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Online search activities and investor attention on financial markets

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ABSTRACT

We investigate the online search activities regarding stock markets and their applications on forecasting trading volumes, stock turnover, and stock volatility. Following Da et al. (2011), we use the Google Search Volume Index (SVI) as a direct proxy for individual investors' attention. For Taiwan's top 50 firms, we show that online search activities are significantly correlated with stock turnover, trading volumes and stock volatility, indicating that online search activities reflect individual investors' attention and thus are associated with investors' investment behaviors.

1. Introduction

The information imbedded in web search behaviors has been widely discussed in various fields. Beatty and Smith (1987) indicate that external search effort is associated with consumers' motivation for purchase decision. Consumers' search behaviors should be a good prediction on sales of products. Nowadays, web searching has been one of the most essential information gathering behaviors, and thus online search activities may reveal users' attention. Choi and Varian (2012) show how to use search engine data to forecast values of economic indicators, such as automobile sales, unemployment claims, travel planning, etc. As for the healthcare sector, Ginsberg et al. (2009) use search engine query data to detect influenza epidemics, and present a method of analyzing larger numbers of Google search queries to track influenza-like symptoms and illness. Based on above studies, search volumes or queries, submitted by millions of users around the world each day, can be a good indicator to represent individuals' behaviors or attention.

In the finance field, researchers are interested in the existence of a good measure for investors' attention on financial markets. Previous attempts to measure investor attention, such as extreme returns (Barber & Odean, 2008), trading volume (Barber & Odean, 2008; Gervais, Kaniel, & Mingelgrin, 2001), news and headlines (Barber & Odean, 2008; Yuan, 2015), or advertising expenses (Grullon, Kanatas, & Weston, 2004; Lou, 2014), are indirect proxies which could be influenced by others factors unassociated with investor attention. Moreover, Da, Engelberg, and Gao (2011) propose that Google search volume index (SVI) can be a better proxy for investor attention, especially for the attention of retail or individual investors. Da et al. (2011) indicate that Google search volume index (SVI) predicts higher stock prices in the next two weeks and price reversal within the year. Joseph, Wintoki, and Zhang (2011) show that online search activities provide the predictive ability to forecast abnormal stock returns, and search intensity in the former period can predict abnormal returns and increased trading volume. These studies demonstrate that people usually use internet search engine to gather information, and Google is the most common tool for internet users. Hence, Google's search volume can represent the search behavior of internet users as a whole.[1] Moreover, when

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[1] According to StatCounter.com, the market share of Google search engines in Aug. 2016 is 89.6% in Worldwide, and 82.44% at Taiwan, which indicate that Google search volume is truly representative both in worldwide and in Taiwan.

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people search for a specific stock, they definitely care about the stock and are paying attention to it. Therefore, Google search volume index (SVI) should be a direct proxy for investor attention on financial markets.

In this study, we adopt Google search volume index (SVI) as the proxy for investor attention and investigate whether it is able to predict trading volume, stock turnover, and stock volatility in Taiwan stock market. Da et al. (2011) and Joseph et al. (2011) show that online search activities provide the predictive ability in the developed financial markets. In addition, in the emerging markets, Huang, Chen, Kuo, and Lai (2016) show that web search activity and media coverage influence stock returns significantly, where firms receiving more investor attention from the Internet have higher stock returns. Besides, Huang (2018) explores the media effect on the Chinese stock market and shows that large firms, growth firms, and firms with high leverage are more frequently featured in media reports, and stocks with much media coverage also exhibit significantly higher alpha, which is contrary to the media effect in the U.S. markets. Based on the prior research, in this study, we aim to investigate whether online search activities, which can be viewed as a direct proxy for investors' attention, is related to trading volume, stock turnover, and stock volatility in Taiwan.

The mixture of distributions hypothesis (MDH) indicates that trading volumes and stock volatility are derived from an unobservable mixing variable, the rate of information flow to the market (Carroll & Kearney, 2015). In addition, investors' attention, proxied by the Google search volume index (SVI), can be regarded as the demand for information. We, therefore, can examine the mixture of distributions hypothesis by investigating whether investor's attention is associated with those market features. One may argue that volatility can be decomposed into components of systematic and idiosyncratic risk, and investors' attention for a stock can be regarded as paying attention on the stock's idiosyncratic information and risk. Nevertheless, we cannot deny that investors may still search for stocks as market (systematic) information and risk comes, especially when investors hold those shares. Therefore, we would like to test whether investors' attention is associated with stock volatility, which may include both idiosyncratic and market risk.

