Network Effect and Investor's Perceptions: An Empirical Investigation

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Abstract

Investors' perceptions, and their understanding related to an investment, are paramount to decision-making in economic and investment settings. Social media is increasingly playing a vital role in influencing investors' perceptions and investors' decisions in the financial arena. Social media is a comfortable and easy tool to use. That's why it has just become a fundamental part of online news sharing and information distribution.

In the first study of this thesis, a network structure is constructed and built social ties circle based on the frequency of communication of investors within the network, and the network size of the investors to develop a comprehensive measurement scale for the social network index. Our findings indicate that the acquisition of information in the social network of investors depends on different components or factors. A significant factor in the network index is the network degree (network connectivity). It implies that network members with higher degrees or connections acquire vast amounts of information. Likewise, investors with larger networks receive enormous amounts of information, notably "following," which is the principal component in terms of network size. As a result, network size appears as the network index's second biggest factor. The smaller contribution comes from social tie circles. However, collectively, all these factors represent the social network index.

In the second study, we argue that the impact of financial information and news on investors' perceptions is moderated by network factors such as network structure, social ties, and network size of the network. The impact of information on an individual's perception is also called a social network or network effect. To tackle the moderating role of these network factors, we employed PLS-SEM as a statistical technique. The findings of this study indicate that network connectivity and social ties are crucial for the acquisition of information within the network. The findings of the study also show that network connectivity and social ties circle plays a central role in determining the impact of financial information. Our study further indicates that the impact of financial information and news on investors' perceptions depends on their theme.

In the third essay of this thesis, we investigate how investors' perceptions and preferences in terms of trading are influenced by their cultural background and network factors. In this study, we considered the moderating role of network factors in a cross-cultural context. The main subjects of our research datasets are investors who buy and sell shares and/or stocks of companies listed on the stock exchanges of New Zealand and South Korea. In this study, we examined data from 214 retail investors from the New Zealand Stock Exchange (NZX) and South Korea. In comparison to non-kiwi investors, the study's findings show that network factors have a major impact on how information is disseminated among Kiwi investors. The results of this study also demonstrate that network factors' effects differ across cultures and countries.

To conclude, Twitter is a major social media platform that helps investors to connect with their counterparts and obtain financial information through back-and-forth interactions. However, access to information on social networks depends on network structure (network connectivity), social ties circle (family, friends, and colleagues), and network size (number of contact or followers and followings). Twitter also enables prompt dissemination of financial news and information, which can substantially impact investors' perceptions. However, the impact of information on investors' perceptions varied cross-culture because of varied network factors.

Keywords: Investor, information, Financial News, Perceptions, Network factors, Network effect, Cross-culture, PLS-SEM,

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List of Abbreviations

APL	Average Path Length
AP	Path Length
C1	Tie Circle No. 1
C2	Tie Circle No. 2
C3	Tie Circle No. 3
C4	Tie Circle No. 4
Cn	Tie Circle n
r	Strength of ties
NS	Network size
PCA	Principal Component Analysis
PLS-SEM	Partial Least Squares-Structural Equation Modeling
NZX	New Zealand’s Exchange
ASX	Australia Stock Exchange

Chapter 1: Introduction

People across the globe use social media platforms for various purposes including information sharing, personal communications, and professional network building (Grover et al., 2022). Social media is also a network that connects people or individuals through distinct networks such as Twitter (information sharing), Facebook (general interaction), LinkedIn (professional), and YouTube (video sharing) to generate and share content, interests, and knowledge (Kietzmann, Hermkens et al. 2011). Chen, Tsai et al. (2016) argued that social media is a network for exchanging Individuals' sentiments, views, and feelings with others. Social media is a comfortable and easy tool to use. That's why it has just become a fundamental part of online news sharing and information distribution. In terms of information and news sharing, Twitter is a leading platform, followed by Facebook, and YouTube (Kümpel, Karnowski et al. 2015). However, The way people utilize social media varies by culture and is dynamic. It varies around the world in terms of information exchange, social relations, contacts, interaction, and content (Wang, Jackson et al. 2012).

A more recent body of literature has investigated the more direct ways through which information spreads among agents in the financial markets. These studies (Pénard and Poussing 2005, Steinfield, Ellison et al. 2013, Golbeck 2015, Drake, Thornock et al. 2017, Piñeiro-Chousa, Vizcaíno-González et al. 2017, khan Feroz, Hassan et al. 2022) point to social interaction, word-of-mouth sharing among neighbors and friends, networks of shared education, etc. as means of information dissemination. They provide evidence that the dissemination of information via social networks has a significant impact on investors' perceptions and investing decisions. With the use of online social networking platforms, people can communicate with any number of peers at once.

Social network particularly Twitter not only promotes online social and professional interaction but also facilitates the exchange of news and financial information. The impact of financial news on investor's perceptions is enlarged when such news and financial information is propagated or released through on Twitter (Miller and Skinner 2015, Elliott, Grant et al. 2018). Lee, Hutton et al. (2015) argued that the social media can propagate the financial news and information to a wider audience. Such propagation of financial news and information on Twitter affects the perception of investors (Lee, Hutton et al. 2015, Miller and Skinner 2015, Cade 2018). Similarly, Shive (2010) argued that investors' perceptions and trades are affected by their social networks and connections. Investors' perceptions or investors' investment decisions to purchase or sell a stock are influenced by information and depend on how informed the investors are (Barber and Odean 2008). Furthermore, the impact of financial news on investors' perceptions is also shown by studies in different countries, and the findings suggest that the impact of financial news on perceptions varies around the world (Calomiris and Mamaysky 2019).

Globally disseminated financial news affects global market outcomes differently depending on the country (Calomiris and Mamaysky 2019). Social media have changed how financial information is disseminated globally. In the current market, one of the most important places to get financial news is online, where all kinds of investors can readily access staggering amounts of financial information (Drake, Thornock et al. 2017). Investors can obtain financial analysis that has been posted on social media sites with internet access as another source of financial news and information (Ding, Zhou et al. 2019). Additionally, social media is now playing a bigger part in changing how financial information is distributed and affecting investors' purchasing and selling decisions (Feng and Johansson 2019). However, the extent to which people are impacted by social media may vary depending on the culture or nation in which they live (Lee, Lee et al. 2014).

The exchange of information within the network occurs between individuals based on the likelihood, mutual benefits, and emotional closeness of the relationship. Such exchange of information within the network affects the perceptions of individuals and investors (Shapiro, Varian et al. 1999, Lee, Hutton et al. 2015, Miller and Skinner 2015, Cade 2018). Similarly, extended ties can also be a source of information in the network. The amount of information available within the network is not similar for everyone or each individual. In other words, being a part of a network does not imply that you will be informed and able to obtain information. That's why network connectivity and links are essential for gathering information. The literature also explains that the use of social media in information sharing, and communication is different around the world (Fong & Burton, 2008; Madupu & Cooley, 2010; Sheldon, Rauschnabel, Antony, & Car, 2017). Furthermore, people from different countries form different groups on social media which imply that social relations or social ties are also different in different countries (eastern vs western) (Albarran, 2009; Kim, Sohn, & Choi, 2011). Similarly, the size of the social network of individuals varies considerably across different countries (Elmasry, Auter, & Peuchaud, 2014; Goodrich & de Mooij, 2014).

Two areas are clearly described in the literature (a) the impact of the social media propagated financial news on investor perceptions and (b) the existence of a social network effect (Katona et al. 2011; Luarn, Yang, and Chiu 2014; Sundararajan 2008; Khan et al. 2020; Murendo et al. 2018; Saxton and Wang 2014). However, three key areas are still missing in the literature (1) how we can measure factors of network effect (network structure, network size, and social ties) thoroughly. Most importantly, the social network effect phenomenon has not been addressed from the perspective of the investors (2) the literature has not defined the extent to which the effect of financial news on investor perception is moderated by network structure, network size, and social ties, and (3) It has also not defined the network effect in the cross-cultural network. Hence, this research will answer those questions which are unanswered in the literature, and it will contribute to the existing literature in the following three ways. (1) Access to information within the network depends on different social network factors (connectivity, network size, and social ties) (Katona et al. 2011; Luarn, Yang, and Chiu 2014; Sundararajan 2008; Khan et al. 2020; Murendo et al. 2018; Saxton and Wang 2014). However, the literature does not specify which network factor is the most significant in terms of information dissemination. This study will attempt to develop a measurement scale for these factors and explain their role in information diffusion within the network.

(2) Investors are looking for information to make financial decisions and understand market performance. Investors use social networks to find and share information about the stock market. It is thus likely that the information on social media could be a useful source of information for investors (Wieczner 2015). Investors seeking out financial reports on the financial market may eventually turn to social media as their main resource. (Zhou et al., 2014). The information spread on social media impacts investors’ perceptions, and behavior. In network literature terminology, the impact of information on one’s perceptions and behavior is a network effect. However, most importantly, the social network effect phenomenon has not been addressed from the perspective of the investors and its implications for investors. To the best of our knowledge, there are no studies that investigate this phenomenon in detail. In this regard, we believe that the social network effect plays a role in determining how much information (financial) is shared across Twitter depending on an individual’s network ties, connectivity, and network links.

(3) Over the past two decades, the use of social media has expanded exponentially, and it has profoundly changed the world (Bizzi & Labban, 2019). Numerous comparative studies have shown the extensive influence of culture on social media usage patterns around the world. These studies (Garcia-Gavilanes, Quercia et al. 2013, Elmasry, Auter et al. 2014, Hsu, Tien et al. 2015) show that culture has an impact on the way individuals communicate, create social ties, and share information online. We believe that the social network effect will be different in cross-culture because of different social relationship circles, the size of the network, and different structures of the network. Previous studies also haven't addressed social network effect phenomena in cross culture context. Hence, this study will cover this gap in the literature.

In simple words, there is a gap in the literature regarding social network effects in the context of investors' social networks and investor perceptions. Hence, in this thesis, we conducted the following research studies to fill up the aforementioned gaps:

Chapter 1: *Towards a Comprehensive scale of Social Network index: A study From Investors Perspectives.*

Chapter 2: *To what extent do network effects moderate the relationship between social media-propagated news and investors' perceptions?*

Chapter 3: *Does the social network effect for investors differ across cultures?*

1.1 Literature Review

1.2. Social Network Theory

We live in a network society, where nations (institutions, people, and businesses) are widely connected through a variety of networks including financial networks, transport networks, and social media networks (Castells 2009, Wu, Chang et al. 2015) and economic networks (Schweitzer, Fagiolo et al. 2009). The network position of nations (Snyder and Kick 1979, Ter Wal and Boschma 2009) and firms (Uzzi 1996, Zaheer and Bell 2005), and individuals (Leibenstein 1950, Emmert-Streib, Baltakys et al. 2017, Baltakys, Baltakienė et al. 2018) is strongly associated with economic prosperity; mainly because of their ability to control the flow of information and material within the network.

A network is a relationship between individuals, groups, organizations, or societies. In networks, relationships are based on information exchange, trust, liking, resources, etc. The relationship can be individual to individual and individual to the group in the network. The network theory focuses on links, relationships, and the centrality of the relationship or location (Brass 2002). The network theory is useful in understanding human behavior at individual levels and addressing research questions and problems by circumventing cross-population interactions. Figure 2 below provides a good visual representation where the black circles, known as nodes, symbolize individuals while lines, known as edges, represent social connections between them. Depending on the number of nodes and edges the size of the network varies. In this example of a network, 17 individuals are labeled in alphabets "a" to "p". Social network approach has been applied in social sciences and psychology for investigating social organizations and human interaction with them.

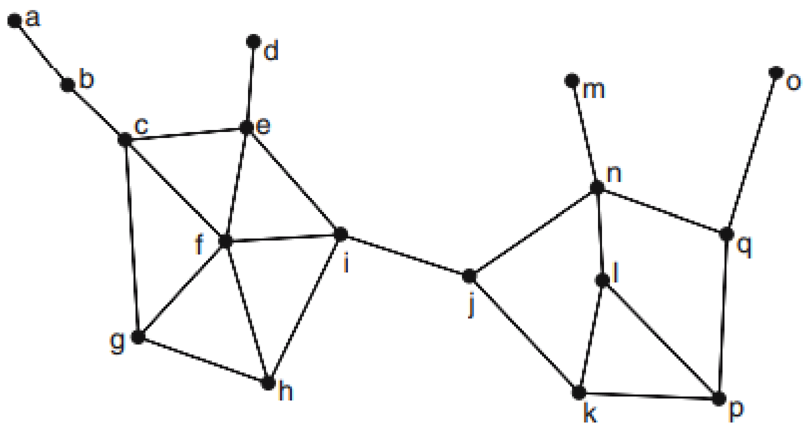


Figure 1. Figure. Example of a social network adopted by (Krause et al., 2007).

The origin of the network approach can be traced to the mathematical graph theory (Scott, 2000). In terms of quantifying social structure at the individual level and group level, the network statistics approach can be utilized to make quantitative inferences in economics research. According to the social network theory, individuals mainly rely on their social network to acquire information that brings them value in terms of doing investments, building relationships and, expanding career opportunities (Cade 2018; Jackson 2011; and Lee et al. 2015).

In the terminology of Brass (2002), network theory is about the consequences of network variables, such as having many ties or being centrally located. Position of the individual matters in the network, not the person. When an individual is linked to more individuals, having closeness and betweenness to others in the network implies that the individual is centrally or well-positioned (Kanter, 1979). Roberts and Dunbar (2011) argued that communication and information are exchanged between individuals based on the likelihood and emotional closeness of the relationship. Hence, individuals (nodes) who are well-positioned or centrally located in the network can obtain information sooner (Stephen P. Borgatti, 2005). Similarly, Matthew O. Jackson (2002) argued that people are connected based on reciprocal benefits in social and economic networks. Relationships are based on shared benefits in such networks. The exchange of information is determined by the connectivity or structure of the network. A variety of networks, including social, economic, and informational networks, connect people, businesses, and investors. Although networks are just connections between people, the exchange of information and resources inside them is crucial since the information has economic worth for each member (Carl Shapiro and Hal R. Varian, 1999; Nancy Katz, David lazer, Holly arrow, Noshir contractor, 2004) where individuals trade information based on the likelihood, mutual benefits, and emotional closeness of the relationship. The perception and decisions of individuals in networks are impacted by such information transmission. However, the network's connectedness, organizational structure, and individual position all affect how easily one can access the information contained therein (Kanter, 1979; Matthew O. Jackson, 2001; Stephen P. Borgatti, 2005; Matthew O. Jackson).

Similarly, the main objective of investors on social media is the retrieval and retention of information. Insightful information is key to trading and investment decisions and makes information a very valuable business resource (McGurk et al. 2020; Schweitzer et al. 2009). Social media networks have become very popular among investors since they are a very convenient source of financial information that can be obtained and retained rapidly (Cao et al., 2020; van den Berg & Struwig, 2020). Social media is a social network and the mechanism of receiving information depends on the individual networks. Information is shared on social networks by circles of network mates, such as close friends, family members, and colleagues. Social network theories (Gamper, 2022; Krause et al., 2007) explain this behavior by enhancing our understanding of social patterns.

Social relationships are dynamic and need constant upkeep if they are to thrive. They are not fixed and static things. Therefore, frequent communication between participants or individuals within a network is crucial for preventing social relationships from deteriorating (Dindia &Canary, 1993). The strength of a social relationship was explicitly described by Granovetter (1983) in his foundational research as a linear combination of time, emotional intensity, intimacy, and reciprocal services. Social connections can be broadly categorized into strong and weak ties, with the former signifying closer connections and the latter representing acquaintances. Weak ties are typically more frequent than strong bonds, in addition to having a lower strength. Because of this, weak relationships may eventually become stronger than strong ties, having a significant impact on social phenomena. That's why the strength of weak ties cannot be ignored.

In-depth research has been done on the communication styles that prevail in close friendships and romantic partnerships. These connections, however, are not isolated; rather, they are part of a larger social network that includes family and friends. Individuals value their closest relationships inside the network. Social network analysis looks at one person's connections with other network members. The "inner" layers of the network, where the most intimate links exist, have nearly always been the focus of studies on communication patterns in these networks (Fischer, 1982; Wellman & Wortley, 1990). The alters in the inner layers of the network (the support clique and sympathy group) are known as strong ties, and they offer the ego significant social, emotional, and material support. Because the partner "is valuable as a unique individual and is interchangeable with none other," maintaining these deep, emotionally intense relationships is extremely cognitively demanding. To establish and preserve these relationships, one needs a long history of communication in a variety of settings as well as emotional dedication. In comparison to somewhat less intimate but still significant connections, very close partnerships have higher rates of face-to-face and telephone contact. It tends to deteriorate over time, even in intimate relationships, if proactive efforts are not made to keep the relationship strong.

Weak ties, on the other hand, are more distant associates of the ego and are less significant in offering social companionship or emotional or material support. However, because they are more numerous, more varied, and - crucially - less connected to one another than strong links, weak ties play a critical role in facilitating access to a wider range of knowledge, concepts, and experiences. Weak relationships serve as a type of social capital, which is defined as investment in social relations with expected returns. These weak ties are communicated less frequently than strong ties, but they may deteriorate with time and may require some level of communication to remain active. The number of weak relationships people may sustain over time at a given level of emotional intensity may be limited by the fact that information regarding the status of the relationship, the traits of the alter, and their connections with others still need to be cognitively retained and managed (Cade 2018; Jackson 2011; and Lee et al. 2015; Granovetter, 1983).

1.2.1. Social networks

Millions of individuals are enabled by social media networks to communicate, share data, and information, and set preferences as well as connect with others (Hofer & Aubert, 2013; Katona, Zubcsek, & Sarvary, 2011). Social media sites not only facilitate communication and user engagement but also allow the competent distribution of information and recommendations on social network sites through private networks (Bakshy et al., 2011; Zhao, Grasmuck, & Martin, 2008). Similarly, individuals are permitted to search, share, and obtain data through private networks on social media sites (Lerman & Ghosh, 2010; Lipsman, Mudd, Rich, & Bruich, 2012). Some individuals can readily induce others to embrace new products or information because they are linked firmly on social media sites (Iyengar, Van den Bulte, & Valente, 2011). People trust social networks and media sites such as Twitter, Facebook, and Instagram and make connections with others. That is why these social media extensively influence them (Dedy Darsono Gunawan a, Kun-Huang Huarng, 2015) Scholars identify social networks and media sites as platforms for building relationships and fostering communications that occur among people at individual or group levels through the distribution of data and information. All of this leads to a specific impact on the participating individuals (Kempe, Kleinberg, & Tardos, 2003). Typically, online communication on web-based social media sites is alike word-of-mouth (WOM). Because social media sites frequently facilitate a wide range of online activities such as thoughts, interactions, events, and interests (Zhaveri, 2013).

On social networks, news sharing is simply proceeded via posting links to news stories as well as sharing the news with other participants. Hence, this makes social media completely different from traditional media's news sharing (Choi, Lee, & Metzgar, 2013). Twitter, Facebook, and blogs are the platforms where extensive communication such as writing stories, sharing views, and sharing valuable information are taking place. Thus, social networking sites facilitate such interaction regardless of the social and geographic closeness of users (Tapscott & Williams, 2006). Shared information on social media has distinguished effects, hence; the magnitude of information affects individuals with slight knowledge comparatively more than well-informed individuals (Dongyoung Sohn, 2013). From the social media site (e.g. Twitter or Facebook) perspective, users are directly or indirectly affected by communication and information released on the walls of friends and people in their networks, such as sharing, commenting, and liking. They may further spread that information (Wilson, Fornasier, & White, 2010).

Social media as an easy use of the internet by users to publish and access information, as well as participate in a common effort and build relationships. Kümpel, Karnowski et al. (2015) argued that social media facilitate and make simple news and information sharing for organizations and individuals. Particularly Twitter is the leading platform in terms of information sharing. Twitter contributes approximately 69% to online news and information followed by Facebook (17%), YouTube (12%), Digg (8%), Flickr (4%), and Google+ (1%) (Kümpel, Karnowski et al. (2015). Twitter, Facebook, and YouTube are well-knows social media sites. The way one utilizes the Internet has been said to have a significant impact on whether using it has a positive or negative impact on social capital. Utilizing the Internet, for instance, primarily for leisure purposes (such as streaming video) rather than for social, interactive, and communicative functions could be detrimental to social capital. Internet use, however, has a beneficial impact on existing bridging or bonding social capital when it is used in a way that allows people to keep their existing links. In other words, by using the Internet as a communication tool, one can retain offline social capital (both bridging and bonding) in the online world, as well as create new links, new social networks, and eventually new social capital (Vergeer and Pelzer 2009, Seidman 2013). In comparison to offline procedures, social networking sites may greatly expand the size of their users' networks in addition to fostering and maintaining social connections. As a result, using network sites can help people create and sustain bridging and bonding social capital both online and offline. Thus, social networking services can both alter social networks and create new ones online (Subrahmanyam, Reich et al. 2008, Lee, Moore et al. 2012, Steinfield, Ellison et al. 2013).

The availability of information is essential to helping investors and consumers make better decisions in contemporary economies and society. Newspapers, television, and radio are just a few of the media outlets that gather information and disseminate it to the general public. People's thoughts and ideas are significantly shaped by the media. Media are increasingly acknowledged as important information providers in the investment and financial sectors. Recent financial literature that has examined the impact of media on investor behaviors and perceptions has found that media can have an impact on stock prices, stock market reactions, trading volume and volatility, firm performance, cost of capital, and business owners' investment decisions (DellaVigna & Gentzkow, 2010; Engelberg & Parsons, 2011; Peress, 2008). Financial studies have shown a lot of interest in research on the impact of market-level emotion. Financial researchers concur that a significant portion of the abnormalities in the financial markets is caused by investors' emotional distortion. Wall Street's catchphrase, buy on fear, sell on greed, suggests that financial experts are aware of how emotion influences an investors’ perceptions and investors’ trading behavior (Kuhnen and Knutson, 2011; Mayew and Venkatachalam, 2012; Price et al., 2016). Academic researchers have found that emotional states affect investors' risk-taking behavior and trading performance Positive emotional states encourage investors to take on risky investment portfolios, according to Kuhnen and Knutson (2011), while negative emotional states prevent them from doing so.

The importance of traditional information sources, such as press releases and other traditional media announcements, financial statements, management commentary, and company websites, as well as expert publications (surveys, reports, analyses, recommendations, etc.), is well-documented in the literature. Social media, which is represented by numerous Internet platforms (social networks, blogs, microblogs, discussion forums, wikis, video-sharing portals, etc.), has steadily replaced them over the past decade. The media is crucial for disseminating information in the financial markets. Recent content analysis and data mining methods have been implemented by academic researchers and professional practitioners to identify the sentiments and emotions of investors as they appear in news media and social media (Tetlock, 2007; Kothari et al., 2009; Chen et al., 2014; Sun et al., 2016). 121 representatives of European investment professionals, primarily from Germany, were polled by Investor Relations Community (IR Club) (DVFA – IR Club, 2015). According to the researchers, there is, at best, a minimal amount of interest in using social media to satisfy information needs. Social media was evaluated as at least somewhat essential by 50% of the respondents, but all other sources that could be used were thought to be more valuable than social media. Unsurprisingly, the issuer of securities was regarded as the most reliable source of information, a finding that was supported by numerous other research, including those including retail (individual) investors). What's crucial is that social media has been more significant for 28% of respondents than in prior years (Tetlock, 2007; Kothari et al., 2009; Chen et al., 2014; Sun et al., 2016).

To determine the impact of social media on their daily business, 256 institutional investors from Europe, the Asia Pacific area, and the USA were surveyed by Greenwich Associates (2015). The survey found that social media was used by 79% of respondents, whereas social media was used for investment decision-making in nearly all of the included organizations (97%). The poll also showed that social media material affects financial market professionals' behavior in the sense that it prompts a range of actions and initiatives. A startlingly high percentage of respondents (48%) acknowledged conducting more research as a result of what they had learned through social media. In total, 37% of the sample shared this information with the decision-makers in their organizations, and 31% used it as inspiration for a recommendation or investment choice.

Social media platforms have gradually taken the place of traditional media as a source of information for investors because of the advancement of the Internet and information technology in the modern century (Wu, 2019). Social media allows for the generation and consumption of information to be interactive rather than a one-way process of producer-communicator-users in the financial market. The way information is gathered, processed, and disseminated in the world today has altered because of the Internet. It has altered how business is conducted. The Internet has made it possible for a wider spectrum of prospective consumers and suppliers to communicate and work together, enabling products to be more easily tailored to customer needs (Mady, Dwivedi, and Gharavi 2007). Social networking platforms are used by businesses to collect, manage, and deliver information to different stakeholders (Shiau, Dwivedi, & Yang, 2017). Due to the growth of social media, there has been a significant advancement where viewers may now contribute information through reviews, blogs, postings, etc. The capital markets around the world have also changed as a result of the quick transmission of information via the Internet (Granfield, 1999). Research has revealed that investors are more likely to follow other investors than to depend on professional guidance. Moving on to dissemination, social media unavoidably expands the channels that businesses have at their disposal for sharing information. But the social media application's design might also encourage and support longer or quicker information processing by investors (Shiau, Dwivedi, & Yang, 2017; Wu, 2019).

