEL CONFIGURATION

The agent-based framework is initialised with a heterogeneous population of value investors and trend followers operating in a synthetic financial market. Each agent is assigned behavioural parameters drawn from bounded distributions to reflect variability in perception and strategy. Trading decisions are executed based on either fundamental mispricing signals (for value investors) or observed price trends (for trend followers), and the resulting order flow collectively influences the evolution of the market price. To capture realistic structural constraints on information transmission, agents are embedded in a modular network composed of densely connected communities and sparse interconnections across groups. The rumour spreads exclusively among value investors through this network via an adapted Ignorant–Spreader–Stifler (ISR) mechanism. Agents update their beliefs and trading behaviour based on their state in the rumour process, with the belief revision either sustained or discarded

over time depending on the absence or confirmation of public signals.

The core simulation model involves a number of parameters governing agent behaviour, market mechanisms, and network structure. Table 4.3 summarises these parameters, categorised into general market settings, value investor attributes, trend follower strategies, and rumour propagation mechanics. The model incorporates heterogeneous behaviour across agents and mimics realistic trading dynamics through stochastic processes, behavioural thresholds, and network-driven information diffusion². Each parameter plays a distinct role in shaping the simulated dynamics. We briefly elaborate on the rationale and function of key parameters across the four major components:

- **General Market Parameters** The market price is initialised at $P_0 = 100$ and evolves through the aggregation of trading flows and an exogenous noise term, with standard deviation $\sigma_{\text{noise}} = 0.003$. The price impact factor λ^{-1} reflects the degree to which net order imbalance translates into price changes. The announcement day $T_m = 45$ represents the exogenous arrival of public takeover news, aligning with empirical findings that typical pre-bid runup periods often span one to two months prior to public disclosure.
- **Value Investors Parameters** The population of value investors consists of $N_{\text{value}} = 6000$ agents who base their trading decisions on perceived mispricing relative to their intrinsic valuation of the asset. Each investor begins with a baseline intrinsic value $v_0 = 100$, which evolves over time according to a stochastic process with volatility $\sigma_{\text{value}} = 0.003$. Trading behaviour is governed by a pair of heterogeneous thresholds: the entry threshold $\tau_i^{\text{entry}} \sim U[0.03, 0.1]$ determines the minimum mispricing needed to open a position, while the exit threshold $\tau_i^{\text{exit}} \sim U[-0.001, 0.001]$ defines the tolerance for closing it. These thresholds encode behavioural variation among investors, capturing differences in responsiveness to valuation gaps. Position sizes are scaled by a constant

² The parameter values are chosen to generate qualitatively realistic behaviour while preserving analytical and computational tractability. They are not calibrated to specific empirical estimates, but instead reflect stylised features of rumour diffusion and financial market dynamics. To mitigate potential sensitivity to parameter choices, results are evaluated across a range of configurations, ensuring that the key findings are robust to variation in model inputs.

Table 4.3: Summary of Model Parameters

Description	Symbol	Value / Range
General Market Parameters		
Initial asset price	P_0	100
Exogenous noise standard deviation	σ_{noise}	0.003
Price impact factor	λ^{-1}	0.001
Announcement day	T_m	45
Value Investors		
Number of value investors	N_{value}	6000
Initial intrinsic value	v_0	100
mispricing coefficient	δ_v	0.2
Intrinsic value standard deviation	σ_{value}	0.003
Entry thresholds	τ_i^{entry}	$U[0.03, 0.1]$
Exit thresholds	τ_i^{exit}	$U[-0.001, 0.001]$
Forced liquidation thresholds	τ_i^{cover}	$U[0.07, 0.11]$
Position scaling factor	C_{value}	1.0
Trend Followers		
Number of trend followers	N_{trend}	6000
Trend thresholds	τ_j^{trend}	$U[0.003, 0.01]$
Sensitivity parameter	s_j	$U[1, 5]$
Look-back period (heterogeneous)	Θ_j	Random integer $[3, 10]$
Position scaling factor	C_{trend}	0.2
Position response function	$\omega_t^{(j)}$	$C_{\text{trend}} \cdot \left(e^{s_j \cdot (\Delta p_j(t) - \tau_j)} - 1 \right)$
Network and Rumour Settings		
Number of communities	N_g	100
Intra connectivity	W_g	0.8
Inter connectivity	B_g	0.01
Spreading rate	α	0.0008/day
Stifling rate	θ	0.0008/day

$C_{\text{value}} = 1.0$, translating perceived mispricing into trade volume. To account for the risk of short positions under adverse price movements, we incorporate a forced liquidation mechanism: agents holding short positions are subject to involuntary exit if cumulative losses exceed an individual-specific cover threshold $\tau_i^{\text{cover}} \sim U[0.07, 0.11]$, approximating margin-call dynamics. The threshold τ_i^{cover} is defined in terms of relative price change since short entry, i.e., $\Delta p = (P_t - P_{\text{entry}})/P_{\text{entry}}$. This formulation captures the real-world practice of margin maintenance levels: the selected range of τ_i^{cover} roughly corresponds to maintenance margin requirements of approximately 35% to 45%, under standard assumptions. This mechanism contributes to nonlinear feedback in the model, as clustered forced covers can accelerate price momentum during upward trends.

- Trend Followers Parameters

Trend followers form the second major group of agents in the model, comprising $N_{\text{trend}} = 6000$ participants who base trading decisions purely on historical price patterns, without reference to intrinsic value or fundamental information. This behavioural simplification reflects empirical observations of momentum-based trading strategies commonly adopted by technical analysts and algorithmic traders. Each trend follower reacts to recent price trends by estimating a momentum signal over a heterogeneous look-back window $\Theta_j \sim U\{3, 10\}$, which introduces variation in responsiveness and strategy time horizon across the population. The net price movement used by agent j at time t is defined as $\Delta p_j(t) = \log P_{t-1} - \log P_{t-\Theta_j}$, capturing cumulative return over the specified look-back period. To avoid spurious trades in response to noise, each agent is assigned an individual trend detection threshold $\tau_j^{\text{trend}} \sim U[0.003, 0.01]$. Only when the magnitude of price change exceeds this threshold does the agent initiate a trade. The trade intensity is modulated by a nonlinear response function designed to reflect stronger reactions to more pronounced trends. Specifically, the net order of trend follower j is determined by the function:

$$\omega_t^{(j)} = C_{\text{trend}} \cdot \left(e^{s_j \cdot (|\Delta p_j(t)| - \tau_j)} - 1 \right) \cdot \text{sign}(\Delta p_j(t)),$$

where $C_{\text{trend}} = 0.2$ is a global scaling factor, and $s_j \sim U[1,5]$ is a sensitivity parameter. The use of an exponential mapping ensures that larger price movements lead to disproportionately larger position shifts, emulating momentum amplification behaviour observed in real markets. The asymmetry in $\Delta p_j(t)$ sign governs the trade direction—positive for upward momentum and negative for downward momentum. By incorporating heterogeneity in both detection threshold and sensitivity, the model captures a stylised range of trend-following behaviours: some agents react swiftly to minor trends, contributing to early-stage momentum, while others require stronger signals, reinforcing price patterns in later phases. This structure introduces a dynamic interplay between short-term noise filtering and longer-term trend amplification in the system.

- Network Parameters

To simulate the diffusion of takeover-related information, we model a communication structure among agents using a community-based network topology. This design reflects the clustered nature of real-world social and professional networks—such as analyst circles, trading desks, and investor forums—where information tends to circulate rapidly within communities before slowly leaking across group boundaries.

The network consists of N_{value} value investors partitioned into $N_g = 100$ communities. The probability of forming a connection between any two agents within the same group is given by the intra-community link probability $W_g = 0.8$, while the probability of inter-community links is governed by $B_g = 0.01$. This construction creates tightly knit clusters with occasional weak ties across groups, supporting both local saturation and global diffusion of information. The transitions between states are driven by two key parameters: The spreading probability $\alpha = 0.0008$, determining the likelihood that a spreader converts an ignorant neighbour into another spreader per unit time; The stifling probability $\theta = 0.0008$, determining the chance that a spreader becomes a stifler upon interacting with another informed agent per unit time. Note that here the unit time is set to be one trading day in real life.

Initially, a single randomly selected value investor is seeded as a spreader. As the simulation progresses, the rumour spreads through the network in a pairwise fashion along existing edges. This mechanism allows us to capture the endogenous emer-

gence of information clusters and the speed of rumour diffusion across sub-networks. The structure and parameters of the network are critical in shaping the rate, reach, and heterogeneity of rumour exposure. These dynamics, in turn, affect the timing and magnitude of trading behaviour shifts in the model, particularly among value investors whose belief updates are directly triggered by rumour acquisition.

Note that α and θ are defined as transition rates with units of day^{-1} . In the agent-based implementation, these rate parameters are applied as daily transition probabilities because the simulation advances in discrete one-day time steps. Thus, the numerical values of α and θ are used as the corresponding daily transition probabilities in the stochastic model. The stochastic implementation was calibrated against the deterministic formulation such that its simulated trajectories remain within the specified confidence range around the corresponding deterministic dynamics as shown in Figure 3.8.

Also, we tuned inter-community connectivity B_g from 0.0005, in Chapter 3, to 0.01; as well as both spreading rate α and stifling rate θ from 0.001 to 0.0008. The reason is to align the experimental time horizon in the simulation with the observed pre-takeover window in the marketplace, which is generally around 45 trading days [26, 36].

Thus, these parameter changes should be understood as a calibrated modelling choice for the integrated stock-price model, rather than as an empirically estimated value of inter-group communication probability or rumour transition rate in the real world.

STOCK PRICE DYNAMICS FROM INDIVIDUAL BEHAVIOUR

5.1 INTRODUCTION

This chapter presents the simulation results of the coupled rumour-spreading and agent-based market model developed in Chapters 3 and 4, respectively. We now integrate these components into a unified simulation environment to investigate how takeover-related information propagates through a network of interacting traders and is subsequently reflected in stock price dynamics.

