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To what extent network effect moderate the relationship between social media propagated news and investors' perception?

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Abstract

As a prominent social media tool, Twitter enables prompt dissemination of financial news and information which can have a substantial impact on investors' perception and decision-making process. The propagation of financial news and information through Twitter can either positively or negatively affect investors' perception. As per network theory, the impact of information on one's perception and behaviour is known as the network effect. Since Twitter is also a network, we tried to contribute more to this theory in this study by considering other factors that can have an impact on the perception of investors. We argue that the impact of financial information and news on investors' perception is moderated by other factors such as connectivity, social ties, and network size of the network. To establish the links between them, we considered three key factors in investors' networks such as network connectivity (network structure), social ties circle (Friends, family, colleagues), and size of the network (number of contacts). In this study we have examined 240 retail investors from New Zealand Stock Exchange (NZX) and from different parts of New Zealand including Waikato, Auckland, Wellington, Christchurch, Palmerston north, Tauranga, Napier, Nelson Bay of plenty, Totara north, and Whangarei. The results of this study indicate that highly connected investors receive more information and hence, the impact of news is derived by connectivity of investors within network. The findings of the study also show that social ties circle play a crucial role in determining the impact of the news. The findings further indicate that impact of news on investors' perception also depends on the theme of the news.

1. Introduction

Investors ' perception, behavior, and preference are driven by financial news and information to trade on the stock market (Abhijeet and Kumar, 2011; Brad and Terrance 2007). Investors obtain financial information for investment decisions in the stock market (Han el at., 2013, Mikhail el at., 2013; Gill el at., 2018). Brad and Terrance (2007) argued that investor's perception investors and investment decision to purchase or sell a stock is influenced by financial information, and information can affect investors in both positive (purchase stock) and negative (sell stock) ways, depending on the information. Where Positive news propagates through media encouraging investors to invest while negative news propagates through media discourages investors about the market and pressures them to sell their assets at reduced prices (Daley and Green, 2012). The perception of investors is greatly influenced by the availability of financial information and news such as poor stock-market return, corporate financial disclosure, bankruptcy of financial institute, reputation of the firm (Jank, 2012; Cade, 2018; DeFond et al., 2007; Landsman et al., 2012; Anna el at., 2011; Chen and Xuefei Li, 2019). The impact of financial news on perception is amplified when such news and information is propagated or released through distant media networks such as social media networks (e.g., Twitter and Faceb
ook) (Joyce, 2013; Miller, Skinner, 2015; Eli el at., 2017; Siikanen el at., 2018) and mass media networks like newspaper (L. Fang, J. Peress, 2009; Abhijeet, Kumar, 2011; C.W. el at., 2013; Yugang, Bin, 2016).

A plethora of literature is available that discuss and investigate that adverse financial events and news lead to fear, anger, sorrow, and uncertainty, which discourage investor trust and impacts investor perception (Barber & Odean, 2008; Chung, Liu, Liu, & Tseng, 2018; Daley & Green, 2012; Liu & Li, 2019; Ozsoylev et al., 2014). Current literature explicitly described the relationship between financial news and investor perception (DeFond et al., 2007; Brad and Terrance, 2007; Daley and Green, 2012; Jank, 2012; Lee et al., 2015; Cade, 2018). However, we posit the social media propagated news is moderated by network structure, size of the network, and social relationship. Because the literature clearly shows that exposure and access to information on social media rely on the density, inter-connectivity, and size of the network (Katona et al., 2011; Gregory, Lili, 2011; Panzeri, 2012; Conrad el at., 2018). Similarly, information is more influential and has an impact on individual perception when it is shared by his/her social relationship (colleague, friends, and family) (Panzeri, 2012; Chen, Marcus, 2012; Joyce, 2013; Gregory, Lili, 2014; Valerio et al., 2015).

Therefore, we posit that the impact of the news is depended on the investor's network structure, size of the network, and social relationship. In simple words, the notion of this study is to quantify the moderating role of social network effect (Network structure, the size of the network, and social relationship) on investor's perception and try to extend it through network effect theory.

2. Background

Social media is increasingly being utilized as an important source of communicating valuable financial information in financial markets (Lee et al., 2015). Because Social media can provide investors an opportunity to exchange financial information, and viewpoints about companies, and market (Cade, 2018). Previous studies (e.g. Miller and Skinner 2015; Joyce 2013) have shown how Twitter has become a prominent social media platform for investors to not only obtain financial information but also connect with their counterparts. That's why Twitter is an ideal platform to share sentiments or opinions and information in a timely manner in stock marker (Eli el at., 2017). Hence, such sharing of financial information on social media (particularly Twitter) has an impact on the perception and behavior of investors (Guggenmos and Bennett, 2017; Elliot et al., 2018). From network effect's theory perspective, when one individual affects another on a network (Murendo et al., 2018; Sundararajan et al., 2013), or one buyer affects the decision of another buyer on the market (Leibenstein, 1950) known as network effect. Such effect occurs through communication or interaction in network (Evans & Schmalensee, 2017). Becker (1999) argued that when there is a network, there is a network effect.

The phenomena of the network effect theory were initially introduced in an economics setting and later replicated in the context of online markets and social networks by researchers (Evans & Schmalensee, 2017; Khan, Mohaisen and Trier 2020). The network effect in economics is described as the proliferation of the use of products, which ultimately leads to a high number of consumers. When the number of consumers using those goods and services determines the value of goods and services, it is called network effect (Liebowitz & Margolis, 1994; Shapiro & Varian, 1999) When consumers make products or goods out to be less valuable, the phenomenon is referred to as a negative network effect (M. L. Katz & Shapiro, 1985)

Online networks have grown exponentially which has made the use of network effect theory in social networks more relevant; researchers have understood this trend and have applied network effect theory to social media. E.g. in the context of network effect theory, David, and Richard (2017) argued the individual is generally influenced through communication or interaction on social network. Gregory and Lili (2014) also argued social network effect is the effect of information and communication on an individual's perception and decision, they further argued that this effect occurs when friends, family members and colleagues share information in social media.