The development of social media platforms can enable and support the processing of investor information in a more timely or comprehensive manner. Social media offers businesses a ground-breaking and remarkable way to communicate with their stakeholders, particularly investors, and share company information (Bonson and Flores, 2011). Traditionally, companies send press releases to certain financial institutions and brokerage firms, newswire services, equities research databases, and other recipients to communicate financial information. Companies broadcast the news in this fashion, but they are unaware of how many people receive it. Social media, in contrast, allow a business to broadcast different financial information throughout time directly to a certain number of people. (Reilly and Hynan, 2014). The way that Twitter is designed encourages the quick sharing of current information. Similarly, to this, it has been demonstrated that news published directly on Twitter, especially when supported by links to traditional press releases, reduces the problem of information asymmetry and enables the distribution of information to all investors within a short period (Zhou et al., 2014). According to recent research that examined the connection between corporate Twitter activity and capital market activity, companies' use of Twitter may have an impact on liquidity, stock returns, pricing, and information asymmetry. Another study contends that the dissemination of investment information, even information with little forecasting value, via Twitter can have an impact on investors; whether a corporation releases information through Twitter or more conventional channels seems to have an impact on investors' behavior and perceptions (Prokofieva, 2014; Okazaki et al., 2019).

1.2.2. Network effects

The network effort concept was introduced by economists in the 1970s. The network effect is defined as an increase in the value of supplementary products or networks owing to the increased use of one good, product, or network (David s. Evans & Richard Schmalensee, 2017). Liebowitz and Margolis (1999) defined the network effect as the proliferation of the use of products which ultimately leads to a high number of consumers. When the value of goods and services are determined by the number of consumers using those good and services, it is called the network effect (Shapiro and Varian, 1999 (Nicholas Economides and Evangelos Katsamakas, 2008). Katz and Shapiro (1985) argued that when consumers make products or goods out to be less valuable, the phenomenon is referred to as the negative network effect. Similarly, if more individuals are linked in the network, then the network is more helpful and valuable. Likewise, social networking sites like Twitter and Facebook are becoming more appealing and worthwhile as more individuals or users join them. Economists called such effects, usage, interaction, or value a network effect (David s. Evans & Richard Schmalensee, 2017; Arun Sundararajan, 2013 & 2018). The network effect is when one buyer influences the decision of other buyers or customers in the market (Leibenstein 1950, Ceci/Kain 1982).

People use social media to disseminate information, which then shows up on the walls of their friends. Users can comment on or "like" the information that has been shared by clicking the "Like" button. Additionally, social media allows users to share information with others without regard to distance or time limits. Such details affect social media users and interpersonal relationships (Tsung-Yi Chen, Meng-Che Tsai and Yuh-Min Chen, 2015). Lisette de Vries, Sonja Gensler, and Peter S.H. Leeflang, (2012) argued that when people like or comment positively on brand posts on social media, this creates a positive effect or positive brand image. Because of the favorable impact of likes and comments, a brand's popularity increases. On the other hand, negative comments or sentiments harm the brand's image and reduce its popularity. This implies that negative sentiments create negative effects. Positive posts, news, information, and comments in social media can have a positive network effect which ultimately affects the perceptions and actions of other users in the network. Similarly, negative information and comments shared on social media can have a negative network effect (de Vries et al., 2012). Liking and sharing information is a kind of recommendation from friends to other friends on the social network, such effects of likes and shares are greater when close friends of users like or share information (Suraworachet, 2012). Similarly, increasing users of social network sites is also considered a network effect.

Social media is also a network that influences individuals' behavior. Most importantly, friends, family, and colleagues play a key role in influencing one's preferences and sentiments (M. Panzeri, 2012). In such social networks, information spreads among people based on individual relationship strength. In social networks sites, when friends affect other friends' behavior or actions through communication and exchange of information, this is known as the social network effect (Arun Sundararajan, Foster Provost, Gal Oestreicher-Singer, Sinan Aral, 2013). Conrad Murendo, Meike Wollni, Alan De Brauw & Nicholas Mugabi (2018) argued that the social network effect is when individuals are influenced by their friends and neighbors to use or purchase goods and services. For instance, people began using mobile money because they were influenced by their friends and neighbors to use it. As a result, the positive effect of their social network led to a significant rise in mobile money consumption. Social network studies have measured the social network effect by the number of posts and likes received by users. These studies showed that individuals or users are influenced by their friends (social circle) to purchase a product through sharing information in the form of posts and likes. The result of these studies suggested that when a customer or user "purchases a product" after receiving likes and posts on social media indicates a network effect and whereas "no purchase" means no network effect (de Vries et al., 2012; Khan, Mohaisen, Trier, 2019; Katona et al. 2011). In the notion of network theory, the effect of social network-related information and communication on one's perception can be viewed as the "network effect". Network theory stated that when there is a network, there is a network effect (Katz and Shapiro, 1985; Shapiro and Varian, 1998).

Similarly, according to Watts (2002), when the network is dense and connected, it signifies that the connections among the individuals is stable and enables them to share information more easily in a greater amount. The ease and distribution of information sharing are higher in the connected and denser network (Sparrowe, Liden et al. 2001). Therefore, network connectivity represents the relationships among people in a network that allows them to share information. Watts (2002) argued that the higher network density indicates that the members of the network are interconnected and that this interconnectivity allows a higher amount of information sharing. The more interconnected individuals are to one another, the higher the network density. Hence, a higher dense network enables the high distribution of information across the network (Sparrowe et al., 2001). Watts (2002) further argued that higher connected network means a higher level of network familiarity within that network, hence, connectivity implies that the extent to which network partners know each other (Kohler et al., 2001) or individuals are close to one another in a network (Wasserman & Faust, 1994). Based on previous studies, Sohn (2009) argued that if a person is linked or connected to several members of the network and those members know each other, this means that the network is connected and dense.

Another significant structural characteristic of a social network is degree distribution. The degree of a node in a directed graph is equal to the sum of its out-degree and in-degree linkages. The frequency of nodes is represented by the network's degree distribution P(k). Different types of graphs can be identified through the determination of the degree distribution (Erdos and Renyi, 1959, 1960). Some common elements of social networks, such as degree distribution, have been identified through research on their structural qualities, and these features have been examined to comprehend how social networks operate. Thus, an understanding of social network characteristics and behavior may contribute to the more effective and efficient design of such networks. Furthermore, increasing that effectiveness and efficiency would require the identification of other crucial network features (Fleming et al., 2011). Furthermore, Hamill and Gilbert (2009) argued that network connectivity is the extent to which one's friends are friends of each other as well. Thus, the literature defines network connectivity as the relationship or interconnectivity between an individual and friends of friends in a network, which enables the high distribution of information within the network, and the individual often obtains information because of such interconnectivity. In simple words, it shows the person is well connected in the network.

The relative position of a node or individual in terms of how near they are to the "Centre" of the activity in a network is referred to as the centrality of a node inside the network. Degree, proximity, and betweenness are metrics for determining node centrality. The most fundamental node centrality metric, known as degree, is determined by the number of ties or links that connect a focused node. High-degree centrality nodes can be seen as highly active nodes in the network, where those nodes may serve as a network hub. This is because nodes with a lot of links could have more access to resources through alternate paths (Freeman,1979),

Meanwhile, the friends or followers (the size of the network) is also the main distributor of information on social networking sites (Sundararajan, Provost et al. 2013). Information is distributed more widely when the number of users' followers or friends is greater (Harrigan, Achananuparp et al. 2012, Luarn, Yang et al. 2014). The exchange of heavy information is amplified by higher network users and followers which results in affecting the individuals or users (McClain 2019). Furthermore, users of social media that have a higher number of followers have access to a larger amount of information and can learn more about thoughts and experiences (Hofer and Aubert 2013). However, people that have larger networks are less emotionally connected. As a result, there can be a trade-off between the network's size and the emotional intensity of each interaction. In comparison to large networks, smaller networks typically have fewer members but a higher degree of emotional connection (Roberts et al., 2009).

Members of the social network that an individual thinks they have a personal connection with and actively try to stay in touch with are considered to be in the "outer" layer of the network (Hill & Dunbar, 2003). Compared to the stronger relationships at the network's inner layers, this outer layer of "weak ties" is crucial for granting access to a wider range of knowledge, perspectives, and experiences. Even these weak links, though, incur costs and deteriorate with time. To prevent additional falls in emotional closeness among the network members in the outer layer of the network, it may be required to communicate at a particular frequency (Granovetter, 1973, 1983). The emotional intensity of the relationship is correlated with the frequency of contact between a person and a network member, the likelihood that someone in the network may offer support, as well as the possibility that the emotional intensity of the connection will diminish with time. To measure the strength of the connection between two individuals within a network, communication frequency (or change in communication frequency over time) is frequently utilized (Hill & Dunbar, 2003).

Tie strength is a broad term used to describe the strength and tightness of a tie between two nodes or individuals within the network. It can be determined by factors like the intensity of a friendship or the frequency of interaction. However, there are situations when weak ties might help people get better employment and spread ideas and information (Granovetter, 1973). In a social network, the concept of "tie strength" is used to describe the nature of interpersonal connections: The strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services that characterize the tie. Ties can be categorized as "weak" or "strong" based on this definition. Weak ties play a crucial role in information diffusion in a network (Burt, 2004; Granovetter, 1973).

According to the literature (Roberts and Dunbar 2011) on interpersonal interactions, relationships can be divided into two categories: exchange connections and communal ties. Benefits are given and received according to social rules and conventions that differentiate between the two forms. In an exchange relationship, people provide one another with benefits with the expectation of getting something similar in return. Receiving a benefit imposes a duty on the recipient to provide an equivalent benefit in return. On the other hand, community interactions, place no obligations on the parties involved. Benefits are instead distributed in response to one another's needs or worries about their welfare. Connections between friends, lovers, and family members are communal, whereas those between business partners are more trade relationships. The relationship in business is one based on exchange. Such a relationship is built more on material benefits than on emotion (Matthews, Barlow et al. 1994). Individuals communicate and share information based on his/her ego network or relationship circle. An ego network is an offline social network that has four groups or circles of ties or relationships such as a support clique (best friends), a sympathy group (close friends), an affinity group (causal friends/family members), and an active network (Dunbar's number) (Roberts and Dunbar 2011). Similarly, the user has also an ego network or relationship circle in social media such as Twitter and Facebook. On Twitter, the user has five relationship circles and on Facebook user has four relationship circles on average (Arnaboldi et al. 2016).

The ego network was described by researchers as a straightforward social network model made up of a single person (the ego) and all the other individuals that the ego is socially connected to (alters). Alters are typically grouped in an ego network in a set of four or five inclusive groupings (referred to as circles) based on the strength of their social ties (Roberts and Dunbar 2011). These circles are all a standard size and tie strength. The frequency of contact between the ego and the alters are generally used to estimate the latter. As is customary in the literature, a circle also includes all the more internal circles (those with stronger ties), but a ring simply includes the alters of a particular circle that is not a part of any more interior circles. Alters with very close social ties to the ego—informally known as best friends—make up the first circle, known as the support clique. The ego will communicate with these alters in the event of severe emotional suffering or financial catastrophe. This circle has a maximum of five members and the ego typically contacts them once a week. Alters who can be considered close friends, in general, can be found in the second circle, known as the sympathy group. This circle has an average of 15 members, and the ego contacts them at least once every month. The affinity group, sometimes known as a band in ethnographic literature, is the next circle and contains roughly 50 alters, most of whom are meant to represent close friends or family members. The active network, which contains roughly 150 members overall, is the final circle in the ego network model. People in this group are those for whom the ego actively expends a sizeable number of resources to sustain the corresponding social connections throughout time. Contacts with members of the active network must take place at least once each year (Roberts and Dunbar 2011).

1.3 Research Purpose and Motivation

This thesis aims to understand the link between the social network effect and investor perceptions. The growth of social media has been phenomenal over the last 20 years. The impacts are widely felt across organizations, industries, society, and economies. Social media can influence individual perceptions and decision-making processes in various settings. In this regard, the network theory helps us understand the formation of social dynamics on social media. Particularly, social circle ties (Arnaboldi et al. 2016; Khan et al. 2020; Murendo et al. 2018) network structure and the size of the network (Katona et al. 2011; Luarn, Yang and Chiu 2014) that originate from the network and their impact on the perceptions, behaviors and financial decisions of the investors (Chen Liu and Xuefei Li 2019; San-Lin Chung 2019) remain unexplored as most studies have overlooked social circle ties and the size of the network as factors of the network effect. In this thesis, we aim to build knowledge and conduct research to understand the link between social media and investor perception through network theory.

Hence, this thesis is particularly focused on three areas. First, it is important to identify and group together the major factors that generate network effects, such as social ties, network structure, and size. To accurately measure the network effect, none of the network studies (Katona, Zubcsek, and Sarvary 2011; Khan, Mohaisen, and Trier 2020; Murendo et al. 2018; Saxton and Wang 2014) considered all network factors. Some research (Katona, Zubcsek, and Sarvary 2011) concentrated on network structure while others talked about social ties (Khan, Mohaisen, and Trier 2020; Murendo et al. 2018; Saxton and Wang 2014). Furthermore, no research or single study has identified a particular network factor as a prominent or significant source of the network effect. We also attempted to identify and classify the factors that contribute most and least to the network effect in this study. Most studies of the network effect are conducted from the viewpoint of customers or regular Individuals. We attempted to quantify the network effect from the perspective of investors, concentrating especially on Kiwi investors. Social networks depend on the culture. Across different countries, people have social ties and networks of varying sizes. As a result, the network effect may vary depending on the social ties, network sizes, and network structure. To the best of our knowledge, none of the network research has compared two different countries or cultures to gauge the phenomenon of the network effect. In this study, we tried to quantify the network effect in cross-cultural context.

1.4 Dissertation Structure

This thesis consists of 6 chapters. Chapter 1 provides an overview of the thesis, its structure, literature review, background, and research objectives. Chapter 2 covers network structure and social circle ties based on the frequency of interaction of investors, and the network size of the investors leading to the development of a comprehensive measurement scale for the social network index. Chapter 3 covers the impact of financial information and news on investors' perceptions is moderated by factors such as connectivity, social ties, and network size of the network (Twitter) by considering three key factors in investors' networks: (1) network connectivity (network structure); (2) social ties circle (friends, family, colleagues); and (3) size of the network (number of contacts). Chapter 4 explores the idea of how social network effects will be different because of different social relationship circles, the size of the network, different structures of the network, and different behaviors while using social media in terms of information sharing and interaction. Chapter 5 provides the overall conclusions for the thesis and discusses implications and contributions.

Chapter 2: Towards a Comprehensive scale of Social Network index: A study From Investors Perspectives

2.1 Introduction

Information acquisition is a primary motive of individuals and investors within social networks because the information has business value and it is a key to trading (Jackson and Watts 2002, Schweitzer, Fagiolo et al. 2009, Ozsoylev, Walden et al. 2014, Chung, Liu et al. 2018). Social networks promptly disseminate financial information and enable investors to obtain financial information rapidly (Lee et al. 2015; Miller and Skinner 2015; Zhang et al. 2018). Network studies suggest that being in a network does not mean that individuals frequently access information but that the access to information depends on centrality or connectivity, the position of the individuals in the network (Borgatti 2005; Kanter 1979), and the social relationship between individuals (Adler and Kwon 2002; Granovetter 1973; Roberts and Dunbar 2011).

In the social network, individuals receive the information shared by circles of network mates, such as close friends, family members, and colleagues (Paul 2012, Saxton and Wang 2014, Arnaboldi, Conti et al. 2016). Similarly, the size of the network (e.g. number of followers/followers) also influences information distribution, and more knowledge and information is accessible to those with greater network size (Ellison, Steinfield et al. (2011) Granovetter (1973) argued that access to information depends on how strong or weak the individual network ties are. In other words, the sources of information within the network could be strong ties (close friends) or weak ties (extended social networks). Likewise, access to such information also depends on one's connectivity in the social network. Borgatti (2005) argued that well-connected individuals in the network could obtain information more readily or sooner. Access to information depends on the individual circumstances rather than the person (Kanter 1979). Similarly, Chung et al. (2018) and Ozsoylev et al. (2014) argued that investors who are centrally located in their networks are more likely to receive information earlier as compared to those investors who are not highly connected. In the area of network studies, one’s network connectivity and position in the network is also called network degree. Network degree is the number of links or connections of an individual within the network (Ted 2009).

Social ties are a key component of a social network. Individuals acquire information and knowledge from their social ties. The "inner" layers of the network, where the closest connections are formed are crucial from the perspective of social bonds. The alters (individuals/friends) in the inner layers of the network (the support clique and sympathy group) are known as strong ties, and they offer the ego (individual) significant social, and emotional support (Menon and Ranaweera 2018). Extended or Weak ties, on the other hand, are more distant associates of the ego and are less significant in offering social companionship or emotional or material support. However, because they are more numerous, more varied, and less connected to one another than strong links, weak ties play a critical role in facilitating access to a wider range of knowledge, concepts, and experiences (Hofer and Aubert 2013). Similarly, Users of social media with larger networks or more friends may have to access more information and can gain insight into other people's opinions and experiences (Azer and Ranaweera 2022; Hofer and Aubert 2013). Therefore, the importance of social ties and network size cannot be ignored.

Network studies have greatly discussed network factors that initiate and disseminate the information within the network (Katona, Zubcsek et al. 2011, Saxton and Wang 2014, Murendo, Wollni et al. 2018, Khan, Mohaisen et al. 2020). Nevertheless, these studies have presented the factors of network index in a bits and pieces instead of a collective term. Some authors have discussed social circle ties (Saxton and Wang 2014, Murendo, Wollni et al. 2018, Khan, Mohaisen et al. 2020), while others have talked about network structure and the size of the network (Sundararajan 2008, Katona, Zubcsek et al. 2011, Luarn, Yang et al. 2014). Similarly, in the financial markets literature, most of the studies (Chen Liu and Xuefei Li 2019; Chung et al. 2018; Colla and Mele 2010; Han N. 2013; San-Lin Chung 2019; Zhang et al. 2018) have focused on the connectivity of investors in the network. Most of these studies have considered the connectivity of investors or network degrees as a key factor in the network and overlooked social circle ties and the size of the network as key factors of the network.

Previous studies have overlooked social ties and network size even though these are important network factors. As a result, we think it's necessary to aggregate and consider all the key factors that impact how information spreads inside the network. Hence, the aim of this paper is to contribute to the existing literature in two ways (1) We brought together all key factors such as network structure, size, and social ties to develop a comprehensive measurement scale for the network index. No research or single study has identified a particular network factor as a prominent or significant source of information distribution within the network. In simple words, we do not know which factor is a leading factor in terms of information generation or distribution within the network. Is network structure a major factor, or social ties, or network size? We, therefore, in this study, attempted to identify and then classify the factors that contribute the most and the least in information distribution within the network. (2) we pioneer the calculation of investors' social tie circles. While most studies of the network factors are conducted from the viewpoint of customers or ordinary users or individuals (Katona et al. 2011; Luarn, Yang, and Chiu 2014; Sundararajan 2008; Khan et al. 2020; Murendo et al. 2018; Saxton and Wang 2014), we attempted to quantify social ties and their importance from the perspective of investors' networks, concentrating especially on Kiwi investors.

In this paper, we provide the theoretical background, and the necessary empirical study for testing the theoretical propositions as follows. We begin with a brief overview of social network theory and define network factors with a particular focus on the importance of each network factor. Our paper focuses on how each factor contributes to the dissemination of information within the network. It further focuses on why we need to have a measurement scale for network factors. Following this, we outline a suitable grounding for the measurements of network factors. Then we report on the conducted network factors measurement procedure by using real Twitter data. We applied Principal Component Analysis (PCA) to categorize factors based on significance.

2.2 Research Background

The central notion of social network theory is that network is a set of nodes (actors/members) and relations among these nodes (Wasserman and Faust 1999). Nodes can represent people, organizations, and even countries. Likewise, ties between these nodes can be material or non-material such as friendship and sharing of information (Wasserman and Faust 1999). Social network theory states that the central benefit of a social network is the acquisition of information and individuals with superior access to information are in a better position to gain mutual benefits such as trading, investment, jobs, and relationship (Adler and Kwon 2002; Cade 2018; Jackson 2011; Lee et al. 2015; Wasserman and Faust 1999). Typically, networks may be formed to exchange information and resources (Katz et al. 2004; Wasserman and Faust 1999). That's why the network position of individuals (Leibenstein 1950; Jackson 2011; Siikanen et al. 2018; Emmert-Streib et al. 2017), firms (Uzzi 1996; Zaheer and Bell 2005), and even nations (Snyder and Kick, 1979; Ter Wal and Boschma 2009) are strongly associated with economic prosperity; mainly because of their (nodes/members) ability to control the flow of information and materials within the network.

Relationships or ties within the social network are social capital that is built to gain information and resources (Williams and Durrance 2008). Adler and Kwon (2002) argued that individuals utilize friendship ties to gain information and advice. Similarly, Granovetter (1973) discussed the importance of the nature of the ties. He argued that weak ties facilitate the flow of information through the network beyond social horizons or extended social ties. On the other hand, strong ties facilitate information flows with certain individuals that are typically reciprocal or based on emotional closeness. Strong ties are formed in networks with like-minded individuals, e.g. colleagues and close friends; whereas weak ties are built with people of various backgrounds or beyond one's social horizon (Granovetter 1973; Haythornthwaite 2002). Furthermore, individual (nodes) position or centrality in social networks (Borgatti 2005) enables an individual to retain information at a time. Likewise, Kanter (1979) argued that the centrality of the individual matters in the network, not the person.

The use of the social network as a communication channel in the financial markets is expanding and it is accepted as a viable channel for communicating important financial information (Lee et al. 2015; Zhang et al. 2018). Cade (2018) argued that social network provides investors the chance to express opinions and gather information for trading which is why investors use social networks to obtain information that can help them to make informed decisions (Bartov et al. 2018; Elliott et al. 2018; Miller and Skinner 2015). Miller and Skinner (2015) argued that social networks particularly, Twitter, become a common social media network for investors because it makes it simple for investors to share financial information and news. Similarly, Joyce (2013) argued that social networks, particularly Twitter, help investors connect with their counterparts and investors and obtain financial information through interaction. Investors use their network position to obtain information in the financial market (Bing and Liyan 2013; Chung et al. 2018; Zhang et al. 2018). Hence, just being on the network is not as important as being connected and well-positioned within it (Chung et al. 2018; Colla and Mele 2010; and Zhang et al. 2018).

A plethora of research in finance is available (Bing and Liyan 2013; Chen Liu and Xuefei Li 2019; Chung et al. 2018; Colla and Mele 2010; Han N. 2013; San-Lin Chung 2019; Zhang et al. 2018) that discusses the importance of connectivity or the network position of investors. However, none of these studies discuss the social ties circles of an investor in their network.

In contrast, network studies greatly emphasize the central role of social ties circle in the diffusion of information in the network and its influence on individuals' access to information across the network. Besides, the role of network size as a key factor in investors' networks is also ignored in the previous literature. We, therefore, in this study, included all three major factors of a network such as a network structure, size of the network, and social ties of the investor.

2.3 Literature Review

As indicated Network literature describes that the dissemination of information within a social network is dependent on three key factors social ties circle, the structure of the network, and the size of the network. Social circle ties are one's friends, colleagues, and family members (Arnaboldi et al. 2016), the network structure is the links of an individual in the network (Perera 2017; Lewis, 2009), and the size of the network is the number of friends or contacts (followers & following) in the network (Harrigan, Achananuparp et al. 2012). To understand social network factors promptly, we have explained each factor below in greater detail.

2.3.1 Social ties circles

Social ties circles refer to the people in the social vicinity of ego (individual) and include colleagues, friends, and family members (Paul 2012, Saxton and Wang 2014, Arnaboldi, Conti et al. 2016). The social ties circles are built based on the frequency of communication or interaction between the ego (individual) and his/her alters (friends/individuals in the network) (Arnaboldi et al. 2016). Social circle ties of an individual in the social network comprised of an average of 4 to 5 circles (Arnaboldi et al. 2016; Roberts et al. 2009). The first circles (C1 or C2) consist of individuals who are very close to the ego (fig 1) and who can be colleagues or close friends where the highest exchange of information occurs (Arnaboldi et al. 2016). On the other side, the last circle (C4 or C5) is an extended user tie where the lowest interaction is taking place (Fig 3) (Arnaboldi et al. 2016). Individuals in the last circle (C4 or C5) have no close ties to the ego (use), but the ego can still get information from them (Arnaboldi et al., 2016).