In the model, there are $N = 6000$ value investors and 6000 trend followers. We isolate the value investors in the community-based network, enabling rumour to spread among them, while trend followers are assumed to be not exposed to the rumour because of their inherent property of trend-triggered only trading mode. We simulate agents with nodes and their pairwise contacts with edges so rumour could spread.

Each iteration of the network system represents one discrete trading day in real life, and so the time step of the model is one day. As the simulation progresses, changes in rumour compartments (Ignorant, Spreader and Stifler) take place with respect to the fundamental differential equations shown in equations 2.8. Subsequently, individual belief on fundamental value is shifted from original intrinsic value to rumoured intrinsic value as one transitions from ignorant to spreader as shown in equation 4.3. Then, undervaluing is likely to occur as the rumour always suggests that the rumoured intrinsic value is always higher than the original one.

Note that value investors trading decisions are modelled to depend on thresholds in mispricing, as shown in Table 4.2. Thus, when the perceived undervaluing exceeds the threshold, buying / a long position is initiated, generating a net order from the corresponding value investor. The net orders submitted by individual agents are then aggregated to form the total order flow at each time step as shown in 4.4.1. This aggregate order flow determines the subsequent price adjustment, thereby linking the

diffusion of the rumour and the resulting changes in investors' beliefs to the dynamics of the asset price as shown below:

$$P_t = P_{t-1} \cdot \exp(f(Q_t)).$$

Then, the primary objective of this chapter is therefore to examine whether the proposed framework above is capable of reproducing the characteristic pre-takeover price run-up observed in empirical studies, while providing insight into the mechanisms through which information diffusion, heterogeneous trading behaviour, and network topology jointly shape market outcomes.

In doing so, we evaluate the model against the cumulative abnormal return (CAR¹), using it as the key measure of price behaviour around simulated takeover events. By analysing the timing, shape, and magnitude of the CAR trajectory, we examine whether the model can capture the gradual pre-announcement drift and sharp announcement-day adjustment price pattern in empirical studies. Particular attention is given to the roles played by value investors, trend followers, and the forced liquidation mechanism in shaping pre-announcement price drift and post-announcement market response.

The results presented in this section are derived from Monte Carlo simulations, where each plot reflects outcomes averaged across 50 independent runs under the same model configuration. Averaging across multiple runs mitigates the impact of stochastic variability and produces smoother aggregate dynamics. It was observed that beyond this number of runs, the key qualitative patterns—such as the timing and magnitude of price drift—remain stable, indicating that the main findings are not sensitive to the exact number of simulations performed.

In section 5.2, we begin by presenting the average CAR on the community-based network and analysing the associated trading and information-diffusion measures that underpin the simulated price dynamics.

In section 5.3-5.7, we analyse the underlying causes of such CAR pattern, across different financial measures on different types of traders, as well as different trading mechanisms, relationship between spreader ratio and buying activity.

¹ Cumulative Abnormal Return (CAR) is defined as the cumulative sum of abnormal returns over a specified event window, where abnormal return is the difference between the observed return and its expected value under a benchmark model. It is commonly used in event studies to measure the impact of events such as takeover announcements on stock prices.

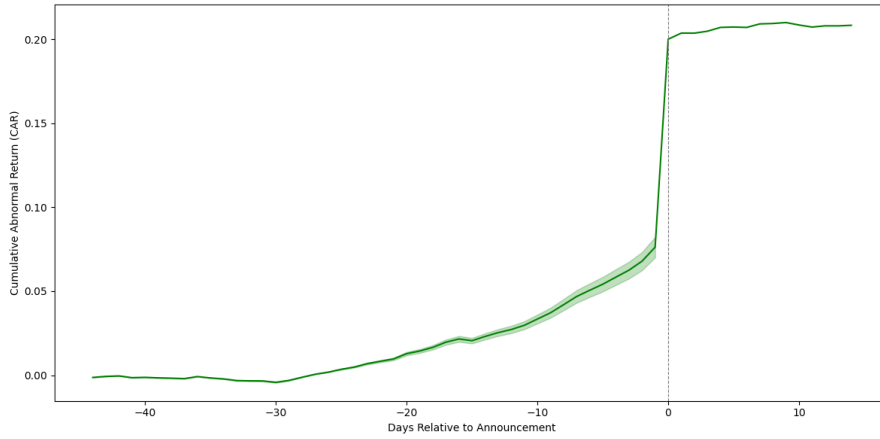


Figure 5.1: Average cumulative abnormal return on community-based network from day -45 to day 15 relative to takeover announcement, day 0. The rumour is spread from day -45. Shaded area represents the 95% confidence intervals across 50 simulation runs.

And in section 5.8-5.10, we discuss the robustness of the CAR pattern against types of network and intra-community connectivity W_g .

5.2 CUMULATIVE ABNORMAL RETURN(CAR)

Figure 5.1 displays the average cumulative abnormal return (CAR) trajectory, aggregated over 50 independent simulation runs. The shaded area indicates 95% confidence intervals around the average value. The CAR trajectory is generated by the coupled rumour-spreading and agent-based market framework developed in Chapters 3 and 4 using the baseline parameter configuration introduced therein.

At each simulation time step, the stochastic rumour-spreading model determines which value investors receive the takeover rumour and consequently revise their perceived intrinsic value according to the adjustment mechanism proposed in Section 4.4.5. These updated valuations, together with the trading rules governing value investors and trend followers, generate aggregate order flow, from which the market price evolves through the price formation mechanism described in Section 4.4.1. Daily stock returns are subsequently calculated from the simulated price series, while the corresponding expected returns are obtained from the evolution of the intrinsic value in the absence of a rumour.

The abnormal return is defined as the difference between these two quantities, and the cumulative abnormal return is obtained by cumulatively summing the abnormal returns over the event window.

The resulting CAR pattern exhibits several important features. The curve begins flat. Around 25 trading days prior to the simulated announcement ($t = 0$), CAR begins to rise steadily. This pre-bid drift accelerates in the final two weeks before the announcement, culminating in a sharp jump on day 0. Post-announcement, the CAR stabilises, reflecting market absorption of publicly available information. This trajectory emerges endogenously from the model's microstructure: value investors revise their intrinsic valuations upon acquiring private takeover rumours, leading to increased buying pressure; trend followers reinforce this movement through momentum-based strategies; and agents holding short positions may be forced to cover as losses mount, contributing to non-linear feedback. Together, these mechanisms produce a price path consistent with empirical observations of takeover targets, where pre-bid run-ups and announcement-day surges are commonly documented.

The magnitude and timing of the simulated CAR are broadly aligned with results in the M&A literature, reinforcing the model's relevance for understanding anticipatory trading behaviour in financial markets.

Notably, Figure 5.1 represents the simulated counterpart of the empirical BRSN price pattern introduced in Figure 1.1. In particular, the model manages to reproduce the characteristic shape of a gradual pre-announcement price run-up followed by a pronounced increase around the takeover announcement, demonstrating the famous pattern : "buy on the rumour".

5.3 VALUE INVESTORS' AND TREND FOLLOWERS' NET POSITION

To quantify the contributions by both types of traders, we carry out the net positions chart held by value investors and trend followers over the 45-day pre-announcement period in Figure 5.2. The net position is defined as the cumulative difference between purchases and sales up to each day, plotted separately for each trader type.

Value investors exhibit a steadily increasing net long position, particularly pronounced from around Day -30 onward. This reflects the model's core mechanism: as the rumour spreads

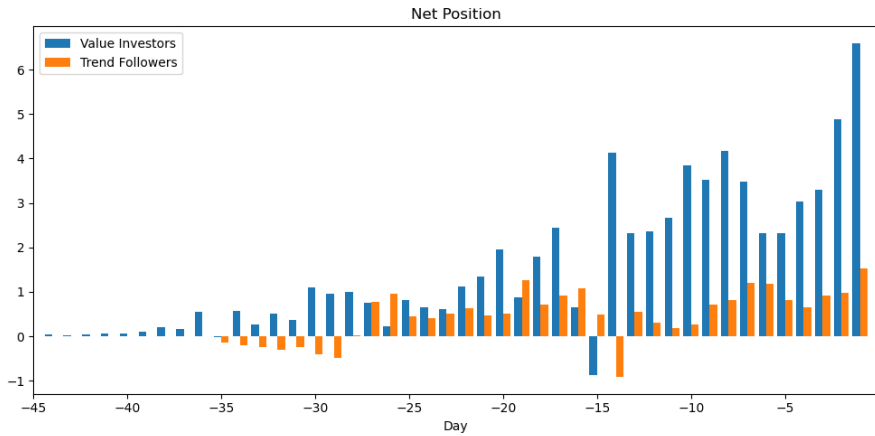


Figure 5.2: Average net positions of value investors (blue) and trend followers (orange) in days relative to the announcement (day 0).

through the network, informed agents revise their intrinsic valuations upward and accumulate shares accordingly. The increasing net position over time illustrates how sequential rumour adoption drives sustained accumulation by value investors.

Trend followers, on the other hand, display a more reactive and oscillatory behaviour. Their positions begin to rise only after observable upward price trends emerge—typically with a delay following value investor accumulation. Occasional reversals or reductions in trend follower positions reflect sensitivity to short-term volatility or temporary price slowdowns. Unlike value investors, trend followers respond not to information but to price momentum, reinforcing trends that have already been set in motion by informed demand.

The divergence in position trajectories underscores the complementary roles of the two trader types: value investors act as the initiators of price pressure via information-driven trading, while trend followers amplify this pressure once it becomes detectable in price movements.

5.4 VALUE INVESTORS' BUY/SELL VOLUME

Figure 5.3 shows the average trading volume of value investors leading up to the takeover announcement day.