Similarly, Conrad el at., (2018) argued that the influence of friends and family on one's decision is the social network effect. Hence, in social networks sites, friends affect other friends' behavior or action through communication and exchange of information, the information spreads in the social relationship circles of individuals on social media (Arun el at., 2013); relationship circles are colleagues, friends, and family members in social network (Roberts el at., 2008, Valerio el at., 2015). Panzeri (2012) argued

Social media becomes a platform that influences individuals' behavior. Most importantly, friends, family, colleagues play a key role in influencing one's perception, preferences and opinions. Bonchia el at., (2010) urged that individual decision to purchase products or service in social media by their friends through exchange of information. The literature described the social network effect and defined some key factors or measurements for measuring the social network effect in bits and pieces.

3. Literature

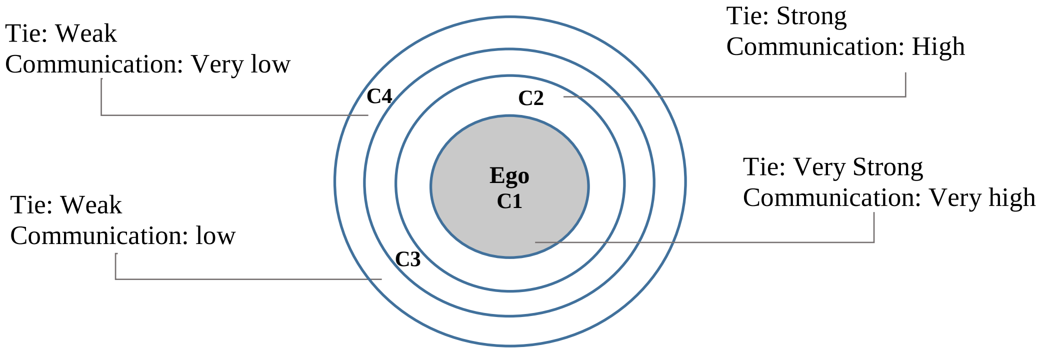
Although there is still little research on the social network effect, some researchers suggested that social network effect is dependent on three factors such as relationship or social circle of the individual in social networks (Khan, Mohaisen and Trier 2020; Gregory, Lili, 201; M. Panzeri, 2012;) network structure of individual in social network (Matthew, 2002; Katona et al, 2011; Craig, 2019), and Size of the network (Katona et al., 2011; Craig, 2019).

3.1. Social Ties circles

There are people in an individual's social sorruounding such as, colleagues, friends and family members. They are called social ties circles of the individual or ego network (Arnaboldi et al. 2016; Paul 2012; Murendo et al.2018; Saxton and Wang 2014). These circles are formed and developed over time depending on how often communication and interactions take places between the individual and people in the vicinity (Arnaboldi et al. 2016). There are variations in the size of circles in social networks of individuals and can depend on frequency of communication and intensity of interaction etc. However, social circle ties of an individual inside a social network are made up of about 4 to 5 circles an average (Arnaboldi et al. 2016; Roberts et al. 2009). These circles can be categorized depending on how close the ego is to people in the network. For example, people in C1 or C2, the first circles, have very close connections to the ego and most of the information exchange occurs in them. People in these circles are usually the colleagues or close friends of the individual. On the other hand, C4 and C5 are considered to be extended user ties where the lowest interaction or information trade takes place. This is because individuals in these circles have no close ties to the individual but information exchange can still occur at times (Arnaboldi et al., 2016).

It is clear that relationships can greatly influence the individuals' ability to exchange information. This is also true in case of investors who trade important financial information with one another based on their relationships (Kestutis 2019). Investors rely on such information Joyce 2013; Kestutis 2019; Miller and Skinner 2015) for decision making. Hence, information plays a vital role in the investment decision of investors. Literature provides a good understanding of why investors rely on information (Joyce 2013; Kestutis 2019; Miller and Skinner 2015) but, these studies have not measured the social ties of investors and have not addressed the importance of strong and weak ties within investors' network.

Fig 1 Social ties circle Structure



These social ties circle structure represent communication and relation strength between ego and his/her friends. Ego is an investor from our study perspective.

3.2. Structure of the network

Social networks have different structures and forms which are dependent on the distribution of degrees (Perera 2017; Lewis 2009). The number of connections or links of a node or user with other individuals within a network is called a degree (Perera 2017; Lewis 2009) which plays a very important role in the generation and dissemination of information within a network (Katona et al., 2011; Luarn et al., 2014). Hence, if there is a network with higher degree, it implies that there is a good interconnecitivity among the individuals (Kim et al. 2011; Katona et al. 2011). Furthermore, the distance or average length of the path between nodes or individuals has an impact on the distribution of information in the network. If there are nodes that are close to each other in the network then the access to information occurs more quickly as compared to more distant nodes (Katona et al. 2011; Lewis 2009; Perera 2017). Also, the higher connected nodes or individuals in the network have a lower average path length which means that they can more quickly receive information (Lewis, 2009).

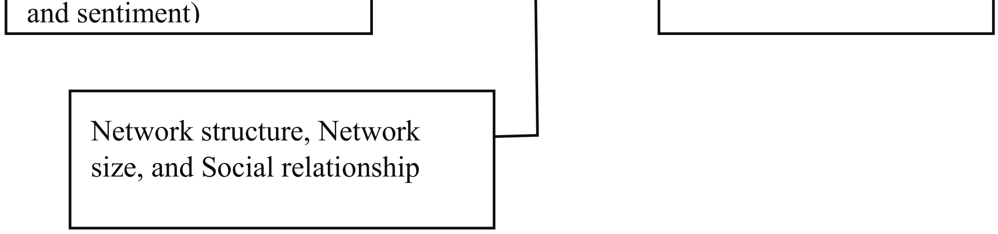
In the context of a social network, information exchange occurs among the investors through social interaction (Miller and Skinner 2015). This is because in a social network, investors usually have direct or indirect links with other investors and share their opinions, emotions, and information in networks (Chen Liu and Xuefei Li, 2019) and access to such information depends on the number of links of the investor in the network (Han N 2013). If investors are more strongly connected with one another they are more often exposed to knowledge and information (San-Lin Chung 2019).

