

# **The Social Network Volume of COVID-19 and Stock Market Response**

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## **Abstract**

This study applies volume of social network activity to examine whether positive or negative social network volume relating to coronavirus (COVID-19) can stimulate stock performance. It also examines whether a professional manager with abundant cash holdings can buffer against an outbreak of COVID-19. The empirical evidence indicates that social network volume can impact stock performance, and firms operated by a professional manager with abundant cash holdings can buffer against an outbreak of COVID-19. This study offers a different perspective on the effect of an epidemic on the economy and risk avoidance strategies regarding similar epidemics in the future.

**JEL classification numbers:** G11, G14, I10, I18.

**Keywords:** Coronavirus Disease (COVID-19), Social Network; Stock Returns, Tourism Sector.

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## 1. Introduction

In China, a local health authority released the first notice of an epidemiologic alert on December 31, 2019. This was followed by a series of limitations and bans on various aspects of daily life by the Chinese Government from January to February 2020. The Chinese economy and industries are facing a dramatic impact caused by coronavirus (COVID-19). The rapid spread of COVID-19 has not only disrupted Chinese economic development but its impact has also expanded globally. COVID-19 has become a daily topic of discussion. The outbreak leads millions of Chinese and Taiwanese to postpone their travel for the Lunar New Year holidays.

Many methodologies have been used in modeling event studies for stock returns and their impact on the market or economy. The “network volume” approach can be applied to measure the effect of an outbreak of infectious disease as an economic event on a firm’s value (or stock return) (Campbell et al., 1997; Nicolau, 2002); this is rarely mentioned in recent literature. Due to the convenient and efficient characteristic of social networks, investors or businesses can obtain abundant information via the internet (Tsapeli, 2017). Recent studies also empirically verify that positive and negative investor sentiment can arise from social networks (Li et al., 2014; Rao and Srivastava, 2012). The effectiveness of social networks’ digital behavior can impact the actions of others (Bordino et al., 2012). The evidence reveals a positive network volume signifies positive investor sentiment and vice versa.

From an economic perspective, the impact of macroeconomics factors on stock returns has been examined in many studies (Fama, 1981; Fama and French, 1988; Abdullah and Hayworth, 1993; Chen et al., 2005). The influence of such factors on stock prices may vary by multiple rational and global events to stock prices (Chen et al., 1989). Nowadays, investors are very sensitive to any forms of online information, especially easily accessible online tools such as blogs, and online news with no global boundaries. The announcement of bad news causes stock markets to suffer a significant negative day effect on the announcement day (Akhtar et al., 2011).

Nason et al., (2016) concluded that a firm holds cash to act as a buffer against crisis and recession. Reeb’s (2003, 2004) empirical results also confirmed the presence of a professional manager diminishes potential corrupt practices by family members and increases firm performance. Hence, the current study assumes firms that have abundant cash holdings and are run by professional managers can increase their ability to deal with the impact brought from the COVID-19 outbreak.

To the best of our knowledge, this study is the first to use the social networks volume as an event day to examine whether the COVID-19 outbreak enhances or weakens a specific industry. Specifically, we examine whether a positive or negative social network volume can stimulate stock market and firm performance. Our empirical results reveal that the social network volume can impact stock performance; specifically, the negative social network volume signifies bad news while positive volume signals good news, both of which will eventually impact on stock performance. In addition, firms operated by a professional manager with

abundant cash holdings can buffer against an outbreak of COVID-19 and increase firm performance. This study offers researchers a new perspective on the impact of epidemics on the economy. In addition, investors may be able to develop risk avoidance strategies regarding similar epidemics in the future.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents data and methodology. Section 4 discusses the empirical results of findings. Finally, concluding remarks are presented in section 5.

## **2. Impact of the COVID-19 Outbreak**

### **2.1 Effective of COVID-19 on stock performance**

Many studies have examined the relationship between specific events and stock market performance (Cao and Wei, 2005; Edmans et al., 2007; Shan and Gong, 2012). Broun and Derwall (2010) obtained a dataset that covers all significant events that directly relate to major economies. The study uses an event study and reveals mildly negative price effects that rebound within in the first week of the aftermath. Chen (2011) reported that most crisis events lead to poor stock performance internationally Grace and Law (2003) took the hotel industry in Hong Kong as a sample to examine the SARS crisis and revealed that the adverse influence of SARS is much larger on the tourism-based economy in Hong Kong than on the manufacturing-based regions.

Chen et al. (2007) demonstrated the influence of the SARS epidemic on Taiwan hotel stock performance and documented that stock price movement has negative accumulative mean abnormal returns. Chen et al. (2009) employed an event study approach and examined the impact of the SARS outbreak on industries in Taiwan. The empirical results reveal the greatest negative impact on tourism, wholesale, and retail sectors. COVID-19 has continued to spread around provinces of China. Taiwan has been on constant alert and ready to act on epidemics arising from China ever since the first report was released from Wuhan, China on December 31, 2019. Taiwan anticipates having the second highest number of cases of COVID-19 due to its proximity to and number of flights between China.

Previous studies also have shown that national disasters have had a severe impact on tourism sector development in Taiwan (Huang and Min, 2002; Wang, 2009). Due to the unique characteristic of the tourism sector, a major event results in enormous shock on business performance. Chen et al. (2018) examined three economic crisis periods (Asian financial crisis, dotcom bubble crisis, and subprime mortgage crisis), and found a significantly positive (negative) relationship among aggregate stock price indices between Taiwan and China. Specifically, Taiwan had more integration relationships with China during 2005-2006, which implies that Taiwan has more integration relationships with China during non-SARS and non-crisis periods. Hence, we posit the existence of abnormal returns from December 2019 to March 2, 2020, during the COVID-19 outbreak.

