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SOCIAL NETWORK AND THE DIFFUSION OF INVESTMENT BELIEFS: THEORETICAL EXPERIMENT AND THE CASES OF GAMESTOP SAGA

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Abstract

It is critical to understand how investment beliefs are transmitted across a community and affect individuals' investment decisions, given the proliferation of online social networks. This study proposes a novel approach to capture the cognitive effects (dissonance and exposure), which outperforms previous social contagion models in terms of expressive power. The cognitive model was analysed across a variety of network topologies and communications patterns. It is found that the cognitive diffusion models that account for the difference in belief scores between previous and new beliefs performed as expected. This study establishes a framework under which researchers studying financial behaviors and social contagion in finance could collaborate to better understand individual investments' decisions. In addition, using a set of more than 286,000 tweets from Twitter, the case study of the GameStop stock price saga in early 2021 provides a better understanding of how different patterns of social networks develop according to varying levels of volatility in the financial markets.

Keywords: social contagion, social network, investment beliefs, investor behaviors

1. Introduction

An overlooked area of financial economics is the transmission of investing beliefs and their effects on individuals' investment decisions. Individual decisions have a mediated effect on others in the majority of investment models through price or quantities transacted in common marketplaces. For instance, market prices completely represent all publicly accessible information and investors' beliefs, according to the Efficient Markets Hypothesis (Fama, 1970). It is based on the notion that market actors would exploit any mispricing and that investors with the right views will benefit from agents with wrong beliefs. Consequently, the majority of investors would lean toward one set of accurate beliefs. Thus, in the world of the Efficient Markets Hypothesis, investors' subjective beliefs are not important as there is always one set of objective and available truths on which a rational investor would base to make investment decisions.

However, a growing body of research on financial behaviours demonstrates severe breaches of individual rationality and the Efficient Markets Hypothesis (Ammann & Schaub, 2020; Brown et al., 2008; Burnside, Eichenbaum, & Rebelo, 2016). Given current advancements in information technology and the proliferation of online social networks, it is critical to integrate the influence of contagion through social contacts when analysing economic and financial behaviour. Additionally, empirical literature demonstrates that social connections influence individual and institutional investors' investing choices, including selecting specific stocks (Gray, Crawford, & Kern, 2012; Shive, 2010).

This study proposes a novel social approach to investor behaviour theory by simulating how the process of idea transmission influences individuals' investment decisions. Based on the work of Rabb, Cowen, de Ruiter, & Scheutz (2022), we demonstrate an in-silico experiment to see how an investing idea or belief from a major influencer (financial institutions or key opinion leaders) transmit to its subscribers on different types of social networks. The findings in this study provide novel empirical evidence on possible and interesting dynamics of investment ideas diffusion among agents in a social network. Primarily, we found that the magnitude of differences between investors' prior investment beliefs and influencers' beliefs significantly affects whether investors will change their beliefs.

In addition to the theoretical experiment, this study provides a real-world case study of how a social network of users might grow during turbulent stock price swings. The case study examines the tale of GameStop stock price from mid-January to late February 2021. Using tweets regarding GameStop throughout various stages of the GameStop story, distinct social networks are explored. The degree to which consumers are linked varies greatly depending on the levels of market volatility. This significantly impacts the dissemination patterns of beliefs and knowledge in a social network. More importantly, the formation of a closely linked network of distinct groups of users in a social network coincides with the most turbulent time of the GameStop stock price. This implies that, in actual market condition, the diffusion or interchange of beliefs and information across various sorts of communities is likely to occur, overcoming disparities in tastes, preferences, and beliefs of distinct user groups. This diffusion of belief is considerably more likely to occur when there is a substantial fluctuation in stock values, reflecting widespread strong views about an investment. In contrast, when stock prices fluctuate slowly, the transmission of investment attitudes is restricted due to the poor linkages between groups of users in the social network.

2. Methodology

2.1. Simple diffusion model

The basic contagion model presupposes that investment ideas may spread disease-like (Shive, 2010). Simply being in contact with someone (agent v) who believes something (b_v) generates a chance, p, that the belief will spread to you (agent u) given your prior belief at time t ($b_{u,t}$). In this simple social contagion mechanism, p is the probability that agent u's belief in time t+1 ($b_{u,t+1}$) will be equal to the belief of agent v, b_v. The simple diffusion model of belief could be defined in Eq.1 as follows:

$$P(b_{u,t+1} = b_v \mid b_{u,t}) = p \qquad \textit{(Eq. 1)}$$

2.2. Complex diffusion model

The complex diffusion model hypothesizes that the propagation of ideas is primarily determined by the degree of consensus among individuals with whom each agent is related (Centola & Macy, 2007). In this mechanism of the complex diffusion model, the belief of agent u at time t ($b_{u,t}$) will change to $b_{u,t+1}$ according to the beliefs of agent u's neigbours and also the frequency of each belief among all the neighbors' beliefs.

In this case, we define a threshold (α) (i.e., 50%) so that if the occurrence of belief b_v is larger than 50% in total neighbors' beliefs, the $b_{u,t+1}$ is defined to be equal b_v. In other words, the proportional threshold generates a percentage of neighbors (α) who must believe something (b_v) for the agent u to believe b_v given its prior belief is $b_{u,t}$. The complex diffusion model could be presented in Eq.2 as follows:

$$P(b_{u,t+1}=b_v|b_{u,t})=\begin{Bmatrix} 1, & \text{number of neighbours with } b_v/\text{total number of neighbours} > \alpha \\ 0, & \text{otherwise} \end{Bmatrix} \qquad (Eq.\ 2)$$

The complex diffusion model is better than the simple diffusion model when accounting for the network effects reflecting the real world of investment beliefs better. Investors usually look and tend to adopt belief which is the most accepted by members of their network (social friends, family members, investment communities, etc.). This complex model reflects the herd behaviour in financial markets (Chiang & Zheng, 2010; Mobarek, Mollah & Keasey, 2014).