The first circle (C1) is also called the support clique. The second circle (C2) contains close friends of the ego, the second circle, is called the sympathy group (Roberts et al. 2009). The last circles of friends are called affinity groups, these are extended social friends and are considered weak ties of ego (Roberts et al. 2009). The First (C1) and second circles (C2) are strong ties of individuals and whereas the last circles (C4 or C5) are weak ties. Krackhardt (1998) argued that one individual's influence in a network over another is dependent on the relationship or ties. He further argued that when ties are strong, the influence of ties is high. These studies (Arnaboldi et al. 2016; Granovetter 1973; Krackhardt's 1998; Roberts et al. 2009) suggested that both strong ties and weak ties enable information to be disseminated throughout the network. Network literature (Arnaboldi et al. 2016; Roberts et al. 2009) presented the structure of social ties circles or ego network as follow:

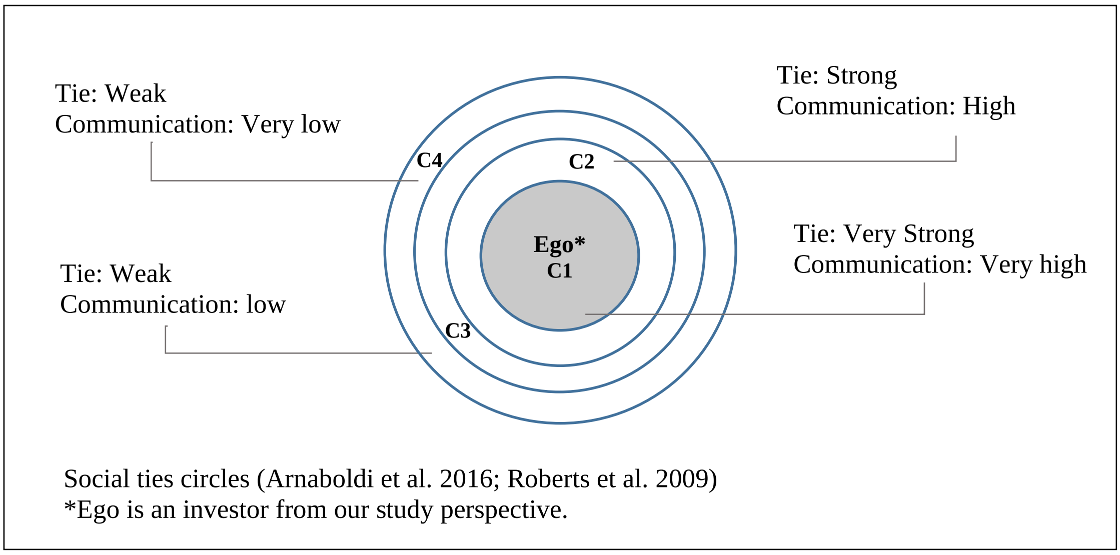


Figure 2. Social ties circles Structure

2.3.2 Structure of the network

Acquisition of information also depends on the structure network (Katona et al. 2011; Luarn et al. 2014). However, network structure varies from network to network such as Random Networks, Small World Networks, and Free Scale networks (Perera 2017; Lewis 2009). For example, a random network has no duplicate connections and isolated nodes or members. Random networks are highly link-efficient networks, which means that higher interconnectivity occurs from a slight increase in the number of links or connections (Perera 2017). In contrast, in a small-word network, most nodes or members of the network are not neighbors of one another but can be connected or reached through other nodes (Watts and

Strogatz 1998). Whereas a scale-free network has few nodes or members with a large number of connections (Caldarelli et al. 2002). The structure of these networks depends on the distribution of degrees (Perera 2017; Lewis 2009). A degree is the number of connections or links of a node (user) with other individuals or friends in the network (Perera 2017; Lewis 2009).

Katona et al. (2011) proposed that the degree plays a key role in generating or attaining of information. Similarly, Luarn et al. (2014) argued that network degree has a positive effect on the dissemination of information in a network. Thus, a higher network degree implies good connectivity (Kim et al. 2011; Katona et al. 2011). Furthermore, the distance or average path length is another key factor in this aspect. The path length is the distance between nodes or individuals in the network (Lewis, 2009) where nodes that are close to each other in the network can access information from each other more quickly than more distant nodes (Katona et al. 2011; Lewis 2009; Perera 2017). Lewis (2009) also argued that the higher connected nodes or individuals in the network have a lower average path length which means that they can more quickly receive information.

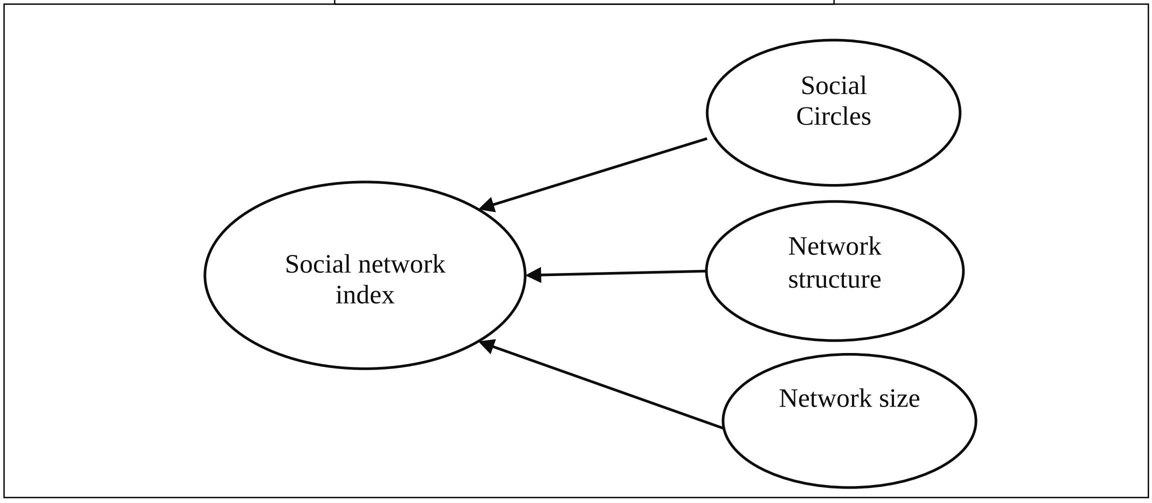
2.3.3 Size of the network

Network size is the number of contacts or network members on a social network (Harrigan, Achananuparp et al. 2012). On social network sites, information is distributed in a social network by users' contacts (Sundararajan, Provost et al. 2013). Williams D. (2006) argued that users or individuals with a higher number of friends and followers receive more information and thus have more exposure to learning about thoughts and experiences. Similarly, Ellison, Steinfield et al. (2011) argued that social network provides an opportunity to build links and network. Lin (1999) also argued that as the network of an individual becomes larger, it makes it easier for the individual to get access to more diverse social contacts.

2.3.4 Modeling social network index

Considering social network studies, we posit that access to information depends on the investor's social circles, network structure, and size of the network (Paul 2012, Saxton and Wang 2014, Arnaboldi, Conti et al. 2016). We present the Social network index's factors in fig 3:

Figure 3. Social network index



Social ties circles simply tell us that an individual does not receive information from all his/her friends in the network (Arnaboldi et al. 2016; Roberts et al., 2009). The individual (ego) receives information from certain friends in the network. The amount of information determines the nature of tie or friends (close friend or least close friend) which means that a high degree of information from certain friends indicate that these friends are close friends of ego/individual. Whereas a low level of exchange of information between ego with her/his friends indicates friends are least trustworthy (Arnaboldi et al. 2016; Granovetter 1973; Krackhardt's 1998; Roberts et al. 2009).

Similarly, investors also receive information from certain individuals in the network (e.g. strong ties and weak ties). Investors build social ties to acquire information, and investors who are closer to one another are more likely to exchange information (Kestutis 2019) hence; investors rely on the information (Joyce 2013; Kestutis 2019; Miller and Skinner 2015). However, these studies (Joyce 2013; Kestutis 2019; Miller and Skinner 2015) have not measured the social ties of investors and have not addressed the importance of strong and weak ties within investors' networks. Hence, considering the importance of social ties revealed by network studies (Arnaboldi et al. 2016; Granovetter 1973; Krackhardt's 1998; Roberts et al. 2009), we argue that social ties circles are a key factor of the social network index because the dissemination of information in a network depends on a certain group of friends, not entire network (all friends).

Liu and Li (2019) argued that investors usually have direct or indirect links with other investors and share their opinions, emotions, and information in networks. Access to such information depends on the number of links or connections of the investor in the network (Han N 2013) and highly linked investors are more often exposed to knowledge and information (San-Lin Chung 2019). In the language of network studies, links or connections in a network reflect the network degree of individuals within the network. A study by Chen Liu and Xuefei Li (2019) showed that network degree is a major factor in the dissemination of information in the network of investors. Similarly, other network studies have suggested that individuals who are well connected in the network have a high network degree and a lower path length which allows nodes or individuals to receive information quickly (Perera 2017; Lewis 2009). Considering these studies, we also posit that information acquisition will also depend on the connectivity of the investors. Similarly, studies (Harrigan et al. 2012; Luarn et al. 2014; Sundararajan et al. 2013) show that network size plays an important role in acquiring information, depending on number of contacts.

2.4 Research Methods

2.4.1 Data

The main subjects of our research datasets are retail 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. We collected data from 192 retail investors from different parts of New Zealand. We created a survey using Qualtrics and sent the link to Investor Associations in New Zealand. Investor associations sent the survey to investors via email and requested them to participate. They also tweeted our survey on their official Twitter account and asked investors to take part. 285 participants responded to the survey in total. Out of the total, 258 participants consented or agreed to participate in the survey, while 63 participants declined. But 66 of the 258 respondents didn't give us their Twitter username for our study and analysis. As a result, we conclude with 192 final samples for our research. As a result, the overall response rate is 67.4%. Our study relies on primary data which is Twitter data (tweets, retweets, mentions, and replies). We started downloading the data via Twitter API (Application Program Interface) using the NodeXL pro application. Initially, we downloaded 69,399 Twitter data, after removing the duplicated tweets as part of the cleaning process, we finalized our sample up to 47,120 tweets for this study. NodeXL (Smith et al. 2009) and SPSS (Mazziotta et al. 2019) were used in the analysis. Table 1 presents a brief description of data.

Table 1. Twitter data

Twitter data	
Total Tweets[1]	47,120
Total reply[2]	9,644
Total mentions[3]	15,895
Total retweets[4]	3,246
Average tweet	197.2
Average reply	40.4
Average mention	58.7
Average retweet	12

Table 1. Descriptive Statistics

Descriptive Statistics			
Indicators	Mean	St. Deviation	Analysis N
Network Degree	6.9999	4.36291	192
AP	1.1447	.51842	192
C1	1.9485	.92534	192
C2	1.9622	1.13162	192
C3	1.9629	.93720	192
C4	1.0775	.44461	192
Followers	453.9375	588.57423	192
Following	1008.7760	1440.44011	192

2.4.2 Procedure

In the first phase of the development of the measurement scale, a systematic literature review was initially performed to identify and define core factors in the network. Based on the comprehensive review of network literature, we identified three main factors that initiate the

---

[1] These are the sentiments and information that investors' twitter contacts/friends have posted. Simply put, investors are exposed to these tweets or vice versa.

[2] These are replies to tweets (sentiments and information) that investors have sent.

[3] Mentions are the contacts/friends who are mentioned by investors. Mentions data are used while calculating social tie circles of investors. Please refer to 4.5 Measurement section.

[4] Retweets are information/sentiments retweeted by investors. Retweets data are used in calculating social tie circles. Please refer to 4.5 Measurement section.

dissemination of information and affect individuals' access to information in the network. These factors include network structure, social ties circles, and network size. By using real network data, we calculated the network index.

In the second phase of our analysis, we first defined and then measured network structure. To do so, we followed the methods defined and identified by Perera (2017). We did this because the network can be random, free scale, and small-world network, and their structure is determined by distribution degree (Perera, 2017; Lewis, 2009). Based on the previous literature (Chen Liu and Xuefei Li 2019; Perera 2017; Lewis 2009), we considered two key network structure properties such as network degree and average path length for our study. To find and calculate social ties circle, we applied the method used by Arnaboldi et al. (2016) and Khan, Mohaisen, and Trier (2019). We first traced the frequency of communication (mentions and retweets) of each investor with his/her friends during a given time. We then divided the frequency of communication of investors to each friend by the total number of mentions and retweets, which gave us the social ties of each investor. We then built a ties circle based on the degree of communication between investors and his/her friends. It is worth noting that higher communication shows the first circle or closest group of friends whereas the lowest communication shows the least or weak ties.

We further calculated the strength of each tie or social ties circle by a method used by Arnaboldi et al. (2016). To do so, we conducted a correlation between information diffusion (retweets) and tie strength (mentions/replies). We did this for each tie circle (c). The strength of each tie circle shows the level of trust between investors and his/her friends. Measuring network size was comparatively simple but time-consuming. We counted followers and the following of each investor on his/her network. Finally, we conducted the Principal Component Analysis (PCA) by loading three key factors or eight items. To identify and select suitable components or factors to develop a single index representation of investors' social networks, we used PCA. Principal Component Analysis is a good statistical tool for reducing the dimensionality of data and it is good for creating indices (Abdi and Williams 2010). That is why researchers often use PCA for index creation (Mazziotta, Mazziotta et al. 2019).

2.4.3 Measurement

Many earlier network studies suggest that the Twitter network is only constructed on the links formed through the follow and following (Ahn & Park, 2015). However, users also create networks on Twitter through their interactions and information sharing in the form of retweets, mentions, and replies (Ahn & Park, 2015; Derek, Ben, & Marc, 2019; Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017) in a such Twitter network; network degree and average path length are key properties. Considering previous literature, we selected network degree and average path length to represent the network structure of the investor. In this section, we showed how to measure or calculated these two key network structural properties using investor Twitter data (Perera et al. 2017; Ted 2009).

2.4.4 Network Structure

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 D1 to maximum Dm in-network V

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

Dv represents the network degree of investor i in network V, mi is the links of investor i in network V and n is the number of nodes or individuals in network V. Below figure 5 shows the degree distribution within investors' network. It shows the 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 connections (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.

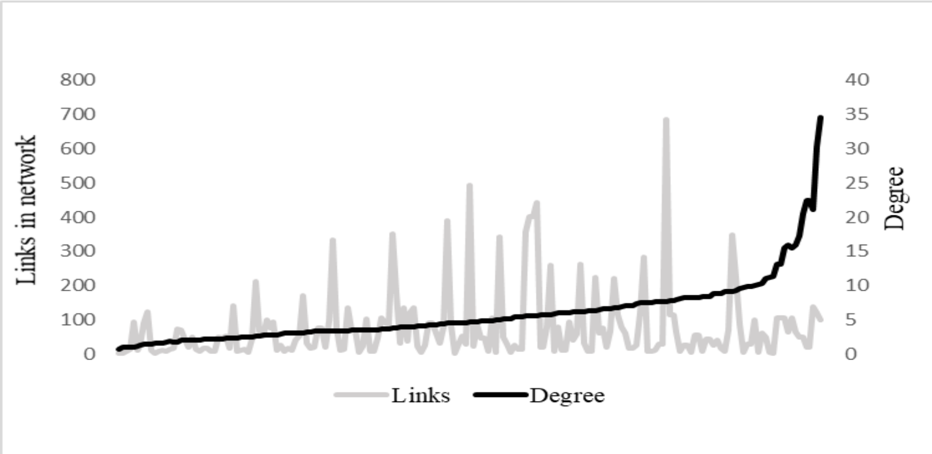


Figure 4. Degree distribution

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 is inversely related (Lewis 2009). Hence, we measured the average path length and density of the network method by following the methods discussed by Lewis (2009).

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

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 represents nodes, and m represents 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 the density and average length path of their network. It shows that investors with the 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 up just 5.5% of the overall data. Below figure 6 shows investors' density Vs. Average path length.

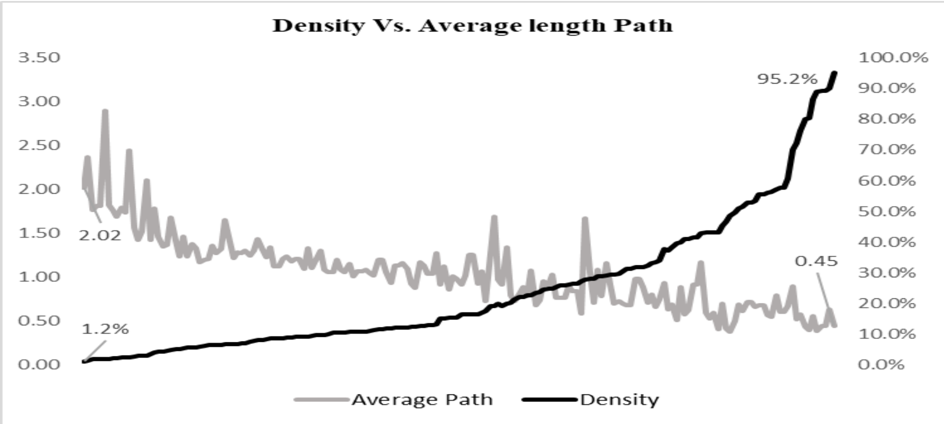


Figure 5. Average length path vs. density

Network size

We 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 figure 7, we presented an investor's network with comparatively large, medium, and small network sizes. It shows that investors with larger network exchanges or communicate information (mentions, retweets, and replies) with a higher average compared with a smaller network. For example, investor "A" with a network size of 3676 friends exchanged 297 information or tweets. Whereas investor "C" with a smaller network size of 131 friends, just exchange 16 tweets.

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 a larger network have received comparatively lower information. For example, investors with an average network size (groups 15 & 19) of 3000- 3200 and 3800- 4000 friends received comparatively fewer tweets (shown in Table 3). But our overall network data shows that investors with a larger network size receive on average higher information or tweets.

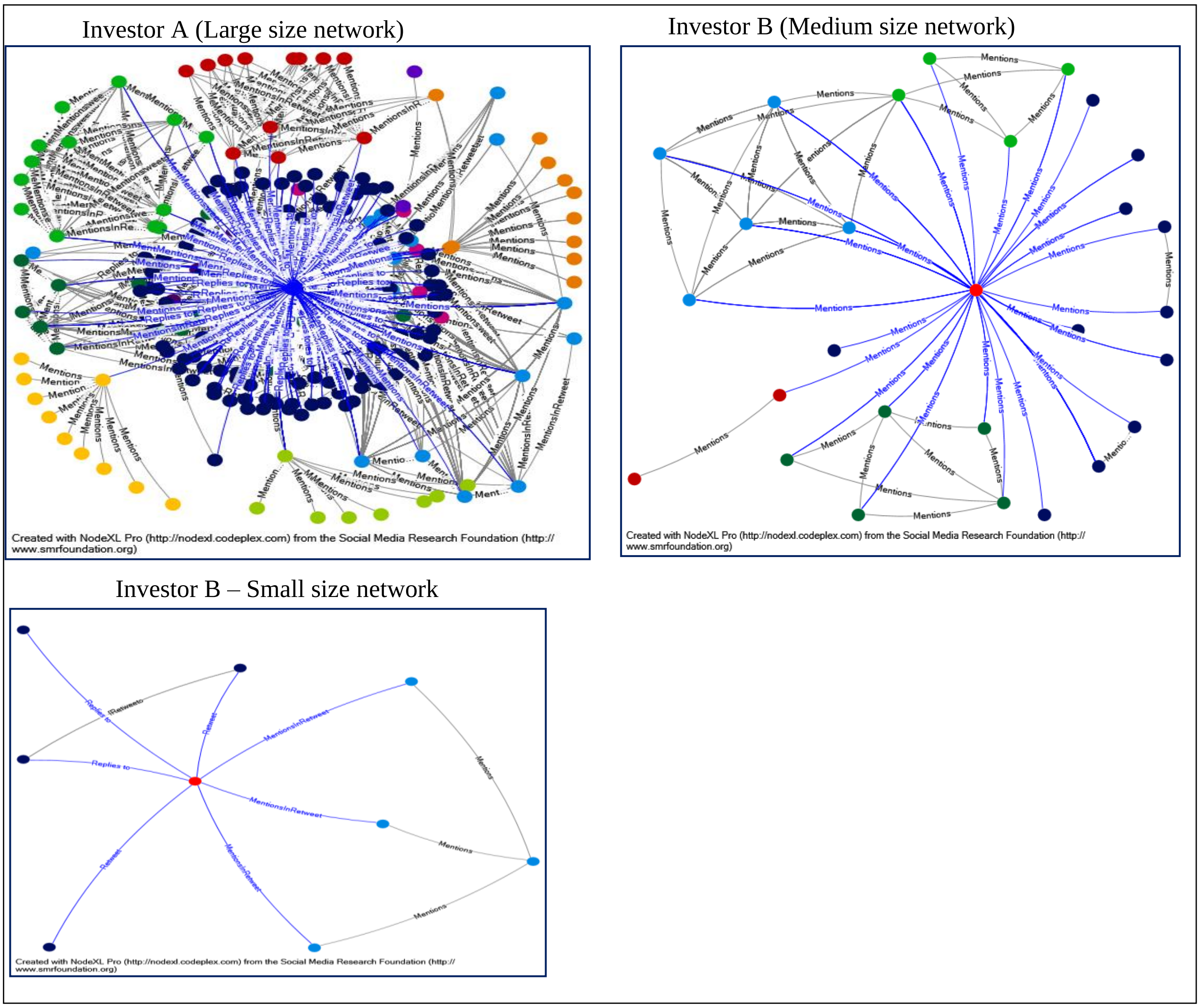


Figure 6. Network Size vs. Tweets

The size of the network is presented:

$$NS = number\ of\ followers + number\ of\ following \tag{2}$$

Table 2. Average Network size 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

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 retweeting acts as a form of endorsement. To calculate Social ties and the strength of the relationship 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 number 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 a certain group of friends from the entire network with whom investor exchange information. The equation for social tie circles is:

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

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.

$$\mathrm{Cij} = \sum_{\mathrm{j} \in \mathrm{m}} \ \mathrm{Mfreq} + \sum_{\mathrm{j} \in \mathrm{rt}} \mathrm{RTfreq} \qquad (3.1)$$

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

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

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:

$$\mathrm{RTfreq} = \frac{\text{Link retweet frequency}}{\text{ego (investor)total retweet frequency}} \qquad (3.1.2)$$

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 whereas 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 an unstable network or extended network of ego or investor. Table 4 shows the social ties circle of investors.

Table 3. Social ties circles of investor

Social ties circles of investor		
Circles	Average communication (mention & retweets)	Average Size of a circle (Friends)
C1	0.335	2.6
C2	0.080	8.1
C3	0.035	18.7
C4	0.003	39.4

Strength of ties (r)

To normalize the social ties circle, we measured the strength of the ties or relationships 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.

$$RTfreq = \sigma + \beta * Mfreq \qquad (3.4)$$

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 4. Strength of ties in each circle

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

2.5 Results

Our principal component analysis (PCA) result suggests four components are significant or contribute at the ideal level to the overall social network index based on the eigenvalues and distribution of the variance. Our shows KMO and Bartlett's Test at 0.663 (>0.5) with .000 significance (<.005). The value of Bartlett's Test was place between 0 to 1. The minimum or acceptable value is 0.5, but closer to 1 is better.

Table 5. KMO Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.663
Bartlett's Test of Sphericity	Approx. Chi-Square	221.079
	df	28
	Sig.	0.000

Based on the variance results, the first four-components have an eigenvalue of more than one and also have a higher % of variances. The first component has 2.345 eigenvalues and 29.4% variance followed by the second component with 1.3228 eigenvalues and 16.6% of the variance. In simple words, these four extracted components contribute higher than other components to an overall latent variable (index). It means that components with higher eigenvalues have a closer relationship with the underlying latent variable (social network index). The total variance explained (table 7) shows the distribution of eigenvalue by each component.

Table 6. Total Variance Explained

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.354	29.419	29.419	2.354	29.419	29.419
2	1.328	16.601	46.020	1.328	16.601	46.020
3	1.117	13.965	59.985	1.117	13.965	59.985
4	1.009	12.616	72.601	1.009	12.616	72.601
5	0.653	8.161	80.762			
6	0.573	7.163	87.925			
7	0.488	6.104	94.030			
8	0.478	5.970	100.000			
Extraction Method: Principal Component Analysis.						