**Hypothesis 1:** Social network volume pre and post the COVID-19 outbreak is likely to impact on tourism sector's returns.

## 2.2 Relevant tools for analyzing the event

Previous research has empirically shown the digital behavior of internet users' reactions or information affects other actions (Bordino et al., 2012). The evidence shows a positive network volume signifies a positive investor and vice versa. In addition, the deep learning model is one of the most advanced artificial intelligence technologies and is a new branch of machine learning. The model is a computational model that imitates biological neural systems. It attempts to use the complex of association network structure by multiple nonlinear transformations to form multiple processing layers of abstract data (Deng and Yu, 2014; LeCun et al., 2015; Schmidhuber, 2015). Recently, various deep learning frameworks have been successfully applied to computer vision and speech recognition, natural language processing (NLP), audio recognition and bioinformatics industries, deep neural networks (DNN), convolutional neural networks (CNN), deep belief networks (DBNs), and recurrent neural networks (RNN).

According to the research of Facebook AI, the long short-term memory (LSTM) model is especially suitable for speech recognition, picture description, and NLP (Hammou et al., 2020). Based on the development of the model, the machine learning method adopted KEYPO to optimize and improve the model to optimize for the characteristics of Chinese and social network articles, and a large number of emotional tagging errors are collected by means of expert tagging and netizens' ratings. After long-term research and testing, the model accuracy rate has been found to reach more than 90%.

Chen (2007) reports that the hotel sector is sensitive to epidemics and a new epidemic and a new epidemic is likely to depress stock markets via a significantly negative impact on the hotel stocks. Chen (2009) also concluded that stock returns of Taiwan's biotech firms experienced positive shocks in the face of the SARS crisis. Zhang (2006) demonstrated information uncertainty has impact on stock returns, greater information drifts lead to relatively higher expected returns following good news and relatively lower expected returns following bad news.

The convenient and efficient characteristic of social networks enables investors to obtain abundant information from the internet (Tsapeli, 2017). Recent studies also empirically verify that stock prices are affected by the social network volume and can lead to positive (negative) (Li et al., 2014; Rao and Srivastava, 2012). This study uses positive and negative social network volume to analyze stock price reactions, which has seldom been examined in the previous literature. We therefore develop the following hypothesis:

**Hypothesis 2:** The negative social network volume due to COVID-19 outbreak is likely to affect stock return of tourism sector.

### **2.3 Professional manager and stock performance**

On the other hand, firm credibility and reliability for sustainable growth is normally responsibility of a professional manager. Previous studies also confirm that the presence of professional managers can help the longevity of a firm's business and performance. Anderson (2003) and Reeb (2004) examined the difference between firms run by family members and professional managers. Their results revealed a positive relationship between a family-owned shares and performance. However, the empirical results also indicate firms operated by a professional manager can reduce potential corrupt practices by family members and increase firm performance. Huson et al., (2004) suggested that firm performance is positively related with the appointment of an outside CEO. Andreou et al., (2015) revealed a positive relationship with managerial ability and firm performance during the 2008 global financial crisis; better managerial ability can improve firm profitability and performance.

In addition, firms' financial flexibility due to abundant cash holdings may be able to overcome market uncertainty due to the stock caused by the COVID-19 outbreak. Nason et al., (2016) concluded that a firm holds cash to gain an advantage by buffering against crisis and recession. La Rocca et al., (2019) took a broad sample of European small and medium-sized enterprises to examine cash holdings and found such holdings have stronger positive relationships with firm operating performance. The current study assumes firms with abundant cash holdings and run by a professional manager are more likely to be able to resist the impact of the COVID-19 outbreak. We therefore formulate the following hypothesis:

**Hypothesis 3:** Firms with abundant cash holdings and run by a professional manager are less likely to be seriously impacted by the COVID-19 outbreak.

## **3. Data and Methodology**

### **3.1 Data**

The "Network Volume" was obtained from the KEYPO big data search engine system (KEYPO) from December 1, 2019, to March 2, 2020, with a total of 1,344,079 topics related to tourism.

The study also uses daily close-of-day (business day) stock prices of tourism sectors listed on the Taiwan Stock Exchange (TSE), and the over-the-counter (OTC), the emerging stock board (ROTC) obtained from the Taiwan Economic Journal Database (TEJ). We take 90 trading days to analyze the COVID-19 outbreak event.

### **3.2 Methodology**

We have adapted the KEYPO social network analysis system that is based on the context of sentences and words. The calculation process is a multi-combination of a deep learning neural model with a sentence length reference and the relationship of the sequence of words, which is used to evaluate positive and negative emotions in online articles. Thus, the network volume is given by the simultaneously

weighted and normalized values of positive and negative emotions at the same time. (Li and Yu, 2014; Cun et al., 2015; Schmidhuber, 2015)

### 3.2.1 Event Study

Many methodologies have been used in modeling event studies for abnormal returns. However, to examine the effect of the COVID-19 outbreak on stock volatility in Taiwan's tourism sector, the current study used a "Network Volume," which is obtained from the KEYPO big data search engine system(KEYPO), approach to measure the effect of an economic event on the value (or stock return) of a firm (Campbell et al., 1997; Nicolau, 2002).