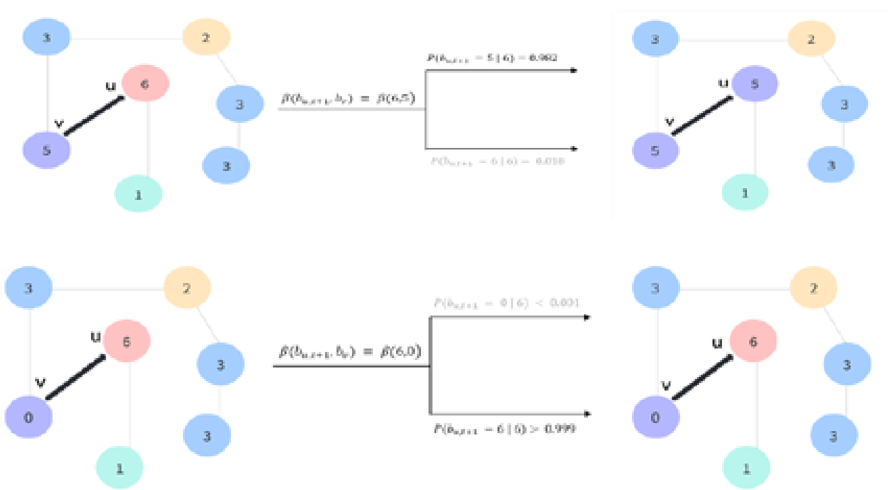
2.3. Cognitive diffusion model

However, the simple and complex diffusion models ignore the magnitude of differences between agents' prior beliefs ($b_{u,t}$) and influencers' beliefs (b_v). Therefore, instead of assuming agents to be affected by an investment idea or not, the cognitive diffusion model will assess a belief strength on a continuous continuum (Guilbeault, Becker, & Centola, 2018). Agent' beliefs could be updated depending on the similarity of two agents' beliefs, do nothing if the beliefs are too far apart, or be bound by logical relationships between beliefs (see Figure 1).

In Figure 1, assuming the belief strength continuum is from 0 (strong disbelief) to 6 (strong belief), and the numeric value in each node (circle) is the belief strength of an agent. There are links between nodes indicating the relationships between agents in a social network. When the prior belief strength of agent u is 6 at time t ($b_{u,t} = 6$), and the influencer belief strength is 5 (b_v= 5). Then the probability of agent u belief strength change to 5 at time t+1 is 0.982 as a result of the function $\beta(b_{u,t+1}, b_v)$ (described in the next section) in Eq.3. In contrast, if the distance of agents' belief strengths is too far ($b_{u,t} = 6, b_v$= 0), the probability of agent u belief strength change to 0 at time t+1 is less than 0.001.

$$P(b_{u,t+1} = b_v \mid b_{u,t}) = \beta(b_{u,t+1}, b_v) \qquad (Eq.\ 3)$$

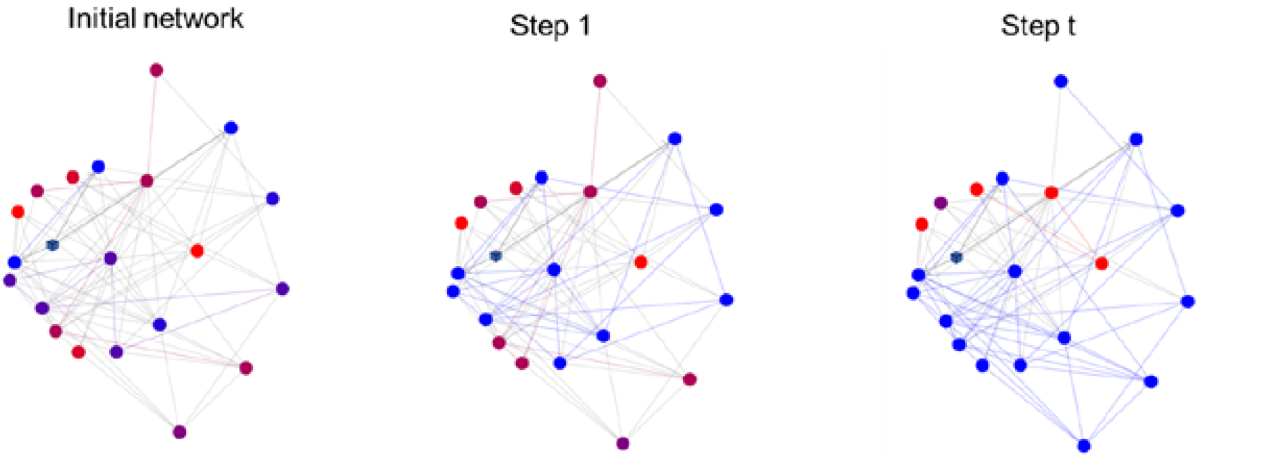
Figure 1: Illustration of the cognitive diffusion model



2.4. Experiment design

The experiment simulated the diffusion of investment ideas from key influencers to their socially connected agents. Then through multiple steps (100 time-steps or t=100), the connections between agents could spread the beliefs (agents with the interested beliefs are blue nodes) all over the network from one key influencer (see Figure 2). Informed by frequently used seven-point scales to convey belief strength in social surveys, we choose seven discrete, equally spaced scores for believing in an investment idea shared by a key influencer in the market (0: strong disbelief to 6: strong belief). The Erds-Rényi (ER) random graph (Erdos & Rényi, 2011), the Watts-Strogatz (WS) small-world network (Watts & Strogatz, 1998), the Barabási-Albert (BA) preferential attachment network (Barabási & Albert, 1999) will be used to evaluate each diffusion approach with the number of agents (nodes) is N = 500. Each network has unique traits that influence how cascading contagions play out. The experiment was conducted using NetLogo software 6.2.