Further, our result shows the proportion of variance by each item in the component matrix (Table: 8). Comparing the value of the item in a component matrix shows that as the first component of the matrix, the average path length (AP) value is comparably low or its variance considerably lower compares with its pair value (degree) e.g. Degree (.720) and AP (.188). It means that the degree contributes higher to the first component (Network structure) or we can say that degree can represents the network structure. Similarly, other items; the followers and followers both have higher variance at 0.63 and 0.704 respectively, this shows that both items contribute almost equally to the third component (network size). The below table (6) and scree plot shows the proportion of variance by each item of the component.

Table 7. Component Matrix

Component Matrix				
Component				
	1	2	3	4
Degree	0.72	0.337	-0.1	-0.211
AP	0.188	-0.25	-0.302	0.866
C1	0.424	0.73	-0.002	0.078
C2	0.65	0.107	-0.502	-0.103
C3	-0.118	0.535	0.627	0.378
C4	0.538	-0.5	0.447	-0.142

Followers	0.631	-0.225	0.411	0.017
Following	0.704	-0.144	0.043	0.188
Extraction Method: Principal Component Analysis.				
a. 4 components extracted.				

2.6 Discussion and Contribution

Due to the dearth of established methods for social network index (SNI) measurement, particularly in the context of investors, we took a first step towards a more thorough and comprehensive social network index measuring approach in this study. We attain this objective by foregrounding the underlying theoretical assumptions about social ties' role in the dissemination of information within the network, higher connected vs lower connected investors and their access to information, and by illustrating s the impact of a larger network vs small size on information distribution within the network.

In the line with the literature (Luarn et al. 2014; Granovetter, 1983; Menon and Ranaweera 2018; Sundararajan et al. 2013), our findings show investors with larger contacts or extended networks receive higher information. Particularly, "investors with higher "following" access to massive information on Twitter. When the "Following" or “follows” of an investor's shares or retweets, and tweets the information on Twitter, it also appears on the investor’s Twitter status. This means that having a large Twitter “following” will enable an investor to access a wealth of information on Twitter. We contend that when it comes to the dissemination of information on Twitter, the strength of extended contacts or following cannot be overlooked.

The finding of network structure is also in line with previous literature (San-Lin et al. 2019; Han N. et al. 2014). To determine how much information each investor has received or been exposed to within the network, we subsequently examined investors’ connectivity within the network. Our study reveals how quickly connected investors can access information as compared to less connected investors. This finding also demonstrates that investors who received more information are frequently connected within networks. However, it is worth mentioning that our PCA (table 7) finding reveals that C4 contributes higher to social ties which contradict our tie strength results (table 4). Furthermore, this finding of our study is also not in line with the previous literature which has pointed out that C4 is a weak tie in terms of strength (Arnaboldi et al. 2016). This finding our study is strange and unusual. However, weak ties is crucial for granting access to a wider range of knowledge, perspectives, and experiences (Hill and Dunbar 2003). Granovetter (1983) argued that the strength of extended or weak ties cannot be ignored.

Our study offers some useful recommendations for stock market traders. Investors require information to make investment decisions as well as to comprehend market behaviours because the information is essential for trading (hung, Liu, and Tseng 2018; Jackson and Watts 2002; McGurk et al. 2020; Ozsoylev et al. 2014; Schweitzer et al. 2009). Such information is readily available on social media, notably on Twitter, a significant source of financial market information. We, therefore, advise investors to not only create a Twitter account but also to use it frequently and remain connected. We also advise investors to follow other investors and stock market companies, as well as build more acquaintances and contacts. As a result, investors will have access to a variety of information on their Twitter network. We suggest that being a part of a network is not as significant as being connected to it. This study also provides investors with guidance that being linked and having stable ties is crucial to acquiring financial information. For the academicians, this study will provide a theoretical grounding for comprehending the role of social network index from investor's network, which could potentially be used to create spin-off research projects. This study further provides a grounding technic that can be applied to other social media platforms particularly on Facebook to measure network indexes.

Our research also omits some key points in the development of a measurement scale. This study only calculated the social network index 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 variations in communication. We, therefore, argue that future studies should look at network factors across different social networks particularly on Facebook to further understand the usage behaviour of investors. Besides, we think future research needs to consider the time window while the social network index. Since social media is culturally dependent. Individuals have diverse social ties, and different sizes of networks across different nations (Albarran, 2009; (Elmasry, Auter, and amp; Peuchaud, 2014). Kim et al., (2011) argued that social circles or social relationships are influenced by the cultural background of individuals. As a result, we believe that when evaluating the impact of network factors on information dissemination within the network, a cultural factor must also be addressed.

2.7 Conclusion

Our findings have suggested a four-component solution meaning that information dissemination in investors' networks is not dependent on a single factor but depends on the number of factors or items. The existing literature (Arnaboldi et al. 2016; Katona et al. 2011; Luarn et al. 2014; Murendo et al. 2018; Saxton and Wang 2014; Khan, Mohaisen, and Trier 2019) have not addressed the effect of all factors collectively on information dissemination in a social network but rather just defined it as a single factor. This study also provides a ground technic that can be applied to other social media platforms particularly on Facebook to tackle investors' network indexes. This study, therefore, offers not only a robust measurement scale but also generates opportunities for spin-off studies to define and quantify key variables representing the "social networks index" from the perspective of investors on other social media networks.

Chapter 3: To what extent do network effects moderate the relationship between social media-propagated news and investors' perceptions?

3.1 Introduction

Information is key to trading, which is why investors are determined to get their hands on financial information in the stock market (Baker & Haslem, 1974; Ozsoylev, Walden, Yavuz, & Bildik, 2014; Pevzner, Xie, & Xin, 2015). Investors use media networks to obtain information that can help them make informed decisions, including social media networks (such as Twitter or Facebook) (Bartov, Faurel, & Mohanram, 2018; Joyce, 2013; Miller & Skinner, 2015; Siikanen et al., 2018) and mass media networks like newspapers or press releases (L. Feng & Seasholes, 2004; Yin & Tan, 2017). Financial information, news, and sentiments (L. F. Lee, Hutton, & Shu, 2015; Miller & Skinner, 2015) sharing through social networks are more influential and involve more people because social media enables the rapid distribution of information. (Chen, Tsai, & Chen, 2016; L. F. Lee et al., 2015; Stieglitz & Dang-Xuan, 2013).

Social media is increasingly being utilized as a source of valuable financial in financial markets (Lee et al., 2015) because it provides investors an opportunity to exchange financial information, and viewpoints about companies, and markets (Cade, 2018). Previous studies (e.g. Miller and Skinner 2015; Joyce 2013) have shown that Twitter has become a prominent social media platform for investors to not only obtain financial information but also connect with other investors. That's why social media, particularly Twitter, is an ideal platform to share sentiments or opinions and information promptly to the stock market (Eli el at., 2017). Miller and Skinner (2015) argued that information exchange occurs among investors through social interaction and access to such information depends on the number of links (degree) of the investor in the network (Han N 2013). If investors are more strongly connected within the network, they are more often exposed to knowledge and information (San-Lin Chung 2019).

Social networks offer great opportunities for people to establish connections and retain a larger number of friends (Network size) (Ellison et al., 2011). Panzeri (2012) argued that social media is a platform that influences individuals' perceptions and behavior. Most importantly, friends, family, and colleagues (social ties) play a key role in influencing one's perceptions, preferences, and opinions. Similarly, the exchange of sentiment and information on social media (particularly Twitter) has an impact on the perceptions and behavior of investors (Guggenmos and Bennett, 2017; Elliot et al., 2018). Brad and Terrance (2007) argued that sentiments and information can affect investors' perceptions in both positive and negative ways, depending on the information.

From a network 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), this is known as a network effect. Such effects occur through communication or interaction in networks (Evans & Schmalensee, 2017; Khan, Mohaisen and Trier 2020). Becker (1999) argued that whenever there is a network, there is a network effect. Similarly, Conrad el at. (2018) argued that the influence of friends and family (social ties) on one's perceptions and decisions is the network effect. Similarly, Bonchia el at. (2010) urged that perceptions and individual decisions to purchase products or services on social media are influenced by their friends through the exchange of information. literature also demonstrates that network size (contacts), and connectivity (network structure) facilitate the dissemination of information within the network (Evans & Schmalensee, 2017; Khan, Mohaisen and Trier 2020; Katona et al., 2011; Luarn et al., 2014. These studies further show that network size and connectivity are key factors that generate network effects through the dissemination of information. However, these studies have not defined the extent to which the effect of sentiments and information on investor perceptions is moderated by connectivity (network structure), network size, and the social ties of investors.

Based on the above literature, we posit the effect of sentiments and information is moderated by network structure, size of the network, and social ties. We argue this because the literature clearly shows that exposure and access to information on social media rely on the connectivity, and size of the network, and such information affects perceptions and behavior (Katona et al., 2011; Gregory, Lili, 2011; Panzeri, 2012; Conrad el at., 2018). Similarly, information is more influential and has an impact on individual perceptions when it is shared by his/her social ties (colleagues, friends, and family) (Panzeri, 2012; Chen, Marcus, 2012; Joyce, 2013; Gregory, Lili, 2014; Valerio et al., 2015). This paper will contribute in the following ways. First, we are conducting this study from New Zealand’s investors' perspective. Second, other studies have measured the impact of social ties on perceptions. But this study is intended to quantify the influence and impact of social ties on investors’ perceptions.

3.2 Research Background and Literature Review

Some researchers have suggested that the network effect has three factors: (1) the relationship or social circles of the individuals in the social network (Khan, Mohaisen and Trier 2020; Gregory, Lili, 201; M. Panzeri, 2012); (2) network structure of individuals in the social network (Matthew, 2002; Katona et al, 2011; Craig, 2019); and (2) size of the network (Katona et al., 2011; Craig, 2019).

3.2.1 Social Ties circles

Colleagues, friends, and family members make up an individual's social circles. They are also called the ego (user) 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 place 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. However, the social circle ties of an individual inside a social network are made up of about 4 to 5 circles on average (Arnaboldi et al. 2016; Roberts et al. 2009). These circles can be categorized depending on how close the ego (individual) is to people in the network.

For example, people in C1 or C2, the first circles (fig 8), have very close connections to the ego and most information exchange occurs in these circles. People in these circles are usually colleagues or close friends of the individual. This is also called strong ties (Granovetter, 1973). Similarly, Roberts et al. (2009) argued that the first circle (C1) has the best friends who have extremely strong social relationships with the ego (individual). On the other hand, C4 and C5 are extended (weak) user ties (fig 1) where the lowest interaction or information trade takes place, it is also called weak ties (Granovetter, 1973). 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). However, Granovetter (1973) argued that the strength of weak ties can't be overlooked as they enable individuals to obtain information from varied or extended social networks.

3.2.2 Structure of the network

Networks have different structures and forms which depend on the connections or links of a user with other individuals. These links are also called degrees (Perera 2017; Lewis 2009). The number of links plays a very important role in the generation and dissemination of information within a network (Katona et al., 2011; Luarn et al., 2014). Katona et al., (2011) argued that individuals with a higher network degree or high network connectivity have greater information access. Furthermore, the distance or average length between nodes is another key factor. The path length is the distance between nodes or individuals in the network (Lewis, 2009). A lower distance between nodes in the network enables them to exchange information more readily. The 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 access to information is more quickly as compared to more distant nodes (Katona et al. 2011; Lewis 2009; Perera 2017). Lewis, (2009) argued that the higher connected nodes or individuals in the network have a lower average path length which means that they can more quickly receive information.

3.2.3 Size of the network

Networks are characterized by having a certain size, which is the number of contacts or network members on a network (Harrigan et al. 2012) (Luarn et al. 2014; Sundararajan et al. 2013). Depending on the nature of ties and links on the social network, individuals who have a higher number of followers and friends are likely to receive more information as compared to individuals with weaker links and a smaller number of followers (Luarn et al. 2014, and thus have more exposure to learning about others' thoughts and experiences. Ellison et al. (2011) argued that large networks would allow individuals to access more information. However, too large a network is not a good thing either. The strength of the ties becomes weaker as the network size expands.

3.2.4 Other factors

In the meantime, the literature has also described the role of non-social media or traditional media (such as television, and newspapers) in the dissemination of news and its impact on perceptions (Feng and Seasholes, 2004; L. Fang, J. Peress, 2009; Abhijeet and Kumar, 2011; C.W. Chen, C. Pantzalis, J.C. Park, 2013; Yugang Yin and Bin Tan, 2016). Television and newspapers are still considered important news sources by many people (Manu Bhandari, 2018). This means that social media is not the sole source of news distribution; the same news can be distributed via non-social media which can affect investors' perceptions at the same time. Furthermore, perceptions and investment decisions also depend on investors' age and experience. Barber and Odean (2001) argued that relatively younger investors take a more aggressive approach to trade than relatively older investors. Similarly, investors who are more experienced tend to have less concentrated portfolios and trade more carefully (Goetzmann and Kumar, 2002). Considering all factors, below is the proposed model.

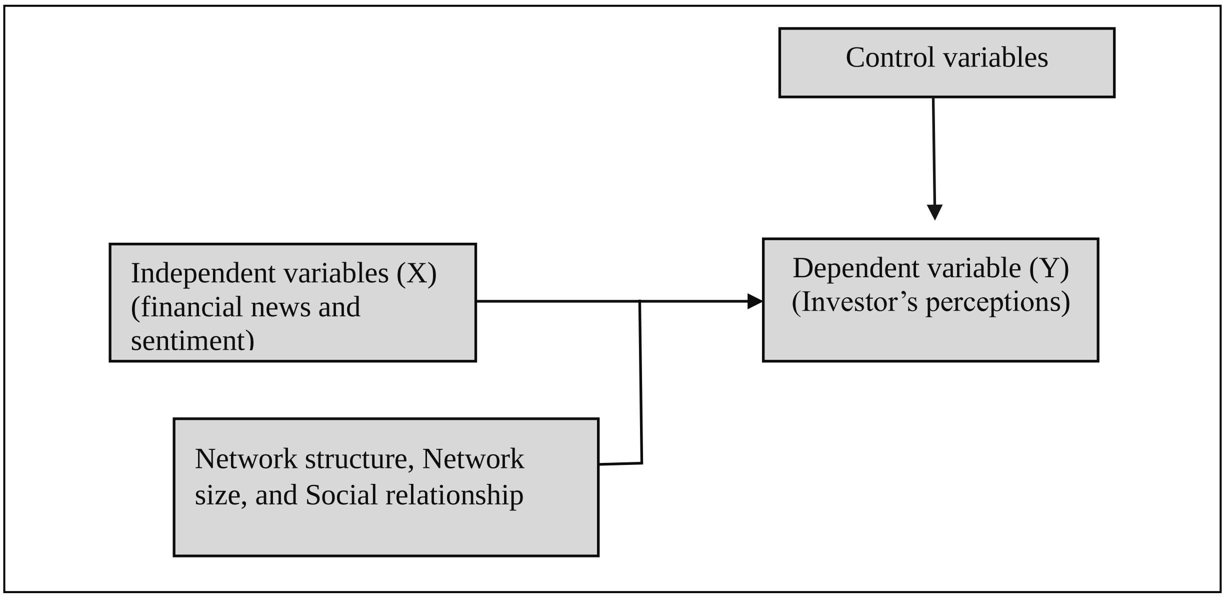


Figure 8. Proposed Model

3.3 Research Methods

3.3.1 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. We examined and collected data from 240 retail investors from different parts of New Zealand[5]. We created a survey using Qualtrics and sent the link to Investor Associations in New Zealand[6]. Investor association sent the survey to investors via emails and requested them to participate. They also tweeted our survey on their official Twitter account and asked investors to take part. 374 participants responded[7] to the survey in total. Out of the total, 311 participants consented[8] to participate in the survey, while 63 participants declined. But 71 of the 311 respondents didn't give us their Twitter username for our study and analysis. As a result, we conclude with 240 final samples for our research. As a result, the overall response rate is 64.1%[9]. Out of the total, 311 participants agreed to participate in the survey, and 63 participants declined to participate. However, out of 311, 71 of them didn't provide us with their Twitter username for our research and analysis. So, we come up with 240 final samples for our study. Hence total response ratio is 64.1%. In the survey, we asked investors about their age, gender, income, investment, experience, newspapers[10], and Twitter user names.

Our study relies on two types of primary data. The first primary data mainly rely on Twitter data (tweets, retweets, mentions, and replies)[11]. Other primary data represent control

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[5] Survey locations: Waikato, Auckland, Wellington, Christchurch, Palmerston north, Tauranga, Napier, Nelson, Bay of plenty, Dunedin.

[6] For our study, we contacted a number of New Zealand-based investment platforms and associations.

[7] 374 participants clicked or entered survey but some of them declined to participate. However, we are unaware of how many investors have received the survey.

[8] The survey had a consent and stated "If you would like to volunteer in this study, please accept this consent by clicking on "Yes, I agree" at the bottom of this page"

[9] Response ratio represents the final list of participants out of total (374).

[10] Investors may be exposed to news through both non-social media (such as newspapers) and social media (such as Twitter). Therefore, we requested information from investors regarding the name of the newspaper they read or rely on for news.

[11] Tweets are the news/information, and sentiments shared by users, contacts, and friends on Twitter.

variables (age, gender, income, investment, experience, and newspaper). We started downloading the data via Twitter API (Application Program Interface) using the NodeXL pro application. Initially, we downloaded 75,904 Twitter data, after removing the duplicated tweets[12] as part of the cleaning process, we finalized our sample up to 47,120 tweets for this study. Table 9 presents a brief description of Twitter data.

Table 8. Twitter data

Twitter data	
Total Tweets[13]	47,120
Total reply[14]	9,644
Total mentions[15]	15,895
Total retweets[16]	3,246
Average tweet	197.2
Average reply	40.4
Average mention	58.7
Average retweet	12

3.3.2 Investor perceptions

To tackle the impact of sentiments and information/news on investors' perceptions, we then conducted sentiment analysis on investors' replies sent to tweets they received. We analyzed replies using an n-gram language model (Algaba, 2020; Gentzkow, Kelly, and Taddy, 2019). In this case, N is the 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), trigram (three words), and 4-gram counts in our N-gram textual analysis. We included all positive, negative, financial, and nonfinancial words. N-gram analysis was used because some single words or unigrams may have either a positive or negative meaning, depending on previous words in the same tweet (Gentzkow, Kelly, and Taddy, 2019). For example, "stocks/stocks down or nice buying/panic buying", with or without "down" or "nice/panic", the words "stocks" and "buying" can deliver a different meanings. Similarly,

[12] Twitter API don't download clean data. We manually cleanse the data. We thoroughly deleted the duplicate tweets after going over each participant's data.

[13] These are the sentiments and information that investors' twitter contacts/friends have posted. Simply put, these tweets are exposed to investors or vice versa.

[14] These are replies to tweets (sentiments and information) that investors have sent.

[15] Mentions are the contacts/friends who are mentioned by investors. Mentions data are used while calculating social tie circles of investors. Please refer to 4.5 Measurement section.

[16] Retweets are information/sentiments retweeted by investors. Retweets data are used in calculating social tie circles. Please refer to 4.5 Measurement section.

some non-financial words may have positive or negative meanings, depending on the context, e.g. “good” is a word with a positive meaning, while “not good” has a negative meaning. However, some single words have particular meanings without depending on previous or other words. For example, investors used “bearish” words that indicate a falling share price while “bullish” indicates an increase or rising of the share price. Hence, these kinds of words come under the unigram category. Hence, we, therefore, applied the n-gram method to reflect the meaning of words appropriately.

We used the Loughran and McDonald financial words list to classify words (n-grams) into positive and negative categories. The word list compiled by Loughran and McDonald has been extensively applied in financial literature. These studies indicate that this word list is the most often used and effective list to gauge sentiments. Additionally, Loughran and McDonald have described their word list in their many articles (Please view). There are 86,533 words in this list, which is also known as the master dictionary. 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.

We counted and coded financial n-grams as positive (+1), negative (-1), or neutral (0). For example, crash, debts, crisis, market tank, financial crisis, recession, economic recession, bullish, bearish, NZX down, Dow down, market down, and fall in Index (please see the attached list of the n-gram in annex-1) are examples of negative n-grams. We also measured non-financial signal words in investors’ tweets that have sentimental value like “good”, “nice”,” bad”, “strong” and so on. 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. For instance, positive words (e.g. great, progress, good, precious, nice, love, well, worth, help, support, happy, better) are scored (+1) whereas negative words (e.g. fear, panic, worst, bad, fear, hate, epidemic, risk, death, worse, problem, hard) are scored (-1). Some investors reply in the form of emojis without using words. Therefore, we also include emojis in our analysis

To further expand our analysis and make it more relevant to the current situation, we included novel keywords used in tweets such as Covid-19, coronavid19, coronavirus, corona, C.virus, CV, virus, flu, and wuhanvirus. The current NodeXL dictionary considers a virus as a negative word. Since corona or covid-19 is also a virus. We, therefore, counted them as negative in our sentiment analysis. We also conducted textual analysis on news from sources other than social media (newspaper). We employed a technique developed by Garz (2018). For this textual analysis, 15 distinct newspapers were used. 11,066 words from these newspapers were examined. Words were categorized as Positive (+1), Negative (-1). In addition to these factors, our study considers factors like age, experience, income, and investment that may affect investors' perceptions. We used a survey to record the responses from the participants, and we then analyzed the responses.

3.3.3 PLS-SEM

We applied PLS-SEM to measure the impact of sentiments and information on investor perception. PLS-SEM is well-known and used for investigating the direct and indirect impacts of variables (Becker et al., 2012; Hair et al., 2017). The structural model is an effective method. It determines the statistical significance of path coefficients between independent and dependent variables, as well as t-statistics/values for degree of significance and variance inflation factor (VIF) values to deal with factor collinearity.

According to several studies (Becker et al., 2012; Hair et al., 2017), PLS-SEM is best suited for models with a small number of factors or indicators (preferably less than six) and a small sample size. Numerous researchers have employed PLS-SEM to study investors' perceptions (Seetharaman, Niranjan et al. 2017), decision-making (Prasad, Kiran et al. 2021), and behavior (TA, DO et al. 2021). In addition, our model comprises four primary indicators (< 6) with a small sample size (240 participants). Hence, considering these studies, we believe that a PLS-SEM is a good instrument for our study.

3.3.4 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 their preferred newspaper from a list of five newspapers (Sharechat, Bloomberg, NZ Herald, Interest news, and Stuff news). The following methodology was used to compile our list of five newspapers. (1) We searched the newspaper in New Zealand with the most viewership. Based on the Roy Morgan[17] report, NZ Herald, and stuff news have the

[17] Roy Morgan is best known and longest established market research company

highest number of readers or viewers in New Zealand, (2) Sharechat was selected at random from a list of news and information providers for the stock market provided on the website of the New Zealand Stock Exchange (NZX) and (3) Interest news and Bloomberg was randomly selected based on google search. In addition, we requested investors to provide us with the list or the names of their favorite newspapers. Investors recommended 10 different newspapers. We finalized a list of 15 different newspapers (Table: 10). We also asked investors about their age, experience, income, and investment via survey. (E.g. What is your age? What is your gender? How long have you been involved in the financial or investment sector?). The participants also have the option of not responding to the questions, if they choose not to (e.g. Prefer not to respond).

Table 9. List of newspapers

Our list	**Recommended list**
SHARECHAT, BLOOMBERG, NZ HERALD, INTEREST NEWS, AND STUFF NEWS	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. We measured the network structure using the comprehensive method used by Lewis (2009). To determine the size of each investor's network, we counted their number of followers and the number of accounts that they were 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, to avoid double-counting. To measure social ties circles, we applied the method used by Arnaboldi et al. (2016). Based on this method, the frequency of communication (mentions and retweets) between the investor and his/her contacts (friends) was measured. The degree of communication shows the level of trust. We then did sentiment analysis as the third part of our data analysis.

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 show how we measured or calculated these two key network structural properties using investor Twitter data (Perera et al. 2017; Ted 2009).

3.3.5 Network Structure

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, following Lewis (2009):

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

Dv represents the network degree of investor i in network v mi is the links of investor i in network v and n is the number of nodes or individuals in the investor's network v. Our analysis shows that more connected investors receive a greater amount of information. Specifically, Table 1 shows that those with the smallest network degree (1.5) received an average of 40 tweets. Investors with the greatest or highest network degree (21.5) received an average of 961 tweets. Because of the change in network degree, we observed a significant shift in information flow on average. This shows that increased network connectivity allows investors to access information faster.

Table 10. Average Network Degree and Average Tweets

Average Network Degree	Average Tweets/information
1.5	40
2.5	52
3.5	101
4.5	164
5.5	267
6.5	279
7.5	321
9.5	346
12.5	358
13.5	438
14.5	791
15.5	940
16.5	941
17.5	861
19.5	855
20.5	951
21.5	961

3.3.6. Average path length (APL)

The average path length is the shortest distance between nodes or individuals in the network.