The semantic system of the KEYPO search engine aims to analyze the online articles context and semantic connotation. Therefore, KEYPO manipulates the adoption of short sentence structure as well as evaluating the characteristic of online social online social networks using free writing style technology. The ultimate goal of KEYPO is to simulate a function of humans' understanding and cognition ability by analyzing words in content in online articles. The cognition of understating online words has been adopted from Facebook AI research that proposed using Fasttext, a shallow word vectorized model that decomposes every statement, words to the text level, and uses the n-gram information of the word level to capture the relationship of word order to enrich the meaning of subtle words. In analysis of text sentences, bi-directional long short-term memory (BiLSTM) model is used to interpret the text and is the most popular sequential deep learning method that utilizes the LSTM model. BiLSTM is similar to an RNN neural network model in that it adds reverse operation to its basis, so the context information can interact and embody with each other to establish mutual influence relationship. (Nguyen and Nguyen, 2018; Huang et al., 2018; Xu et al., 2019).

If an event increases stock value, we refer to this as a "positive" effect, while a "negative" effect signals bad news and a decrease in stock value.

### 3.2.2 Measure of returns and hypothesis

This study applies Fama and French's (1993) methodology and uses the following equation:

$$X = R_{it} - R_{ft} = \alpha + \beta_1(R_{mt} - R_{ft}) + \beta_2SMB_t + \beta_3HML_t + \epsilon_t \quad (1)$$

where  $X$  is the social network and represents a positive and negative effect of social network volume.  $R_{it}$  is the return on stock  $i$  at day  $t$ ,  $R_{ft}$  is risk-free rate at day  $t$ ,  $R_{it} - R_{ft}$  is the abnormal stock return while  $R_{mt} - R_{ft}$  is the abnormal market return.  $SMB_t$  represents market risk premium at day  $t$ ,  $HML_t$  represents book risk premium at day  $t$ .

We then take a group of Taiwanese listed tourism sector stocks and divide these into two major groups: group (1) is the positive online COVID-19 topic volume (Positive), while group (2) is the negative online COVID-19 topic volume

(Negative). To test the coefficient of the effect of the professional manager and cash holdings relationship, we use the following baseline regression equation (2):

$$Y_t = \alpha + \beta_0 \text{CASH} + \beta_1 \text{PM} + \beta_2 \text{CASH} \times \text{PM} + \beta_3 \text{SIZE} + \beta_4 \text{LEV} + \beta_5 \text{RO} + \beta_6 \text{MS} + \beta_7 \text{LGS} + \beta_8 \text{BDSZ} + \beta_9 \text{BDS} + \beta_{10} \text{FRS} + \beta_{11} \text{DMS} + \beta_{12} \text{GTS} + \beta_{13} \text{SC} + \epsilon \quad (2)$$

This is a logit model where  $Y_t$  is the dummy variable assuming value one if  $\text{CAR} [-10, -1] > 0$  and  $\text{CAR} [0, 10]$  and zero otherwise. CASH is firm’s cash and cash equivalent, PM represents professional executives, SIZE is firm’s total assets, LEV is the ratio of firm’s liability, ROE is the consolidated income. MS is the total number of shares held by professional executives, LGS is the major shareholder, BDSZ is the size of the board of directors, FRS represents shares held by foreign financial investors, DMS represents shares held by domestic financial investors, GTS represents shares held by government institutes, and SC represents the numbers of seats on the board.

## 4. Empirical result

### 4.1 The effect of COVID-19 on social network volume

In order to distinguish the COVID-19 volume on social network, the study analyzes the preference of positive and negative social network volume regarding of the COVID-19 topic via KEYPO after the COVID-19 was first reported from Wuhan, China in 31 December 2019. The result has shown a reversal point between positive and negative of social network volume of COVID-19 and has occurred around 13 January 2020 (see Figure 1).

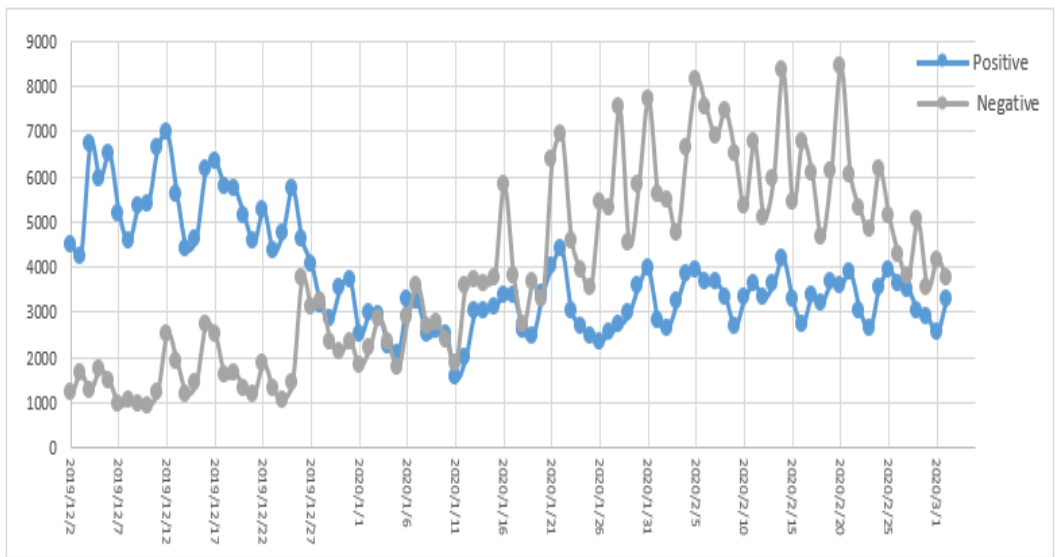


Figure 1: The reversal point for positive/negative social network volume





or prevent the COVID-19 disease at Taiwanese border.