Figure 2: Illustration of the diffusion of investment ideas over multiple time-steps in a network



Following the approach of Rabb et al. (2022), we test the three message sets for each network type to investigate the impacts of various influence tactics over time. The initial message sent will be referred to as "single" since the key influencer just broadcasts one message for the duration of the simulation: bi(t) = (6) (from time-steps t=1 to t=100). The second set will be referred to as "split" since the influencers moves from the belief of bi(t) = (6) (from time-steps t=1 to t=50) to the belief of bi(t) = (0) (from time-steps t=51 to t= 100) halfway through the simulation. We name the last set "gradual" because the institution begins by broadcasting bi(t) = (6) belief, but after every 10 time steps, shifts to bi(t) = (5), bi(t) = (4), and so on until it finishes the last 30 time steps by broadcasting bi(t) = (0).

Based on the work of Rabb et al. (2022), we use the sigmoid function for β as Eq.4 below:

$$\beta(b_{u,t+1}, b_v) = \left(\frac{1}{1 + e^{\mu(|b_{u,t} - b_v| - \gamma)}}\right) \qquad \textit{(Eq. 4)}$$

To describe the strictness and threshold, this study chooses the combination of μ = 4 and γ = 2 to represent investors who are strict in their assessment of believing in investment ideas or not. The larger the μ, the more important the distance between agents' beliefs is for the probability of diffusion (higher μ means lower probability of belief transmission given a particular distance of belief strength).

The parameter γ presents the minimum distance of belief strength considered as the barrier to belief transmission. The likelihood of infection for the simple model is set as p = 0.15, and the threshold for consensus in the complex model is set as $\alpha\ =\ 0.35$ for this experiment.

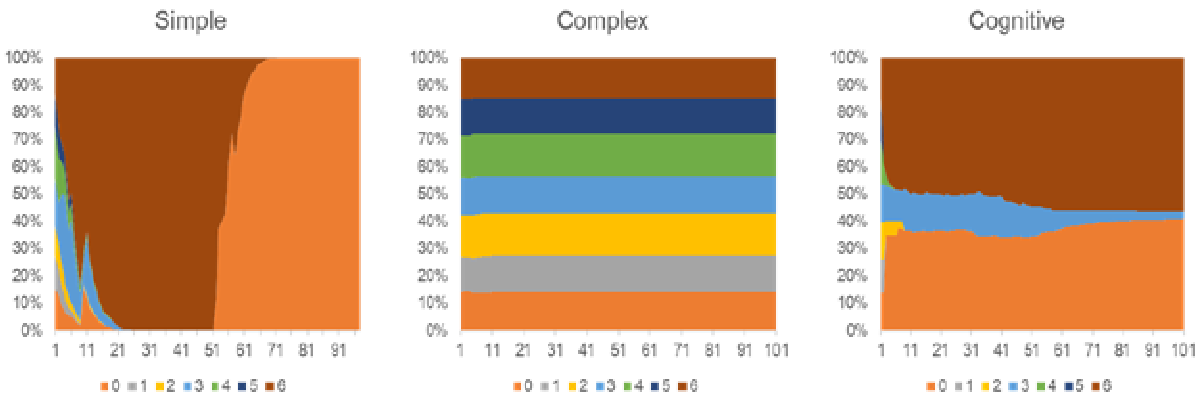
3. Results

3.1. Diffusion of investment ideas between models

The results in Figure 3 show significant differences in how the polarized beliefs (bi(t) = 6) are diffused using different functions. The x-axis is the time-step of the stimulation, and the y-axis represents the percentage of investors (N= 500) according to their score of believing in investment belief b.

With a simple diffusion model, within only about 20 time-steps, the epidemic of investment ideas dominated the network, even with the sudden changes in the investment ideas. The intensity level of belief from the key influencer was swiftly absorbed by the populace. The complex diffusion model showed no significant changes in belief overtimes with the proportional threshold. The cognitive diffusion model shows that the message with a belief score at time t of bi(t) = 6 from key influencers completely infected investors who have belief scores of bi(t) = 5, or bi(t) = 4. Investors who have a belief score bi(t) = 3 were only partially affected. No investors with the belief score of bi(t) = 0 or bi(t) = 1 were infected because the differences in belief were too far to bridge. Among the three models, the cognitive model result is nearest to the dynamic of investment beliefs diffusion and the survival of diverse investment strategies described in financial behaviors literature (Hirshleifer, Lo, & Zhang, 2021). Thus, we choose the cognitive diffusion model to evaluate how investment ideas transmit with a different set of message patterns.