It shows how many links a node or individual has within the network (Lewis 2009). Hence, we measured the average path length and density of the network method by following Lewis (2009):

$$APL = \frac{log\,(\frac{n}{\lambda})}{loglog\,(\lambda-1)\,+1} \qquad (2)$$

n is the number of nodes or individuals in the given network where λ is the average node

3.3.7. Network size

We calculated investor network size by summing up their current total friends or contacts (following/followers).

$$NS = number\ of\ followers + number\ of\ following \qquad (3)$$

Our data shows that the information (mentions, retweets, and replies) depends on the size of the investor's network. progressively increases. In figure (3), we presented an investor’s network with comparatively different network sizes. It shows that investors with larger network exchanges or communicate information (mentions, retweets, and replies) with a higher average compared with a smaller network. For example, investor “A” with a network size of 58 friends exchanged 17 information or tweets. Whereas investor “B” with a smaller network size of 354 friends, exchange 111 tweets. Similarly, investors C and D relatively large network sizes of 1322 and 2,898 friends, exchanged 349 and 786 tweets respectively.

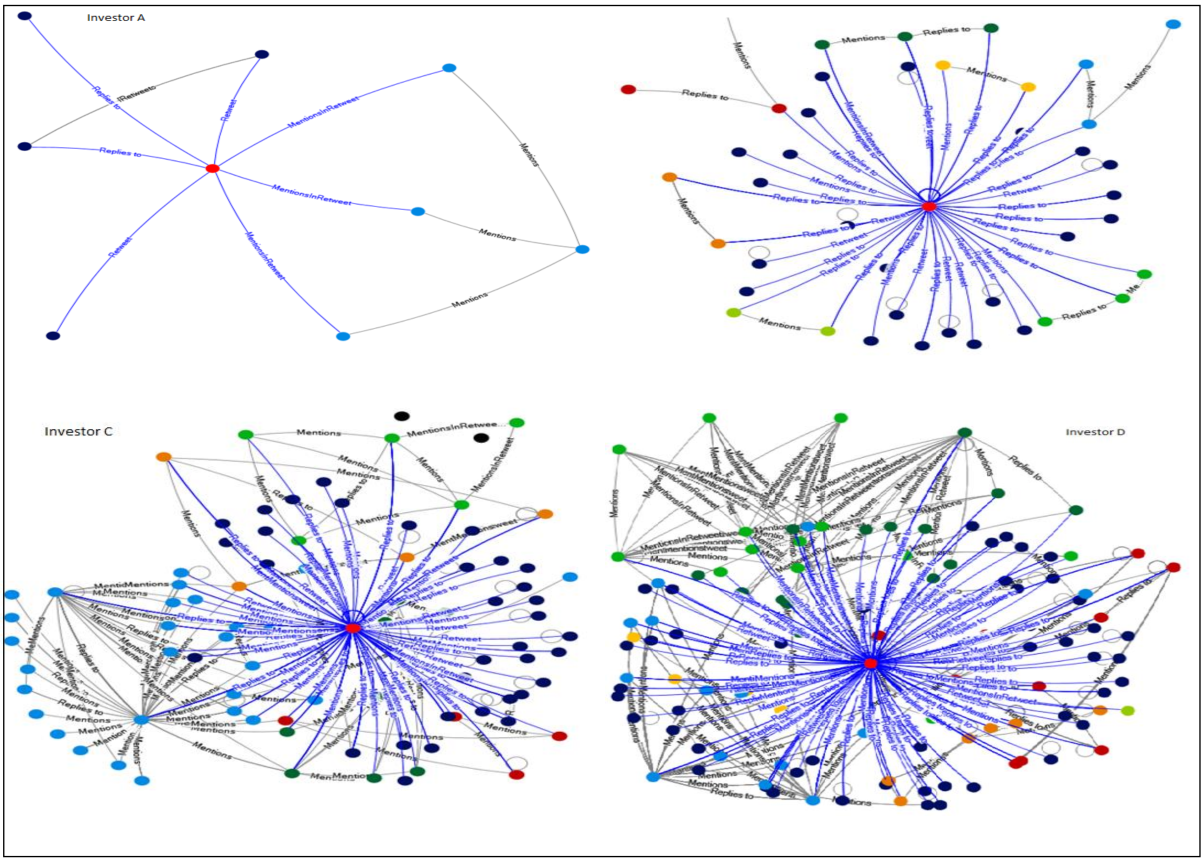
In our dataset, the average minimum network size (group 1) is 200 friends with 32.3 tweets while the average maximum network size (group 24) is 7800 friends with an average of 1542.3 tweets. However, our data also shows that some investors with a larger network have received comparatively lower information. For example, investors with an average network size (groups 15 & 19) of 3000- 3200 and 3800- 4000 friends received comparatively fewer tweets (shown in Table 12). 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:

Table 11. Network size vs Tweets

Group	Average Network size	Average Information (Mentions, retweets, replies)
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	883.0
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

Figure 9. Network Size



3.3.8. 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 act as a form of endorsement. To calculate social ties and the strength of the relations 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 number 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) and the number of extended friends (weak ties) of an investor in his/her entire network. In simple words, the following equation gives us a certain group of friends from the entire network with whom the investor exchanges information. The equation for social tie circles is:

$$\mathrm{STC} = \sum_{i=1}^{n} \left(\frac{C1}{100}(r1) + \frac{\mathrm{C2}}{100}(r2) + \frac{C3}{100}(r3) + \frac{\mathrm{C4}}{100}(r4) \ldots\ldots \frac{\mathrm{Cn}}{100}(rn) \right) + L \qquad (4)$$

C represents the size (number of friends) 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 himself/herself 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.

$$\mathrm{Cij} = \sum_{\mathrm{j \in m}} \mathrm{Mij} + \sum_{\mathrm{j \in rt}} \mathrm{RTij} \qquad (3.1)$$

Mij are the individuals mentioned by the investor i in his reply/tweets. RTij are the individuals j mentioned by investor i in his reply/tweets. Mention is measured as below

$$Mij = \frac{Link\ mention j}{ego\ (investor i) total\ mention} \qquad (3.1.1)$$

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

$$RTij = \frac{Link\ retweet j}{ego\ (investor i) total\ retweet} \qquad (3.1.2)$$

Link retweet is retweets of a friend j's tweet by an investor i. Total retweet is the retweet of all friends' tweets (alters) by investors i.

Based on our analysis, investors exchange information (mention & retweets) with his/her friend based on circles, which is comprised of four circles on average. The first circle (C1) of the investor or ego represents the friends with stable relations or strong ties where the highest communication (mention & retweets) took place. The first circle size is 2.6 of average friends with an average communication of 0.256 whereas the last or fourth circle (C4) of friends has a larger size (39.4 friends) with the lowest average of 0.0103 communications or interaction that shows an unstable network or extended network of ego or investor. Below table 13 shows the social ties circle of investors.

Table 12. Social ties circles of investor

Circles	Average communication (mentions & retweets)	Average Size of circle (Friends)
C1	0.256	2.6
C2	0.0938	8.1
C3	0.0501	18.7
C4	0.0103	39.4

3.3.8.1 Strength of ties (r)

To normalize the social ties circle, we measured the strength of the ties or relationships 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.

$$RTij = \sigma + \beta * Mij \qquad (3.2)$$

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 13. Strength of ties in each circle

Circles	r (Strength of ties)	Size of each circle (Friends)	Average exchange of information (mentions & retweets)
C1	0.34	2.6	0.256
C2	0.17	8.1	0.0938
C3	0.14	18.7	0.0501
C4	.036	39.4	0.0103

3.3.9 Investor Perceptions

Some social network studies have measured the network effect or impact on perceptions 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 network effect in investors' networks via replies of investors to the information and news received on Twitter. The replies (positive or negative words) of investors to the news indicate the effect of information on investors' perceptions. Studies show that 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). To do so, we also conducted a comprehensive sentiment or text analysis.

Particularly, the "reply" of investors and individuals to financial information and news better reflects the perception where a positive reply indicates a positive perception and a negative response indicates a negative perception (Kipp, Zhang, Tadesse, 2016; Bian, 2016). Stieglitz & Dang-Xuan, (2013) argued that communication, language, or words used in replies on social media demonstrate individual feelings and feelings of individual perceptions (Hall, Jobson, & Langdon, 2014).

We measured investor perception as:

$Pij = (PRij - NRij)$ (4)

Pi indicates a perception of i investor. PRi is the positive word used in replies of investor i to j news and information, and NRi are the negative words in replies of investor i to j news and information. Investors used different types of positive, negative, and financial words in their replies to the financial news. We tackle those words using the n-gram method. We presented these different categories of words below Tables 5 & 6, and graphs 1, and figure 4. Graph: 1 represents the top positive, negative, and Hashtags used in the tweets. Table 5 represents the sample of the n-gram words and table 6 shows the emojis used in the investors' replies. We also used R studio to develop word clouds and presented them in figure 4.

Our sentiment analysis shows (graphs 1) that investors used the word "bad" (10.5 %) in their replies to news or tweets, making it the most negative word, followed by risk (8%), and panic (7%). Investors also used the word "death" (4.4%) in their replies, referring to the people who died as a result of the covid-19. Similarly, investors used words like "good" (24.3%), "well" (13.6%), "excellent" (11.2%), and so on. Furthermore, the current market scenario was extensively addressed by investors. For instance, they used financial terms such as bullish (3.9%) to indicate upward movements of specific stocks and bearish (1.8%) to indicate market tanking.

Investors also used the word recession (1.5%) to describe the market's terrible situation because of Covid-19 and lockdowns. In terms of hashtag usage, the word "coronavirus" was the most popular (20.5%), indicating that investors have a pessimistic perception of the market. Investors also used the hashtag "Gold" (17.2%), indicating a bullish trend in gold stocks on the stock market. Investors also use the hashtags ASX (4.7%) and NZX (3.1%) to refer to the Austrian and New Zealand stock exchanges, respectively. Besides, investors used emojis to express their perceptions. They replied to news and tweets with good, negative, and neutral emojis (table:15). (Please refer to annexes 1 & 2 for the words list)

Figure 10: Sentiments Analysis

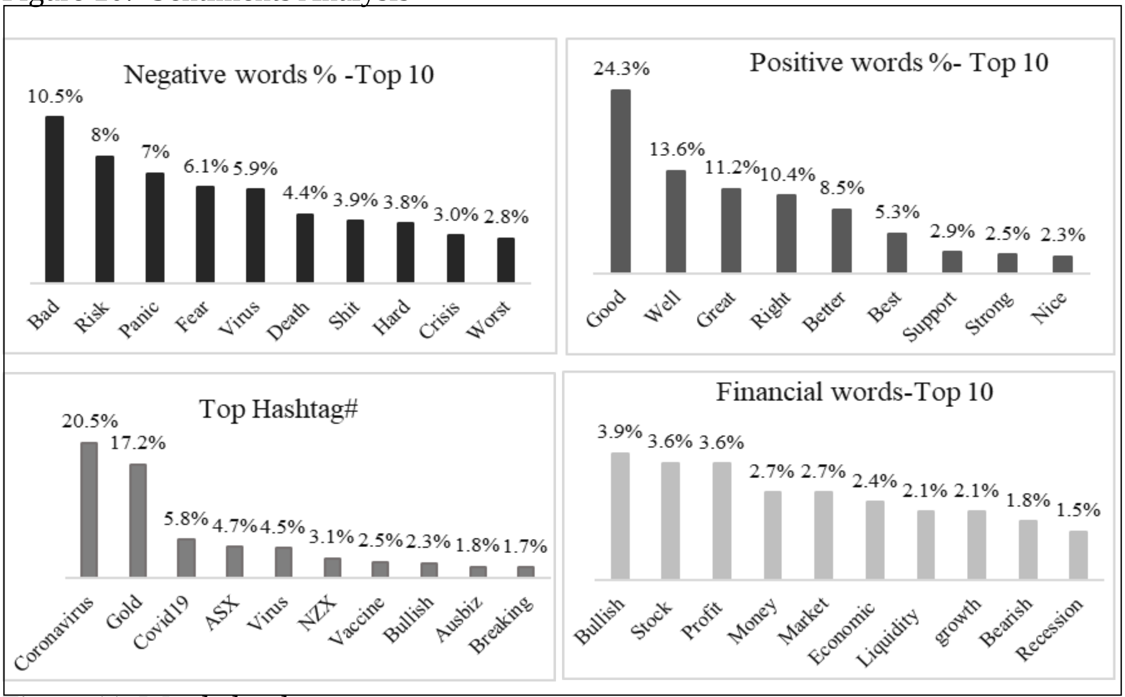


Figure 11. Word cloud

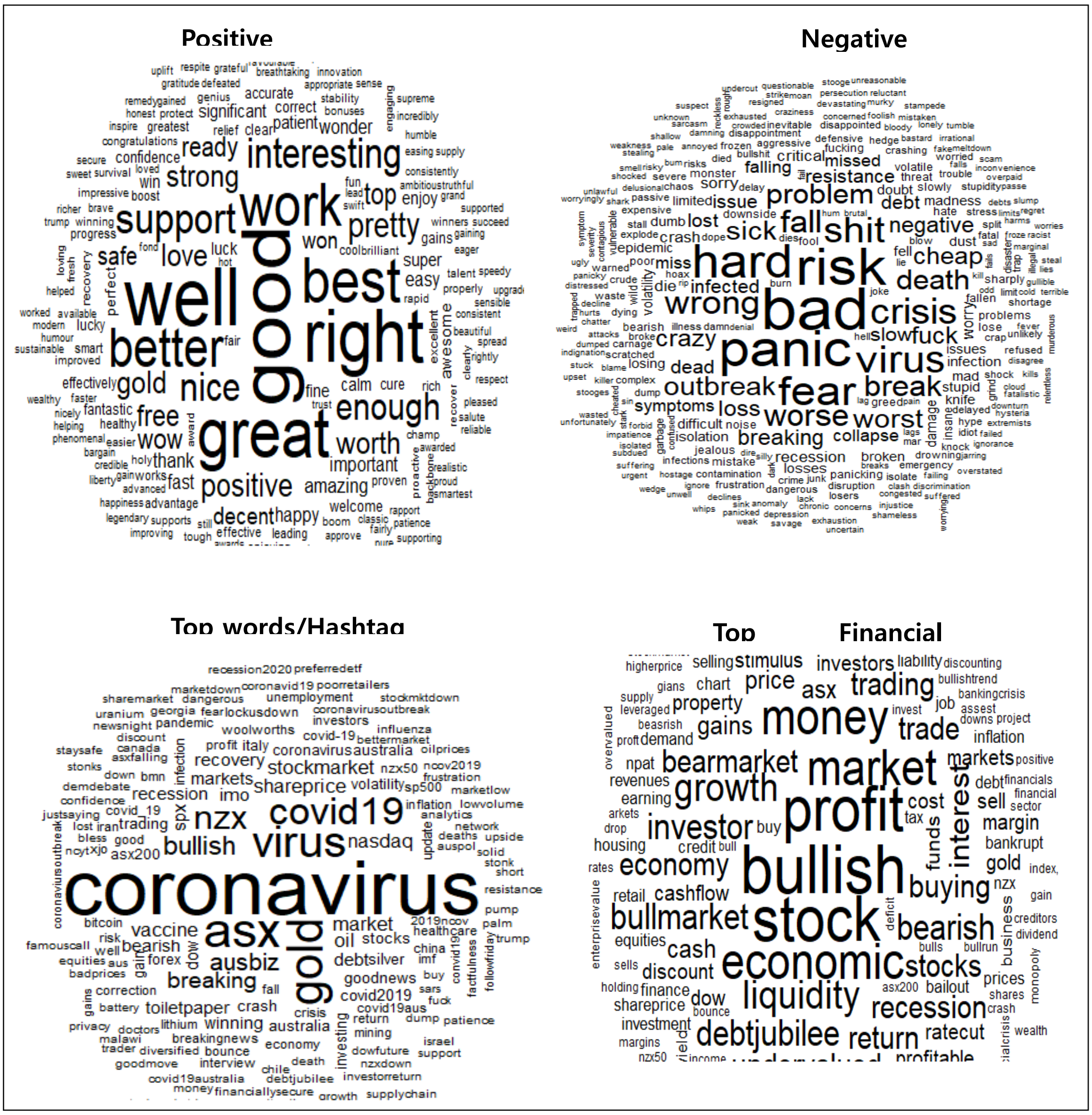


Table 14. Emojis in tweets

Positive	**Negative**	**Neutral**
👌 **good**	😱 fear	😷 mask
😋 **happiness**	💀 death	😲 surprise
👍 **well done**	😭, 😢 cry	
😂 **joy**	😬discomfort	
👊 **support**	😮 bad	
😆 **smile**	😖 lost hope	
👏 **congratulation**	🤮 offensive	
🚀 **flying**	😔 sad	
😘 **love**	😫 sadness	
💪 **strong**	😩 frustration	
🙏 **pray**		
💖 **love**		
😉 **appreciation,**		
😂 **happy**		
💪 **win**		
😊 **smile**		
😃 **pleasure**		
🏆 **win**		

3.4 Control Variables

We have a couple of control variables that could affect investors' perceptions as well.

Financial newspaper

Studies show that financial newspapers play a key role in the dissemination of financial news that affects investors ' perceptions (L. Feng & Seasholes, 2004; Yin & Tan, 2017). We have considered 15 different well-known and leading financial newspapers (Sharechat, Bloomberg, Herald, Interest news, Stuff news, Business Desk, National Business Review, Newsroom, New York Times, Economist, Guardian, Dominion Post, Headliner, The Press, and Yahoo Finance) for our analysis. We will measure also financial newspapers by the method used by (Garz, 2018).

$$Financial\ news = \frac{Number\ of\ Positive\ words - Number\ of\ negativewords}{Total\ number\ of\ words}$$

We also control for income, age, experience, investment, and income level of investors. While conducting a survey we asked investors to provide or answer the question regarding income, age, experience, investment, and income level. It is worth noting that the answers were volunteer based.

3.5. Results and Discussions

In the Our current factor-based PLS algorithm outer loading values represent a measurement model of multi-dimensional investor's perception, i.e. Twitter news, network size, network structure, and social ties. Most of the loaded items of first-order contracts meet the minimum threshold and are in line with the recommended level of Hair et al., (2011) and presented in Tables 6 and 7. Studies conducted by (Becker et al., 2012; Hair et al., 2017) classified Cronbach's α, Composite Reliability, Average Variance Extracted (AVE), T- values, and variance inflation factor (VIF) as important elements in the structural model. They also recommended level of the threshold for each of them. The recommended threshold for T-value is > 1.64 and for VIF is < 5, for composite Reliability and Average Variance Extracted (AVE) is > 0.50.

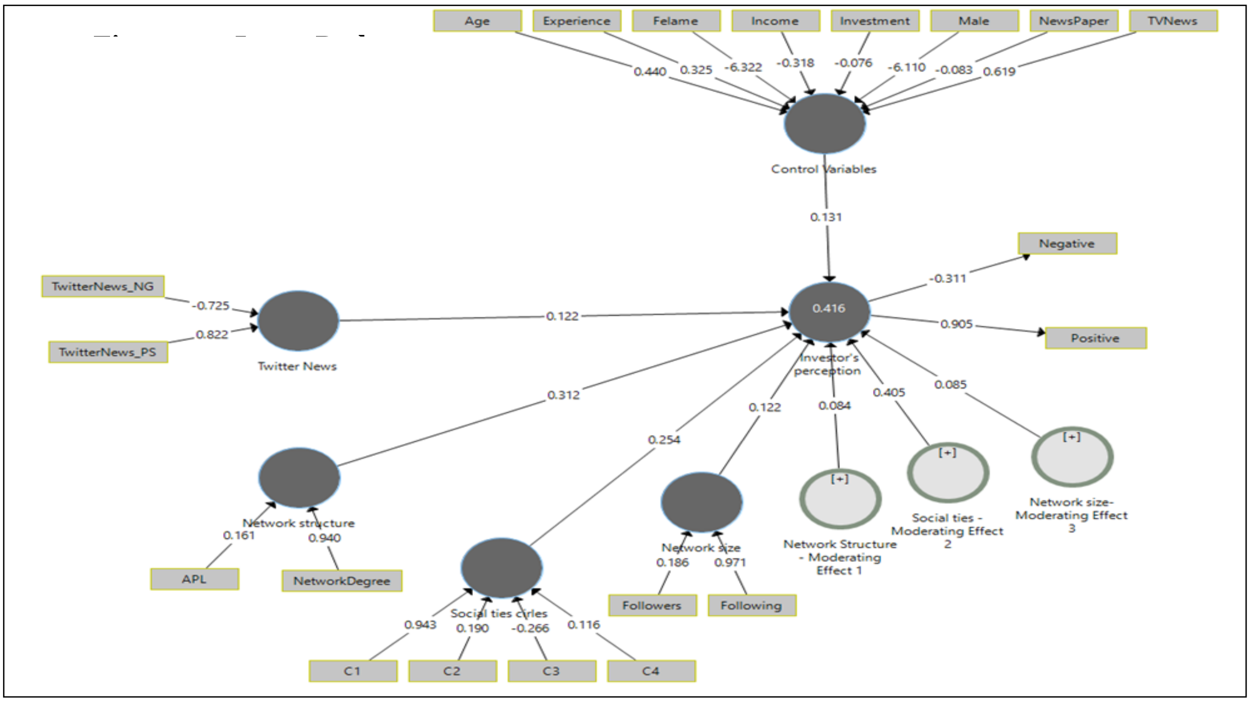
Our results in Table: 6 show that the network structure contributes has a direct positive impact on investor's perceptions. It has $\beta = 0.350$, P-value 0.001 ($P < 0.01$), T-value = 1.951 ($T > 1.64$), and has VIF value at 1.411 ($VIF < 5$). Investors with higher network connectivity have greater access to financial information, resulting in a significant impact on investor perceptions ($\beta = 0.350$). According to our analysis (table: 1), an increase in network degree corresponds to an increase in information access. Our findings further back this up by indicating that, network degree contributed the most (0.94) in terms of network structure (Figure 5: path diagram). This simply demonstrates that greater connectivity equates to more information, which in turn leads to a stronger effect on investor perception.

Social ties circle also has a comparatively higher direct positive impact on the investor's perception with $\beta = 0.254$. Its T-value is 1.903 ($T > 1.64$), and VIF value is at 1.253 ($VIF < 5$). Investors receive higher information from close friends because they are the most trustworthy ($R = 0.34$). That is why, within social relations circles, close friends or colleagues have a greater impact on investor perception ($C1 = 0.943$) (Figure 5: path diagram). Furthermore, our findings reveal that low trust or low tie strength ($R=0.036$) has a minor impact on perception. ($C4=0.116$). From the moderating effect perspective, Social ties circle contributes higher with β = 0.505 and P-value 0.000 (P < 0.01). This makes it a key moderating construct. Total effect of the constructs on investor's perception is with β = 0.416 and P-value 0.000 (P < 0.01). We presented PLS-SEM in the diagram below. Furthermore, our results indicate that the impact of news on investors' perceptions is dependent on the news's theme (Figure 5: path diagram). In simple words, positive news has a positive effect, whereas negative news has a negative effect. Our path model shows positive impact of the news is (positive= 0.905) and the negative impact is (negative= -0.311).

Table 15. Path Coefficients, T-Values, VIF Values, P- Values

Item	Path Coefficients	T-Values	VIF Values	P-Values
Investor's perception	0.416	4.164		0.000
Network structure -> Investor's perception	0.312	1.951	1.411	0.06
Social ties circles -> Investor's perception	0.254	1.903	1.253	0.062
Social ties - Moderating Effect 2 -> Investor's perception	0.405	2.678	1.342	0.000
Control Variables	0.274	4.388	1.463	0.002
Twitter News -> Investor's perception	0.122	0.781	1.512	0.435
Network Structure - Moderating Effect 1 -> Investor's perception	0.111	0.823	1.175	0.410
Network size -> Investor's perception	0.085	0.729	1.413	0.466
Network size- Moderating Effect 3 -> Investor's perception	0.081	0.390	1.025	0.696

Figure 12: path diagram



It represents Cronbach's α of Twitter news measure (α = 0.765) with 2 items, Network structure (α = 0.734) with 2 items; and social ties circle (α = .989) with 4 items. The results confirm that all construct attributes met a satisfactory level of Cronbach's α having values greater than the threshold, i.e.⩾0.70 (Hair et al., 2017; Henseler et al., 2014). Table: 4 also provides results of Composite Reliability and Average Variance Extracted (AVE) for all measures including multi-dimensions of investor perception. Composite Reliability is considered a better tool to measure the accurate reliability findings (Hair et al., 2011). These results show that Composite Reliability and Average Variance Extracted (AVE) are also greater than the threshold, i.e. 0.50. Hence, these values confirm unidimensional composites and the authenticity of convergent validity.