3.3. *Size of the network*

Networks are characterized by having a certain size which is the number of contacts or network members on a social network (Harrigan et al. 2012) where information is distributed by user's contacts (Luarn et al. 2014; Sundararajan et al. 2013). Depending on the nature of ties and links on social network, individuals who have a higher number of followers and friends is likely to distribute more information as compared to the ones with weaker links and lesser number of followers (Luarn et al. 2014). Hence, users or individuals with a higher number of friends and followers receive more information and thus have more exposure to learning about thoughts and experience. Nonetheless, too many friends on Twitter might share too much information that might lead to an overload of information (Williams D., 2006). Social networks offer great opportunities for people to establish connections and links and retain a larger number of friends that would allow individuals to access more information. However, too large network is not a good thing either. Since the strength of the ties becomes weak as network size expands (Ellison et al. (2011). Therefore, the strength of the network ties can't be overlooked as it enables individuals to obtain information from varied or extended social networks (Granovetter 1973). When the network of individuals becomes expands it makes access to more diverse social resources for the individuals easier (Lin, 1999).

Current literature explicitly described the relationship between financial news and investor perception (DeFond et al., 2007; Brad and Terrance, 2007; Daley and Green, 2012; Jank, 2012; Lee et al., 2015; Cade, 2018). However, we posit the social media propagated news is dependent or moderated by network structure, size of the network, and social relationship. Because the literature clearly shows that exposure and access to information on social media rely on connectivity, and size of the network (Katona et al.,2011; Gregory, Lili, 2011; Panzeri, 2012; Conrad el at., 2018). Similarly, information is more influential and has an impact on individual perception when it is shared by his/her social ties (colleague, friends, and family) (Panzeri, 2012; Chen, Marcus, 2012; Joyce, 2013; Gregory, Lili, 2014; Valerio et al., 2015). Therefore, we posit that the impact of the news is depended on the investor's network structure, size of the network, and social relationship. In simple words, the notion of this study is to quantify the moderating role of social network effect (Network structure, the size of the network, and social relationship) on investor's perception and try to extend it through network effect theory. Figure 3: shows our proposed model.

Figure 3: Proposed Model



4. Methodology

4.1 Data

The main subjects of our research datasets are investors who engage in buying and selling shares and/or stocks of companies that are listed on the stock exchanges of New Zealand and Australia. In this study we have examined 240 retail investors from New Zealand Stock Exchange (NZX) and from different parts of New Zealand including Waikato, Auckland, Wellington, Christchurch, Palmerston north, Tauranga, Napier, Nelson Bay of plenty, Totara north, and Whangarei. Our study relies on both primary and secondary data. The primary data represents control variables, which includes age, gender, income, investment, experience, and newspaper. Whereas, secondary data mainly rely on Twitter data (retweets, mention, and replies). Initially, we conducted a survey. The survey was sent to investors via email by New Zealand shareholder Association. The survey contained a consent form. Based on the consent form, we assured participants that their participation in this study would be anonymous. The data will remain anonymous and information is identified as private by Twitter rules and policies (Privacy), 2019 will also not be included in the study. Secondary data mainly focused on tweets including retweets, mentions, replies sent and received by investors in the Twitter network. We started data mining via Twitter API (Application Program Interface) using the NodeXL pro application. Initially, we downloaded 90,399 tweets, after removing the duplicated tweets as part of the cleaning process, we finalized our sample up to 75,904 tweets our study.

4.2. Procedure

Our data analysis and study were divided into three phases. We gathered non-media news sources (newspapers) in the first step using a survey. We sent out a survey to investors, asking them to choose from a list of newspapers (The list included 5 different newspapers). In addition, we requested investors to provide or the list the names of their favourite financial newspapers. Hence, for our study, we gathered and finalized 15 different newspapers. These newspapers include Sharechat, Bloomberg, Herald, Interest news, and Stuff news, Business Desk, National Business review, Newsroom, New York times, Economist, Guardian, Dominion Post, Headliner, The Press, and Yahoo Finance.

In the second step of data analysis, we measured three main factors, such as network structure, network size, and social ties of network effect, or three key moderating variables. We then measured the network structure using the —- method. To determine the size of each investor's network, we counted their number of followers and following. It's worth mentioning that if a single person or investor's friend is both a follower and a following, we counted them as one individual or one contact. We did this to avoid counting the same person twice. To build social ties circles, we applied a method used by Arnaboldi et al. (2016). Based on this method, the frequency of communication (mentions and retweets) between the investor and his/her friends was measured. We kept track of each investor's communication with his or her mate. The degree of communication shows the level of trust. This means that the highest level of communication and information sharing between investors and their friends demonstrates the highest level of trust.

We then conducted sentiment analysis. We analyzed tweets using the n-gram language model to identify and categorize words with particular meaning positive or negative used in tweets by investors. In the economic and finance literature "N-gram" method is used extensively to evaluate texts in greater detail (Gentzkow, Kelly, and Taddy, 2019; Algaba, 2020). In this case, N is a number of words or phrases tracked in the text or document. For a more comprehensive analysis of investors tweets, we included unigram (one word), bigram (two words), and trigram (three words), 4-gram counts in our N-gram textual analysis by considering economic, financial, and non-financial or economic words in tweets. We did this because some single words or unigram has a positive or negative meaning depending on previous or other words (Gentzkow, Kelly, and Taddy, 2019). For example, "profit/no profit or positive return/negative return, with or without "no" or "negative/positive", the profit and return can possibly deliver a different meaning. We, therefore, included bigram (two words), and trigram (three words), and 4-gram counts while analyzing the tweets to present proper meaning of words. However, some single words have particular meanings without depending on previous or other words. For example, investors used "bearish" words in the tweets that indicate falling share price while "bullish" indicates an increase or rising of the share price. Hence, these kinds of words come under unigram category. We finally applied PLS-SEM to measure the impact of the financial news and information on investor perception. We therefore applied the PLS-SEM because PLS-SEM has the ability to calculate the direct, indirect and moderating effect.

4.2. Measurement

Considering previous literature, we selected degree or network degree and average path length to represent the network structure of the investor. In this section, we showed that how measured or calculated these two key network structural properties using investor twitter data (Perera et al. 2017; Ted 2009).