To relate the notions of buy and sell volume to the model variables introduced in Chapter 4, we define trading volume in terms of individual net orders. Recall that each agent i submits

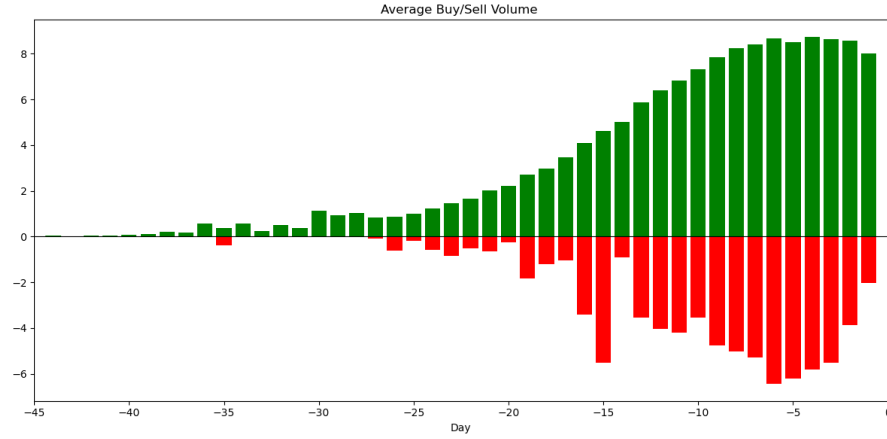


Figure 5.3: Average buy and sell volume of value investors over time. The green bars represent aggregate daily purchases, while the red bars capture aggregate sales. Time is measured in days relative to the announcement (Day 0).

a net order $\omega_t^{(i)}$ at time t , where positive values correspond to buy orders and negative values correspond to sell orders.

Aggregate buy and sell volumes can therefore be expressed as

$$V_t^{\text{buy}} = \sum_{i: \omega_t^{(i)} > 0} \omega_t^{(i)}, \quad V_t^{\text{sell}} = \sum_{i: \omega_t^{(i)} < 0} |\omega_t^{(i)}|.$$

The net order in the market is then given by

$$Q_t = V_t^{\text{buy}} - V_t^{\text{sell}},$$

which determines price changes through the price formation mechanism described in Chapter 4. In this sense, buying pressure corresponds to an excess of positive net orders, while selling pressure reflects an excess of negative net orders.

A distinct pattern emerges: both buying and selling volumes increase gradually as the announcement day approaches, but buying activity dominates consistently in magnitude.

The rising buying volume over time is primarily driven by informed value investors—those who have acquired the rumour through the network. Upon adopting the belief that the stock is undervalued due to a potential takeover, these agents adjust their intrinsic value estimates upward and initiate long positions accordingly. Because the rumour spreads gradually through the network, the buying pressure emerges in a cascading fashion, reflecting the sequential adoption of belief across the popula-

tion. This dynamic produces a sustained net demand effect that accumulates as more agents become informed. The pattern is consistent with the model's structure, in which value-based trading decisions are governed by the perceived mispricing between market price and agent-specific intrinsic value. Thus, the observed buying behaviour illustrates how distributed rumour acquisition can generate a coherent market response, mirroring the pre-announcement drift seen in real takeover targets.

On the other hand, the increase in selling activity toward the announcement day does not originate from informed agents closing long positions. Rather, it stems from uninformed (ignorant) value investors who maintain their original intrinsic value belief. As the market price rises—driven by the buying pressure of informed spreaders—these agents perceive an increasing mispricing in the opposite direction and respond by submitting sell orders, effectively going short. This behaviour is consistent with the model's logic of value-based trading: uninformed agents act rationally on the belief that the asset has become overvalued relative to their unadjusted valuation. Thus, the model captures not only informed herding behaviour, but also counteracting rational dissent, a feature commonly observed in real markets with asymmetric information.

5.5 AVERAGE MISPRICING

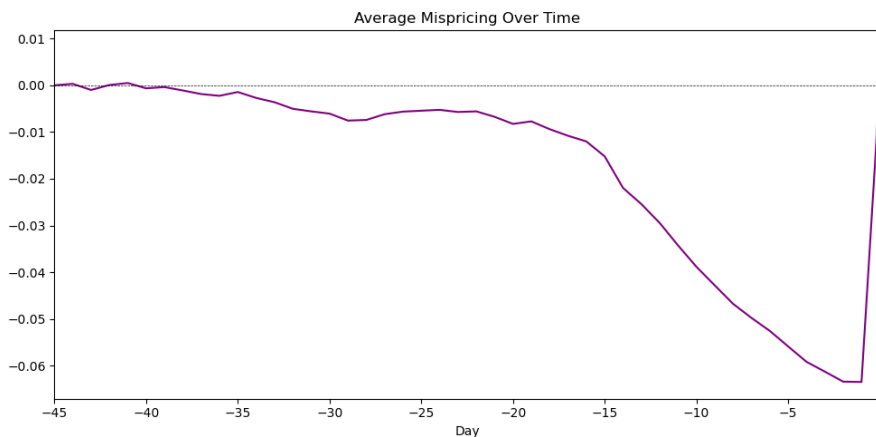


Figure 5.4: Average mispricing of all value investors from day -45 to day 0 relative to announcement day.

To better understand the behavioural forces behind the observed trading activity, we examine how the value investors' internal valuations evolve over time. Since only spreaders update

their belief upon acquiring the rumour, the average perceived intrinsic value of the population gradually increases as the spread progresses.

The mispricing measure considered in this section follows directly from the definition introduced in Chapter 4. For each value investor i , the mispricing at time t is defined as

$$m_t^{(i)} = \log P_t - \log v_t^{(i)},$$

where P_t denotes the simulated market price and $v_t^{(i)}$ is trader i 's perceived intrinsic value after any rumour-induced adjustment described in Section 4.4.5. Figure 5.4 shows the resulting average mispricing, $\bar{m}_t$, defined as the mean of log difference between the current market price and each agent's perceived intrinsic value, at each time step:

$$\bar{m}_t = \frac{1}{N_{\text{Value}}} \sum_{i=1}^{N_{\text{Value}}} m_t^{(i)}. \quad (5.1)$$

Consequently, the reported mispricing is an aggregate outcome of the coupled framework, reflecting both the endogenous evolution of market prices through the price formation mechanism and the heterogeneous intrinsic-value beliefs generated by the rumour-spreading process.

This trajectory reflects the cumulative effect of information diffusion: as more value investors acquire the rumour, the average perceived value rises, yet the market price lags behind due to frictions in information flow and liquidity. The sharp reversal at Day 0 captures the point at which public information is released and all agents align their beliefs, effectively eliminating informational asymmetry. This plot thus reinforces the core mechanism of the model: gradual information acquisition creates a persistent divergence between price and belief, which in turn drives the trading behaviour responsible for the pre-announcement price drift.

5.6 BUY VOLUME VS. SPREADER RATIO

Figure 5.5 presents this comparison, plotting the average daily buy volume alongside the spreader ratio during the pre-announcement window. The two curves show a high degree of correspondence in both shape and timing, supporting the notion that buy-side activity in the model is directly driven by the spread of the

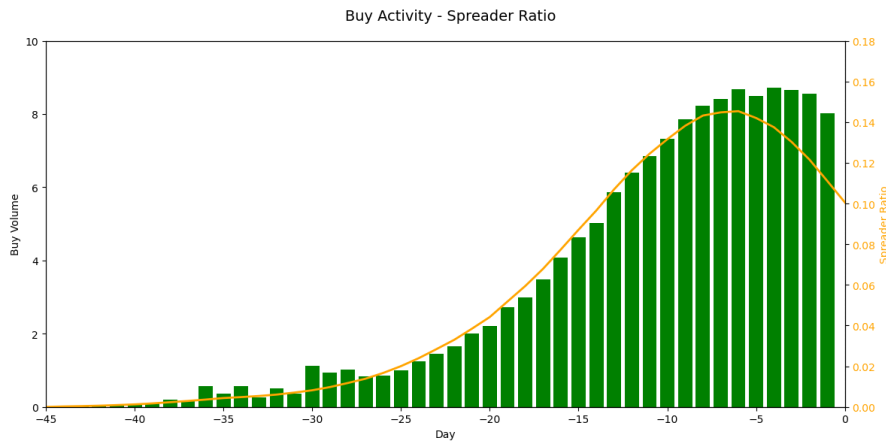


Figure 5.5: comparison plot of spreader proportion (orange line) and buying volume (green bar).

takeover rumour. Initially, the spreader ratio remains near zero, and buy volume is minimal. As rumour transmission progresses and more agents transition into the spreader state, the spreader ratio begins to rise gradually. This is accompanied by a steady increase in buy volume, reflecting the growing number of agents who revise their valuation and act on the perceived mispricing. The synchronized rise continues until approximately one week before the announcement, at which point both the spreader ratio and buy activity peak. This alignment confirms that the intensity of trading activity is closely governed by the extent of rumour adoption. The subsequent decline in spreader ratio reflects the natural saturation of the network, as most reachable agents have already acquired the rumour or become stiflers. However, while the spreader ratio and buy volume follow a closely aligned trajectory throughout most of the pre-announcement period, a notable deviation emerges in the final days.

As shown in Figure 5.5, the spreader ratio peaks and begins to decline, reflecting the saturation of rumour adoption across the network. However, the buy volume remains elevated and even continues to rise slightly during this period. This divergence is consistent with the model's inclusion of a forced covering mechanism. As the market price increases—driven by the cumulative impact of informed buying—ignorant short sellers begin to accumulate unrealised losses. Once these losses exceed a pre-defined threshold, they are forced to close their positions by buying back shares. These covering transactions add to the overall buy volume, even though the agents initiating them have not adopted the rumour and do not belong to the spreader group.

The widening gap between buy volume and spreader ratio in the final days reflects the growing contribution of forced covers to market demand. This outcome confirms that the model captures not only belief-driven trading but also constraint-induced reactive behaviour, which reinforces price pressure and contributes to the final surge in the CAR curve.

It shows that the simulated price pressure—ultimately reflected in the CAR trajectory—emerges not from exogenous trading shocks but from endogenous, network-driven information dynamics. In this framework, the rate and reach of rumour propagation play a central role in determining the timing and magnitude of the pre-announcement run-up.