Table 16. Cronbach's α, Composite Reliability, Average Variance Extracted (AVE)

Item	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Network structure	0.734	0.534	0.631
Twitter News	0.764	0.663	0.638
Social ties circles	0.989	0.788	0.733
Network size	0.757	0.668	0.765

3.6. Conclusions

Our research encompasses a wide range of components, including both social and non-social network factors, that contribute to information diffusion and have an impact on investor perception. In this study, we used 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 investors' perceptions. Furthermore, our research identifies and categorizes financial, non-financial, positive, and negative information that has been shared through the investors' networks.

Based on our findings, investors frequently discussed and shared financial-related information such as bullish, profit, bearish, bull market, and economy, debtjublee, revenue, return, bear-market, interest, money, cashflow, property, stock, buying, selling, growth, recession, funds, trade, NZX, and ASX etc. (sentiment analysis: 4.2.4). From a non-financial perspective, Coronavirus or Covid-19-related news and information were primarily exchanged. Our findings reveal that investors reacted or responded to news based on the news's theme. i.e. When investors are exposed to positive financial news or information, they respond positively by using words like great, strong, good, nice, and better, wow, worth, support, amazing, right, love, best, happy etc. Similarly, whenever investors are exposed to negative financial or Covid-19-related news, they react negatively. Investors used a variety of negative responses to negative news, including bad, panic, risk, crisis, fear, worse, loss, fall, problem, collapse, death etc. It is also worth mentioning that investors (sentiment analysis: 4.2.4). Prior literature described the impact of information on investors' perception and behavior is a social network effect. Likewise, our research also revealed that financial news and information obtained by investors via Twitter had a positive and negative impact on investors. Simply put, this positive or negative impact on investor perception via financial information is a social network effect.

On a broad level, our findings show that each network factor contributes to the generation of information at a certain, which has an impact on investor perception. However, the impact of the network size is statistically insignificant. On a specific level, our findings highlight the central factors (i.e. network degree, social ties) that primarily originate information distribution and influence investor perception. Simply put, this study identifies which factors are the most significant in influencing investor perception. Unlike prior studies, our study considered non-social network characteristics that have an impact on investors, which puts it apart from earlier studies. According to our findings, as network connectivity improves, so does information share inside the network (table:1) and generates an impact on investor perception (table:4)

Our findings also indicate that investors communicate and exchange information based on relationship strength or trust (table 3). 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 (table: 2). Our result showed that close ties of investors are comparatively influential and have higher impacts on investors' perceptions. 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). This study provides investors with guidance that being well-connected and having stable ties is crucial to acquiring financial information. This study also suggests that Twitter can be utilized as a financial information retrieval tool by investors in financial markets, rather than just a social networking platform. For the academicians, this research study provides a theoretical ground for understanding the role of social network indexes from investors' networks, which could potentially be used to create spin-off research projects.

A limitation of this study is that we only calculated the social network effect from the Twitter network of a small sample of investors in New Zealand. The investors are likely to have contacts in another social network (e.g. Facebook), as well as offline networks. 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). Facebook is for general interactions and is 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 than a professional tie (Barker 2009). The other limitation is that this study doesn't demonstrate causality. It was also based on a short period of time, and longitudinal approaches might yield further insight. We also believe the effect of the news on investor perceptions will be different in different cultural settings due to the diversity of social ties, and size of the networks (Albarran, 2009; (Elmasry, Auter, & Peuchaud, 2014). Kim et al., (2011) argued that social circles or social relationships are influenced by the cultural background of individuals. As a result, we believe that when evaluating the impact of news on investor perception, a cultural factor must also be addressed.

Chapter 4: Does the social network effect for investors differ across cultures?

4.1.Introduction

The dissemination of financial information worldwide has been transformed by the Internet and social media. In today's economy, one of the most significant sources for accessing financial news is social media where all types of investors can easily gain stupendous amounts of financial information (Drake, Thornock et al. 2017). Internet-enabled social media platforms are sources of financial news and information, where financial analyses are posted and accessed by investors (Li, Wang et al. 2019). The perceptions of investors and their decisions to trade stocks are influenced by their access to financial news. Financial news and information on the stock market determine the perception of investors about whether to trade or not (Chandra and Kumar 2011). The influence of financial news goes two ways. When negative news is propagated in media, it can result in a negative impact and when positive news is propagated it can have a positive impact (Brad & Terrance 2007; Daley & Green, 2012). The dissemination of news via social media has an impact on perceptions, particularly news distributed via Twitter, which exacerbates the impact of news on investor perceptions. (Joyce, 2013; Miller, Skinner, 2015; Eli el at., 2017; Siikanen el at., 2018). The impact of financial information differs by country and is culturally dependent (Grinblatt and Keloharju 2000, Wang, Su et al. 2021). Sheldon, Rauschnabel et al. (2017) argued that the degree to which individuals are affected by information through social media varies depending on their culture or country of origin.

Social media has become an emerging cultural phenomenon (Qiu, Lin et al. 2013). The nature of social media use is dynamic and culture-dependent, e.g. number and types of contact (a member of the social network), interactivity, and content (Su, Wang et al. 2005), information sharing (Fong and Burton 2008)s social integration (Madupu and Cooley 2010), communication (Sheldon, Rauschnabel et al. 2017), and social ties or social relationships are influenced by the cultural background of individuals (Kim, Sohn et al. 2011). The behavior of social media users, in terms of information sharing, is various and different in Western cultures from that of Eastern cultures (Cho 2010, Qiu, Lin et al. 2013). Interaction, discussion, and sharing of information differ across different cultures on social media. For example, Hsu, Tien et al. (2015) studied user behavior of social media (e.g. Facebook) of users in five countries (Australia, Austria, Japan, Taiwan, and the USA), and revealed that information-seeking was a stronger purpose on social media in Western cultures, while socialization was a stronger intention in Eastern cultures.

Investors' perceptions and preferences in terms of trading are influenced by their cultural background, and they may react differently to stock market information(Cillo, Griffith et al. 2018). In the stock markets, the culture where people come from influences investor preferences for certain stocks (Grinblatt and Keloharju 2000). Calomiris and Mamaysky (2019) argued that financial news distributed worldwide has a different impact on market outcomes in different countries. Vieira (2011) showed that investor sentiment and response to financial news or announcements vary by country.A plethora of research has studied cultural factors that influence the individual perceptions and decision-making of investors. These studies also reveal that the impact of financial information on investor perceptions and preferences varies between cultures due to differences in how investors interpret information (Grinblatt and Keloharju 2000, Vieira 2011, Goodrich and De Mooij 2014, Singh, Li et al. 2017, Prasad, Kiran et al. 2021). From the perspective of network theory, the impact of information on one's perception is referred to as a network effect (Murendo et al., 2018; Sundararajan et al., 2013). Since diverse interpretations of information have different impacts, the network effect will also be distinct. These studies also show that individuals from different cultures have social relationships or social ties of individuals. Furthermore, the size of the social network of individuals varies across different countries. We, therefore, posit that the social network effect will be different because of different social relationship circles, size of the network, and different structure of the network, and different behaviors while using social media in terms of information sharing and interaction.

4.2.Background

Individuals across various cultures interpret and perceive information differently depending on their values, ideas, and thoughts (Hofstede 2001). A culture where people come from affects their perceptions, expectations and emotions. In the stock market, investors' preferences are influenced by their culture when trading stocks (Grinblatt and Keloharju 2000).. Grinblatt and Keloharju (2000) also argued that due to cultural and linguistic differences, investors may interpret or understand financial information differently. Similarly, Cillo, Griffith et al. (2018) argued that investors have different perceptions and preferences when it comes to trading, and they react to information in the stock market differently because of their different cultural backgrounds.

The importance of culture as a determinant of investor perception, preference, and behavior in financial markets has been thoroughly demonstrated in the financial literature (Grinblatt and Keloharju 2000, Cillo, Griffith et al. 2018, Wang, Su et al. 2021). These studies show that culture has a direct impact on investor decision-making and should not be overlooked as a factor in financial market research. Similarly, Chang and Lin (2015) argued that the importance of cultural factors in investment decision-making cannot be overstated. The bulk of investors' trading preferences in a stock market are influenced by their country's culture. Wang, Su et al. (2021) indicate that the markets in various economic conditions have diverse cultures, which can influence investor sentiment and stock market performance.

Culture has been studied in variety of contexts, including the effect of culture on perceptions (Grinblatt and Keloharju 2000, Madupu and Cooley 2010, Kastanakis and Voyer 2014); investment choice and behaviour (Singh, Li et al. 2017), information sharing on social media (Fong and Burton 2008), social integration (Madupu and Cooley 2010), and social circles or social relationships (Kim, Sohn et al. 2011). Similarly, studies demonstrate that culture has a significant impact on how individuals use social media. It has an impact on social media information sharing and social integration (Fong and Burton 2008, Madupu and Cooley 2010). Users from various cultures belong to or create different social groups, and the social ties or relationships between individuals varies from one culture to another. In addition, the size of social media networks differs per country. These studies also reveal that the impact of information on individual perception varies by nation due to cultural differences in how people process information. Rationally thinking, if information has a different impact due to cultural variations, then the network effect in a cross-cultural setting would be different as well. To the best of our knowledge and based on literature, what is not addressed is to what extent the impact of news on investors' perception will be moderated by the size of the network, network structure and social ties of the investors in a cultural context.

4.3. **Literature**

4.3.1. Social tie circles

Every user on social media has social ties or relationships. Colleagues, friends, and family are members of these social tie circles. These relationships or social tie circles are built based on communication and interaction within social networks (Arnaboldi et al. 2016). These individuals are influential in the user's (ego) network and have the ability to influence the user's perception and decision-making. It's worth noting that social tie circles differ from one country to another. Studies show that the nature or type of friends differs depending on the culture. Eastern cultures (e.g. South Korean, Chinese) have socially closer relationships on social media (e.g., family and close friends) compared to Western cultures (e.g. USA), suggesting that the relation-building or relationship circles in Eastern cultures differs from those in Western cultures (Fong and Burton 2008, Kim, Sohn et al. 2011, Qiu, Lin et al. 2013)

In Western cultures, people are more likely to be seekers of information and are looking for information beyond their family circle and immediate families, are less reliant on others and prefer more factual information sources, and have more faith in experts and seek expert knowledge (Hofstede 2001, de Pablos 2005, Goodrich and De Mooij 2014). Whereas in Eastern cultures, individuals obtain information from close social sources (e.g. family) (Hofstede 2001, Schultz and Block 2009, Garcia-Gavilanes, Quercia et al. 2013). It's worth mentioning that these studies ((Hofstede 2001, Schultz and Block 2009, Garcia-Gavilanes, Quercia et al. 2013) haven't considered the size of each culture's social ties. Simply put, these studies overlook and do not reveal how many friends people have as social ties or relationships in various cultures.

The social ties circle is a key factor in the network effect, and the network effect is formed by information shared by colleagues, friends, and family members. Hence, distinct social ties, we believe, will create different levels of network effects. The purpose of this research is to look into the network effect of social ties circles in different cultural settings

4.3.2. ***Network size***

The size of an individual's network is another significant factor to consider when assessing the social network effect (Katona, Zubcsek et al. 2011, Saxton and Wang 2014, McClain 2019). The number of followers/friends or network members on social media is referred to as network size (Harrigan, Achananuparp et al. 2012). Like social tie circles, social media users' network sizes also vary considerably from society to society and country to country, e.g. in Japan, the average number of friends is 29 on social media, while it is 63 in China, and 95 in France (Van Belleghem, Thijs et al. 2010, Goodrich and De Mooij 2014). On the other hand, the average size of the network of an individual is larger in some countries e.g., it is 200 in the United States, 360 in Brazil (Van Belleghem, Thijs et al. 2010), 174 in Qatar, and 609 in Egypt (Elmasry, Auter et al. 2014).

However, these studies(Van Belleghem, Thijs et al. 2010, Goodrich and De Mooij 2014) haven't addressed the impact of network size on information access within the network. Also, these studies have not been done from the New Zealand perspective, particularly from an investors' perspective. Our previous study (khan Feroz, Hassan et al. 2022) found that users or individuals with a higher number of friends and followers receive more information and thus have more exposure to learning about thoughts and experiences. We argue that investors with different network size, as observed between different cultures, and therefore different access to information, will experience different effects of financial news.

*4.3.3. **Network structure***

Network structure simply means connetivity of nodes or individuals within the network (Katona et al., 2011; Luarn et al., 2014). Such connectivity is enabled through two factors: (1) network degree; and (2) average path length. Network degree is the number of links of individuals in network. Average path length is the average distance between nodes or individuals within the network (Katona et al., 2011; Luarn et al., 2014; Lewis 2009). Chen Liu and Xuefei Li, 2019; Han N (2014) have found that investors usually have direct or indirect links with other investors in networks. Based on this literature, there is a correlation between connectivity and information access. However, none of these studies have considered network connectivity in cultural context. Hence, we will try address this gap from cross cultural and investor perspectives.

4.4. Methodology

4.4.1. Data

The sample for our research is investors who engage in buying and selling shares and/or stocks of companies that are listed on the stock exchanges of New Zealand, Australia, and South Korea. We collected data from 347 retail investors from different parts of New Zealand and South Korea. We created a survey using Qualtrics and sent the link to investors in New Zealand and South Korea. We asked investors about their age, gender, experience, income, investment, and their preferred financial newspapers. At the end of the survey, we also asked participants to provide their Twitter Username or ID for network and sentiment analysis. It is worth noting that the participants also have the option of not responding to the questions, if they choose not to.

In South Korea, 145 participants responded to the survey. Out of 145 participants, 128 of them consented to participate in the survey, which means 17 participants declined to participate. Of the 128 respondents, 21 didn't provide their Twitter username, and are excluded, leaving a final sample of 107. Participation was larger from New Zealand investors in survey. 311 participants consented to participate in the survey, while 63 participants declined. But 71 of the 311 respondents didn't give us their Twitter username for our study and analysis. As a result, we conclude with 240 final sample (New Zealand).

Like our previous study (khan Feroz, Hassan et al. 2022), this study relies on two types of primary data. The first primary data are Twitter data (tweets, retweets, mention, and replies) . Other primary data are survey variables (age, gender, income, investment, experience, and newspaper). We downloaded the Twitter data from the Twitter API (Application Program Interface) using the NodeXL pro application. We downloaded 72,130 twitter data in total. Out of total tweets, 38,670 tweets from New Zealand investors and 33,460 tweets from korean investors. Tables 18 and 19 show Twitter data and descriptive statistics for each group

Table 18. Twitter data

Twitter data	**KIWI**	**NON-KIWI**
Total Tweets	38,670	33,460
Total reply	9,644	3,122
Total mentions	7,738	2,340
Total retweets	3,246	1,414
Average tweet[18]	361.40	312.71
Average reply	90.13	19.18
Average mention	72.32	21.87
Average retweet	30.34	13.21
Average network size	722.21	793.36

Table 19. Descriptive Statistics

Descriptive Statistics					
	Kiwi		**Non-Kiwi**		
Indicators	Mean	St. Deviation	Mean	St. Deviation	Analysis N
Network Degree	6.6	4.3	5.9	4.2	214
AP	1.19	0.48	1.4	0.83	214
C1	1.9	0.90	1.6	0.74	214
C2	1.8	1.0	1.6	0.96	214
C3	2.0	1.0	1.7	0.98	214
C4	1.0	0.51	1.0	0.48	214
Followers	540.3	685.5	704.9	1079.7	214
Following	904.0	1245.3	881.7	1266.6	214

To compile data from Non-social media platform (newspapers), we applied the followed procedure (1) We conducted a search for the newspaper in New Zealand with the most

[18] To get the averages, we divided each investor's tweets, replies, and retweets by the total of the group's tweets, replies, and retweets.

viewership. Based on the Roy Morgan[19] report, NZ Herald, and stuff news have highest readers or viewers in New Zealand, (2) Sharechat was selected at random from a list of news and information providers for the stock market provided on the website of the New Zealand Stock Exchange (NZX) and (3) Interest news and Bloomberg were randomly selected based on Google search results. In addition, we requested investors to provide us with the list or the names of their favorite newspapers. In terms of investors recommendation, New Zealand investors recommended 10 different newspapers. While Korean investors recommended 7 different newspapers. Table 19 shows our list and recommended list of different newspapers by both group of investors.

Table 20. List of newspapers

Newspapers		
Group	**Our listed newspapers**	**Recommended list newspaper by investors**
KIWI	NZ Herald, Bloomberg, Sharechat, Interest News, and Stuff News	Desk, National Business Review, Newsroom, New York Times, Economist, Guardian, Dominion Post, Headliner, The Press, and Yahoo Finance
NON-KIWI	Korean Herald, Bloomberg Financial, Financial Times, The Korea Economic Daily	The Wall Street Journal, Nikkei news, The Asahi Shimbun, Naver, CNN money, Reddit

4.4.2. Procedure

We also gathered survey participants preferred non-social-media news sources (newspapers) from a list provided in the survey (see Table 3). In addition, we requested investors to provide or the list the names of their favorite financial newspapers. Next, we calculated three main factors – network structure, network size, and social ties – which will be the three key moderating variables in the analysis. We measured network structure (network degree and average path length) using the comprehensive method of Lewis (2009). In terms of network size, we counted the number of followers and following for each investor. We applied a method used by Arnaboldi et al. (2016) to measure social ties circles. We created social tie circles based on the investor's and his/her friends' frequency of communication (mentions and

[19] Roy Morgan is best known and longest established market research company https://www.roymorgan.com/

retweets). We measured strength of ties between the investors and their friends using the method of Arnaboldi et al. (2016).

To tackle the impact of sentiments and information/news on investors' perceptions, we then conducted sentiment analysis on investor's replies to tweets that they received (khan Feroz, Hassan et al. 2022). We analyzed replies using an n-gram language model (Algaba, 2020; Gentzkow, Kelly, and Taddy, 2019). 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), trigram (three words), and 4-gram counts in our N-gram textual analysis. We included all positive, negative, financial, and nonfinancial words.

We used the Loughran and McDonald (2020) financial words list to classify words (n-grams) into positive and negative categories. This word list , which contains 86,533 words, has been extensively applied in the financial literature to gauge sentiments(Loughran, T., & McDonald, B. 2020; Loughran, T., & McDonald, B. 2016; Loughran, T., & McDonald, B. 2011). For non-financial words, we counted positive and negative words by using the NodeXL pro application, with an automated dictionary of 6,785 words. Furthermore, we employed a technique developed by (Garz, M., & Martin, G. J. 2021; Garz, M., & Pagels, V. (2018) to measure newspapers' sentiments. For this textual analysis, 26 distinct newspapers were used, and 15,321 words from these newspapers were examined. Words were categorized as Positive (+1), or Negative (-1).

We finally applied PLS-SEM to measure the impact of financial news and information on investor perception. The structural equation model is an effective method for investigating the direct and indirect impacts of variables (Becker et al., 2012; Hair et al., 2017). PLS-SEM is best suited for those models which have a small number of factors or indicators (preferably less than six) and a small sample size (Becker et al., 2012; Hair et al., 2017). Most importantly, our model meets criteria set by researchers. Our model comprises of five primary indicators: Twitter news, network size, structure, and social relationships, (< 6) with a small sample size (214 participants). Similarly, research has shown that PLS-SEM is an effective method for measuring the impact of direct and indirect variables on investor perception, behavior, and decision making (Prasad, Kiran et al. 2021; Seetharaman, A., et al.

2017; TA, V.L., et al. 2021).

4.5. Measurement

4.5.1. Network Structure

4.5.2. Network Degree Distribution

We used the similar method which we applied in our previous study (khan Feroz, Hassan et al. 2022) to measure network degree. We calculated number of connections or links (edges) of each node (investors) with other individuals or friends in the network. We calculated network degree of each investor individually. We used following formula by Lewis (2009):

5. $$Dvi = \frac{2mi}{n} \qquad (1)$$

where D_{vi} 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 the investor's network *v*

4.5.3. Average path length (APL)

Similarly, we calculated the average path length also by similar method (khan Feroz, Hassan et al. 2022) used by (Lewis 2009). We calculated links of investor who has within the network, we then divided them by number of nodes in the network. We calculated average path length of each investor. We measured the average path length by following method used by Lewis (2009):

$$APL = \frac{log\ (\frac{n}{\lambda})}{log(\lambda-1)\ +1}\ (2)$$

where ni is the number of nodes or individuals in the given network and λ is the average node

4.5.4. Network size

We've calculated investor network size by summing up their current total friends or contacts (following/followers). We calculated network size of each investor individually. We used the following method to measure network size of investors (khan Feroz, Hassan et al. 2022).

$$NS = number\ of\ followers + number\ of\ following \quad (3)$$

4.5.5. Social circles ties

To calculate social ties circles and the strength of the ties of investors, we applied the method used by Arnaboldi et al. (2016) and Khan, Mohaisen, and Trier (2019). The equation for social tie circles is:

$$\mathrm{STC} = \sum_{i=1}^{n}\left(\frac{C1}{100}(r1) + \frac{\mathrm{C2}}{100}(r2) + \frac{C3}{100}(r3) + \frac{\mathrm{C4}}{100}(r4) \ldots\ldots \frac{\mathrm{Cn}}{100}(rn)\right) + L \quad (4)$$

C represents the size (number of friends) 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 the 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 the ego (investor) rationally trusts himself/herself 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.

$$\mathrm{Cij} = \sum_{\mathrm{j \in m}} \mathrm{Mij} + \sum_{\mathrm{j \in rt}} \mathrm{RTij} \quad (4.1)$$

Mij are the individuals mentioned by the investor i in his reply/tweets. RTij are the individuals j mentioned by investor i in his reply/tweets. Mention is measured as below

$$Mij = \frac{Link\ mention j}{ego\ (investor i) total\ mention} \quad (3.1.1)$$

Link mention is the mention of a friend (alter) j by investor i in his comments, tweets, or replies. Total mention is the mention of all friends (alters) by investors i in their comments, tweets, or replies. The retweet is measured below

$$RTij = \frac{Link\ retweet j}{ego\ (investor i) total\ retweet} \quad (3.1.2)$$

Link retweet is retweets of a friend j's tweet by an investor i. Total retweet is the retweet of all friends' tweets (alters) by investors i.

4.5.5.1.Strength of ties (r)

we measured the strength of the ties or relationships between investors and his/her friends (also see). 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.

$$RTij = \sigma + \beta * Mij \qquad (4.2)$$

We conducted linear regression for each social tie circle of investors to calculate the tie or relationship strength of each circle.

4.6. Investor Perceptions

We measured the impact of news and financial information on investors' perception via the sentiment of replies of investors to the information and news received on Twitter (khan Feroz, Hassan et al. 2022). Studies demonstrate that sentiment analysis is a useful tool for assessing how individuals and investors view financial information (Kipp, Zhang, and Tadesse, 2016) (Bian et al., 2016). Particularly, the "reply" of investors and individuals to financial information and news reflects the perceptions where a positive reply indicates a positive perception and a negative response indicates a negative perception (Kipp, Zhang, and Tadesse, 2016; Bian, 2016). Stieglitz and Dang-Xuan (2013) argued that language or words used in replies on social media demonstrate the feelings of an individual and the feeling of one is perceptions (Hall, Jobson, and Langdon, 2014). We measured investor perception as:

$$Pij = (PRij - NRij) \qquad (4.3)$$

Pi indicates a perception of i investor. PRi is the positive word used in replies of investor i to j news and information, and NRi are the negative words in replies of investor i to j news and information.

4.7. Result

We constructed three different PLS-SEM factor models. In the first model, both Kiwi and non-kiwi investors are included. The second one is constructed for kiwi investors and the third one for non-kiwi investors. Our overall factor-based PLS-SEM outer loading values represent a multiple-dimensional measurement model of investor's perceptions, i.e. Kiwi, non-kiwi investors, Twitter news, network structure, network size, social ties and control variables.

Becker et al. (2012) and Hair et al. (2017) classified and recommended a level threshold for Cronbach's α, Composite Reliability, Average Variance Extracted (AVE), T- values, and variance inflation factor (VIF). These studies also consider these elements an important and key factor in the structural model. The recommended threshold for T-value is > 1.64 and for VIF is < 5, for composite Reliability and Average Variance Extracted (AVE) is > 0.50. Our results show that most of the loaded items of first-order contracts meet the minimum threshold recommended by Becker et al., 2012 and Hair et al., (2011) studies and presented in Tables 21 and 22.