As shown in Table 1, abnormal returns in the tourism sector are found to have dispersed around the event date. Overall, the average abnormal return is -3.8%. The hotel industry has the most abnormal returns within the tourism sector, for example, the highest is -25.89% at the Hoya resort, the lowest is -13.48% at the Ambassador Hotel. In addition, the travel industry shows the second highest abnormal returns, for example, CJW International Co., Ltd. has returns of -15.89% while Lion Travel has -8.05%. Additionally, most abnormal returns occurred immediately before and after the event day. According to the time interval column of CAAR [0, 3], and CAAR [0, 10] in table 1, the abnormal returns were found to last for at least ten days after the event day.

The hotel industry still has the most abnormal returns within the tourism sector; the highest is -43.45% at the Hoya resort and the lowest is -13.48% at the Ambassador Hotel. The finding has verified hypothesis 1 that the greatest impact on tourism sector stock is likely to occur in the period immediately before and after the COVID-19 outbreak. The Holiday Garden Hotel had abnormal stock returns of -9.949%, which illustrates the serious impact of the COVID-19 outbreak on the tourism sector. The negative social network volume signifies bad news for a stock or sectors while positive volume signals good news (see Appendix A).

**Table 1: The Taiwan tourism sector's returns (Event date of 11 January 2020)**

SECURITY	Name	Market	CAAR [-3,3]	CAAR [-3,-1]	CAAR [0,3]	CAAR [-10,10]	CAAR [-10,-1]	CAAR [0,10]
1259	An-Shin	OTC	-2.07%	-0.52%	-1.55%	-2.56%	-1.17%	-1.39%
1268	Hi-Lai Foods	OTC	-1.80%	-0.81%	-0.99%	-6.29%	-0.09%	-6.20%**
1269	Kanpai	ROTC	-3.66%	-3.27%	-0.40%	5.65%	9.77%*	-4.12%
2701	Wan Hwa	TSE	-1.07%	-0.19%	-0.88%	-3.16%	0.87%	-4.02%**
2702	Hotel Holiday Garden	TSE	-11.35%**	10.78%***	-22.13%***	-19.23%**	20.27%***	-39.50%***
2704	Ambassador Hotel	TSE	-5.49%***	7.99%***	-13.48%***	-13.11%***	4.79%*	-17.91%***
2705	Leofoo	TSE	-0.92%	0.47%	-1.39%	-16.72%*	-0.01%	-16.71%**
2706	First Hotel	TSE	-1.11%	0.66%	-1.76%	-4.99%	0.98%	-5.96%***
2707	Formosa Intl Hotels	TSE	-0.66%	2.84%	-3.49%	-12.02%*	0.19%	-12.21%***
2712	FGH	TSE	-12.13%	-6.16%	-5.97%	-17.39%	-2.51%	-14.88%
2718	PH	OTC	-0.73%	0.12%	-0.85%	-5.53%	-0.60%	-4.93%
2719	Star Travel	OTC	-2.04%	4.07%	-6.11%	-21.38%	5.70%	-27.08%**
2721	Kai Chieh	ROTC	-15.43%***	-2.46%	-12.97%***	-18.11%***	-7.84%*	-10.27%**
2722	Chateau	TSE	-3.13%	2.86%	-6.00%**	8.83%	10.37%**	-1.55%
2723	Gourmet	TSE	1.90%	1.57%	0.33%	-13.27%	6.55%	-19.82%***
2724	FX Hotels	OTC	1.90%	1.01%	0.89%	-4.62%	2.92%	-7.54%
2726	Yummy Town	OTC	6.09%	2.87%	3.21%	7.97%	16.56%**	-8.59%
2727	Wowprime	TSE	-0.34%	-0.03%	-0.31%	-12.44%***	-2.00%	-10.44%***
2729	TTFB	OTC	-0.22%	-0.32%	0.10%	-10.23%**	-3.20%	-7.03%**
2730	Miramar Hotel	ROTC	-0.04%	-0.14%	0.09%	-1.44%	1.12%	-2.56%
2731	Liontravel	TSE	-1.17%	6.88%***	-8.05%***	-14.96%***	4.41%**	-19.38%***
2732	La Kaffa	OTC	0.17%	-2.74%	2.91%	-0.25%	-2.88%	2.63%
2733	Vigor Kobo	ROTC	-9.57%*	1.33%	-10.91%***	-13.65%	8.29%	-21.95%***
2734	Ezfly	OTC	1.02%	3.58%	-2.57%	-9.20%	3.78%	-12.98%*
2736	Hoya	OTC	-20.66%***	5.22%*	-25.89%***	-22.56%***	20.89%***	-43.45%***
2739	MHH	TSE	1.19%	4.08%***	-2.89%**	-9.07%***	6.94%***	-16.02%***
2740	Mr. Onion	OTC	6.49%	3.34%	3.15%	8.79%	4.34%	4.45%
2741	Oldsichuan	ROTC	-0.84%	0.10%	-0.94%	-15.03%*	-2.80%	-12.23%**
2743	Richmond	ROTC	-8.84%	-0.92%	-7.92%*	-30.10%**	-4.95%	-25.15%***
2745	Life Travel	OTC	-3.10%	4.97%***	-8.07%***	-12.18%**	8.48%**	-20.67%***
2748	FDC	TSE	-1.33%	-0.05%	-1.28%	-10.67%***	0.76%	-11.43%***
2750	Orchard Park	ROTC	0.53%	0.29%	0.24%	0.32%	2.31%	-2.00%
2752	TOFU	OTC	1.56%	2.61%	-1.05%	-7.62%	-0.76%	-6.86%
2754	Kura Sushi Asia	ROTC	-7.77%	-3.53%	-4.24%	-74.56%	-25.59%	-48.97%
2755	YoungQin	ROTC	-2.54%	-0.83%	-1.70%	1.34%	-0.05%	1.39%
2928	RHGroup	OTC	2.87%	1.79%	1.07%	2.97%	1.14%	1.83%
3252	Haiwan	OTC	-0.48%	-0.66%	0.18%	-2.70%	-0.37%	-2.33%
3522	Toplus	OTC	-1.73%	1.24%	-2.97%	-6.71%	1.17%	-7.88%
4804	Da Lue	OTC	-3.56%	-0.50%	-3.06%	-31.31%***	-7.46%	-23.85%***
5301	CJW	OTC	-11.23%**	4.66%	-15.89%***	-15.24%*	17.65%***	-32.89%***
5364	Lealea Hotels	OTC	-1.15%	4.98%	-6.13%*	-1.64%	8.01%	-9.65%
5701	Janfusun	OTC	-2.37%	2.96%	-5.33%	-10.74%	1.66%	-12.40%*
5703	Landis Taipei	OTC	5.16%	2.89%	2.27%	1.72%	-1.25%	2.97%
5704	Chihpen Royal	OTC	-3.03%	0.87%	-3.90%	2.02%	4.53%	-2.51%
5706	PHX Tour	TSE	0.24%	8.06%***	-7.82%***	-9.53%***	6.92%***	-16.44%***
8077	Green World Hotels	OTC	-6.76%	-0.76%	-6.00%*	-2.22%	2.64%	-4.87%
8359	Cashbox	ROTC	-3.86%	-3.31%	-0.54%	-14.15%	-5.17%	-8.98%
8462	Fitness Factory	TSE	0.07%	2.34%	-2.26%	-15.48%*	-5.40%	-10.08%
8940	New Palace	TSE	-0.41%	0.52%	-0.93%	-8.47%	-1.00%	-7.47%
9943	Holiday	TSE	-0.18%	-0.21%	0.02%	-6.43%*	-2.06%	-4.37%*
Ptf CARs			-2.40%**	1.44%*	-3.83%***	-9.06%***	2.39%	-11.45%***