This study contributes finance literature associated with the investor attention and stock volatility in two folds. First, in this study, we attempt to use Chinese character symbols of a stock as the keyword to obtain the Google search volume index (SVI) of a stock, which is different from the previous studies (Huang et al., 2016), where the search volume index (SVI) is constructed by abbreviated company's English names. As individual investors pay attention to a certain stock in Taiwan markets, they usually search the company's information by using its Chinese name at web search engine. Therefore, constructing the Google search volume index (SVI) by companies' Chinese name should be a direct proxy for individual/retail investors' attention in Taiwan markets. Second, following Da et al. (2011), we take time-series difference of logarithm on Google search volume index (SVI). We show that the variation of logarithm of Google search volume index (SVI) is significantly positively correlated with the trading volume, the turnover ratio, and stock return volatility, respectively. The findings indicate that online search activities are highly associated with financial markets since online search activities reflect individual investors' attention and thus are associated with investors' investment behaviors.

The rest of this paper is organized as follows. In Section II, we review the literature that is relevant to searching activities and investors' attention in finance research. Section III describes the sample and variables used in the empirical analysis. Section IV presents empirical results. Section V concludes the paper. Appendix presents detailed definitions of the variables used in the analyses and regressions.

2. Literature review

2.1. Search activities and economic prediction

Search behaviors by consumers and sales prediction is of interests to researchers. Beatty and Smith (1987) indicate that external search effort is associated with consumers' motivation for purchase decision. Consumers' search behaviors should be a good prediction on sales of products. Therefore, consumers' search behavior is able to improve sales managers' prediction on products' demand.

As for the prediction power of online search activities, Choi and Varian (2012) show how to use search engine data to forecast values of economics' indicators, such as automobile sales, unemployment claims, travel planning, etc. Although they do not claim that Goggle data helps in predicting the future, they claim that it may help in predicting the present.[2] For instance, the search volumes on automobile sales in a week may be associated with the auto sales several weeks later. They find that queries can be useful leading indicators for subsequent consumer purchases if consumers begin planning for purchases before they actually want to buy the products.

In the health science area, search activities are also adopted to do various predictions. Ginsberg et al. (2009) use search engine query data to detect influenza epidemics, and present a method of analyzing larger numbers of Google search queries to track influenza-like symptoms and illness. They find that the relative frequency of the queries is highly correlated with the proportion of physician visits where a patient presents with influenza-like symptoms, and thus they can estimate the current level of weekly influenza activity. These findings show that search activities may contain valuation information that enables to predict subsequent outcomes.

2.2. Investors' attention and financial markets

In the finance research, studies pay attention to how to measure investors' attention and what appropriate proxies for investors' attention are. Barber and Odean (2008) propose attention grabbing purchase theory and empirically examine the theory by several proxies for investors' attention, such as extreme returns, trading volumes, and news and headlines. However, these proxies can only measure investors' attention indirectly, and some factors unrelated to investors' attention may also drive these proxies as well. Da et al. (2011) propose that Google search volume index (SVI) can be a good proxy to investor attention, especially for the attention of retail or individual investors. They argue that search activity is a revealed attention measure; for instance, if an individual searches for a certain stock in Google, she is interested in the stock and pays attention on it. Da et al. (2011) show that Google SVI captures investor attention directly and predicts higher stock price in the next two weeks and price reversal within the year.

There are quite a few studies implementing Google SVI in financial markets. Joseph et al. (2011) show that online search volume index (SVI) provide the predictive ability to forecast abnormal stock returns and trading volumes. Huang et al. (2016) show that web search activities and media coverage influence

[2] Google search data can be accessed at Google Trend: https://www.google.com/trends/.

stock returns significantly, where firms receiving more investor attention from the Internet have higher stock returns.[3]

Theoretical framework also shows the relationships between investor attention and asset prices. Traditional models usually assume that when information arrives, stock prices instantly absorb the latest information. However, this condition requires that market participants pay adequate attention on the information. In fact, market participants may only pay limited attention on the markets, which affects asset prices in a certain way (Hirshleifer & Teoh, 2003; Peng & Xiong, 2006). Besides, Andrei and Hasler (2015) propose a theoretical framework to show that investor's attention and market uncertainty are crucial determinants of asset prices, and stock return variance or risk premia increase with both attention and uncertainty.