We have mixed results in terms of Cronbach's α, Composite Reliability, and Average Variance Extracted (AVE). The Cronbach's α of Twitter news measure is α = -0.445 with 2 items (> 0.50.) which doesn't meet the recommended threshold (Hair et al., 2017; Henseler et al., 2014). However, its composite Reliability and Average Variance Extracted (AVE) meets recommended threshold (> 0.50.). Moderators and network effect meet all recommended thresholds (> 0.50.). Control variables don't meet recommended threshold except for Composite Reliability,

Table 21. PLS-SEM

PLS-SEM			
Factors	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Twitter News	-0.455	1.043	0.545
Moderators	0.574	0.868	0.505
Network effect (Investor perceptions)	0.683	0.887	0.558
Control variables	0.348	0.596	0.260

Our overall results in Table: 5 and Path Diagram: 1 show that the Social ties circle has a comparatively higher direct positive impact on the investor's perception. All sub-indicators of the social ties circle have contributed significantly e.g. C_1 has $\beta = 0.754$. with P-value 0.000 ($P < 0.01$).. Its T-value is 21.581 ($T > 1.64$), and its VIF value is at 1.702 ($VIF < 5$). It shows that C_1 is more influential ties of Investors followed by C_2 (see Diagram: 1 Table: 5). Network size result is unusual and varied contributions to network effect. Followers are not statistically significant. It has It has $\beta = -0.027$, P-value 0.775 ($P < 0.01$), T-value = 0.286 ($T > 1.64$), and has VIF value at 1.204 ($VIF < 5$). While following has significant contribution with $\beta = 0.423$, P-value 0.000 ($P < 0.01$), T-value = 4.291 ($T > 1.64$), and has VIF value at 1.305 ($VIF < 5$). Similarly, network structure has also varied contribution (Diagram: 1 Table: 5) e.g. network degree has positive impact ($\beta = 0.515$) whereas average path length has negative contribution with $\beta = -0.538$. Diagram: 1 Table: 22 also show a mixed result for control variables. E.g. gender (male & female), income, newspaper, and tv are not statistically significant. However, investment and age are statistically significant.

Table 22. OVERALL RESULT (New Zealand & Korean)

OVERALL RESULT (New Zealand & Korean)				
Sub-Indicators	**Path Coefficient**	**T-value**	**VIF**	**P values**
TwitterPositiveNews <- Twitter News	0.987	4.053	1.036	0.000
TwitterNegativeNews <- Twitter News	-0.342	0.909	8.093	0.364
PostiveNE <- Network effect (Investor perceptions)	0.687	2.293	1.007	0.022
NegativeNE <- Network effect (Investor perceptions)	0.666	2.476	1.007	0.013
C1 <- Moderators	0.754	21.581	1.702	0.000
C2 <- Moderators	0.734	19.609	1.806	0.000
C3 <- Moderators	0.634	9.381	1.805	0.000
C4 <- Moderators	0.555	9.565	1.515	0.000
AveragePathLength <- Moderators	-0.538	9.222	1.702	0.000
NetworkDegree <- Moderators	0.515	5.486	1.522	0.000
Followers <- Moderators	-0.027	0.286	1.204	0.775
Following <- Moderators	0.423	4.291	1.305	0.000
NONKIWI <- Moderators	-0.864	19.433		0.000
KIWI <- Moderators	0.864	19.433		0.000
MALE <- Control variables	0.261	0.760	10.286	0.447
Income <- Control variables	0.388	2.561	1.309	0.010
Investment <- Control variables	0.726	4.928	1.895	0.000
Newspaper <- Control variables	-0.160	1.022	1.041	0.307
TVnews <- Control variables	0.386	2.658	1.039	0.008
Age <- Control variables	0.681	4.079	1.487	0.000

Experience <- Control variables	0.800	5.354	1.461	0.000
FEMALE <- Control variables	-0.235	0.684	10.060	0.494

From New Zealand investors perspective, our finding show that network moderators have significant contribution to network effect (Path diagram 2). Total network moderators' effect is β = 0.322 with P-value 0.000 (P < 0.01) and particularly, social tie circles (C1 to C4) and network structure have highest contribution (Path diagram 2). However, only followers from network size is least significant among moderators. Similarly, control variable is also comparatively less significant. However, result from Korean PLS-SEM shows that network moderators don't have a significant impact or have a low contribution to the network effect. The total network moderators' effect is β = -0.285 which is negative, and it is a bit strange (Path diagram 3). But it is worth noting that Twitter news has a significant effect (β = -0.340) and has the highest contribution to the network effect. This means that network moderators are not crucial from non-kiwi investors' network perceptive.

Figure. 13. Path diagram: Overall PLS-SEM Result (New Zealand & Korean investors)

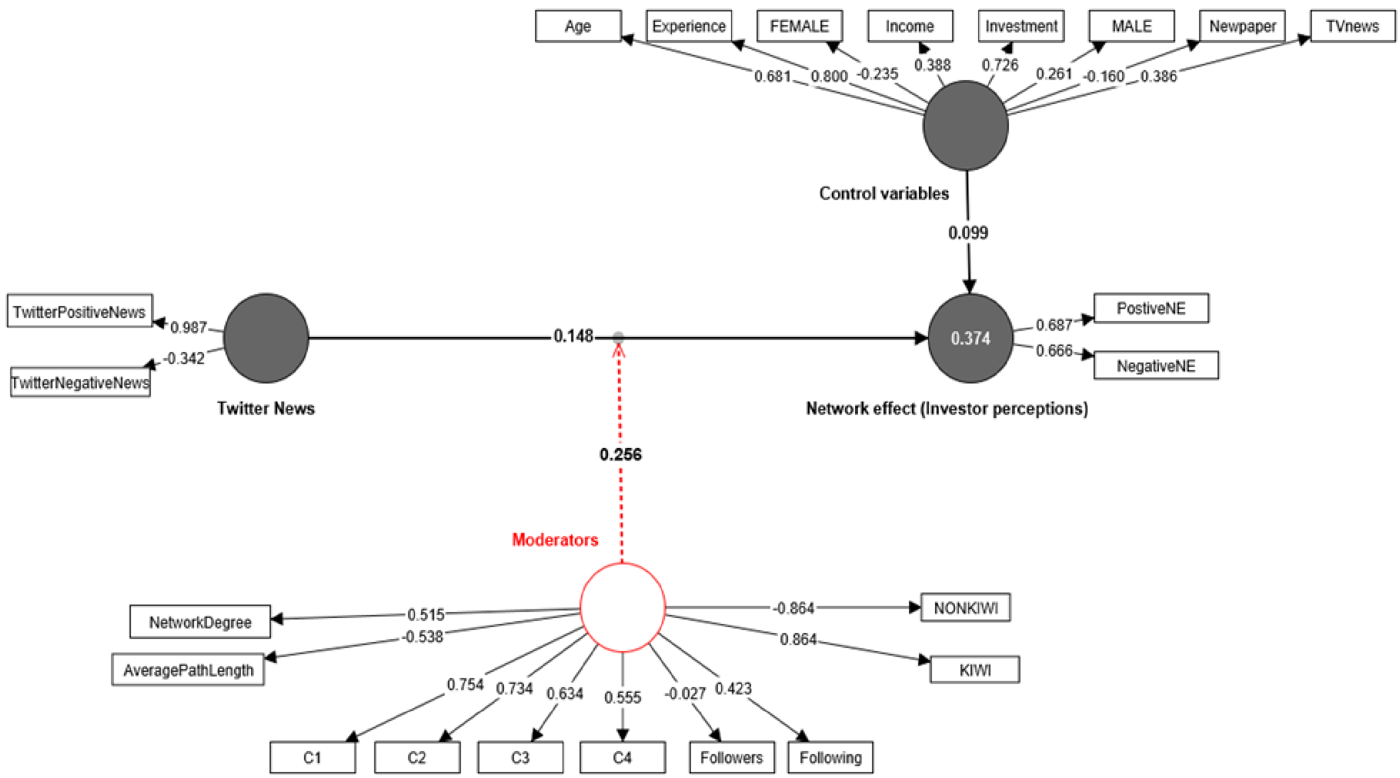


Figure. 14. Path diagram: PLS-SEM (New Zealand Investors)

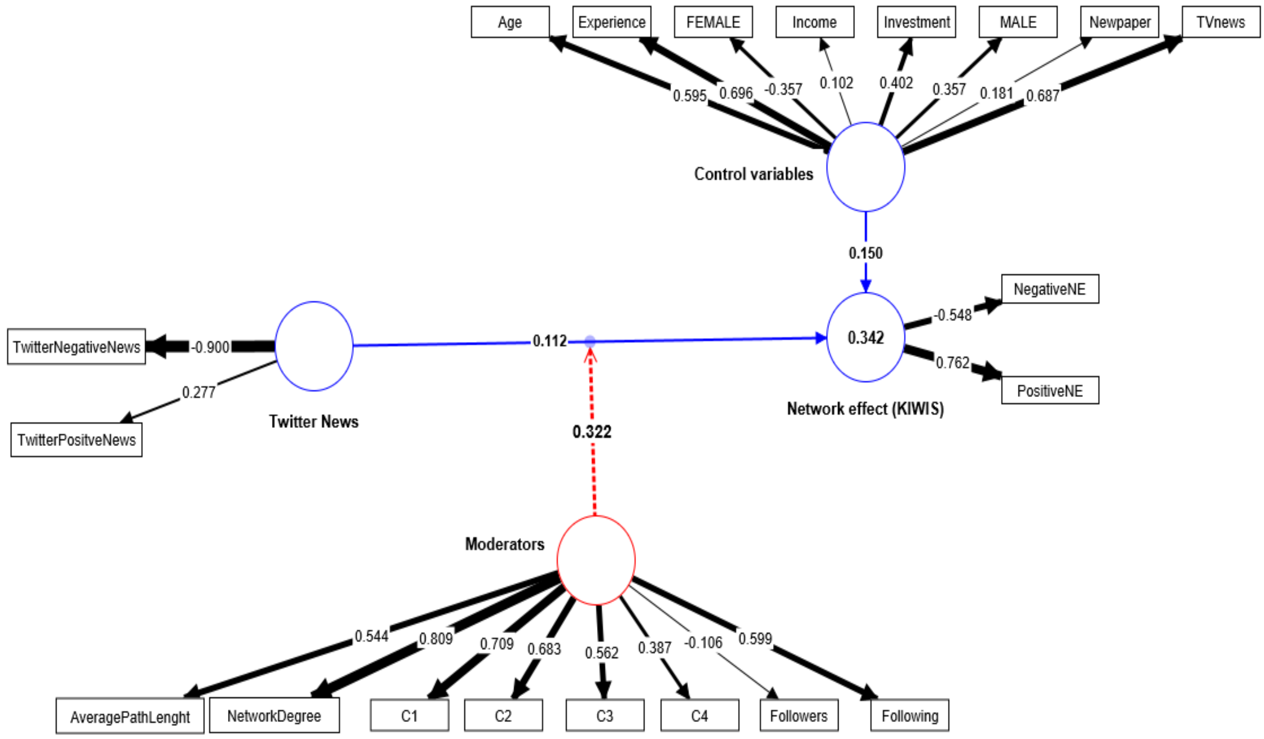


Figure 15. Path diagram: PLS-SEM (Korean INVESTORS)

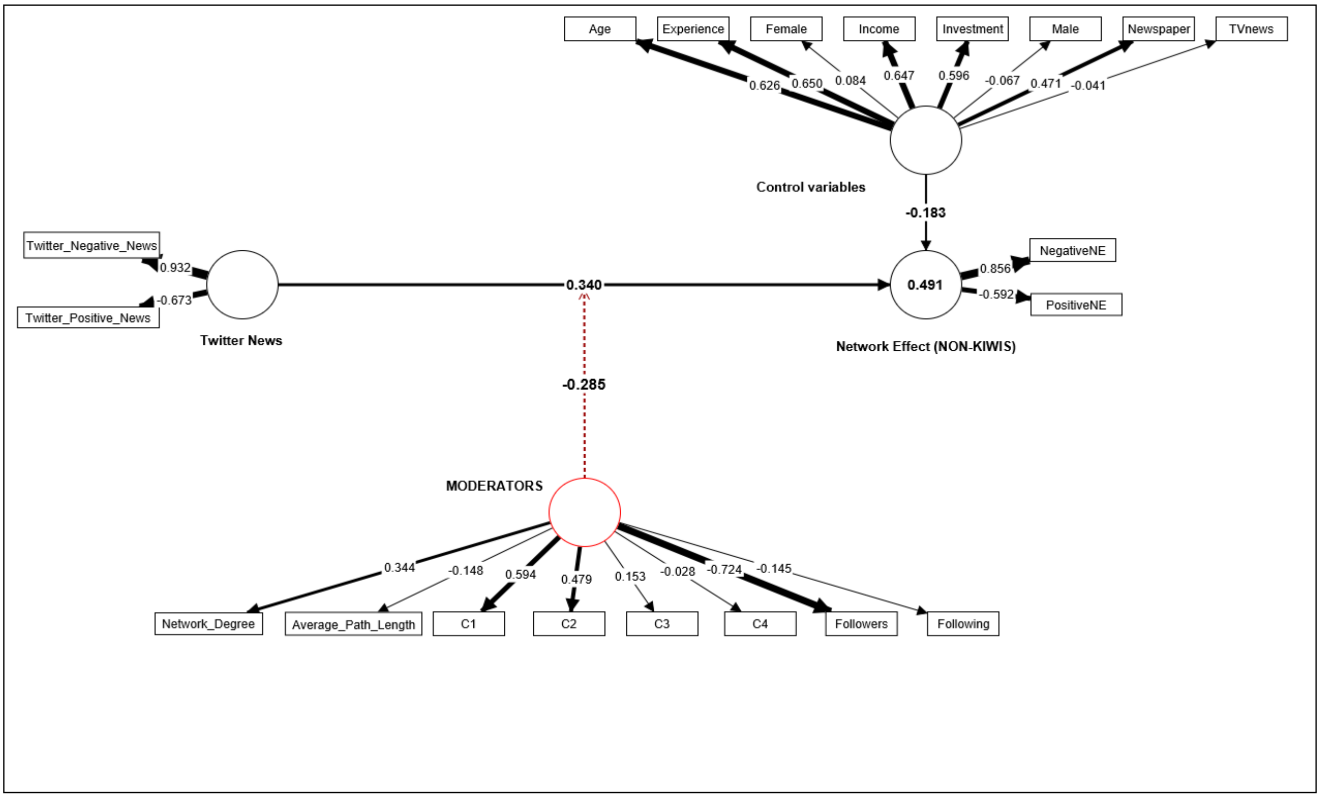


Table 23 indicates that social ties circles are more strengthened between New Zealand investors. Also, degree of communication between New Zealand investors is considerably high. Whereas Korean ties strength is low with lower level of communication. Similarly, size of friends in each tie is larger in New Zealand social ties circles. Furthermore, our PLS-SEM results also show that Korean social ties circles contribute more to the network effect than Korean investors. Hence, we can say there is considerable a difference betw een New Zealand vs Korean social ties in every aspect.

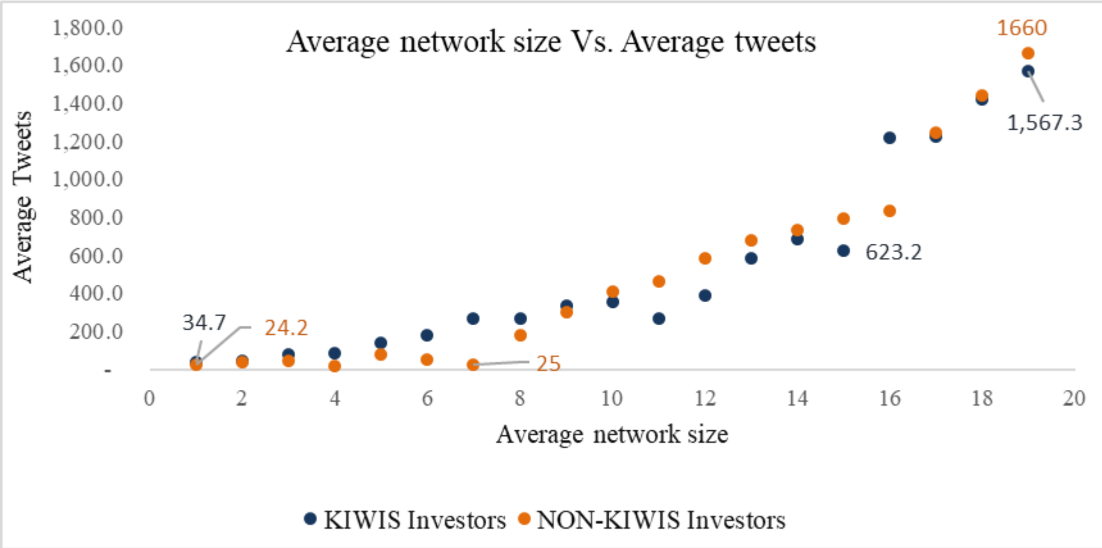
Table 23. Social ties circles (New Zealand VS. Korea)

Social ties circles (New Zealand VS. Korea)						
Social cir cles	**Strength of tie (r)**		**Average mentions & ret weets**		**Average Size (Friends)**	
	New Zealand	*Korean*	*New Zealand*	*Korean*	*New Zealand*	*Korean*
C1	0.344	0.017	0.34	0.166	2.60	1.8
C2	0.2	0.013	0.08	0.059	8.07	4.0
C3	0.144	0.002	0.03	0.018	18.66	7.4
C4	0.036	0.001	0.003	0.005	39.36	11.7

In terms of network size, our findings from both New Zealand and Korean investors show that the information access depends on the size of the investors' network. It shows that on the average basis, investors with a larger network receive or expose to information higher compared those with a smaller network. Figure: 16 shows New Zealand investors with an average network size of 200 friends received *34.7* information or tweets. Whereas Korean investors with an average network size of 200 friends received *24.2* information or tweets. Similarly, investors with large network sizes received higher tweets. For example, both New Zealand and Korean investors with average network size of 8000 friends received 1567.3 and 1160 tweets respectively (Figure. 16). However, some investors with larger network size received lower or fewer tweets.e.g., some non-kiwis' investors with an average network size of 1400 friends received just 25 tweets. But it is worth noting that investors with larger network size receive higher tweets on an average basis. In simple words, larger network means higher exposure to information. Meanwhile, our PLS-SEM result shows that the network size of both kiwis and non-kiwis contributes considerably different (Path diagram 1

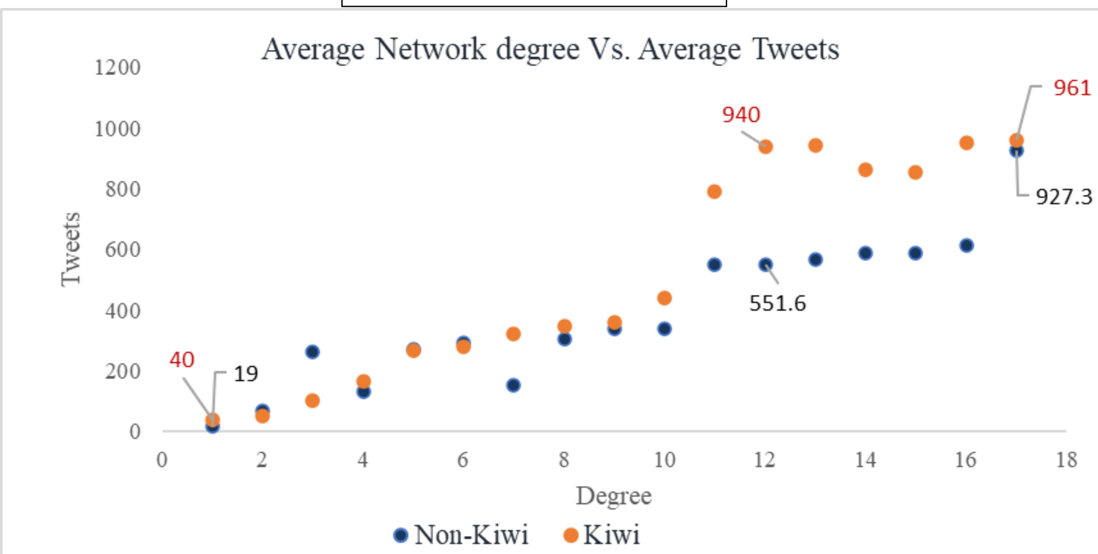
& 2). Below Figure 16 represents network size Vs. tweets.

Figure. 16: Network Size



Similarly, our network degree result (figure.17) shows investors with the highest network degree received higher tweets. Whereas those with the smallest network degree received fewer tweets. However, New Zealand investors comparatively received higher tweets. e.g. New Zealand investors with an average network degree "1" received 40 tweets and investors with largest degree *(17)* received 961 tweets. on the other hand, non-kiwi with an average network degree *"1"* received only 19 tweets as an average and largest degrees one received 927.3 tweets. However, this shows that higher network degree or increased network connectivity allows investors to access more tweets or information. In figure.17, we presented Network degree vs. tweets.

Figure. 17: Network degree



In terms of sentiments analysis (figure 18), both groups of investors responded or replied to news and tweets based on the themes of news. Investors discussed a variety of topics such as financial, positive, negative, covid-19 related news. In terms of financial words, recession, money, and stock were only the most common topics which were discussed by both groups of investors. Some investors particularly Korean also discussed Russian Ukraine war, energy crises, and prices.

Figure 18: Top 10 Financial words (New Zealand Vs. Korean Investors)

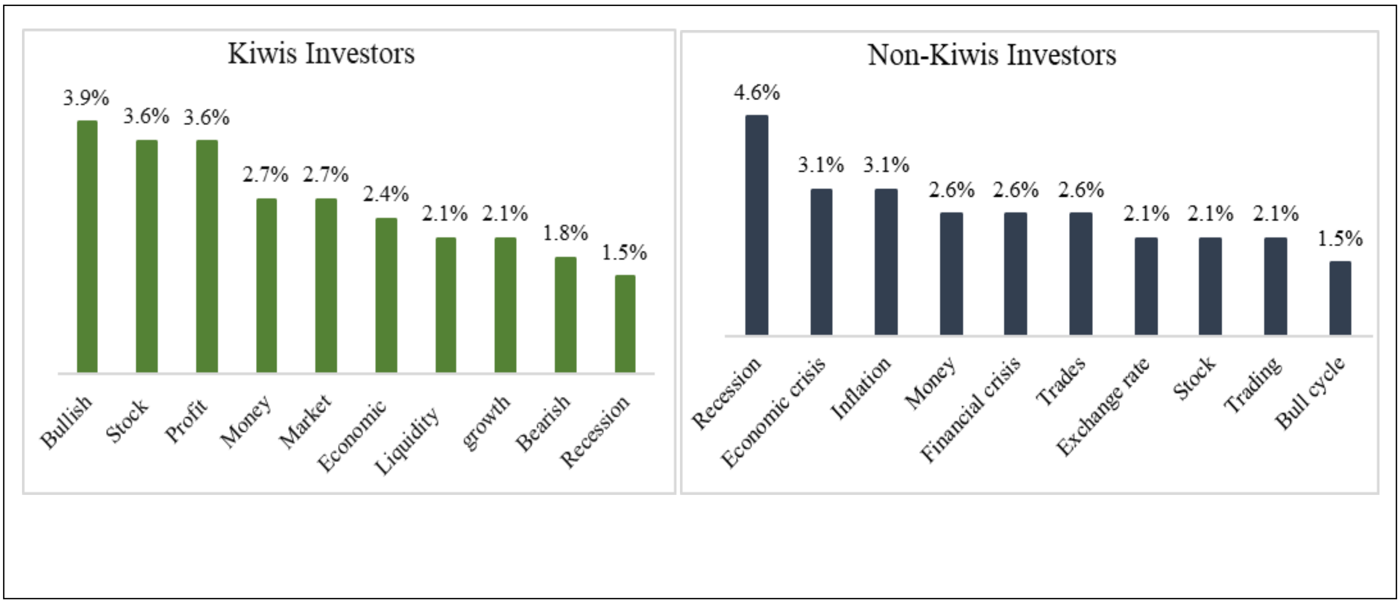


Figure 19: Top 10 Negative words (New Zealand Vs. Korean Investors)