4.2.1 Network Structure

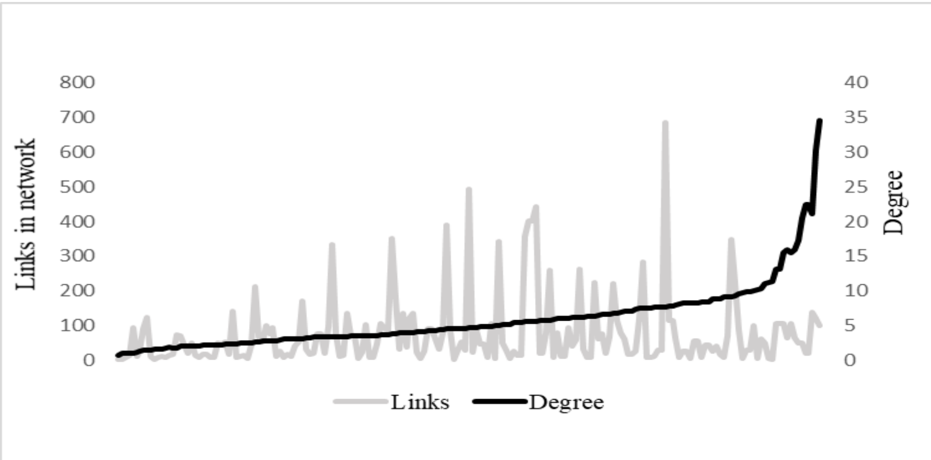
4.2.1.1. Network Degree Distribution

The degree is the number of connections or links (edges) of the node (investors) with other individuals or friends in the network. We first calculated the network degree of each investor by the method given by (Lewis, 2009). We have then presented it in a graph by adding minimum Degree D_1 to maximum D_m in-network V

$$Dv = \frac{2mi}{n} \qquad (1)$$

Dv represents the network degree of investor i in network V, m_i is the links of investor i in network V and n is the number of nodes or individuals in network V. Below fig (3) shows the degree distribution within investors' network. It shows nodes (friends/individuals) and links (edge) of each investor. We calculated the network degree of each investor. We first added or counted the number of links or connection (m) of an investor in his/her network and then divided it by the number of nodes (n) in the network. So that we get a network degree for each investor. The graphs indicate that investor with higher connections within the network has higher network degree. It is also worth noting that some small-network investors (friends) have higher degrees compared to larger networks. We can say that degree does not depend on the size of the network but depends on the number of investor links within a given network. It simply shows investor connectivity as Perera (2017) argued that the higher average degree implies good interconnectivity. The below graph shows an average degree distribution of the entire sample dataset.

Fig 3 Degree distribution



4.2.1.2. Average path length (APL)

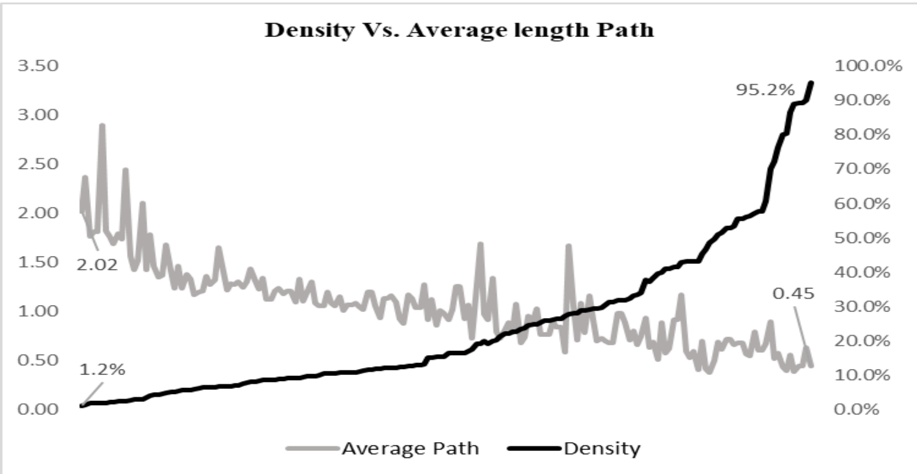
The average path length is the shortest distance between nodes or individuals in the network. Density shows the ties or link parentage within the network. It shows how many links a node or individual has within the network (Lewis 2009). In random networks, the average path length decreases by increasing the links or increasing the density or inversely related (Lewis 2009). Hence, we measured the average path length and density of the network method by following methods discussed by Lewis (2009).

$$APL = \frac{\log(\frac{n}{\lambda})}{\log(\lambda - 1) + 1} \quad (1.1)$$

n is the number of nodes or individuals in the given network where λ is the average node degree. $\lambda = \frac{2m}{n}$. Where $Density = \frac{2m}{(n(n-1)}$ n represent nodes, and m represent links in the network.

Our network data also shows that an average path length and density are inversely related. It shows that investors with low average path length have a higher density of the network and vice versa. In the below graph (3a), we presented investors with their density and average length path of their network. It shows that investors with 1.2 % lowest network density have a higher average path length of 2.02 which means this network is not well interconnected. Similarly, an investor with the highest density (95.2 %), has lowest the average path length at 0.45 which shows good interconnectivity. However, it should be noted that the average path length of some investors was comparatively less affected by the density. Some investors have higher density but their average path length is still high instead of low average path length, which makes just 5.5% of the overall data. Below fig (3a) shows investors density Vs. Average path length