3. Data and variables

In the empirical analysis, we focus on Taiwan top 50 corporations listed at Taiwan stock exchange. The sample period is from 2004 to 2016. We input two keywords in the query to obtain SVI of each company, Chinese character symbol for each company and a common Chinese character of "Taiwan 50". We then adjust the SVI of each company by aligning the SVI of the common term. In addition, we follow Da et al. (2011) to take the time-series difference of the logarithm of adjusted SVI to observe the variation of the search volume index for a company during the month. Specifically, the variation of the search volume index, $\Delta\ \ln(SVI_{i,t-1,t})$, is defined $\ln(SVI_{i,t}) - \ln(SVI_{i,t-1})$, where $SVI_{i,t}$ denotes the search volume index for stock i in month t obtained from Google Trends by using the company's Chinese character as the keyword. The adjusted SVI and the variation of search volume index, therefore, can be treated as direct proxies for individual investors' attention in Taiwan stock markets and allow us to compare the investor attention across companies.

We obtain stock characteristics related to trading volatility, including trading volume ($\text{Volume}_{i,t}$), the variation of trading volume ($\Delta\text{Volume}_{i,t-1,t}$), the monthly volatility ($\text{Volatility}_{i,t}$), the variation of monthly volatility ($\Delta\text{Volatility}_{i,t-1,t}$), monthly turnover ratio ($\text{Turnover}_{i,t}$), and the variation of monthly turnover ratio ($\Delta\text{Turnover}_{i,t-1,t}$). Other stock and market characteristics, such as monthly return for the stock ($\text{Return}_{i,t}$), market capitalization ($\text{Size}_{i,t}$), and monthly return for the market (Market Return_{t}), are also obtained. The detailed definition for each variable is summarized in Appendix.

Table 1 presents the summary statistics for major variables for stocks listed in Taiwan 50 index. Variables include search volume index (SVI), logarithm of search volume index, monthly rate of return, trading volume, return volatility, turnover ratio, size, and logarithm of size. Mean, median, standard deviation, minimum, and maximum of each variable and the number of observations are presented. In our sample, the mean of search volume index (SVI) is 234.87, and the median of search volume index (SVI) is 47.17, which indicates that most of the time search volume index is relatively small, but it could jump to a peak level once there is big news on a single stock. Besides, the mean of Volume is 15,725, and the median of Volume is 9,344, which indicates that some stocks may share larger proportion of total trading volume.

The original dataset contains 7319 observations in our study. Since we consider the variation of the variables in our regression, every two consecutive monthly data would result in one amount of change of monthly data. In the regression model, we include lagged terms as independent variables, and thus the first month

Table 1
Summary Statistics. Table 1 presents the summary statistics for major variables for stocks listed in Taiwan 50 index. Variables include search volume index (SVI), logarithm of search volume index, monthly rate of return, trading volume, return volatility, turnover ratio, size, and logarithm of size. Mean, median, standard deviation, minimum, and maximum of each variable and the number of observations are presented.

	Mean	Median	Std.	Min	Max
SVI	234.87	47.17	780.26	0	10000
ln(SVI)	3.9476	3.8538	1.5550	−16.1181	9.2103
Return (%)	1.1312	0.9009	9.2456	−50.2645	92.3073
Volume ($mil)	15,725	9344	19,185	10	200,073
Volatility (%)	8.6223	7.7917	4.1882	0.6930	34.5362
Turnover (%)	7.8976	5.3264	8.1558	0.0772	92.2829
Size ($mil)	261,484	154,144	357,914	1345	4,472,990
ln(Size)	11.9994	11.9456	0.9877	7.2041	15.3136
Obs.	7319				

observations for each stock are excluded in the regression model. Our dataset contains 50 top firms in Taiwan stock market, and hence the sample size of our regression model in Table 3, Table 4, and Table 5 are 7269 observations, where the difference between 7319 and 7269 is 50 first-month observations. Table 2 presents the correlation table among logarithm of SVI, trading volume, turnover ratio, volatility, monthly return, market return, and logarithm of size. The detailed definitions of these variables are reported in the Appendix. Table 2 shows that these variables are not highly correlated. For instance, the highest correlation among these variables is 0.5516, which is the correlation between stock returns and market return. The lowest correlation among these variables is −0.1945, which is the correlation between turnover and the logarithm of firm size. Therefore, we may implement these variables in the regression model and investigate the relationship between SVI index and several financial measures: trading volumes, stock turnover, and stock volatility.

4. Empirical results

We conduct a regression model to investigate the effect of the search volume index on the trading volume. The dependent variable is the trading volume in the regressions (1), (2), (3), and (4); the dependent variable is the variation of trading volume in the regressions (5) and (6).[4] Independent variables are the variation of logarithm of SVI, monthly return, market monthly return and logarithm of size. In the regressions (3) and (4), we add the lagged trading volume as one of the regressors. Firm fixed effects and year fixed effects are controlled as well.