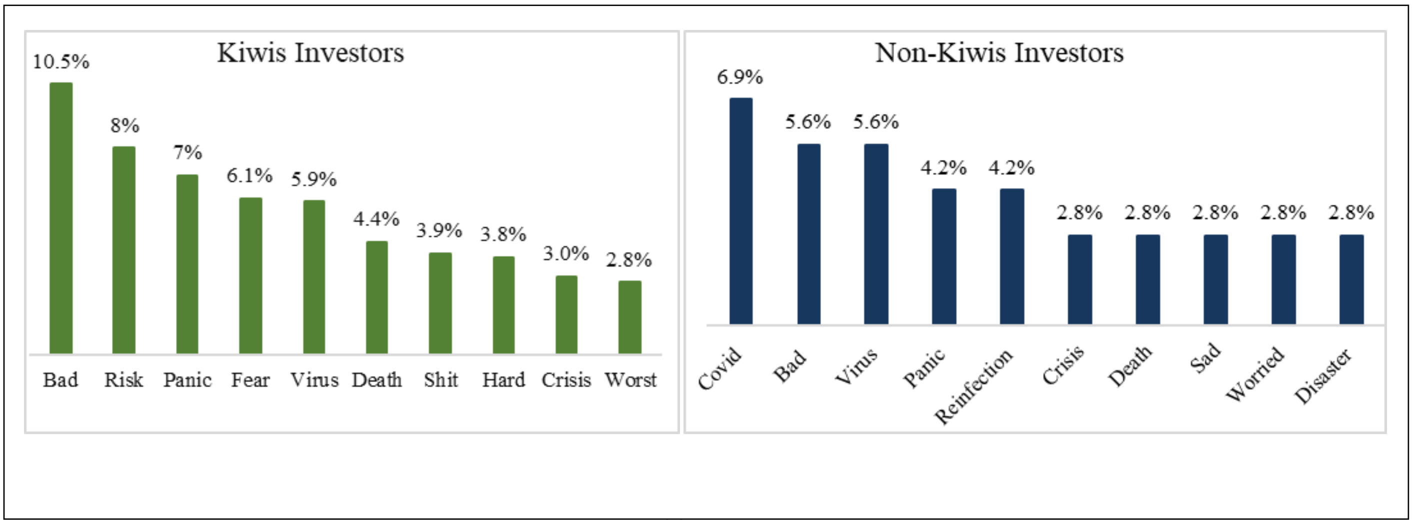
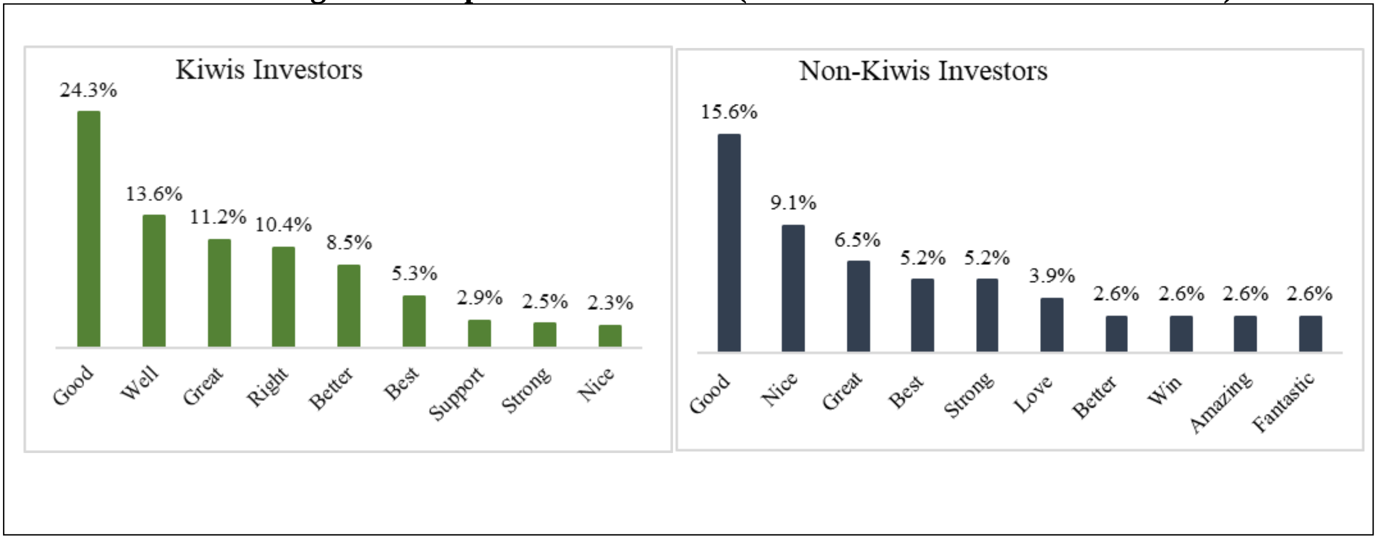


Figure 20: Top 10 Positive words (New Zealand Vs. Korean Investors)



4.7. Discussion

In this study, we considered a range of factors, including both social and non-social network factors, dummies, and control variables to measure the network effect in cross-culture investors' networks. To do so, we used the actual data of two different investors' networks (Twitter) to illustrate the impact of network structure, network size, and social relationships on information diffusion and signify their impact on investors' perceptions. Furthermore, we conducted a textual analysis of financial, non-financial, positive, and negative information from both sources' social media and non-social media.

On a broad level, our results show that network factors have an overall moderating effect (table:). However, on a specific level, there is a considerable difference between New Zealand vs Korean investors in results. In other words, Twitter news itself is a major factor in generating an effect or having an impact on New Zealand investors' perceptions. Furthermore, the network factor has a negative moderating effect which is also outstanding. Results from New Zealand investors show that Twitter news is not a major factor in generating an effect. Hence, it clearly shows network effect is different in a different cultural setting. Our finding also shows that both investors have discussed and shared financial-related information. However, it is worth noting that such financial-related tweets and discussions are comparatively different in both groups (figure 18) This finding of our study is somewhat in line with previous literature (Vieira 2011) which demonstrated that sharing and communication on social media are varied in cross-culture. However, both investors' groups also discussed similar financial topics such recession, money, stock.

Unlike financial sentiment, non-financial sentiment is similar in both investor groups. Both groups use identical language or words while replying or responding to tweets. i.e., positively by using words like great, strong, good, nice, and better, amazing (figure 20). Similarly, whenever investors are exposed to negative tweets or news they react negatively. Investors used a variety of negative replies or responses to negative news (figure 19). Previous studies (Van Belleghem, Thijs et al. 2010, Goodrich and De Mooij 2014) found the average number of friends in different countries. However, these studies neither addressed New Zealand network size nor investors' social ties. Our study comes up with a lot of findings such as average network size, average tweets, replies, average mentions, etc. (Table 21). This finding also shows that kiwis investors are more actively engaged on social media as compared to Korean investors in terms of tweets, replies, retweets, mentions (table 21).

This study further shows kiwis investors who are well-connected and has stable ties as compared to non-kiwis' investors, are enabled to receive comparatively more financial information (Table 22 & figure 13). Hence, this study suggests that connectivity within the network is crucial for investors to receive information promptly. This study further suggests that Twitter is more than just a social media platform; individuals who are interested in the financial markets can use it to obtain financial information. This research study also gives academics a theoretical foundation for comprehending the function of social network variables from a cross-cultural perspective, which may be used to develop future research initiatives. The major limitation of this study is that we only calculated the social network effect in two distinct cultures with a small sample size. More nationalities might give a comprehensive understanding of network factors moderators. In addition, similar to our previous study (khan Feroz, Hassan et al. 2022), we included data only from the Twitter network. The investors probably have connections in other social networks (like Facebook) and offline networks. We believe that because social media networks differ in some ways, the effects of network factors may vary across various social networks. The other limitation is that it was only focused on a brief time frame, and longitudinal studies might provide more information.

Chapter 5: Dissertation Conclusions, Implications, and Contributions

5.1 Conclusions

In today's connected global society, information is created and distributed at phenomenal speed and scale, People from all walks of life are affected by this plethora of information distributed through the aforementioned networks. Internet use has the potential to lead to the development of new social networks or the formation of relationships with people you have never met (Woodward, Benstead et al. 2010). People can keep in touch with more people in their online networks than in their offline networks. Social media is more than just a tool to share photos, and status, build a relationship, and exchange personal conversations, it is a platform to gain information and insights on business expansion, marketing, investment attraction, and economic development (Qualman, 2009). Twitter can boost social relationships in a similar way to traditional social networking sites by assisting users in establishing new connections and maintaining those they already have.

Social media, a modern societal juggernaut, consists of a huge and diverse range of online forums which provide access to an unlimited supply of user-generated content. Social media comes in many forms including social networking websites (Twitter, Facebook, Youtube etc.), Internet discussion boards and forums, sites containing digital audio, images, movies and photographs, blogs, discussion boards, chat rooms, and consumer product or service rating sites. Social media plays a significant role in fostering communication and providing engagement opportunities online for different interest groups including, investors. Twitter has emerged as a major social media platform that helps investors to connect with their peers. The financial information that is available on Twitter is disseminated based on individuals' ties, positions, and network connectivity. Prospective investors, in specific, are affected by information and news either positively or negatively (Barber & Odean, 2008; Bartov et al., 2018; Pevzner et al., 2015). However, the use of social media across the world is different and varies across nations in terms of information sharing and building connections. Therefore, while analyzing user behavior on social media around the world, social media studies have focused on the differences between western and eastern cultures. This is because these nations are different in many ways, including language, preference, culture, tradition, and others (Hofstede and Hofstede 2001, Fong and Burton 2008, Garcia-Gavilanes, Quercia et al. 2013, Elmasry, Auter et al. 2014, Hsu, Tien et al. 2015).

In the first study of this thesis, we used econometric methodology to understand the link between information dissemination, and an individual's position in a network. In this study, we also attempted to address the significance of each network factor in terms of information initiation within the network. To develop a measurement scale for the network index, we used the PCA method to categize network factors based on their significance in terms of information diffusion within the network. We concluded that the acquisition of information in the social network of investors depends on different components which cooperatively represent the social network index.

The second study further escalated research on the extent to which network effects moderate the relationship between social media-propagated news and investors' perceptions. As per network theory, the impact of information on one's perception and behavior 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 network factors that can have an impact on the perceptions of investors. To establish the links between them, we considered three key factors in investors' networks: (1) network connectivity (network structure); (2) social ties circle (friends, family, colleagues); and (3) size of the network (number of contacts). Using PLS-SEM, we investigated how the impact of financial information and news on investors' perceptions is moderated by factors such as connectivity, social ties, and network size of the network on Twitter.

In the final study, we compare two groups of investors from different cultural backgrounds, New Zealand, and the Republic of Korea. This study's major motive is to tackle the moderating role of network factors in a cross-cultural context. The propagation of financial news and information across social networks, particularly on Twitter, can impact individuals' and investors' perceptions. However, the impact of such financial news varies across different nations. This is because investors or individuals may interpret information and sentiments differently due to differences in cultural background. Similarly, the social network factors such as network connectivity, social ties, and size of the network also vary across nations. Rationally thinking is that if network factors are varied, the impact of information may also differ, or the network effect may differ. By using PLS-SEM, we concluded that the social network effect will be different because of the cultural background.

5.2 Theoretical and Practical Implications

This thesis has many implications for academia and practice. In the first study, we constructed a network structure and built social circle ties based on the frequency of interaction of investors, and the network size of the investors to develop a comprehensive measurement scale for the social network index. Findings from the first study indicate that the acquisition of information in the social network of investors depends on different components or factors. This study opens exciting new opportunities for research in social networks, social media, behavioral finance, and economics. The impact of social media on behavioral economics is of significant value for economists and quantifying it would greatly contribute to practices in economic theory and finance. In the age of digital transformation, economic decisions and activities of organizations are increasingly shaped by the contribution of social media. The manner of communication of individuals on social media leads to the formation of a social network effect that has an impact on perceptions. Practitioners in the field can greatly benefit from the findings of this study by findings ways to improve social media communication among peers that will lead to better financial decisions.

This thesis contributes to interdisciplinary literature on behavioral finance and economics. To the best of our knowledge, there is no measurement scale of the social network index from the investors' perspective as of now. This research contributes to knowledge building and literature in novel ways as we have calculated the social network index by bringing together all those factors and sub-factors that initiate and disseminate information in investors' networks. This research builds on previous literature in terms of information diffusion over social media platforms and shows that information diffusion within investors' networks depends on investors' connection or degree. The findings from this study show that the degree of investor (network structure) contributes higher to the social network index. Findings also indicate that investors communicate, and exchange information based on relationship strength or trust. This can assist organizations to rethink their corporate social media engagement strategies when it comes to different cultures. This study has employed actual data from investors' networks to illustrate the impact of network structure, network size, and social relationships on information diffusion and represent social network index from an investor which we consider to be a unique feature of the study. Findings from this thesis can provide a theoretical ground for the measurement of social network index from investor’s networks.

5.3 Future work

We carried out three separate studies in this dissertation that offer new insights for researchers and practitioners, and open new areas for discussion and research. We mainly focused on the qualitative aspects of research. For a study to be more comprehensive, there is a need for mixed methodology including qualitative. The human nature of social media’s influence on personal decision-making processes necessitates further qualitative research in this regard. We also intend to do a follow-up study in near future. It will focus on structural changes in network factors. Because network size and social tie circles are changeable (Arnaboldi et al. 2016) and we are interested to find out to what extent such changes could affect information diffusion within the network.

We are further interested to conduct a comparative study on social network effects in different social networks and to observe whether network effect differs in the different networks (e.g. Facebook, & LinkedIn). Because social networks platform came up with relatively different scopes, features, or functions. Social networking is the key function of Facebook, which is to build and maintain relationships between people (Shelton and Skalski 2014). On other hand, Twitter is designed for fast updates and sharing of information. LinkedIn is a social network site that enables users to make professional connections with their colleagues. Being a business-oriented professional network, LinkedIn enables individuals to share their professional expertise, business information, and updates with their network members (Golbeck 2015).

We also want to further extend our cross-culture study to a wider group of investors to understand network effect phenomena thoroughly. Recent cross-cultural research has looked at differences in thinking style on the basis that cognitive processes reflect holistic and analytical thinking styles and differ between different nations (Norenzayan, Choi et al. 2002, Miyamoto, Nisbett et al. 2006, Oh and Kim 2014) because of the different thinking style in cross-culture, people interpret information differently. These above studies investigated and hypothesized that people's perceptions and understandings differ due to cultural differences.

Author contributions

Noushad khan Feroz: Conceptualization; Data curation; Formal analysis; Investigation; Software; Visualization; Roles/Writing - original draft; Writing. **Dr. Gazi Hassan, and Dr. Micheal Cameron:** Methodology; Project administration; Supervision; Validation; review & editing.

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Abstract Investors differ in their decisions with respect to risk, returns and market analysis. The present study attempts to examine the influence of financial literacy on retail investors' decisions in relation to return, risk and market analysis. The study uses convenience sampling to collect data from the retail investors through stock brokerage managers. Factor analysis has been employed for understanding factors of financial literacy. Financial literacy is composed of Accounting Information; Market Information; Broad Overview; and Technical Knowledge. The factors of Investment decisions are: Return Analytics; Risk Analytics; and Market. The risk and return analytics have stronger impact on investors decision than market analytics. PLS SEM has been employed for examining relation between financial literacy and Investment decision. The results suggest a significant positive relation between financial literacy and investment decision.

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Annex 1 – Financial, Positive, and Negative words – Kiwis investors

Financial words used in Tweets	**Usage %**
Bullish	3.9%
Stock	3.6%
Profit	3.6%
Money	2.7%
Market	2.7%
Economic	2.4%
Liquidity	2.1%
growth	2.1%
Bearish	1.8%
Recession	1.5%
stocks	1.5%
trade	1.5%
economy	1.5%
buying	1.2%
investor	1.8%
undervalued	1.5%
debtjubilee	1.5%
trading	1.2%
return	1.5%

bullmarket	1.5%
ASX	1.2%
gains	1.5%
FinancialCrisis	0.3%
Interest rates	0.3%
markets price	0.3%
yield	0.6%
inflation	0.3%
supply	0.3%
stimulus	0.9%
ratecut	0.9%
bearmarket	0.6%
upswings	0.3%
cashflow	0.9%
inflation	0.3%
sell	0.9%
capex	0.6%
Economicimpact	0.3%
cash	1.2%
crash	0.3%
overvalued	0.3%
indexes	0.3%
bankingcrisis	0.3%
interest	0.6%
index	0.3%
spx	0.3%
prices	0.3%
property	0.9%
premium	0.3%
downs	0.3%
sharemarket	0.3%
shares	0.3%
houseprices	0.6%

stockmarket	0.3%
drop	0.3%
bounce	0.3%
bull	0.3%
higherprice	0.3%
credit	0.3%
discounting	0.3%
debts	0.3%
revenues	0.6%
debt	0.6%
traders	0.3%
stock	3.6%
trader	0.9%
markettank	0.6%
profitable	0.9%
cost	0.9%
assists	0.3%
globalgrowth	0.3%
earning	0.6%
funds	0.9%
buy	0.6%
price	0.9%
shareprice	0.6%
financials	0.3%
holding	0.3%
assest	0.3%
margin	0.9%
markets	0.9%
efficientmarkets	0.3%
deficit	0.3%
investment	0.6%
demand	0.6%
gain	0.3%

monopoly	0.3%
unemployment	0.6%
leveraged	0.3%
starstocks	0.3%
credit	0.3%
Dow	0.9%
gold	0.9%
mortgage	0.3%
financially	0.9%
dividend	0.3%
economies	0.3%
investors	0.9%
bearmarket	0.9%
project	0.3%
interest	0.6%
bulls	0.3%
finance	0.6%
margins	0.3%
futuresup	0.3%
capital	0.3%
bankrupt	0.6%
solvencycrisis	0.3%
bailout	0.6%
wealth	0.3%
prices	0.3%
creditors	0.3%
business	0.6%
production	0.3%
tax	0.6%
balancesheet	0.3%
equities	0.6%
income	0.3%
selling	0.6%

retail			0.6%
invest			0.3%
recessions			0.3%
financial			0.3%
sector			0.3%
discount			0.9%
NZX			0.6%
unemployed			0.3%
housingprices			0.3%
MarketSlump			0.3%
housing			0.6%
hedgeAUD			0.3%
USD			0.3%
pound			0.3%
ASX200			0.3%
nzx50			0.3%
NPAT			0.6%
job job			0.6%
bullrun			0.3%
shitcompany			0.3%
bearishpattern			0.3%
bullishtrend			0.3%
cashbalance			0.3%
uraniumbulls			0.3%
banking			0.3%
liability			0.6%
goldprice			0.3%
enterprisevalue			0.3%

Negative words used in Tweets	**words %**	**Positive words used in Tweets**	**Words %**

Bad	10.5%	Good	24.3%
Risk	8.0%	Well	13.6%
Panic	7.0%	Great	11.2%
Fear	6.1%	Right	10.4%
Virus	5.9%	Better	8.5%
Death	4.4%	Best	5.3%
Shit	3.9%	Support	2.9%
Hard	3.8%	Strong	2.5%
Crisis	3.0%	Nice	2.3%
Worst	2.8%	Worth	1.9%
infection	3.1%	won	1.8%
wrong	2.7%	pretty	1.2%
problem	1.6%	fine	0.8%
collapse	1.4%	love	1.3%
died	2.2%	amazing	1.2%
die	2.5%	happy	1.0%
outbreak	2.2%	enjoy	0.9%
crazy	1.9%	perfect	0.3%
regret	0.7%	positive	0.2%
outbreak	0.3%	lucky	0.1%
damage	0.5%	succeed	0.1%
shock	0.1%	confidence	0.1%
discrimination	0.9%	awesome	0.3%
depression	0.1%	cure	0.2%
losing	0.7%	gains	0.3%
sorry	0.6%	wow	0.9%
worry	0.8%	decent	0.3%
dying	1.5%	easy	0.5%
attacks	0.2%	patient	0.1%
infected	2.4%	correct	0.2%
fails	0.1%	success	0.2%
lost	0.8%	brilliant	0.6%

epidemic	0.3%	impressive	0.2%
crashing	0.4%	genius	0.1%
break	0.4%	talent	0.1%
pain	0.2%	protect	0.1%
terrible	0.2%	excellent	0.4%
hard	0.0%	confidence	0.3%
hype	0.3%	awesome	0.2%
shocked	0.1%	interesting	0.8%
sorry	0.1%	smart	0.2%
monster	0.1%	thank	0.4%
resigned	0.1%	safe	0.4%
bastard	0.1%	welcome	0.2%
dump	0.1%	bright	0.1%
bullshit	0.3%	cool	0.1%
loss	0.7%	relief	0.1%
suffering	0.1%	patience	0.1%
crash	0.4%	effective	0.4%
falling	0.1%	helping	0.1%
decline	0.4%	relief	0.1%
fall	2.3%	recovery	0.1%
illegal	0.4%		
negative	1.1%		
suffered	0.3%		
threat	0.3%		
brutal	0.1%		
unlawful	0.1%		
crime	0.1%		
stress	0.2%		
debt	0.2%		
resistance	0.1%		
weak	0.5%		
sick	0.7%		

bloody	0.4%		
trouble	0.2%		
fatal	0.1%		
liars	0.1%		
hell	0.1%		
upset	0.1%		
reluctant	0.2%		
fuck	1.0%		
rip	1.0%		
kill	0.1%		
isolation	0.7%		
dangerous	0.5%		
symptoms	0.5%		

Annex 2 - Financial, Positive, and Negative words – Non-Kiwis investors

Financial words used in Tweets	Usage %
recession	4.6%
economic crisis	3.1%
inflation	3.1%
money	2.6%
financial crisis	2.6%
trades	2.6%
market	2.1%
stock	2.1%
trading	2.1%
bull cycle	1.5%
StockMarket	1.5%
profits	1.5%
profit	1.5%
margins	1.5%
invest	1.5%

exchange rate	2.1%
investment	1.5%
Crypto	1.5%
traders	1.5%
deposits	1.5%
capital	1.5%
liquidation	1.5%
shareholders	1.5%
income	1.5%
Growth	1.0%
market volume	1.0%
bull market	1.0%
buy	1.0%
bullish	1.0%
investors	1.0%
falling dollars	1.0%
trade-opportunities	1.0%
Bitcoin	1.0%
commodity Rising	1.0%
interest	1.0%
commodity inflation	1.0%
buying	1.0%
foreign investors	1.0%
price	1.0%
energy sector	1.0%
Bearish	1.0%
bull market	1.0%
currency inflation	0.5%
institutional investors	0.5%
leverage	0.5%
assets going down	0.5%
jobs	0.5%

monetary policy	0.5%
fair value	0.5%
commodity stock	0.5%
assets goes down	0.5%
securities	0.5%
bounced	0.5%
negative asset	0.5%
reserves	0.5%
bailout	0.5%
trading skills	0.5%
solid companies	0.5%
suppliers	0.5%
Yield	0.5%
account falls	0.5%
rising dollar	0.5%
dump	0.5%
less-capitalized	0.5%
financial infrastructure	0.5%
dollar	0.5%
foreign currency	0.5%
unfairly sales	0.5%
Samsung	0.5%
Ethereum	0.5%
account freezing	0.5%
Dogecoin	0.5%
energy prices	0.5%
spot	0.5%
eco-friendly energy	0.5%
real-economy	0.5%
bullish	0.5%
assets	0.5%
money savings	0.5%

cryptometric	0.5%
sales	0.5%
cashing out	0.5%
bank	0.5%
Bear	0.5%
nervous Fed	0.5%
bankrupt	0.5%
tax evasion	0.5%
economic	0.5%
realprice	0.5%
reinvestment	0.5%
liquidate	0.5%
bonds rise	0.5%
Safe Asset	0.5%
liquid market	0.5%

Negative words used in Tweets	**words %**	**Positive words used in Tweets**	**Words %**
covid	6.9%	good	15.6%
bad	5.6%	nice	9.1%
virus	5.6%	great	6.5%
Panic	4.2%	best	5.2%
reinfection	4.2%	strong	5.2%
crisis	2.8%	love	3.9%
death	2.8%	better	2.6%
sad	2.8%	win	2.6%
worried	2.8%	amazing	2.6%
dead	2.8%	fantastic	2.6%
difficult	2.8%	incredible	2.6%
wars	2.8%	cool	2.6%

disaster	2.8%	potential	2.6%
wrong	2.8%	cute	1.3%
war	2.8%	sweet	1.3%
nukes	2.8%	incentives	1.3%
dirty	1.4%	quality	1.3%
idiot	1.4%	pretty well	1.3%
lose	1.4%	creativity	1.3%
hell	1.4%	genius	1.3%
problem	1.4%	genius' work	1.3%
damage	1.4%	work harder	1.3%
uncomfortable	1.4%	Respect	1.3%
Storm	1.4%	Stability	1.3%
Impossible	1.4%	reliable	1.3%
violent	1.4%	welldone	1.3%
tsunamis	1.4%	fun	1.3%
brutal	1.4%	lucky	1.3%
worst	1.4%	performing \	1.3%
gaveup	1.4%	opportunities	1.3%
robbed	1.4%	strength	1.3%
horror	1.4%	wonderful work	1.3%
Shit	1.4%	Praise	1.3%
Stress	1.4%	grateful	1.3%
afraid	1.4%	efficiency	1.3%
delusion	1.4%	won	1.3%
terrorist	1.4%	reward	1.3%
stability issue	1.4%	welcome	1.3%
scam	1.4%	successful	1.3%
threat	1.4%	impressive	1.3%
battle	1.4%	workinghard	1.3%
lost	1.4%		
failure	1.4%		
Killing	1.4%		

weapons	1.4%		
crimes	1.4%		
enemies	1.4%		