Note: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. TSE is Taiwan security exchange Corporation, OTC is Over-The-Counter and ROTC is an emerging stock Board, these are the listing markets in Taiwan.

#### 4.2 The regression of correlation between return and social network volume

We further examine the correlation of positive and negative social network volume and return base on the reversal point of COVID-19 as shown Figure 1. In addition, Table 2 shows that the tourism sector has an average return of -0.1808 during the period December 1, 2019, to March 2, 2020. The average value of positive social network volume of COVID-19 is 4,129.9890 per day while the negative value is 3,793.7050. The COVID-19 outbreak has led the negative social network value to increase from a minimum of 901 to maximum of 8,435, which indicates an increased volume of negative discussion on social networks.

In addition, we also examined the average the positive and negative social networks volume before and after the event day. On average, the negative volume has increased from a mean of 2,830.167 before the event day to a mean of 5,440.567. Obviously, the tourism sector has suffered the greatest impact during the COVID-19 outbreak. The results indicate that stock prices of the tourism sector has dropped by 18.7%, and turnover has decreased by 33.24% (see Appendix B and C).

**Table 2: The descriptive statistic result**

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
Return	-0.1808	2.3097	-14.8325	10.7407
Positive	4129.9680	1177.5390	1550.0000	6954.0000
Negative	3793.7050	2162.8710	901.0000	8435.0000
MKT	-0.0453	1.0615	-5.7584	1.7542
SMB	-0.0131	0.4587	-1.2259	0.8344
HML	-0.0336	0.3766	-1.1919	0.7871

**Table 3: The correlation of positive/negative social network volume and return**

	<b>Return</b>	<b>Return</b>	<b>Return</b>
Positive	0.498		-0.024
	(1.512)		(-0.064)
Negative		-0.592***	-0.598***
		(-3.309)	(-2.914)
MKT	0.775***	0.773***	0.773***
	(12.122)	(12.321)	(12.146)
SMB	1.014***	1.025***	1.025***
	(9.158)	(9.257)	(9.252)
HML	-0.040	-0.063	-0.064
	(-0.284)	(-0.444)	(-0.458)
Constant	-0.340**	0.090	0.102
	(-2.272)	(1.261)	(0.485)
<i>N</i>	2850	2850	2850
<i>R</i> <sup>2</sup>	0.135	0.137	0.137
adj. <i>R</i> <sup>2</sup>	0.133	0.136	0.136
Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t values are in parentheses.			