To test the robustness of the observed relationship between the spreader ratio and buy volume, we conduct a comparative analysis under different values of β , defined as the ratio of the rumour spreading rate to the stifling rate. A higher β results in a faster diffusion process, while a lower β slows down the spread. Figure 5.6 presents two simulation outcomes: the top panel corresponds to $\beta = 0.5$, and the bottom to $\beta = 2$. In both cases, the average buy volume and the spreader ratio are plotted over the 45-day pre-announcement window. Despite the clear difference in the rate and timing of information propagation, the overall shape and alignment of the two trajectories remain consistent. The curves exhibit synchronized rises and peaks, suggesting that the buying behaviour of value investors is robustly governed by the spreader compartment, regardless of how quickly or slowly rumour adoption unfolds.

This result confirms that the positive correlation between spreader ratio and buying intensity is not a special case arising from a specific calibration. Rather, it is an inherent feature of the model's structure: value investors act upon belief revisions triggered by network-based rumour acquisition, and the aggregate trading pressure they generate mirrors the shape of the spreading curve.

While both scenarios in Figure 5.6 confirm a strong alignment between buy volume and spreader ratio, a noteworthy deviation emerges in the case of accelerated rumour diffusion $\beta = 2$. In the final days before the announcement, the spreader ratio begins to decline as the network approaches saturation, yet buy volume continues to rise sharply. This divergence is consistent with the model's forced covering mechanism, which becomes more pronounced under fast-spreading conditions.

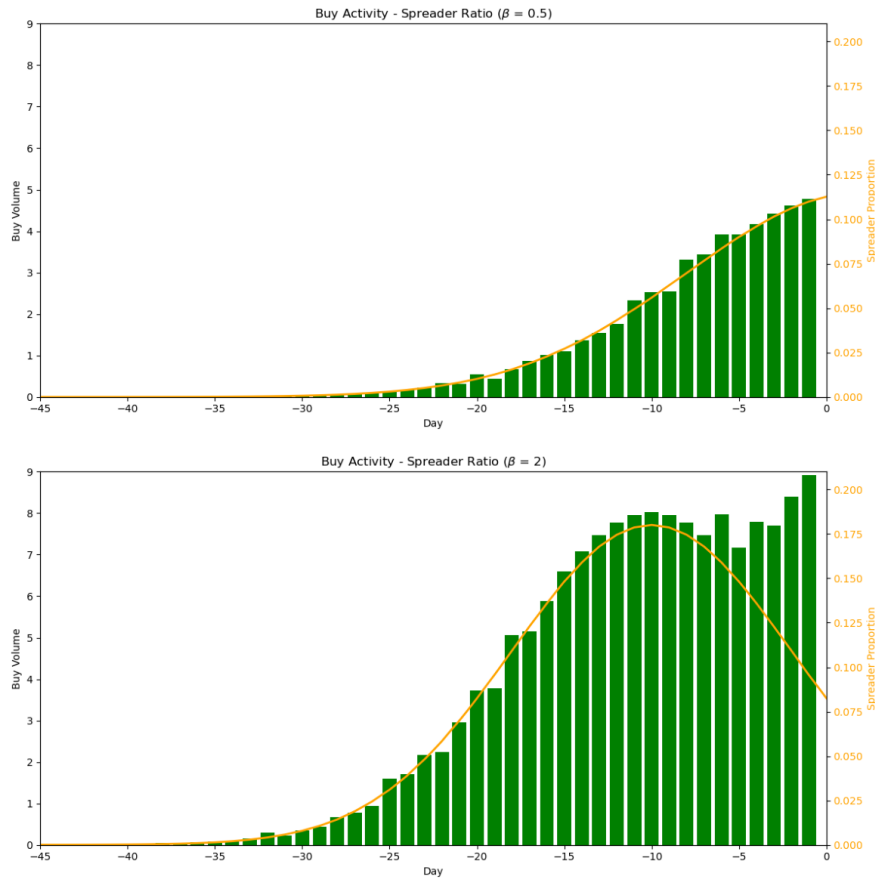


Figure 5.6: Comparison plot of spreader proportion (orange line) and buying volume (green bar) under various rumour transition rates β . Top panel shows the measures under $\beta = 0.5$, spreading rate being half as much as stifling rate. Bottom panel indicates the relative curves under $\beta = 2$ where spreading is twice as efficient as stifling.

As rumour adoption accelerates, a larger share of value investors becomes informed earlier, leading to more intense and earlier buying pressure. This, in turn, drives the market price upward at a faster rate. Uninformed (ignorant) value investors, who retain their original valuation, begin to perceive increasing overvaluation and respond by entering short positions. When the price continues to rise and their losses surpass risk thresholds, they are forced to cover their positions, adding to overall buy volume despite not belonging to the spreader group.

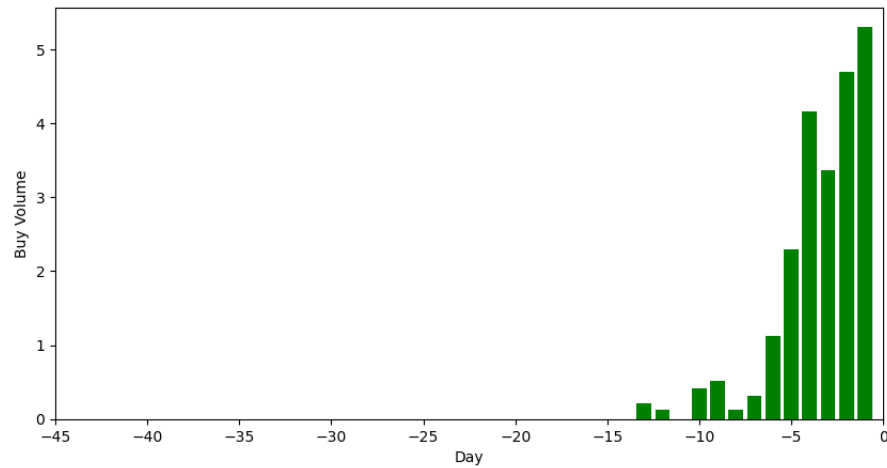


Figure 5.7: Time series of forced cover volume for $\beta = 2$

5.7 FORCED COVER VOLUME

To corroborate this interpretation, Figure 5.7 plots the average daily volume of forced covering activity under the fast-spreading scenario ($\beta = 2$). The pattern reveals a clear escalation in forced buy-backs beginning approximately 10 trading days before the announcement, with volume increasing steeply as the price accelerates toward day 0. This dynamic aligns with the theoretical expectation that rapid price movement—driven by early and intense informed demand—exposes uninformed short sellers to larger and earlier losses. Once their losses exceed the model's risk threshold, these agents are compelled to exit their short positions through market purchases, contributing substantially to the observed buy-side pressure.

This figure confirms that the divergence between buy volume and spreader ratio in the fast-spreading case is not anomalous, but rather an emergent feature of the interaction between belief heterogeneity, trading rules, and price feedback effects. The magnitude of this forced buy-back effect appears to be endogenously related to the speed of information diffusion. In slower spreading environments ($\beta = 0.5$), price increases more gradually, limiting both the perceived mispricing and the extent of short-selling activity. As a result, fewer agents face forced exits before the announcement, and the buy volume remains closely tied to the spreader ratio throughout. These dynamics suggest that the rumour spreading speed not only governs the trajectory of informed demand, but also amplifies downstream market re-

sponses among uninformed agents, reinforcing the price run-up through an endogenous feedback loop.

In summary, the spreader proportion and buy volume show high consistency. This is as expected because in our simulation framework, the buying activity of value investors is directly tied to their information state. Each value investor adopts a new, higher intrinsic valuation upon acquiring the rumour, transitioning from the *ignorant* to the *spreader* state. This rumour transition process follows an ISR (Ignorant–Spreader–Stifler) dynamic on a network topology, and only spreaders update their valuation and begin buying the asset. Ignorant agents, by contrast, retain their original belief and refrain from initiating buy orders unless mispricing becomes extreme in the opposite direction.

Consequently, the aggregate buy volume among value investors at any point in time is endogenously linked to the spreader population—that is, the proportion of agents who have adopted the new belief and perceive the asset as undervalued. This mechanism gives rise to a natural correspondence between the trajectory of rumour diffusion and market-wide buying pressure.

Having demonstrated that the evolution of buying volume among value investors is intimately connected to the trajectory of rumour diffusion—with a high degree of consistency observed during the initial phases, and additional effects arising from constraint-induced forced buy-backs as the process accelerates—we underscore the critical importance of information transmission dynamics in shaping aggregate market outcomes. The results thus far suggest that the speed and extent of belief propagation within the agent population are central to understanding both endogenous trading pressure and the resulting price patterns.

However, the propagation of information in such systems does not occur in a vacuum; rather, it is fundamentally conditioned by the underlying network. Structural features such as clustering, modularity, and average path length can profoundly influence the rate and reach of rumour transmission, with downstream effects on trading behaviour and market efficiency. Recognizing this, we now broaden our analysis to systematically investigate the role of network topology in governing the emergent phenomena captured by the model.

In the following sections, we vary the structure of the agent interaction network and examine its impact on key model outputs, including the cumulative abnormal return (CAR) and other

behavioural and informational metrics. By comparing results across random, small-world, and community-based network configurations, we aim to elucidate how differences in connectivity and local clustering modulate the interplay between information flow and market dynamics.