According to the results in the regression (1) of Table 3, we show that the coefficient between the variation of logarithm of search volume index (SVI) and the trading volume is 1490.66, which is significantly positive at 1% significance level. The result indicates that the variation of logarithm of search volume index (SVI) is significantly positively correlated with the trading volume. In the regression (2), in which we add market return at the previous period as one of the controlling variables, the variation of logarithm of search volume index (SVI) is still significantly positively correlated with the trading volume. In the regressions (3) and (4), we add the lagged trading volume as one of the regressors and redo the above procedure. The results in the regressions (3) and (4) also indicate that the variation of logarithm of search volume index (SVI) is significantly positively correlated with the

[3] Huang et al. (2016) formulate the SVI by firms' abbreviated company names.

[4] Appropriate controlling variables, such as firm fixed and year fixed effect variables, have been added as regressors in the regression model.

Table 2

Correlations for Major Variables. Table 2 presents correlation among logarithm of SVI, trading volume, turnover ratio, volatility, monthly return, market return, and logarithm of size. The detailed definitions of these variables are reported in Appendix.

	ln(SVI)	Volume	Turnover	Volatility	Return	Market Return	ln(Size)
ln(SVI)	1.0000						
Volume	0.2835	1.0000					
Turnover	0.0749	0.4113	1.0000				
Volatility	−0.0894	0.2271	0.5206	1.0000			
Return	−0.0150	0.0400	0.1227	−0.0281	1.0000		
Market Return	−0.0146	−0.0010	0.0322	−0.2172	0.5516	1.0000	
ln(Size)	0.3507	0.5339	−0.1945	−0.2077	0.0150	0.0189	1.0000

Table 3

Relationship between Internet Search and Trading Volume. Table 3 presents the effect of the search volume index (SVI) on the trading volume. Estimated coefficients for the regression are shown in each model. The dependent variable is the trading volume in the regression (1), (2), (3), and (4) and the variation of trading volume in the regression (5) and (6). Independent variables are the variation of logarithm of SVI, monthly return, market monthly return and logarithm of size. In the regression (3) and (4), we add the lagged trading volume as one of the regressors. Firm fixed effects and year fixed effects are controlled as well. The associated t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Volume	Volume	Volume	⊿Volume	⊿Volume
Intercept	−132536.9***	−131918.1***	−47547.46***	−46221.17***	50.23	−127.89
	(-38.06)	(-37.94)	(-15.58)	(-15.22)	(0.02)	(-0.04)
			0.61***	0.61***		
			(65.27)	(65.98)		
	1490.66***	1426.47***	2311.21***	2227.42***	2795.76***	2809.67***
	(5.27)	(5.05)	(10.29)	(9.97)	(11.35)	(11.41)
	128.52***	85.45***	101.36***	41.91***		
	(9.65)	(5.51)	(9.59)	(3.42)		
		149.81***		206.24***		
		(5.39)		(9.40)		
	12728***	12678.27***	4559.13***	4445.08***		
	(42.14)	(42.03)	(16.87)	(16.53)		
					180.00***	194.19***
					(15.47)	(14.31)
						−49.65**
						(-2.03)
					−63.99	−50.73
					(-0.24)	(-0.19)
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	0.7220	0.7231	0.8253	0.8274	0.0446	0.0451
Obs.	7269	7269	7269	7269	7269	7269

trading volume. Moreover, we adopt the variable, the variation of trading volume, as the dependent variable in the regressions (5) and (6). Consistent with our expectation, the variation of logarithm of SVI is significantly positively correlated with the variation of trading volume at 1% significance level as well. Therefore, the empirical results in Table 3 indicate that the large amount of change on logarithm of SVI should be accompanied with the high trading volume.

Table 4 presents the effect of the search volume index (SVI) on the stock turnover ratio. Estimated coefficients for the regression are shown in each model. The dependent variable is the turnover ratio in the regressions (1), (2), (3), and (4) and the variation of the turnover ratio in the regressions (5) and (6). Independent variables, the same as the independent variables in Table 3, are the variation of logarithm of SVI, monthly return, market monthly return and logarithm of size. In the regressions (3) and (4), we add the lagged turnover ratio as one of the regressors. Firm fixed effects and year fixed effects are also controlled.