**Table 4: The Lag 1 to Lag 3 of a positive/negative social network volume and return**

	<b>Return</b>	<b>Return</b>	<b>Return</b>
Positive t-1	-10.254		-12.253
	(-1.226)		(-1.408)
Positive t-2	9.862		14.532
	(1.181)		(1.519)
Positive t-3	0.124		-13.005
	(0.011)		(-1.137)
Negative t-1		-13.479**	-15.000**
		(-2.276)	(-2.411)
Negative t-2		11.922	10.503
		(1.260)	(1.122)
Negative t-3		-0.878	-2.618
		(-0.096)	(-0.241)
MKT	0.609***	0.665***	0.616***
	(4.950)	(4.926)	(3.589)
SMB	0.624***	0.618***	0.643***
	(3.640)	(3.128)	(3.232)
HML	0.129	0.278	0.190
	(0.508)	(1.119)	(0.663)
Constant	0.060	0.180	0.801
	(0.220)	(1.232)	(1.266)
<i>N</i>	950	950	950
<i>R</i> <sup>2</sup>	0.042	0.046	0.050
adj. <i>R</i> <sup>2</sup>	0.036	0.040	0.041
Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t values are in parentheses.			

To test the effect of social network volume by a specific topic and its relationship with return, Table 3 shows the correlation of positive and negative social network volume and return regarding the COVID-19 outbreak. The result indicates that the stock return and social network volume are correlated with each other and are likely impact on tourism sector. Next, we further examine the time interval and its effect on tourism stock return by taking lag 1 through lag 3 days. Table 4 indicates that the negative social network volume has a negative impact on stock return. Specifically, we find that the time interval for lag 1 is the most significantly negative compared to lag 2 and lag 3. The empirical evidence reveals the negative social network volume has an impact on the tourism sector, which is consistent hypothesis 2. Hence, the greater the volume of negative topics, the greater impact on the tourism stock returns.

This study results provide a different perspective on the effect of epidemics on the economy. By using the social network volume to investigate the relationship with

stock performance, this study is the first to apply the positive and negative network volume regarding a specific epidemic disease to assess its impact on a specific sector.

We also extend our analysis to examine the correlation of stock performance. Following Nason, Rober, and Pankaj (2016), who empirically show that firm holds cash to take an advantage by buffering against the crisis and recession. Table 5 summarizes our empirical results, which show firms with abundant cash holdings and runs by a professional manager have positive stock performance. The intersection of the coefficient of firm cash holdings and professional manager is -116.5, which indicates that firms with abundant cash holdings and run by a professional manager are less likely to suffer from negative impact of the COVID-19 outbreak.

Unlike previous research that takes a specific announcement or event as an event day to examine the coefficient of business or stock performance, this study is the first to use the social network volume as an event day to examine whether the coronavirus (COVID-19) enhances or weakens a specific industry. Our empirical result reveals that the social network volume can impact on stock performance; a negative social network volume signifies bad news and eventually impacts on stock performance while positive volume signals good news. By using the social network volume to investigate the relationship with stock performance, this study is the first to apply a positive and negative network volume on specific sectors.

The study has shown that a professional manager with abundant cash holding firm can buffer against an epidemiologic on COVID-19 and increase firm performance. In addition, investors may be able to develop strategies to avoid the same risk.

**Table 5: The correlation of professional manager and firm cash holdings**

	<b>Returnd</b>	<b>Returnd</b>	<b>Returnd</b>	<b>Returnd</b>
CASH		-6.138*		-8.537**
		(-1.66)		(-1.97)
PM			-3.634**	-0.468
			(-2.52)	(-0.15)
CASH*PM				-116.5**
				(-2.27)
SIZE	0.421	0.121	0.730	0.0718
	(1.13)	(0.31)	(1.51)	(0.14)
LEV	-0.00396	0.00198	-0.00329	0.00145
	(-0.23)	(0.12)	(-0.17)	(0.07)
ROE	-0.0459	-0.0241	-0.0628**	-0.0542
	(-1.44)	(-0.75)	(-2.03)	(-1.30)
MS	0.000198	-0.0213	0.140	0.0627
	(0.00)	(-0.09)	(0.70)	(0.16)
LGS	-0.000188	-0.00684	0.00652	0.00438
	(-0.01)	(-0.23)	(0.20)	(0.12)
BDSZ	0.105	0.0726	0.242	0.221
	(0.68)	(0.51)	(1.26)	(1.17)
BDS	0.0145	0.0145	0.0258	0.0328
	(0.60)	(0.61)	(0.94)	(0.97)
FRS	1.054	1.209	2.596*	25.60**
	(1.20)	(1.48)	(1.81)	(2.40)
DMS	0.0426	0.0140	-0.00300	-0.0255
	(0.24)	(0.07)	(-0.02)	(-0.14)
GTS	-0.125	0.426	0.518	6.595*
	(-0.09)	(0.22)	(0.40)	(1.80)
SC	0.00882	0.00530	0.00440	0.000187
	(0.42)	(0.24)	(0.20)	(0.01)
Constant	-7.646	-2.094	-13.60*	-2.966
	(-1.33)	(-0.34)	(-1.84)	(-0.35)
Pseudo R2	0.0850	0.1319	0.2003	0.3482

Note: This model is logit model. The Y=Returnd is the dummy variable assuming value one if CAR [-10,-1] >0 and CAR [0,10] and zero otherwise. CASH is firm's cash and cash equivalent; PM represents professional executives, SIZE is firm's total asset; LEV is the ratio of firm's liability; ROE is the consolidated income; MS is total number of shares held by professional executives; LGS is major shareholder; BDSZ is the size of the board of director; FRS represents shares held by foreign financial investor; DMS represents shares held by domestic financial investor; GTS represents shares held by the government institutes; SC represents the numbers of board seat control. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively; t values are in parentheses.