5.8 CROSS-NETWORK CAR

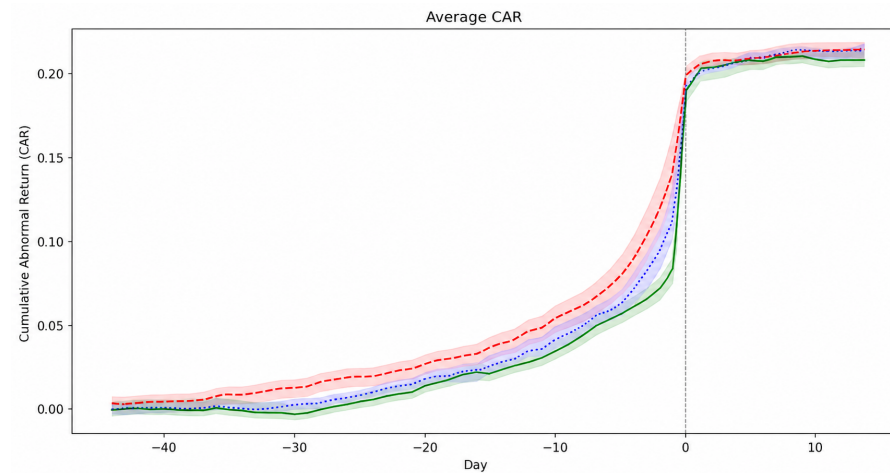


Figure 5.8: Average CAR trajectories generated under the random (red), community (green) and small-world (blue) network structures. The red dashed, green solid and blue dotted lines represent the respective average CAR, while the shaded areas indicate the 95% confidence intervals across 50 Monte-Carlo simulation runs. The vertical dashed line at Day 0 denotes the takeover announcement.

Figure 5.8 depicts a comparative analysis of the cumulative abnormal return (CAR) across three distinct network structures: random (red dash), community-based (green solid), and small-world (blue dot). Each curve represents the average of multiple Monte Carlo simulation runs for a given network structure, with the vertical dashed line indicating the announcement day. The shaded area indicates the 95% confidence interval around the average value.

A number of salient features emerge from the figure, underscoring the critical influence of network topology on both the **tempo** and the **magnitude** of pre-announcement price dynamics.

First, in terms of the timing and steepness of the run-up, the random network (red dashed line) clearly exhibits the earliest and most pronounced acceleration in CAR. The upward drift in CAR begins sooner and climbs more sharply than in the

other two configurations, indicating that private information is rapidly assimilated by the market when agents are connected in a maximally random fashion. This swift rumour diffusion enables value investors to collectively recognize and act on the information almost as soon as it enters the system, resulting in the most efficient price anticipation process among the network types tested.

Turning to the magnitude of the run-up—defined as the level of CAR reached immediately prior to the announcement—the random network again stands out, displaying the highest cumulative abnormal return at Day 0. The small-world network (blue dotted line) also produces a substantial run-up, but its CAR at the announcement is clearly lower than that of the random network. The community network (green solid line), characterised by tightly knit clusters with sparse inter-cluster connections, yields the smallest CAR run-up. Its curve not only rises more slowly but also attains a lower run-up by the time of the announcement, suggesting that structural impediments to information flow can significantly dampen the aggregate price impact of private information.

These differences in CAR magnitude reflect the efficiency with which information traverses each network. In the random network, the absence of clustering or local bottlenecks ensures that the rumour reaches nearly all agents rapidly, maximizing the buying pressure and the resultant price drift. The small-world network, while still permitting some long-range transmission through shortcut links, nonetheless retains some local structure that partially impedes global diffusion, leading to a run-up intermediate in size and timing between the random and community cases. The community network, in contrast, is marked by a strong tendency for information to remain trapped within local clusters for extended periods, only gradually leaking out to the broader population. This process not only delays the collective trading response but also limits the overall magnitude of price adjustment attributable to the rumour.

The comparative analysis of CAR trajectories across random, small-world, and community network structures demonstrates clear and persistent differences in both the timing and magnitude of pre-announcement price run-ups. Notably, these differences mirror the ordering observed in our earlier examination of rumour spreading dynamics under the stochastic model, where network topology was shown to strongly affect both the speed and intensity of information diffusion. This parallel suggests a

deeper, mechanistic link between the network-driven propagation of private information and the emergent patterns of price adjustment in financial markets.

Accordingly, we hypothesize that the variation in CAR behaviour across network types is fundamentally rooted in the distinct spreading patterns—particularly the evolution of the spreader compartment—induced by each topology. In other words, we posit that the observed differences in CAR are driven by the degree to which information can percolate through the network, which in turn governs both the scale and tempo of informed trading activity. To investigate this hypothesis, we next examine the simulation outputs for key behavioural variables, including the trajectory of the spreader ratio and the aggregate buy order volume, under each network configuration. By establishing the correspondence between these micro-level information dynamics and the macro-level CAR outcomes, we aim to provide a comprehensive account of how network structure shapes the market’s collective response to private information.

5.9 CROSS-NETWORK COMPARISON OF VALUE INVESTORS’ AND TREND FOLLOWERS’ NET TRADE

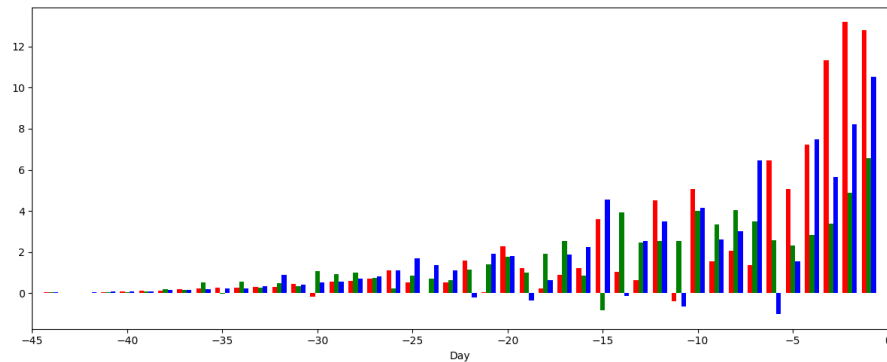


Figure 5.9: Value investors’ daily trading volume on random (red), community (green) and small-world network (blue)

Having shown that the CAR exhibits a gradual but accelerating increase as the announcement day approaches, we next examine the daily trading activity of value investors and trend followers to uncover the behavioural sources of this pattern.

Figure 5.9 and 5.10 display the daily trading volumes of value investors and trend followers, respectively, for the random (red), community (green) and small-world (blue) network configurations. Each day features three bars, enabling direct comparison

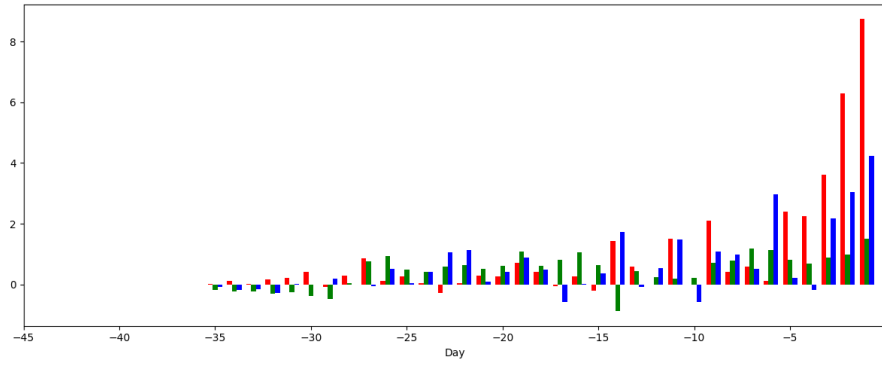


Figure 5.10: Trend followers' daily trading volume on random (red), community (green) and small-world network (blue)

of trading intensity across network types as the announcement approaches.

Both panels reveal two key features. First, trading activity for both value investors and trend followers exhibits a marked increase over time, intensifying as the announcement day nears. This upward trajectory reflects the endogenous buildup of market activity in response to the diffusion of private information and the evolving price trend. This pattern is consistent with the gradual increase previously observed in the CAR trajectories: as private information diffuses through the network, both trading volume and aggregate returns accumulate in tandem, culminating in a surge of market activity immediately before the event. Second, for virtually every trading day, the relative order of volumes is preserved: the random network consistently generates the highest trading intensity, followed by the small-world and then the community network. This ordering mirrors the differences in both CAR magnitude and the speed of information diffusion discussed previously.

The consistency between the rising CAR and the upward trend in trading volumes is not coincidental. Rather, it stems directly from the gradual nature of rumour diffusion in the network: as more value investors acquire the rumour over time, they revise their intrinsic value upwards and initiate buying, leading to a cumulative build-up of trading activity that mirrors the information spread.

This cascade of informed buying not only propels the price upward, but also creates the price trends that trend followers respond to. As the upward price drift becomes established—driven by value investors' accumulating orders—trend followers increasingly enter the market, amplifying the price run-up. The

magnitude of this effect, visible in the trading volume of trend followers, is itself modulated by the efficiency of information diffusion: random networks, which allow for the fastest and most extensive rumour spreading, result in the highest levels of both value investor and trend follower activity, while community networks, with their bottlenecks to information flow, show more subdued trading volumes.

In summary, the gradual increase in trading activity among value investors is a direct consequence of the endogenous rumour spreading dynamic, and the resulting price movement induces a parallel rise in trading by trend followers. The observed ranking of trading volumes—random exceeding small-world, and small-world exceeding community—reiterates the centrality of network structure in determining the market’s collective response to private information. The close association between value investor activity and the diffusion of private information suggests an intrinsic connection between agent-level belief updating and aggregate market demand. To probe this mechanism more explicitly, we now examine how the evolution of buy volume corresponds with the spreader ratio over time, aiming to clarify the extent to which trading intensity is governed by the sequential adoption of new information.