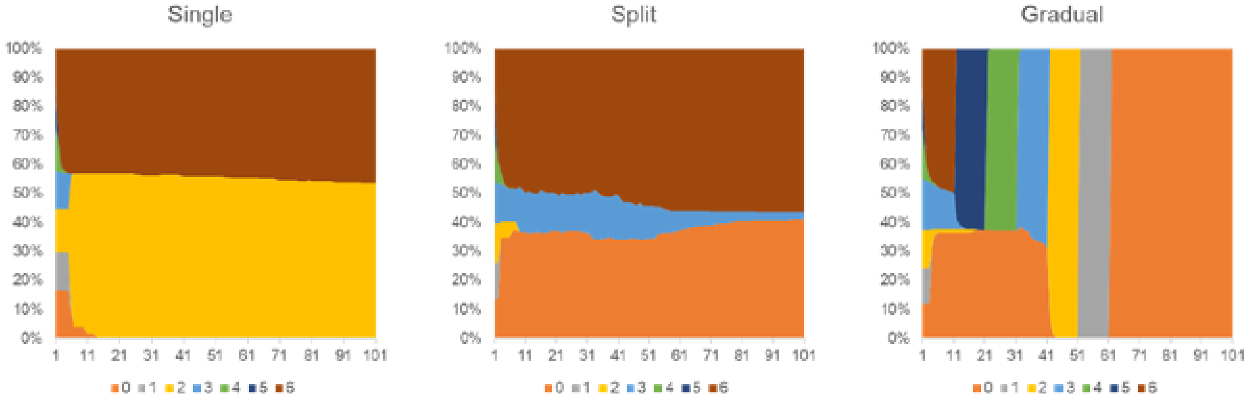
Figure 3: Diffusion of investment ideas M in ER network using "split" message set.



3.2. Diffusion of investment ideas on different message sets

Figure 4 confirms that the investors' prior beliefs are crucial in accepting the new investment ideas. When key influencers only spread the message one as in a single message set, they were only able to influence investors i at time t with bi(t) = 5, or bi(t) = 4, with a few bi(t)= 3 investors seeming to be swayed. In a split message set, the initial message with bi(t) = 6 from t=1 to 50 had the same infected effects as in the case of a single message sent. More importantly, very few investors were convinced by the split condition's message modification. The gradual message set is the only one that was able to sway all agents over to bi(t) = 0.

Figure 4: Diffusion of investment ideas M with different message sets in ER social network



The results for investment ideas diffusion on WS and BA networks (Figures 5 and 6, respectively) are similar to those analysed in ER. With consistent patterns of diffusion regardless of the type of social networks, the cognitive diffusion model proves its power in describing the dynamic of investment ideas contagion.

Figure 5: Diffusion of investment ideas M with different message sets in WS social network

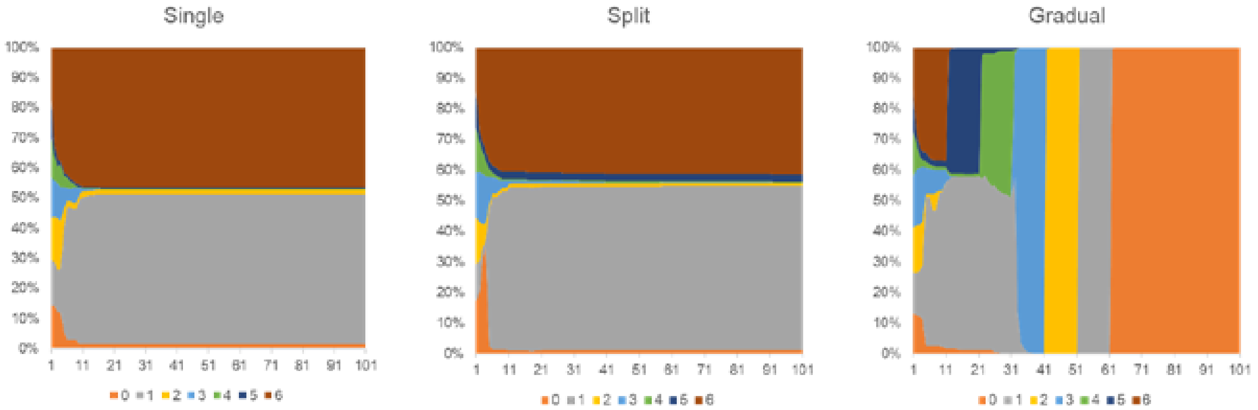
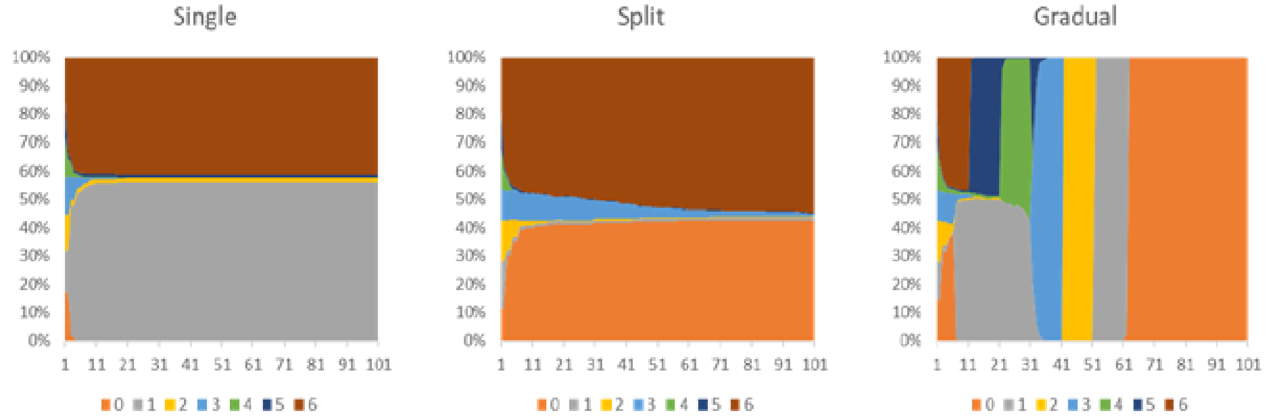