Fig 3a Average length path vs. density

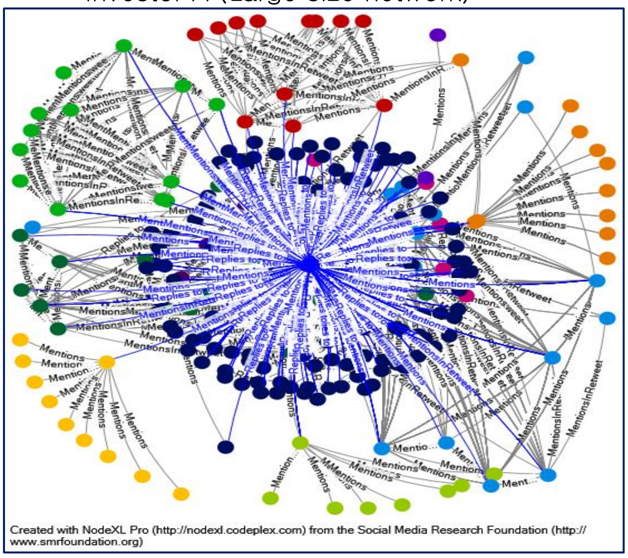


4.2.2. Network size

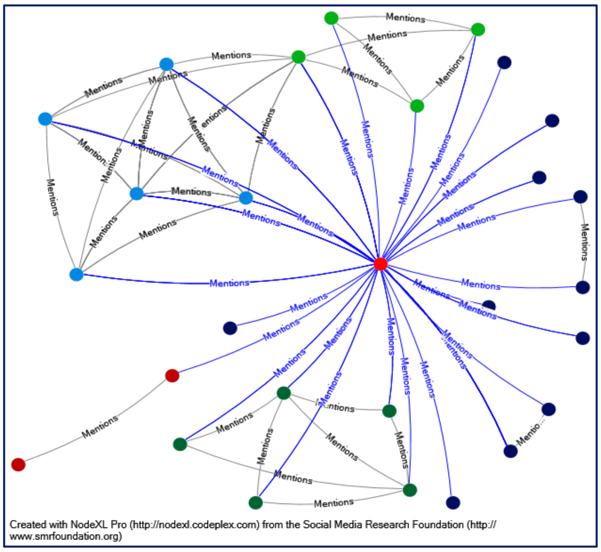
We've calculated investor network size by summing up their current total friends or contacts (following/followers). Our data shows that as the size of the network increases, the number of information in form of mentions, retweets, and replies also progressively increases. In fig (4), we presented an investor's network with comparatively large, medium, and small network sizes. It shows that investors with larger network exchanges or communicates information (mentions, retweets, and replies) higher an average compared with a smaller network. For example, investor “A” with a network size of 3676 friends exchanged 297 information or tweets. Whereas investors “C” with a smaller network size of 131 friends, just exchange 16 tweets. Network comparison is presented in below fig (4):

Fig 4 Network Size vs. Tweets

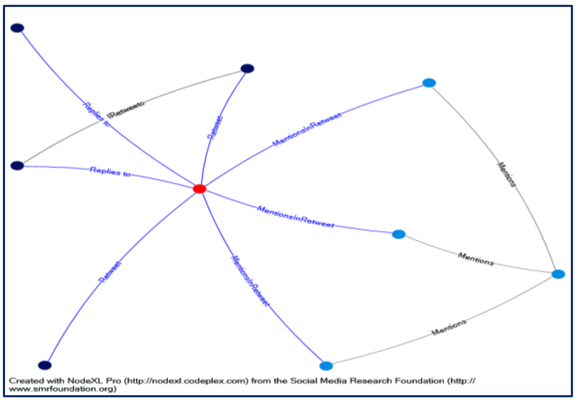
Investor A (Large size network)



Investor B (Medium size network)



Investor B – Small size network



Size vs. Tweets comparison

Investor	Followings	Followers	Total (Network size)	Tweets
A	321	3355	3676	297
B	196	676	872	37
C	86	45	131	16

In our dataset, the average minimum network size (group 1) is 200 friends with 32.3 tweets while the average maximum network size (group 24) is 7800 friends with an average of 1542 tweets. However, our data also shows that some investors with the larger network have received comparatively lower information. For example, investors with average network size (groups 15 & 19) of 3000- 3200 and 3800- 4000 friends received comparatively fewer tweets (showed in Table 1). But our overall network data shows that investors with a larger network size receive on average higher information or tweets. The size of the network is presented:

$$NS = number\ of\ followers + number\ of\ following \qquad (2)$$

Table 1. Average size of network vs. Average Tweets

Group	Average Network size	Average Tweets
1	0-200	32.3
2	200-400	44.1
3	400-600	75.2
4	600-800	83.2
5	800-1000	134.5
6	1000-1200	178.2
7	1200-1400	269.6
8	1400-1600	269.1
9	1600-1800	330.9
10	1800-2000	351.3
11	2000-2200	374.2
12	2200-2400	386.0
13	2400-2600	583.7
14	2800-3000	683.0
15	3000-3200	469.0
16	3200-3400	685.0
17	3400-3600	703.0
18	3600-3800	980.7
19	3800-4000	278.5
20	4600-4800	1,218.7
21	4800-5000	1,226.0
22	5200-5400	1,251.0
23	6400-6600	1,422.0

24	7600-7800	1,542.3

4.2.3. Social circles ties

Communication or interaction occurs in the social network through mentions and retweets (Arnaboldi et al. 2016; Riquelme and González-Cantergiani 2016; Stieglitz and Dang-Xuan 2013). Conover et al. (2011) argued that users of Twitter interact with each other in two ways: retweets and mentions. Mentions are meant to address a specific individual directly and retweet acts as a form of endorsement. To calculate Social ties and the strength of the relation of investors, we applied the method used by Arnaboldi et al. (2016) and Khan, Mohaisen, and Trier (2019). The following equation provides us with the numbers of friends that how many friends are in each circle and how much information or communication (mentions/retweets) takes place in each circle. This equation further gives us the number of close friends (strong ties) number of extended friends (weak ties) of an investor in his/her entire network. In simple words, the following equation gives us the certain group of friends from the entire network with whom investor exchange information. The equation for social tie circles is:

$$\mathrm{STC} = \sum_{i=1}^{n} \left(\frac{C1}{100}(r1) + \frac{\mathrm{C2}}{100}(r2) + \frac{C3}{100}(r3) + \frac{\mathrm{C4}}{100}(r4) \ldots\ldots \frac{\mathrm{Cn}}{100}(rn) \right) + L \tag{3}$$