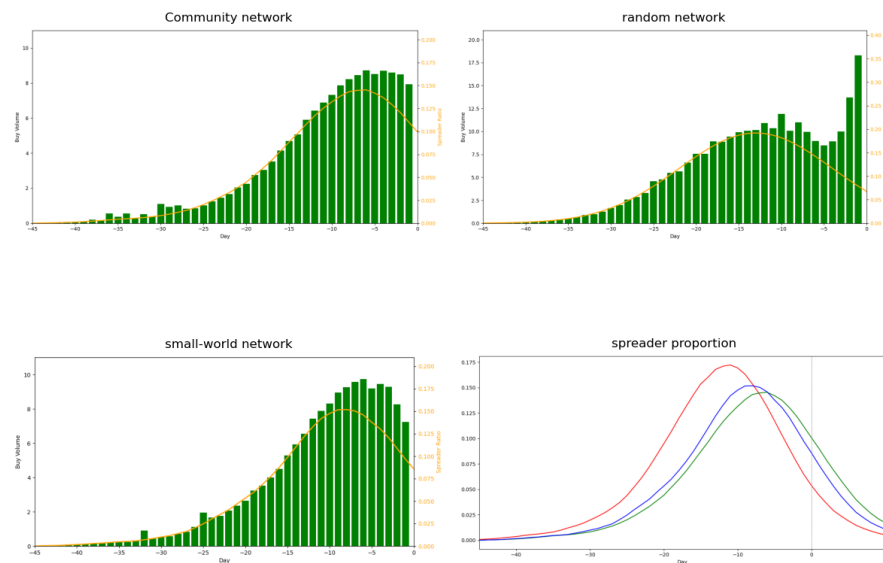


Figure 5.11: Value investors’ average daily buy volume (green bars, left axis) and spreader ratio (orange line, right axis) over time on community (top left); random (top right) and small-world network (bottom left). Bottom right plots the spreader ratio on random (red), community (green) and small-world network (blue)

Figure 5.11 presents a comparative panel of the key micro-level variables—spreader proportion and value investors' buy volume—across community network (top left), random network (top right) and small-world network (bottom left), alongside a comparative plot of spreader proportion on bottom right. This side-by-side visualisation allows us to assess whether the market-level anomalies observed in the CAR plot indeed have their roots in the joint dynamics of information adoption and coordinated trading, and to what extent these relationships are mediated by network structure.

The bottom right panel furnishes a direct comparative analysis of the evolution of the number of spreaders across the three network topologies. The analytical motivation for this plot is to rigorously interrogate whether the heterogeneity observed in market-level outcomes, such as CAR and aggregate trading volume, can be causally attributed to fundamental differences in the microstructural propagation of private information. By explicitly contrasting the trajectories of the spreader proportion, we are able to quantify the respective **intensity** (as measured by the maximal spreader ratio attained) and **velocity** (as captured by the time to peak) of information diffusion under each network configuration.

The random network topology engenders the most rapid and comprehensive dissemination of the rumour, achieving both the earliest and highest peak in the spreader proportion. The small-world network, while benefiting from long-range shortcuts, nevertheless manifests a discernible lag and reduced maximum relative to the random case. The community network, characterised by pronounced modularity and local clustering, displays the slowest and least intense diffusion, with the spreader ratio peaking later and at a substantially lower value. The analytical import of these findings lies in their ability to provide microstructural confirmation of the causal pathway hypothesized in earlier sections: namely, that network topology dictates the flow of private information, which in turn governs the market's aggregate response. The observed ordering and separation of spreader trajectories are entirely consistent with the prior stochastic model analysis, wherein similar topological effects on spreading speed and saturation were identified. This plot thus offers direct empirical validation of the claim that the emergent macro-level price anomalies and trading behaviours are, at root, determined by the granular mechanics of rumour propagation across heterogeneous network structures.

The comparative analysis across network types demonstrates a high degree of regularity in the relationship between spreader proportion and buy volume. In all configurations, these variables exhibit closely aligned trajectories throughout the majority of the pre-announcement window, underscoring the central role of informed agent activation in driving aggregate demand. As noted in earlier sections, a systematic divergence emerges in the final stages, with buy volume exceeding the spreader ratio, particularly as the announcement approaches. This pattern is entirely consistent with the deviations observed in the standard model and in the discussion above, and, importantly, persists regardless of network topology.

The magnitude of this late-period deviation exhibits a clear ordering: it is most pronounced in the random network, moderate in the small-world network, and least apparent in the community network. This reflects the degree to which each topology facilitates rapid and comprehensive rumour diffusion, thereby intensifying price pressure and, in turn, the frequency and scale of forced cover buy-back activity among uninformed short sellers. This substantiates a direct, mechanistic relationship between the forced cover process and the observed deviations, reinforcing the view that network-driven rumour dynamics are fundamental determinants of market response to private information.

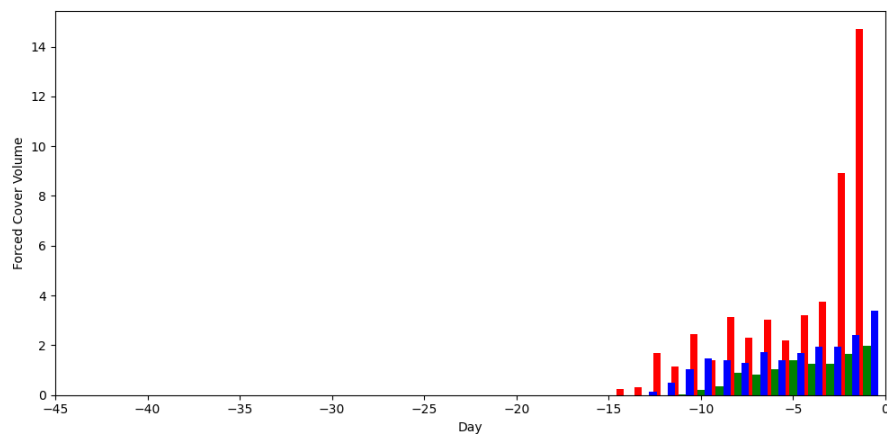


Figure 5.12: Daily forced cover volume on random (red), community (green) and small-world network (blue)

To visualise the relative intensity and timing of forced buy-back activity across network types, Figure 5.12 plots the daily volume of forced covering for random, small-world, and community networks. All three network structures exhibit an overall

increase in forced cover volume as the announcement day approaches, reflecting the compounding effects of information diffusion and price escalation. Notably, the random network consistently produces the highest forced cover volume, followed by the small-world and then the community network. This hierarchy aligns with the respective efficiencies of rumour propagation identified earlier: rapid and widespread diffusion in the random network accelerates the price run-up, exposing a greater number of uninformed short sellers to loss and triggering more frequent forced exits. In contrast, community networks, with slower and more localised information flow, generate the lowest levels of forced covering.

5.10 ROBUSTNESS TEST AGAINST INTRA-COMMUNITY CONNECTIVITY

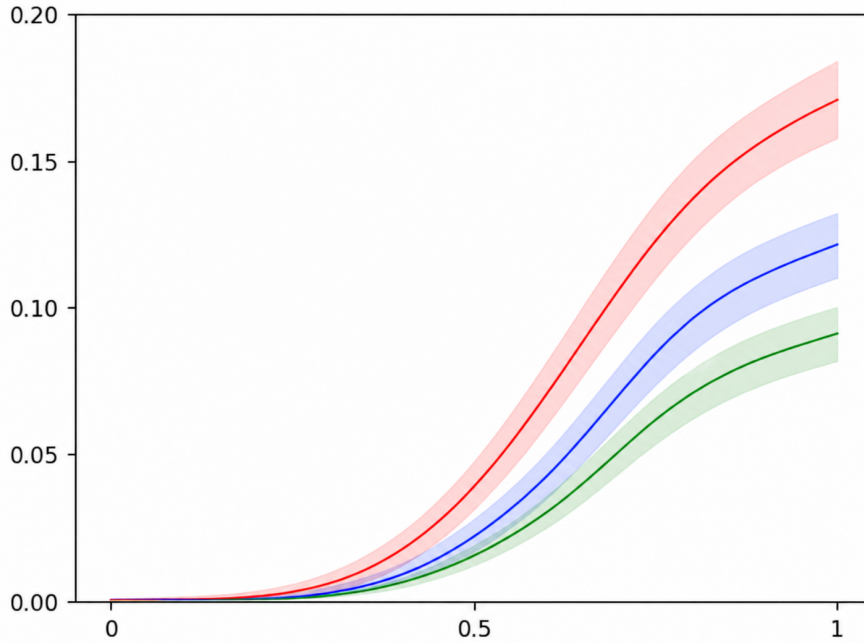


Figure 5.13: Average run-up on random (red), community (green) and small-world network (blue), against intra-community connection probability W_g on the x-axis. The shaded area indicates 95% confidence intervals across 50 Monte Carlo simulations.

To assess the robustness of the run-up magnitude (CAR on day 0) patterns observed in the baseline simulations, we extend the analysis by varying the intra-community connection probability over its full feasible range (0 to 1) and measuring

the corresponding pre-announcement CAR size across the three network topologies. The objective of this exercise is to determine whether the relative ordering in run-up magnitude—random network producing the largest pre-takeover appreciation, followed by small-world and then community networks—persists under systematically altered structural connectivity, or whether it is merely an artefact of the baseline parametrisation.

The results, presented in Figure 5.13, demonstrate a clear and consistent pattern. For all tested values of intra-community probability, the random network curve lies above that of the small-world network, which in turn lies above the community network curve. This ordering is invariant to changes in intra-community connectivity, indicating that the differences in run-up magnitude are an intrinsic consequence of network topology rather than a product of specific connection densities. In other words, the structural features that distinguish these topologies—such as the presence of shortcuts in the small-world network or the high clustering with sparse inter-community bridges in the community network—exert a persistent influence on the rate and reach of rumour propagation, and thereby on the intensity of pre-announcement price pressure.

In addition to confirming the robustness of the ordering, the plot also reveals a monotonic relationship between intra-community probability and run-up size within each topology. As intra-community connectivity increases, information flows more efficiently among linked agents, accelerating the accumulation of informed buying pressure and producing larger CAR magnitudes by the announcement date. The persistence of the gap between topologies across the full connectivity spectrum underscores that while connection density amplifies the overall scale of the run-up, network topology fundamentally determines its relative intensity.

Collectively, these findings provide strong support for the hypothesis that the topology-dependent differences in CAR behaviour are rooted in the structural constraints and facilitation channels governing rumour diffusion, rather than being incidental to a particular choice of parameters. The consistency of the ordering across varying intra-community probabilities reinforces the generality of the mechanism linking network architecture, information adoption rates, and pre-announcement

price dynamics.