Figure 6: Diffusion of investment ideas M with the different message set in BA social network



3.3. Likelihood of receiving mediated investment ideas

One of the important features of a social network is to see how ideas could be transmitted from the original source via intermediate agents to other target agents. Table 1 shows the proportion of 100 social network graphs (N=500) with at least one path of investment ideas (bm) leading from key influencers to an investor u with a belief score for the ideas of bu via investors v with a belief score of vu with |bm – bv| < τ. The results in Table 1 show that with τ = 1, it is very likely that investment ideas will be transmitted and reach investors via intermediate agents (the lowest probability is 62%). With τ = 2, the probability is lower but still at a high level. Thus, in most cases, all investors would have a chance to be exposed to the investment belief. However, investors' prior belief is crucial to determine if an investor would buy investment ideas or not.

Table 1: Probability of agents receiving mediated investment ideas from key influencer given their belief score of the message

τ = 1	**bu =0**	**bu =1**	**bu =2**	**bu =3**	**bu =4**	**bu =5**	**bu =6**
ER	0.98	1	1	1	1	1	1
WS	0.64	0.76	0.62	0.78	0.86	0.78	1
BA	0.82	0.88	0.9	0.84	0.86	0.84	1

τ = 2	**bu =0**	**bu =1**	**bu =2**	**bu =3**	**bu =4**	**bu =5**	**bu =6**
ER	0.88	0.98	0.96	0.94	1	1	1
WS	0.52	0.68	0.64	0.62	0.58	0.46	1
BA	0.7	0.66	0.76	0.76	0.7	0.62	1

Note: ER: The Erds-Rényi random graph, WS: the Watts-Strogatz (WS) small-world network, BA: the Barabási-Albert preferential attachment network.

3.4. GameStop social network case

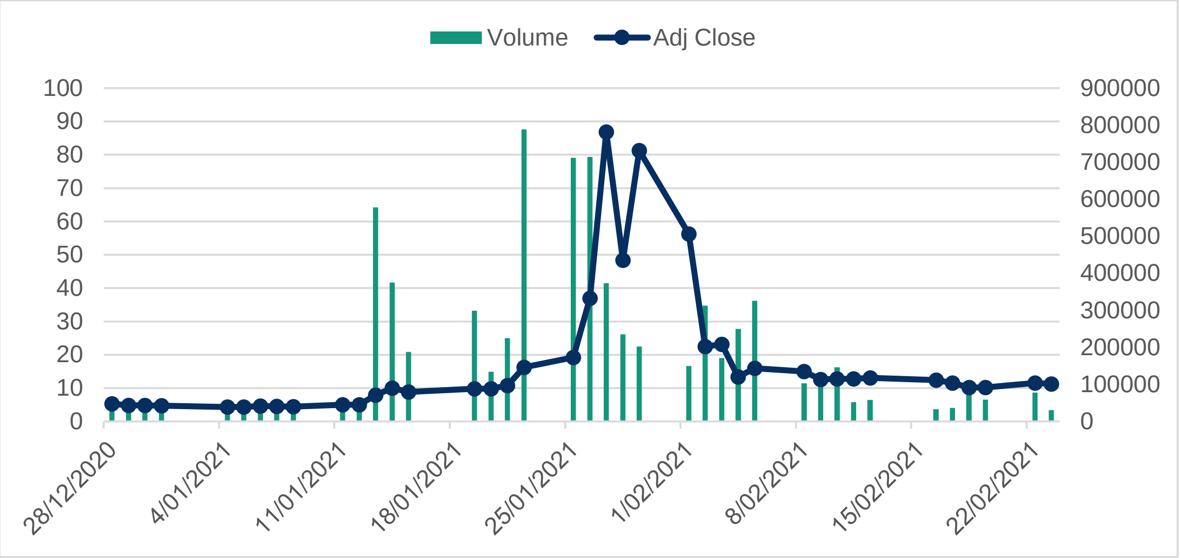
This study uses GameStop tweets gathered from Twitter (keywords: GAMESTOP or GME) from 28th December 2020 to 23rd February 2021 to demonstrate how investing beliefs transfer in the social network and greatly impact asset prices in the real world. This is the time when GameStop stock began to gain popularity among retail investors, and its price skyrocketed 16 times from $5.2 to a peak of $86.8 on 27th January 2021, before falling to $11.2 on 23rd February 2021 (Figure 7). According to Umar et al. (2021a), the media-driven sentiment was one of the key drivers of this dramatic GameStop stock price saga.

Table 2 represents five social networks by time according to the stock price movements. Each network's number of users (nodes) and the number of links between users (edges) when users retweet, quote, or reply to other users' tweets are also recorded. Using the modularity algorithm (Fortunato & Barthelemy, 2007), each network is divided into different communities of users (modules) which have close relationships based on their strong linkages within the module and relatively weaker linkages to other modules. Maximizing the modularity algorithm enhances this fundamental concept by optimizing the number of non-random linkages inside the module and is defined as follows (Fortunato & Barthelemy, 2007):

$$Q = \sum_{s=1}^{m} \left[\frac{l_s}{L} - \left(\frac{d_s}{2L} \right)^2 \right] \quad (Eq.\ 5)$$

where ls is the number of links in module s, L is the total number of links in the network, and ds is the node degree in module s. The first term of Eq. 1 is the proportion of links inside module s; the second term is the predicted fraction of links in module s if links were randomly located in the network. If, given a subgraph s of a network, the first term ($\frac{l_s}{L}$) is much greater than the second $\left(\frac{d_s}{2L}\right)^2$, this indicates that s has many more meaningful links than random links. This suggests that s is, in fact, a module. The Eq.1, the modularity algorithm and other network statistics are calculated using the Gephi software for social network analysis (Bastian, Heymann & Jacomy, 2009).