C represents the size (number of a friend in each circle) of each circle and r represents the tie strength of each circle. The strength of the tie reflects the influence of each circle because of the level of information exchange. r1 is the strength of the relationship between the investor (ego) with his/her friend (alter) in the social ties circle (c1). Similarly, r2 represents the strength of relation in C2. To simplify the social circle ties equation, L is added to the equation, L represents the ego (investor). The value of L is 1 since ego (investor) rationally trusts him/her the most. To calculate the size of each circle (C), we applied the method used by Arnaboldi et al., (2016). The size of each circle (C) is measured based on the number of mentions and retweets done by the investor.

$$\mathrm{Cij} = \sum_{\mathrm{j} \in \mathrm{m}} \mathrm{Mfreq} + \sum_{\mathrm{j} \in \mathrm{rt}} \mathrm{RTfreq}$$

(3.1)

Mfreq is the set of individuals mentioned by the investor i in his reply/tweets. RTfreq is the set of individuals mentioned by the investor i in his reply/tweets. Mention frequency is measured as below

$$\mathrm{Mfreq} = \frac{\text{Link mention frequency}}{\text{ego (investor)total mention frequency}} \quad (3.1.1)$$

Link mention frequency is the mention of a friend (alter) j by investor i in his comments, tweets, or reply. Total mention frequency is the mention of all friends (alters) by investors i his comments, tweets, or reply. Retweet frequency is measured as below

$$\mathrm{RTfreq} = \frac{\text{Link retweet frequency}}{\text{ego (investor)total retweet frequency}}$$

(3.1.2)

Link retweet frequency is retweets of a friend j's tweet by an investor. Total retweet frequency is the retweet of all friends' tweets (alters) by investors i. Based on our analysis, investors exchange information or communicate with his/her friend based on circles, which is comprised of four circles. The first circle (C1) of the investor or ego represents the friends with stable relations or strong ties where the highest communication took place. The first circle size is 2.66 of average friends with an average communication of 0.33 where the last or fourth circle (C4) of friends has a larger size (39.4 friends) with the lowest average of 0.003 communications or interaction that shows unstable network or extended network of ego or investor. Below figure: 4.2.3 shows the social ties circle of investors

Table 2. Socil ties circles of investor

Circles	Average communication (Tweets & retweets)	Average Size of circle (number of friends in each circle)
C1	0.335	2.6
C2	0.080	8.1
C3	0.035	18.7
C4	0.003	39.4

4.2.3.1. Strength of ties (r)

To normalize the social ties circle, we measured the strength of the ties or relationship between investors and his/her friends. To do so, we conducted a linear regression to calculate the correlation between the frequency of mentions and the frequency of retweets by following the equation given by Arnaboldi et al. (2016). The equation indicates the strength of ties and the diffusion of information in the network.

$$RTfreq = \sigma + \beta * Mfreq$$

(3.4)

We conducted linear regression for each social tie circle of investors to calculate the tie or relationship strength of each circle. Our study shows the strength of the tie relay on information exchange, rather than circle size. It also shows that investors often share information with a small number of friends. It means investors maintain a stable or strong relationship with limited friends through higher contact or information exchange. Based on our analysis, the first circle of social ties has the highest R-value at 0.34 which shows the strength of the tie of the first circle and also shows that investors have higher trust in friends of this circle. Since social ties circles down from C1 to C4, the strength of ties (r-value) also decline from 0.34 to .036. R is the correlation between RTfreq and Mfreq and the estimated parameters α and β are reported in the below table.

Table 3. Strength of ties in each circle

Circles	r (Strength of ties)	Size of each circle (Friends)
C1	0.34	2.6
C2	0.17	8.1
C3	0.14	18.7
C4	.036	39.4

4.2.4. Investor perception

Some social network studies have measured the social network effect by the number of posts and likes received by users (de Vries et al., 2012; Khan, Mohaisen, Trier, 2019; Katona et al. 2011). However, we measured the existence of social network effect in investors network via replies of investors to the information and news received on Twitter. The replies (positive or negative) of investors to the news indicate the effect of information on investors' perception. As social studies stated that impact of information on one's perception and behavior is a network effect (de Vries et al., 2012; Khan, Mohaisen, Trier, 2019; Katona et al. (2011). To do so, we conducted a comprehensive sentiment or Text analysis. Since sentiment analysis is an effective method of measuring the perception of investors and individuals through the impact of financial information (Kipp, Zhang, Tadesse, 2016) and social interaction (Bian et al., 2016). Particularly, the "reply" of investors and individuals to financial information and news better reflects the perception where positive reply indicates positive perception and negative response indicates negative perception (Kipp, Zhang, Tadesse, 2016; Bian, 2016). Stieglitz & Dang-Xuan, (2013) argued that communication, language, or word used in replies in social media demonstrates individual feelings and feeling of individual is perception in general (Hall, Jobson, & Langdon, 2014). We measured investor perception as:

$$Pi = (\mathrm{PRi} - \mathrm{NRi}) - 2$$

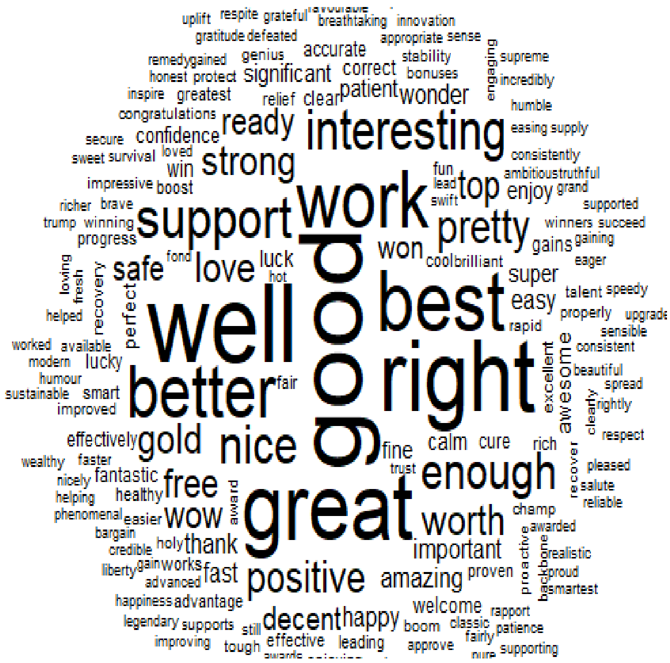
Pi indicates perception of i investor. PRi is the positive words used in replies of investor i to j news and information, Where NRi are the negative words in replies of investor i to j news and information. we subtracted 2 from (positive – negative) to normalize the definition range from [2,10] to [0,8]