To conclude, this subsection has shown that each leg of the price-formation process is tightly governed by the rumour's diffusion path. Because diffusion speed and reach are themselves determined by network topology, differences in connectivity and clustering translate into systematic differences in the magnitude and timing of all three channels. Informed value-investor demand scales with the share and timing of adopters; trend-following activity scales with the strength and persistence of the drift that informed demand creates; and constraint-induced buy-backs by uninformed shorts require both the drift to lift prices above short-entry thresholds and sufficient pre-announcement time for losses to breach margin constraints. Thus, the pre-takeover runup simulated in this model is a result of a multiple channels' interplay, each highly dependent on the network topology.

The consequence is a clear mapping from network to market outcome: networks that propagate the rumour quickly and broadly generate larger informed buying, stronger and earlier trend amplification, and more pre-announcement forced covering, culminating in a larger CAR run-up; networks that diffuse information slowly and locally mute each channel and produce smaller run-ups. The ordering observed throughout—random exceeding small-world, exceeding community—therefore reflects structural properties of the interaction network rather than idiosyncratic calibration. In short, variation in rumour-spreading efficiency across networks induces corresponding variation in trading volumes across mechanisms, and this heterogeneity aggregates into the observed cross-network differences in pre-takeover CAR.

CONCLUSION

Understanding how financial markets incorporate information into prices remains a central concern in both theoretical and empirical research [97]. In the context of corporate takeovers, this issue becomes particularly pronounced, as market participants respond to events that are often anticipated but not yet formally disclosed [41]. A recurring empirical observation in this setting is the presence of a sustained upward movement in target firm stock prices prior to the official announcement of a bid, commonly reflected in cumulative abnormal return (CAR) run-ups [13]. Such patterns pose a challenge to standard interpretations of market efficiency, as price adjustments appear to precede public information releases.

6.1 RESEARCH MOTIVATION

Existing literature has primarily attributed this phenomenon to insider trading and information leakage, as well as rational anticipation among market participants. While these perspectives offer useful interpretative frameworks, they remain limited in their ability to characterise the underlying process through which such information propagates across the market [12]. In particular, the mechanisms governing how information is transmitted between agents, how heterogeneous traders respond to it, and how these interactions aggregate into observable price dynamics are not explicitly modelled. As a result, although prior studies recognise the presence of informed or anticipatory behaviour, they provide relatively limited insight into how these behaviours collectively give rise to the observed price patterns.

So the key research questions are: How does takeover-related information translate into stock price movements before public announcement? How does takeover-related rumour spread among market participants through financial networks? How does the interaction between information diffusion and trading behaviour shape the observed pre-takeover price pattern? What roles do heterogeneous market participants play in converting information into price changes?

We present answers to the above questions in the following section.

6.2 KEY RESULTS

Chapter 1

Chapter 1 introduces the problem of pre-takeover stock price drift and reviews the competing explanations of insider information leakage and rational market anticipation. It argues that existing approaches do not explicitly model how takeover-related information propagates through trader networks and influences market behaviour. To address this gap, the chapter proposes a network-based agent-based modelling framework in which rumour diffusion, heterogeneous trading behaviour, and price formation are integrated to investigate whether these mechanisms can reproduce the pre-announcement cumulative abnormal return (CAR) observed in empirical takeover markets.

Chapter 2

Chapter 2 reviews the empirical and theoretical literature on pre-takeover stock price drift, highlighting insider information leakage, rational market anticipation, and rumour spreading as the principal explanations for abnormal pre-announcement returns. We then establish the methodological foundation of the thesis by introducing the ISR rumour-spreading model and the agent-based simulation framework that underpin the subsequent analysis.

Chapter 3

Chapter 3 establishes the theoretical foundation for selecting an appropriate network topology to represent interactions among institutional investors. By comparing random, small-world, and community networks through their structural properties and rumour-spreading dynamics, we demonstrate that the community network possesses distinct characteristics, including strong local clustering and modularity, that more closely resemble real-world financial communities. Simulation results further show that while all network types eventually reach similar levels of information coverage, the community network significantly delays information diffusion by restricting communication between communities, justifying its adoption as the underlying network structure for the agent-based financial market model developed in the following chapters.

Chapter 4

Chapter 4 develops an agent-based financial market model that integrates the community network established in Chapter 3 with heterogeneous investor behaviour to simulate how takeover rumours influence trading activity and stock prices. The model distinguishes between value investors, who trade according to perceived intrinsic value, and trend followers, who respond to recent price movements, allowing information transmitted through the network to be translated into market dynamics. In this setting, agents are endowed with heterogeneous characteristics and behavioural rules, allowing them to form beliefs and make trading decisions based on perceived mispricing and evolving information. The focus of this chapter lies in capturing how individual decision-making processes translate into aggregate market outcomes, independently of the specific mechanisms of information diffusion.

Chapter 5

Chapter 5 integrates the network-based information diffusion process developed in Chapter 3 with the agent-based market framework introduced in Chapter 4. Within this unified model, information propagates through the network while simultaneously influencing agents' beliefs and trading behaviour. This interaction enables the simulation of how local information transmission and heterogeneous responses can collectively reproduce the emergent takeover price patterns. In particular, simulation results demonstrate that the interaction between rumour diffusion and heterogeneous trading behaviour generates realistic patterns of price adjustment and trading activity, providing the foundation for investigating whether these mechanisms can reproduce the pre-takeover cumulative abnormal return observed in empirical markets.

Schematic of the network-driven price-formation mechanism

In summary, we present a systematic investigation of critical model outputs, including the comparative trajectories of buy volume, spreader ratio, and forced cover incidence, each examined across a range of network architectures. Through this multifaceted analysis, we have sought to elucidate the principal mechanisms underlying pre-announcement price anomalies and to identify the channels through which network structure shapes aggregate market behaviour. The patterns revealed in these simulation experiments are not the result of idiosyncratic parametrisation or statistical artifact; rather, they reflect the oper-

ation of a reproducible and theoretically grounded endogenous process.

To more explicitly visualise this mechanism, we present the process as a workflow in Figure 6.1. This schematic diagram lays out the sequential and interconnected steps by which private information diffuses through the network, alters agent behaviour, and produces the observed price dynamics: rumour diffusion $\rightarrow$ informed demand $\rightarrow$ momentum amplification $\rightarrow$ constraint-induced buybacks $\rightarrow$ CAR

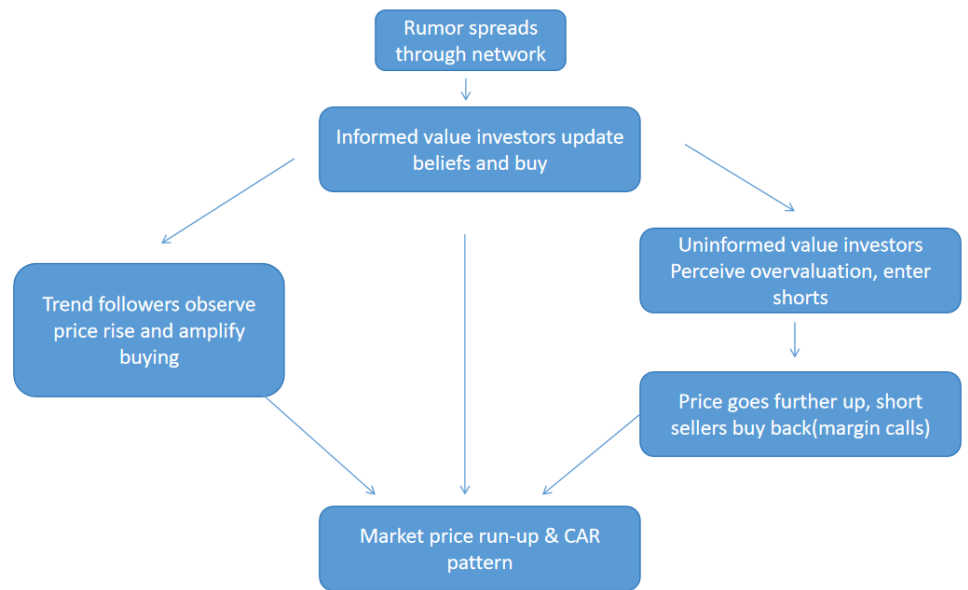


Figure 6.1: Fundamental mechanisms in shaping the runup

At the heart of this model lies a dynamic interplay between information flow, agent decision-making, and feedback effects, all modulated by the network's structural features. The emergence of a private rumour sets off a chain of belief revisions among value investors, whose acquisition of the information is contingent upon their position within the network. The model's logic can be understood as a cascading sequence of interdependent mechanisms, beginning with the introduction of a private rumour, which gradually permeates the agent network according to its topological constraints. As the information spreads, value investors who receive the rumour update their intrinsic value estimates and act on the perceived mispricing, collectively submitting buy orders that set the price in motion.

This initial wave of informed trading does not exist in isolation. As the price begins to drift upward, trend followers—agents who respond to observed momentum rather than fundamentals—enter the market, further reinforcing the incipient rally. Their participation is not arbitrary: the strength of their response is endogenously determined by the scale and persistence of the price movement. The more forceful and persistent the initial run-up, the more pronounced the trend-following amplification.

On the other hand, uninformed value investors—those who have not yet received the rumour—experience the rally from the opposite perspective. With their beliefs anchored to pre-rumour fundamentals, they begin to see the asset as increasingly overvalued and respond by entering short positions. If the price escalation continues—particularly in networks where information diffuses rapidly—these short sellers face mounting unrealised losses. Should their losses exceed margin thresholds, they are forced to buy back shares, further fuelling the upward momentum just before the announcement.

In aggregate, the model reveals that the strength and timing of the pre-announcement run-up are governed by the efficiency of rumour diffusion implied by network structure.