Figure 7: GameStop price and volumes traded from 28th December 2020 to 23rd February 2021



According to Bedi & Sharma (2016), it is believed that users usually share similar beliefs, tastes, choices, and preferences within a module. In contrast, different beliefs, tastes, and preferences are usually recorded between different communities of users in a social network. Therefore, this study uses the linkage between different modules as a proxy for the transfer of different beliefs between users in a social network. In addition, a number of statistics such as average degree, number of weakly connected components, and network diameter are calculated for each network to measure how strong the connections between users in each network are (Table 2).

The dynamic cognitive diffusion model mentioned above states that the level of beliefs diffusion between investors depends on how close their current beliefs about investment are at a particular period. However, if there is only one single set of beliefs from an influencer, even if the belief is a strong one, the diffusion of this belief only spreads to investors with similar beliefs (Figures 3, 4, and 5). In the normal condition, the social network of GameStop conveys this concept by showing many different groups of users (presented in different colors) which have strong connections with an influencer (the big-sized node) but very few connections between these groups (Figures 8).

More importantly, according to the cognitive diffusion model, it is assumed that the strong linkages between different communities of users only happen when there is a common belief shared by a large number of users across different groups. In other words, in this condition, the belief scores are now similar between users even across different groups because of this extremely strong common belief or fact. The extreme volatility of GameStop stock price from December 2020 to February 2021 provided a real case for testing this implication of the proposed cognitive diffusion model. In the mentioned period, news about GameStop's stock price was shared intensively on different mainstream media channels as well as online social media platforms (Umar et al., 2021a). Therefore, it is assumed that the belief of GameStop as a high risk-high return investment opportunity was ubiquitous at that time among a large number of investors (Hasso et al., 2022; Umar et al., 2021b). Thus, observing how the social network of GameStop stock evolved could give ideas on how the theoretical cognitive diffusion model applies in the real context.

Network 1 (Figure 8) depicts the social network between Twitter users who discussed stories about GameStop just before the saga of GameStop stock from mid-Jan to the end of Feb 2021. It is a totally disconnected network where different modules (depicted in different colors) do not have linkages connecting them. It means that there are very limited beliefs and information transfer between different communities of users in the network 1.

Figure 8: Network 1 of GameStop from 28th December 2020 – 12th Januray 2021

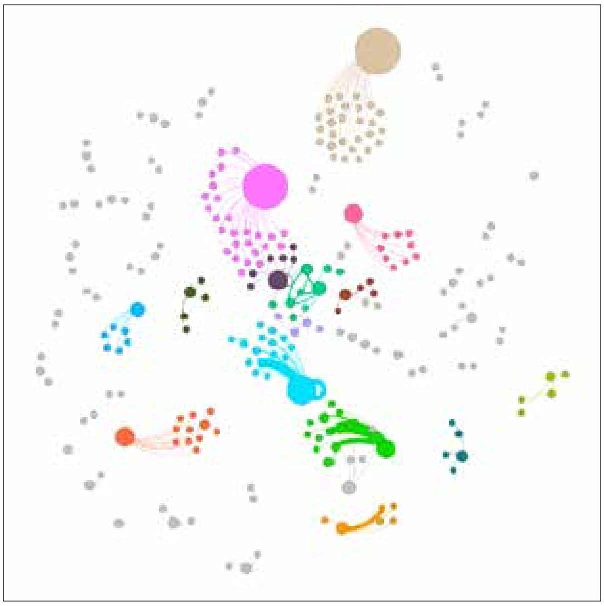
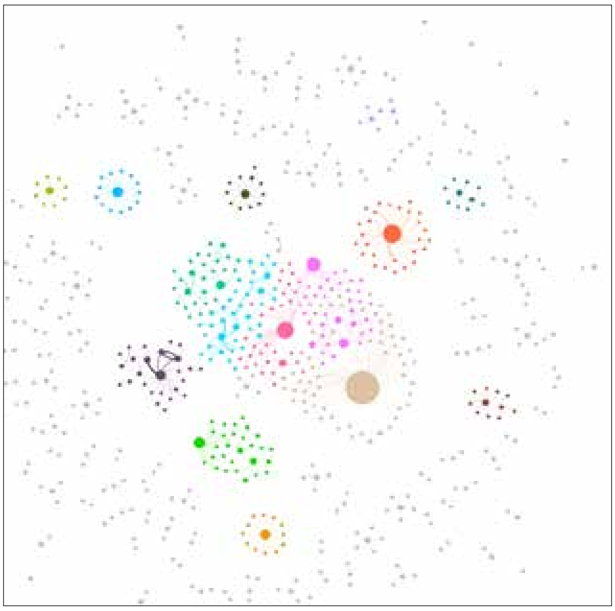


Figure 9: Network 2 of GameStop from 13th January – 25th January 2021



Network 2 (Figure 9) depicts what happened during the initial phases of the GameStop stock saga. There are much more users who discuss stories about GameStop, and linkages between different modules have started to appear. These linkages between modules increased the probabilities of

different types of beliefs and information being transferred between users who belonged to different communities and held different beliefs and information.