We counted and coded financial and economic words used in tweets while considering the financial and economics literature on textual analysis. For example, High dividend (+1), low dividend (-1), no dividend, drop or low S&P (-1) or SP (share price), bounce S&P, high S&P, return, low return, high return, stock, stock price, increase in stock price, decrease in stock price, market tanking, no interest, low interest, high interest, economy, trade, fund, profit, making profit, no profit, Capex, low CAPEX, high CAPEX, bullish, risk, crash, debts, crisis, bearish, fall in Index. We also traced non-financial signal words in investors' tweets which have sentimental value like "good", "nice"," bad", "terrible" and so on. Meanwhile, there are some words which have positive or negative meaning but something their meaning possibly change from positive to negative and vice versa e.g. "good" is a word with positive meaning while "not good" is most likely present negative meaning or "not bad" can be used in positivity terminology. Hence, we also consider such words which depend on previous words that could possibly change the meaning of that particular word.

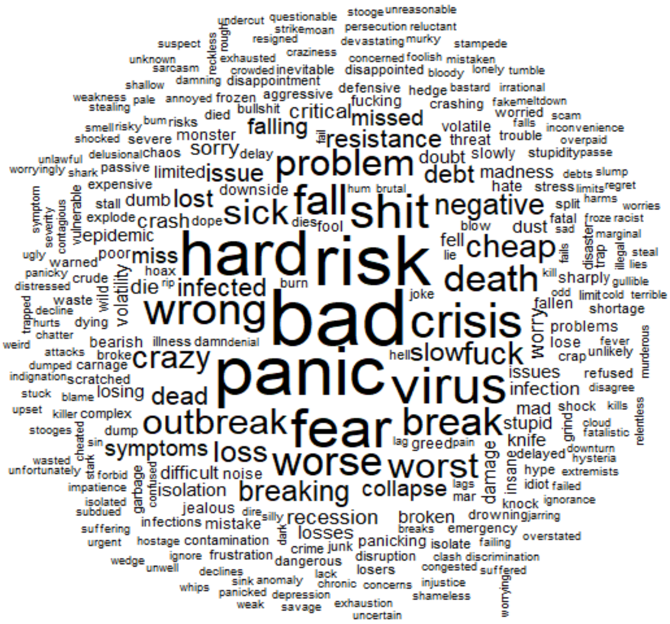
For the non-financial words, we counted positive and negative words by using the NodeXL pro application with an automated dictionary of 6,785 words list. For instance, positive words (e.g. great, progress, good, precious, nice, love, confidence, well, worth, help, support, happy, better) are scored (+1) where negative words (e.g. worry, insane, bad, fear, hate, epidemic, delusional, death, worse, problem, idiot, inevitable) are scored (-1). Some investors reply in the form of emojies in Twitter without writing something. Therefore, we decided to include emoji in our analysis because emoji can also represent one's perception and emotion both positive and negative. We categorize emojies into three categories: Positive (+1), negative (-1), and neutral (0). For instance, positive emoji are 😆 😃 😂 😝 ☺ 😘 😎 👀 👍 👊 💪 🐐 🙏 👏 👌 🚀, where negative emoji are 😒 😴 😢 😭 😬 😶 ♂ 💀 👎, and neutral are 😲 😐 🎬.

To further expand our analysis and make it more relevant to the current situation, we included novel keywords used in tweets such as keywords such as Covid-19, coronavid19, coronavirus, corona, C.virus, CV, virus, flu, and wuhanvirus. The current NodeXL dictionary has neither positive nor negative meaning for these words. However, these are words more likely used as in negative terminology in the tweets. We used R studio to develop word cloud. We also presented the positive, negative and top hashtag in below word cloud.