## **5. Conclusion**

This study is the first to use the social network volume as an event day, that is, the volume of discussion on social networks. Previous scholars have empirically shown the digital behavior of internet users' reactions or information affects other actions (Bordino et al., 2012). Bollen et al., (2011) took "network semantics" to analyze the correlation between investors' decision and network volume. The evidence shows a positive network volume signifies positive investor sentiment and vice versa.

This study applies the network volume to test how stock prices react to an outbreak of infectious disease in the short-term. Our empirical result shows the social network volume has ability to impact on stock performance, especially the negative social network volume signifies bad news and will eventually impact on stock or firm performance while positive volume signal as good news. The empirical result has same implication as Akhtar et al., (2011) indicated that the announcement of bad news enables stock market suffering a significant negatively day effect at the announcement day. Our empirical evidence shows that the social network volume can impact stock performance. In addition, a firm runs by a professional manager and with abundant cash holdings can buffer against epidemics such as COVID-19 outbreak and increases firm performance. We offer a different economic perspective on the effect of epidemics on the economy and the examination of the social network volume provides new insights into the effect of a major event effect. In addition, business, investors may be able to develop risk avoidance strategies regarding similar epidemics in the future.

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**Appendix A: The returns of tourism stock during the COVID-19**

Stock Code	Company	Listing	Paid in Capital (NTD)	Established Date	20200130 Closed price	Volume (*000share)	Return(%)
1259	An-Shin	OTC	323895000	1990/11/23	73.9	54	-3.2723
1268	Hi-Lai Foods	OTC	376857300	2003/01/09	137.5	135	-1.7857
1269	Kanpai	ROTC	186072830	1999/10/13	85	12	-3.4091
2701	Wan Hwa	TSE	4499678380	1958/02/26	13.15	344	-1.8657
2702	Hotel Holiday Garden	TSE	1104855380	1959/07/29	17.65	448	-9.949
2704	Ambassador Hotel	TSE	3669233430	1962/12/01	25.45	785	-8.2883
2705	Leofoo	TSE	1865366300	1968/01/27	14.15	836	-8.7097
2706	First Hotel	TSE	4999983460	1968/09/27	15	1128	-4.1534
2707	Formosa Intl Hotels	TSE	1274019720	1976/07/07	151.5	1109	-9.5522
2712	FGH	TSE	1050000000	1991/01/15	45.65	14	-5.2905
2718	PH	OTC	425760000	1977/04/08	19.5	31	-2.5
2719	Star Travel	OTC	182721000	2003/02/24	4.97	16	-3.6822
2721	Kai Chieh	ROTC	1045500000	2008/10/01	7.81	0	0
2722	Chateau	TSE	1115229610	1995/09/27	24.5	54	-1.8036
2723	Gourmet	TSE	1800000000	2008/09/26	114	362	-9.8814
2724	FX Hotels	OTC	681722900	2002/01/15	3.15	0	0
2726	Yummy Town	OTC	349085430	2009/12/22	69.3	17	-10
2727	Wowprime	TSE	769878830	1993/12/07	70.6	1262	-9.949
2729	TTFB	OTC	232660000	2000/09/08	249.5	144	-8.9416
2730	Miramar Hotel	ROTC	372800000	2004/02/20	6.65	2	0
2731	Liontravel	TSE	700000000	1977/06/09	72.9	682	-9.8888
2732	La Kaffa	OTC	405383210	2004/02/16	187.5	285	-9.8558
2733	Vigor Kobo	ROTC	165984000	2003/06/26	22.31	12	-6.2605
2734	Ezfly	OTC	302597600	1999/12/22	11.45	76	-2.1368
2736	Hoya	OTC	489923830	2008/07/11	12.15	338	-9.6654
2739	MHH	TSE	1115260000	2000/01/17	24	73	-6.4327
2740	Mr. Onion	OTC	94763960	2007/02/13	7.6	7	-4.5226
2741	Oldsichuan	ROTC	211189040	2007/12/28	45.7	112	-5.7732
2743	Richmond	OTC	320317000	1988/05/25	17.8	132	-14.8325
2745	Life Travel	OTC	293085260	1988/08/22	19.8	122	-9.795
2748	FDC	TSE	656370000	2012/11/22	46.05	391	-8.9921
2750	Orchard Park	ROTC	460114000	2009/04/27	14.9	6	-2.2951
2752	TOFU	OTC	213658000	2008/01/23	110.5	232	-4.7414
2754	Kura Sushi Asia	ROTC	378730000	2014/01/21	92.99	33	-8.4474
2755	YoungQin	ROTC	180000000	2015/08/21	64	3	0
2928	RHGroup	OTC	473011540	2011/06/08	32.65	22	-0.6088
3252	Haiwan	OTC	501957540	1994/07/19	15.6	182	-5.7402
3522	Toplus	OTC	726000000	2001/09/26	15.85	213	-7.3099
4804	Da Lue	OTC	446949200	2011/08/05	10.65	59	-9.7458
5301	CJW	OTC	1379750000	1978/10/06	11.7	203	-9.6525
5364	Lealea Hotels	OTC	140999400	1990/01/24	16.8	4	-3.17
5701	Janfusun	OTC	2537569570	1986/08/07	1.64	269	0
5703	Landis Taipei	OTC	702395940	1977/05/25	25.3	0	0
5704	Chihpen Royal	OTC	388616580	1990/03/19	22.9	0	0
5706	PHX Tour	TSE	612943530	1957/04/30	36.05	856	-9.875
8077	GreenWorld Hotels	OTC	1097283430	1994/07/22	13.85	12	-1.773
8359	Cashbox	ROTC	1365000000	1986/11/03	135.89	104	-6.9183
8462	Fitness Factory	TSE	702420320	2005/10/04	177.5	610	-8.9744
8940	New Palace	TSE	674910320	1993/07/19	10.95	209	-3.9474
9943	Holiday	TSE	1473176000	1993/04/10	66.9	1769	-6.9541