It is easy to detect a strong magnitude of belief transfer between different communities of users in a social network when it is associated with the period of strong stock price volatility in Figure 10 of Network 3. This strongly connected network of different users communities during the strongest volatility of GameStop stock price (from $19.19 to $81.25) suggest that the diffusion of investment beliefs using online social networks like Twitter is one of the key drivers of the huge explosion in stock prices in a very short timeframe from 26th January to 29th January 2021. With these strongly connected networks between different user communities, it is very likely that retail traders who use social networks could learn investment beliefs and information diffusions from influencers in other communities. This increases the chance that unique investment beliefs will ultimately dominate among investors and move stock prices swiftly in one direction, which is what happened to GameStop's price during its saga in 2021 (Umar et al., 2021a; Glassman & Kuznetcova, 2022).

Figure 10: Network 3 of GameStop from 26th January – 29th January 2021

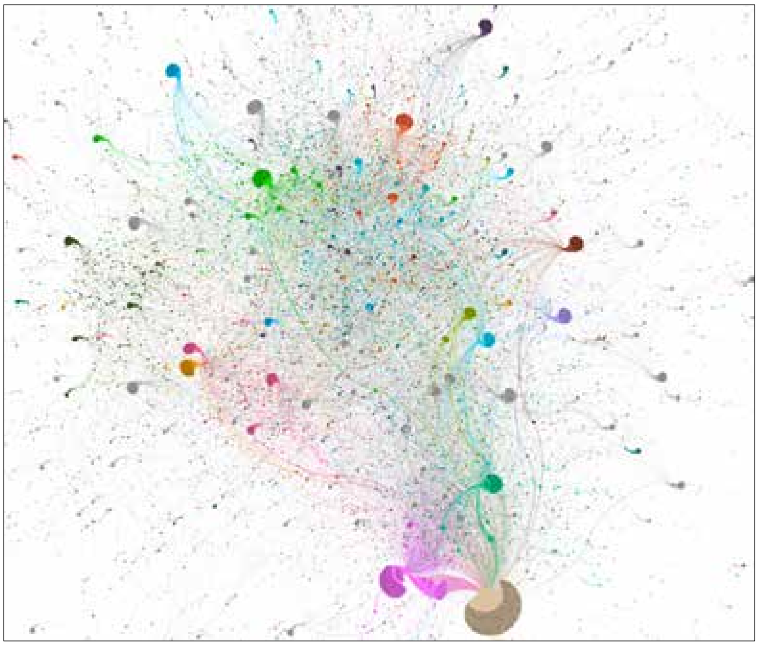


Figure 11: Network 4 of GameStop from 1st February – 4th February 2021

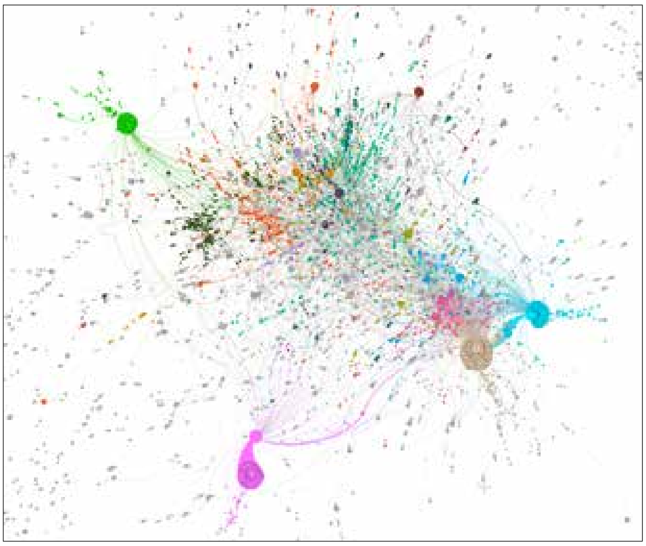


Figure 12: Network 5 of GameStop from 5th February – 23rd February 2021

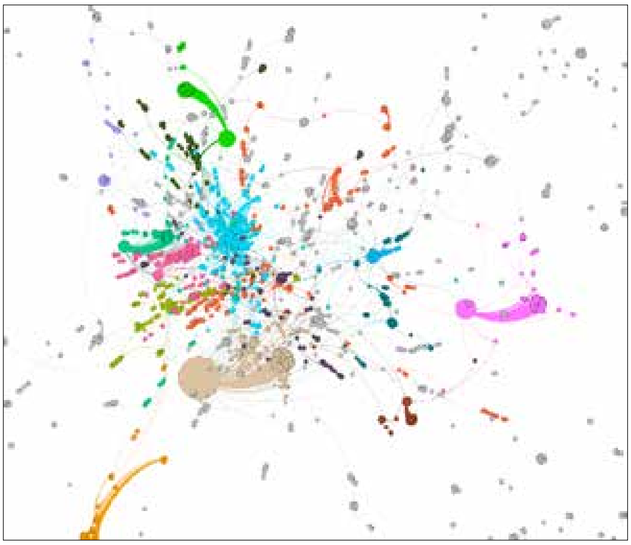


Figure 11 of network 4 depicts another strongly connected network between different communities, which is similar to the features of network 3. During the formation of network 4, GameStop's stock price also volatile dramatically and plunged from $81.25 to $13.37 within just four trading days. In contrast, when the stock price started to cool down and moved in a much narrower range (from $10.7 to $15.9) compared to the previous phases of the saga, the closely connected between different user communities featured in the social network (network 5 in Figure 12) is also significantly weaker.