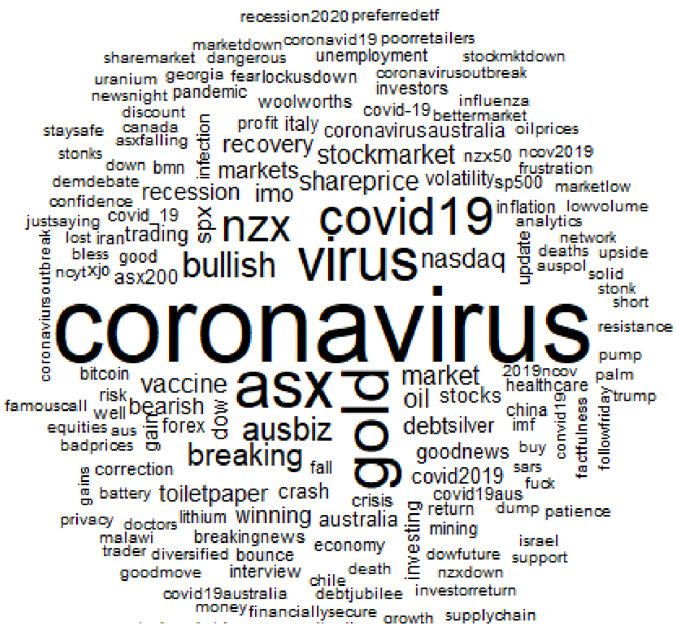
Positive words



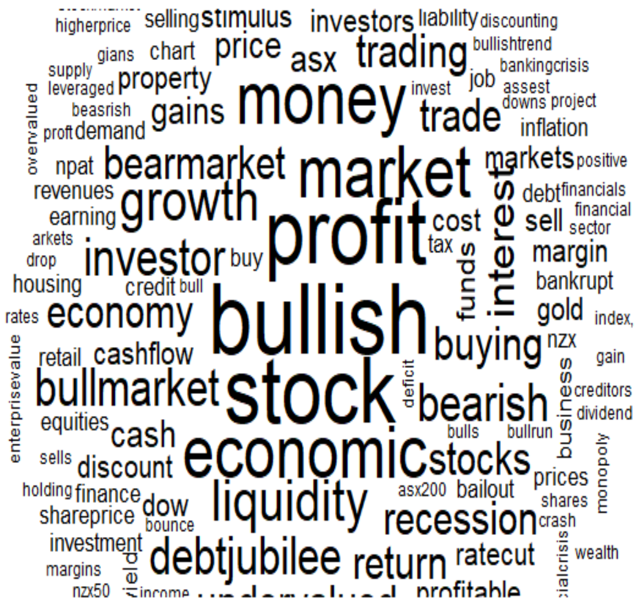
Negative words



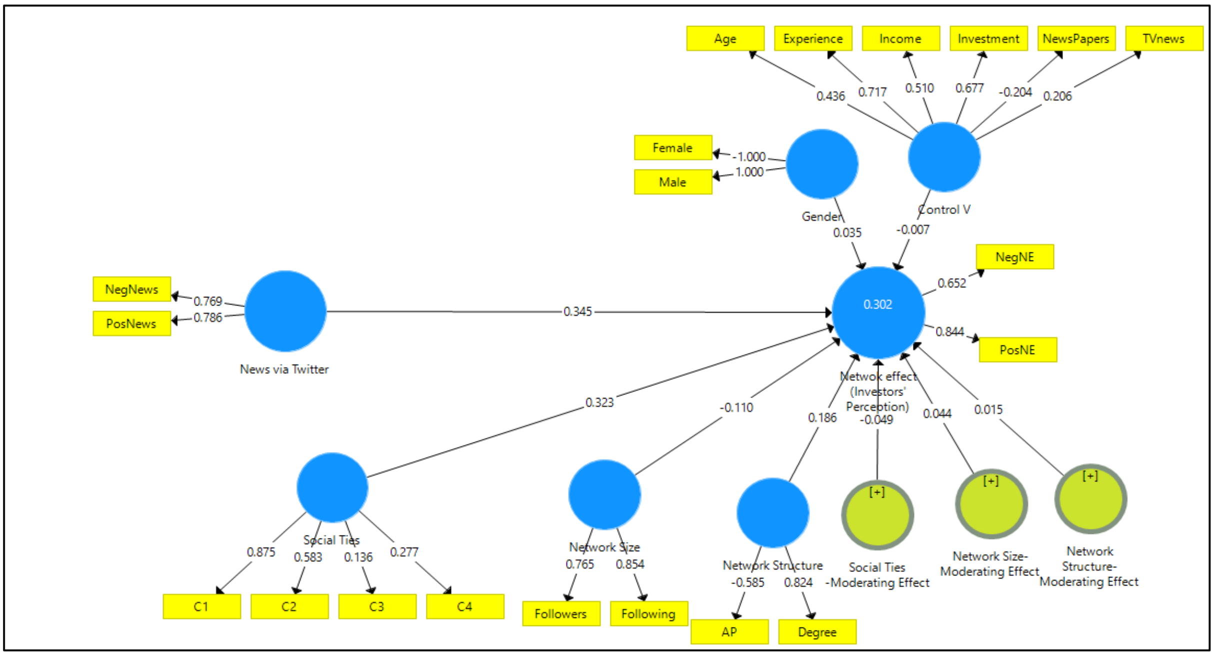
Top words/Hashtag



Top Financial words



5. Result



We conducted PlS-SEM by loading 6 factors with 18 items. News factor is an independent variable showing direct effect on dependent variable (investor's perception. Whereas, social ties, network size, and network structure represent are the moderators showing moderating effect. Meanwhile, age, experience, income level, investment, newspapers, and TV news are control variables. Our result PlS-SEM result shows R is 0.302. From direct impact, news via Twitter has a total direct impact of β .0345 (p <.01) on investors' perception. Of which, positive news has direct impact of 0.786 on investors' perception, and negative news has direct impact of 0.769 on investors' perception. Whereas, indirect impact from social ties is β 0.323, network size is β -0.110, and β 0.186 is from network. Social ties contribute higher from the indirect impact

DIRECT EFFECT	INVESTORS' PERCEPTION
CONTROL V	-0.007
GENDER	0.035
NETWOK EFFECT (INVESTORS' PERCEPTION)	
NETWORK SIZE	-0.110
NETWORK SIZE- MODERATING EFFECT	0.044
NETWORK STRUCTURE	0.186
NETWORK STRUCTURE- MODERATING EFFECT	0.015
NEWS VIA TWITTER	0.345
SOCIAL TIES	0.323
SOCIAL TIES -MODERATING EFFECT	-0.049

6. Contribution

A unique feature of this study is that it uses the actual data of investors' networks (Twitter) to illustrate the impact of network structure, network size, and social relationships on information diffusion and represent their impact on investor's perception. For the academicians, this research study will provide a theoretical ground for understanding the role of social network index from investor's network; which could potentially be used to create spin-off research projects. This study provides investors with guidance that being well connected and having stable ties is crucial to acquiring financial information Our findings also indicate that investors communicate and exchange information based on relationship strength or trust. We find that the exchange of information and communication results in multi-level tie-circles. First circle ties (C1) and second circles (C2) are particularly more influential given the level of trust with the highest level of information. This finding of our study is in line with the previous literature which has pointed out that individuals build ties with other individuals to exchange information and the exchange of information occurs based on such ties (Arnaboldi et al. 2016).

7. Limitation

A limitation of this study is that it only calculated the social network effect from the Twitter network of investors. The investors are likely to have contacts in another social network (e.g. Facebook), as well as offline networks. Further, this study lacks a time dimension. Arnaboldi et al. (2016) argued that over time social ties circle size varies because of variation in communication. We think that social network factors can be different across different social networks because social media networks are different in terms of some features. For example, Twitter is designed for fast updates and the sharing of information and news (Golbeck 2015). While, Facebook is for general interactions and broadly popular for online socializing (Hughes, Rowe, Batey, and Lee 2012) and designed to maintain an existing social relationship (e.g. family and friends) rather a professional ties (Barker 2009). We, therefore, argue that future studies should take a look at network factors across different social networks particularly on Facebook to further understand the usage behavior of investors. Besides, we think future research needs to consider the time window while social network index.

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