**Appendix B: The ranking of stock returns by sectors in Taiwan**

<b>Sector</b>	<b>Closed price 2020/1/10</b>	<b>Closed price 2020/2/10</b>	<b>Return</b>	<b>Rank</b>
Tourism	102.19	86.09	-18.70%	1
Glass & Ceramics	31.68	28.26	-12.10%	2
Shipping & Trans	66.88	61.11	-9.44%	3
Oil, Gas and Elec	125.91	115.91	-8.63%	4
Other electronics	87.35	81.24	-7.52%	5
Automobile	349.09	326.21	-7.01%	6
Rubber	262.27	245.43	-6.86%	7
Building & Cons.	308.91	289.91	-6.55%	8
Others	282.01	266.16	-5.96%	9
Optoelectronic	43.29	41.04	-5.48%	10
Elec. & Cable	48.41	46.01	-5.22%	11
Elec. Parts	116.75	111.3	-4.90%	12
Plastics	259.06	247.25	-4.78%	13
Biotech	64.51	61.57	-4.78%	14
Textiles	528.96	505.44	-4.65%	15
Cement	173.81	166.59	-4.33%	16
Electronics	530.78	509.67	-4.14%	17
Semiconductor	228.08	219.15	-4.07%	18
Biotech. & Med.	98.63	95.08	-3.73%	19
Elec. Machinery	185.01	180.05	-2.75%	20
Chemical	103.71	100.93	-2.75%	21
Iron and Steel	101.33	98.7	-2.66%	22
Department.	253.54	247.83	-2.30%	23
Computer & Per.	104.14	101.85	-2.25%	24
Elec. Products	118.24	115.69	-2.20%	25
Paper	197.05	193.12	-2.04%	26
Comm. Internet	125.07	122.91	-1.76%	27
Inf. Service	116.52	115.5	-0.88%	28
Finance	1,356.18	1,353.16	-0.22%	29
Food	1,790.42	1,786.83	-0.20%	30

**Appendix C: The ranking of turnover by sectors during the COVID-19 outbreak in Taiwan**

Date	Stock	Monthly Consolidated Revenue(000')	Month over month (000')	Growth (%)	Rank
2020/02	Tourism	5731,514	8,585,182	-33.24%	1
2020/02	Rubber	12,644,779	16,121,429	-21.57%	2
2020/02	Other Electronic	243,024,432	296,480,156	-18.03%	3
2020/02	Elec. & Cable	12,306,589	14,652,245	-16.01%	4
2020/02	Optoelectronic	72,912,327	86,673,065	-15.88%	5
2020/02	Plastics	67952,,859	80,536,822	-15.63%	6
2020/02	Shipping & Trans.	57,785,629	67,906,212	-14.90%	7
2020/02	Computer & Per.	337,831,086	393,841,037	-14.22%	8
2020/02	Others	58,284,009	65,139,773	-10.52%	9
2020/02	Trading & Cons.	46,731,320	52,051,229	-10.22%	10
2020/02	Oil, Gas and Elec	50,487,439	56,176,874	-10.13%	11
2020/02	Elec. Machinery	20,245,123	22,233,939	-8.94%	12
2020/02	Textiles	37,606,289	40,527,784	-7.21%	13
2020/02	Glass & Ceramics	2,461,238	2,627,710	-6.34%	14
2020/02	Comm. Internet	56,135,296	59,662,715	-5.91%	15
2020/02	Electronics	1,125,500,840	1,185,990,892	-5.10%	16
2020/02	Elec. Parts	85,329,869	89,687,483	-4.86%	17
2020/02	Paper and Pulp	11,395,626	11,941,413	-4.57%	18
2020/02	Iron and Steel	56,221,492	58,464,249	-3.84%	19
2020/02	Chemical	18,667,091	19,404,775	-3.80%	20
2020/02	Biotech. & Med.	27,799,931	27,959,081	-0.57%	21
2020/02	Cement	9,122,019	9,031,099	1.01%	22
2020/02	Foods	48,545,335	45,886,437	5.79%	23
2020/02	Chem. Biotech.	9,132,840	8,554,306	6.76%	24
2020/02	Finance	229,973,308	210,763,353	9.11%	25
2020/02	Building & Cons.	17,851,337	16,107,551	10.83%	26
2020/02	Elec. Products	112,938,313	97,749,308	15.54%	27
2020/02	Automobile	36,554,653	30,743,504	18.90%	28
2020/02	Inf. Service	5,584,075	4,369,732	27.79%	29
2020/02	Semiconductor	211,745,442	157,527,396	34.42%	30