Results in Table 2 also suggest that Network 3 is the strongest one in terms of the effectiveness of beliefs and information transmission over a network. There was an explosion in terms of the number of nodes and edges in networks 3, 4, and 5 compared to the previous period. Network 3 has the lowest percentage of weakly connected nodes (5.2%). Most of the users in network 3 are strongly connected to each other using direct paths. The likelihood that beliefs and information are transferred could be magnified if there are direct links between users. In addition, when controlling for the width of the network using network diameter, network 3 has the average shortest lengths of the most distant users. This finding once again suggests the strongly connected network between users within the network 3.

Table 2: Descriptions and key statistics of GameStop social networks on Twitter through its sage

	Descriptions	Network 1	Network 2	Network 3	Network 4	Network 5
Time	Time of the network	28th Dec 2020 – 2th Jan 2021	13th Jan – 25th Jan 2021	26th Jan – 29th Jan 2021	01st Feb – 04th Feb 2021	05th Feb – 23rd Feb 2021
Stock Price range	The ranges of GameStop stock prices during the time of the network	From $5.19 to $4.98	From $4.98 to $19.19	From $19.19 to $81.25	From $81.25 to $13.37	From $13.37 to $11.24
Number of nodes	Number of users of the network	249	691	71746	41922	10062
Number of edges	Number of connections between users in the network	210	590	78354	43276	9604

Average degree	Average number of edges that a node has with other nodes	0.843	0.854	1.092	1.032	0.954
Number of weakly connected nodes/total of nodes	Number of users who are connected with at least another user using mediating nodes (nodes in between)	20.9%	20.7%	5.2%	5.6%	12%
Average path lengths	The average number of steps taken along the shortest pathways for all connected node pairs. It is a metric used to assess the effectiveness of information or mass transmission over a network.	1.038	1.014	1.089	1.101	1.315
Network diameter	The shortest distance between the two most distant nodes in the network calculating by using the longest of all the calculated path lengths	2	2	5	4	5
Average path length/Network diameter	It is a metric used to assess the effectiveness of information or mass transmission over a network taking into the width of the network	0.519	0.507	0.218	0.275	0.263

Note: bold number is the best statistics for the metrics

Although network 3 has nearly double the nodes in its network compared to the second largest network (network 4), network 3 still has the highest average degree value (1.092). This means that, on average, a node in network 3 has 1.092 connections with other nodes. It is clear that an average user in network 3 is much more active in their networking tasks and increases dramatically the chances of belief and information transferred from and to them compared to other networks.

Networks 1, 2, and 5 have formed when GameStop stock price movement is in a relatively narrower range. In contrast with networks 3 or 4, networks 1, 2, and 5 have an average degree under 1, indicating that there are major of users in these networks were not so active to form connections with other users to pass beliefs and information about GameStop. These networks also have higher portions of weakly connected nodes suggesting that beliefs and information from one user will have to take longer steps to reach another user, on average. Along these paths via multiple mediating nodes, the impacts of the information and beliefs could be deteriorated and weaken.

Overall, in a social network, the emergence of a strongly connected network of various groups of users correlates with the most volatile period of the GameStop stock price. This suggests that in the real world, the diffusion or exchange of attitudes and information across diverse types of communities is likely to occur, overcoming differences in the tastes, preferences, and beliefs of different user groups. However, this dispersion of belief is far more likely to occur when stock prices fluctuate significantly, showing a widespread opinion about an investment. When stock prices vary slowly, however, the transmission of investing attitudes is limited owing to weak links between groups of users in the social network.

Results from the GameStop network analysis above support the dynamic cognitive diffusion model by providing different network patterns according to various settings of beliefs. Specifically, in the condition when many different sets of beliefs exist simultaneously among users, users with similar beliefs are likely to form local communities around influencers (networks 1, 2, and 5). The connections between local communities of users are limited because of the disparities in preferences and beliefs about GameStop. In contrast, when the idea of investing in GameStop stock is ubiquitous among users in a period of high volatility in the GameStop stock price in one direction (networks 3 and 4), local communities of users are strongly connected. The unidirectional moves in GameStop's stock price during the formation of networks 3 and 4 suggest that most of the users had the same investment beliefs and ideas about GameStop at that moment. The strong linkages between different local communities of users show the crucial role of common belief conditions in the diffusion of information across users, even though they used to have different preferences and ideas about GameStop before.

Conclusion

The experiment demonstrated that simple and complex diffusion models modify agent belief strengths independently of what they previously believed. As a result, these two models of social contagion do not adequately account for the cognitive processes underpinning financial investors. The cognitive diffusion models that account for the distance in belief score between prior belief and the new one, on the other hand, functioned as predicted. The findings were reasonably robust when applied to a variety of graph topologies. In addition, the only message sets that effectively influenced the whole population in our studies were ones that progressively eased agents from one belief level to another. These findings on the social contagion of investment beliefs better understand individual investment choices and serve as a framework for future research.

In addition to the theoretical experiment, this study also represents a real-world case study of how the social network of users could form during different volatile settings of stock price movements. The saga of GameStop stock price from mid-January to late February 2021 is used as the case study. Different social networks are studied using tweets about GameStop during different phases of the GameStop saga. The levels of users' connectedness change significantly according to the extent of stock volatility. This dramatically changes the diffusion patterns of beliefs and information in a social network. Whether these changes in belief diffusion patterns follow the theoretical experiments and how they affect the financial asset prices could be further explored in future research.

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