(i) Informed value investors

Informed value-investor demand is a direct function of the rumour's diffusion path. Each time the rumour reaches a new agent, that agent revalues the asset upward and immediately becomes a marginal buyer. As the share of informed agents rises, two things happen simultaneously: the level of buying increases because more traders now perceive undervaluation, and the timing of orders is pulled forward because adoptions arrive sooner. Faster diffusion therefore stacks more buy orders into the pre-announcement window and sustains them for longer, producing a larger cumulative impact on price. Network structure determines this diffusion profile. Topologies with short paths and high mixing (e.g., random) generate earlier and higher adoption, whereas clustered, modular networks (e.g., community) slow and localise the spread. Consequently, informed buying is strongest where the network transmits information most efficiently and weakest where it does not. The panel in Figure 5.9 is consistent with this logic: informed buy volume is largest and arrives earliest in the random network, intermediate in the small-world network, and smallest in the community network—mirroring their spreader trajectories rather than reflecting any change in trader behaviour. The implication for the macro

outcome follows immediately: because pre-announcement CAR aggregates the price effects of order flow, networks that deliver quicker and broader rumour adoption also deliver a larger informed-demand contribution to the run-up, even before considering trend-following or forced covering.

(ii) Trend following

Trend-following activity in the model functions as an amplification channel whose intensity is governed by the diffusion-induced price path rather than by the rumour directly. As information spreads faster and more broadly, informed demand produces a steeper and more persistent upward drift; slower, localised diffusion yields a weaker, intermittent drift. Because the trend followers' trading rule keys off this drift, their activation and scale inherit the properties of the diffusion process: networks that transmit information efficiently generate earlier and stronger momentum signals, while modular networks attenuate and delay them. Importantly, the position-sizing rule for trend followers is non-linear in the strength of the trend. Larger and more persistent price moves elicit disproportionately larger orders (e.g., through thresholding, pyramiding, or convex exposure to a momentum proxy), whereas small or short-lived moves elicit little or no participation. This non-linearity converts differences in diffusion speed into pronounced differences in aggregate trend-following volume: once the drift becomes strong and sustained—as it does under rapid diffusion—the incremental participation of trend followers rises more than proportionally.

Two timing consequences follow. First, trend-follower volume systematically lags informed buying because it requires the drift to form and persist. Second, when diffusion is rapid, late-stage constraint-induced buybacks by short sellers steepen the drift further, reinforcing the momentum signal and drawing in additional trend followers near the end of the window. The comparative volume plots are consistent with this mechanism without any change to the trend-following rule itself. Taken together, the non-linear mapping from drift strength to trend-follower order size, coupled with the diffusion-determined drift, implies a monotone transmission of the network ordering—random exceeding small-world, exceeding community—from information spread to momentum demand and, by amplification, to the ultimate magnitude of the pre-announcement CAR.

(iii) Uninformed value investors' buy-back (forced covering) and its dependence on diffusion

This channel is activated only when two conditions are met in sequence and within the pre-announcement window. First, a short-entry condition: uninformed value investors must perceive sufficiently positive mispricing to initiate short positions once the rumour-driven price drift pushes the market price above their unchanged intrinsic valuations. Second, a loss (margin) condition: after shorts are established, the price must continue to rise long enough and far enough for unrealised losses to breach risk limits, forcing buy-backs. The contribution of forced covering to the pre-announcement run-up therefore depends jointly on the intensity of the drift and on the calendar-time available before day 0. Diffusion speed governs both margins of activation. Faster and broader rumour transmission brings forward the informed-buying wave, steepening the price path early; this raises the pool of short sellers sooner (more agents cross the short-entry threshold) and leaves more time for losses to accumulate to the margin threshold. The hazard of a forced exit thus increases with the slope and persistence of the drift, making pre-announcement forced-cover volume strongly increasing—and typically convex—in the efficiency of diffusion. Slow or localised diffusion has the opposite implications: the price may either fail to trigger widespread short entry or do so only late, leaving insufficient pre-announcement time for margin breaches to materialise. Any covers that occur only after the announcement—when beliefs jump to the bid—do not belong to the pre-takeover run-up by construction.

Network structure maps directly into this timing logic as shown in Figure 5.12. Random networks, with short path lengths and high mixing, generate early, persistent drift and therefore the largest pools of shorts and the highest pre-announcement forced-cover volumes. Small-world networks are intermediate on both margins. Community networks, with pronounced modularity and weak inter-cluster bridges, often delay short entry and compress the time available for loss accumulation, producing low or zero pre-announcement forced covers. This explains the observed late onset of activity in the forced-cover series and the cross-network ordering documented earlier.

Taken together, the results of this thesis suggest that the interaction between information diffusion and heterogeneous trading behaviour plays a central role in shaping the observed price

dynamics. Within the proposed framework, takeover-related information is not assumed to be instantaneously available to all market participants, but instead propagates gradually through a structured network of agents. As the rumour spreads, value investors adjust their perceived intrinsic values and initiate trading based on emerging mispricing, thereby exerting upward pressure on the stock price.

This initial movement in price subsequently interacts with the behaviour of trend-following agents, who respond to observed price changes rather than underlying information. Their participation reinforces the prevailing trend, contributing to a cumulative effect in which local information transmission and behavioural responses are amplified at the aggregate level. In this way, the model provides a coherent representation of how decentralised information flow and heterogeneous agent interaction may jointly give rise to price patterns that are consistent with the gradual build-up observed in cumulative abnormal returns prior to takeover announcements.

Importantly, this synthesis does not imply that the mechanisms modelled here directly correspond to those operating in real markets. Rather, it illustrates that a system combining network-driven information diffusion with agent-based trading behaviour is capable of generating empirically relevant dynamics in a controlled setting. As such, the framework offers a structured perspective on how micro-level processes may translate into macro-level market phenomena.

6.3 STRENGTHS AND LIMITATIONS

This thesis presents several strengths in both its conceptual approach and methodological design. First, it offers an integrated framework that brings together network-based information diffusion and agent-based financial market modelling. By combining these two strands of literature, the study is able to move beyond aggregate or purely statistical representations and instead provide a micro-founded perspective on how individual interactions may give rise to observable market phenomena. This interdisciplinary integration allows for a more structured examination of the relationship between information asymmetry, trader behaviour, and price dynamics.

Second, the modelling framework explicitly incorporates heterogeneity among market participants, distinguishing between value investors and trend followers with differing behavioural rules and responses to information. This enables the analysis to capture a richer set of dynamics than representative-agent models, particularly in terms of how different trading strategies interact and reinforce one another over time. In addition, the use of alternative network structures, including community-based configurations, allows the study to explore how variations in connectivity and clustering influence the diffusion of information and the resulting market outcomes.

Third, the simulation-based approach provides a controlled environment in which complex interactions can be examined systematically. By isolating key mechanisms and varying structural parameters, the model offers insights into how specific components—such as network topology or spreading efficiency—affect the emergence and shape of the cumulative abnormal return pattern. This contributes to a clearer understanding of the conditions under which such dynamics may arise.

Despite these strengths, several limitations should be acknowledged. Most importantly, the model remains a stylised representation of real financial markets and does not incorporate direct empirical validation. While the simulated outputs exhibit patterns consistent with observed CAR run-ups, the absence of calibration to real market data limits the extent to which the model can be used for quantitative prediction or empirical testing.

Furthermore, the structure of the interaction network is assumed rather than empirically observed. Although the use of community-based networks is motivated by existing literature on financial and social connectivity, the model does not incorporate real-world network data, and thus the extent to which the simulated structures accurately reflect actual market relationships remains an open question.

In addition, certain simplifying assumptions are made in order to maintain tractability. These include the exclusion of institutional constraints such as market liquidity, regulatory effects, and more complex behavioural factors that may influence trading decisions. While such simplifications are common in

agent-based modelling, they may limit the model's ability to fully capture the richness of real-world market dynamics.

Taken together, these limitations do not undermine the validity of the framework, but rather highlight areas in which further refinement and empirical grounding could enhance its applicability. The model should therefore be understood as an exploratory and illustrative tool, designed to investigate plausible mechanisms rather than to provide definitive explanations of market behaviour.

6.4 FUTURE RESEARCH

Although the proposed framework demonstrates how rumour propagation through different communication network structures influences trader behaviour and pre-takeover stock price dynamics, several opportunities remain for further development. The model presented in this thesis was intentionally designed to provide a tractable framework for investigating the interaction between information diffusion and financial markets. Future research could therefore focus on extending the model by improving its empirical realism, broadening the range of network structures considered, and adopting more sophisticated rumour-spreading dynamics.

Empirical calibration

A natural extension of this work is the empirical calibration of the model parameters using real-world financial data. Rather than relying on stylised parameter values, future studies could estimate communication frequencies within and between financial institutions, such as brokerage firms, investment banks, hedge funds and asset managers, through market surveys or empirical transaction data. These observations could provide benchmark values for parameters governing intra- and inter-community interactions, while historical takeover cases could be used to calibrate the behavioural parameters of market participants. Such an approach would improve the quantitative realism of the model and facilitate closer comparisons between simulated and observed market behaviour.

Network structure variations

A second avenue for future research is to investigate a wider range of communication network structures. While this thesis focuses on community, random and small-world networks, financial communication networks may exhibit more complex

topological characteristics. Extending the analysis to alternative network models, such as scale-free, hierarchical or empirically reconstructed financial networks, would provide further insight into how different structural properties influence rumour propagation and the resulting stock price dynamics. Such comparisons would also help assess the robustness of the conclusions obtained from the network topologies considered in this thesis.

ODE extension

Finally, future work could consider more complex and realistic rumour spreading models. The Ignorant–Spreader–Stifler framework adopted in this thesis provides a simple and transparent description of information diffusion, allowing the influence of network topology to be isolated. However, more sophisticated models could incorporate additional mechanisms such as spontaneous forgetting of rumours, time-dependent spreading rates, or open-population dynamics in which market participants enter and leave the system over time. These extensions would allow the framework to capture a broader range of information diffusion processes while providing a more realistic representation of evolving financial markets.

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