According to the results in the regression (1) of Table 4, we show that the coefficient between the variation of logarithm of search volume index (SVI) and the turnover ratio is 0.825, which is significantly positive at 1% significance level. The result indicates that the variation of logarithm of search volume index (SVI) is significantly positively correlated with the turnover ratio. In the regression (2), in which we add market return at the previous period as one of the controlling variables, the variation of logarithm of search volume index (SVI) is still significantly positively correlated with the turnover ratio. In the regressions (3) and (4), we add the lagged turnover ratio as one of the regressors and then redo the above procedure. The results in the regressions (3) and (4) also indicate that the variation of logarithm of search volume index (SVI) is significantly positively correlated with the turnover ratio. Moreover, we adopt the variable, the variation of the turnover ratio, as the dependent variable in the regressions (5) and (6). Consistent with our expectation, the variation of logarithm of SVI is significantly positively correlated with the variation of the turnover ratio at 1% significance level as well. Hence, the empirical results in Table 4 indicate that the large amount of change on logarithm of SVI should be accompanied with the high turnover ratio.

Table 5 presents the effect of the search volume index (SVI) on the return volatility. Estimated coefficients for the regression are

Table 4
Relationship between Internet Search and Turnover Ratio. Table 4 presents the effect of the search volume index (SVI) on the turnover ratio. Estimated coefficients for the regression are shown in each model. The dependent variable is the turnover ratio in the regression (1), (2), (3), and (4) and the variation of the turnover ratio in the regression (5) and (6). Independent variables are the variation of logarithm of SVI, monthly return, market monthly return and logarithm of size. In the regression (3) and (4), we add the lagged turnover ratio as one of the regressors. Firm fixed effects and year fixed effects are controlled as well. The associated t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(3)	(4)
		Turnover	Turnover	Turnover	⊿Turnover	⊿Turnover
Intercept	−3.6269**	−3.3992*	1.5053	1.9528	3.1477**	3.0226**
	(-1.98)	(-1.86)	(1.06)	(1.39)	(2.06)	(1.97)
			0.6378***	0.6423***		
			(69.86)	(70.62)		
	0.8250***	0.8014***	1.3456***	1.3066***	1.5677***	1.5775***
	(5.55)	(5.39)	(11.70)	(11.42)	(12.59)	(12.67)
	0.0798***	0.0639***	0.0242***	−0.0048		
	(11.40)	(7.84)	(4.43)	(-0.76)		
		0.0551***		0.0996***		
		(3.77)		(8.85)		
	1.3571***	1.3388***	0.2126*	0.1714		
	(8.55)	(8.44)	(1.72)	(1.39)		
					0.0926***	0.1026***
					(15.74)	(14.96)
						−0.0349***
						(-2.82)
					−0.3338**	−0.3245**
					(-2.52)	(-2.45)
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	0.5738	0.5746	0.7459	0.7486	0.0487	0.0496
Obs	7269	7269	7269	7269	7269	7269

Table 5
Relationship between Internet Search and Return Volatility. Table 5 presents the effect of the search volume index (SVI) on the return volatility. Estimated coefficients for the regression are shown in each model. The dependent variable is the return volatility in the regression (1), (2), (3), and (4) and the variation of the return volatility in the regression (5) and (6). Independent variables are the variation of logarithm of SVI, monthly return, market monthly return and logarithm of size. In the regression (3) and (4), we add the lagged return volatility as one of the regressors. Firm fixed effects and year fixed effects are controlled as well. The associated t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Volatility	Volatility	Volatility	⊿Volatility	⊿Volatility
Intercept	7.0125***	6.7225***	3.3281***	3.3659***	−0.1057	−0.7477
	(6.43)	(6.19)	(3.47)	(3.51)	(-0.10)	(-0.69)
			0.4796***	0.4900***		
			(46.60)	(45.86)		
	0.4333***	0.4634***	0.7457***	0.7403***	1.0841***	1.1343***
	(4.89)	(5.25)	(9.57)	(9.50)	(12.00)	(12.92)
	−0.0036	0.0166***	−0.0034	−0.0116***		
	(-0.87)	(3.61)	(-0.92)	(-2.69)		
		−0.0702***		0.0286***		
		(-8.09)		(3.61)		
	0.2639**	0.2872***	0.1572*	0.1454*		
	(2.79)	(3.05)	(1.89)	(1.75)		
					−0.0045	0.0466***
					(-1.07)	(9.63)
						−0.1789***
						(-20.53)
					−0.0091	0.0386
					(-0.10)	(0.41)
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R2	0.4243	0.4294	0.5576	0.5583	0.0205	0.0745
Obs	7269	7269	7269	7269	7269	7269

shown in each model. The dependent variable is the return volatility in the regressions (1), (2), (3), and (4) and the variation of the return volatility in the regressions (5) and (6). Independent variables are the variation of logarithm of SVI, monthly return, market monthly return and logarithm of size. In the regressions (3) and (4), we add the lagged return volatility as one of the regressors. Firm fixed effects and year fixed effects are controlled as well.

According to the results in the regression (1) of Table 5, we find that the coefficient between the variation of logarithm of search volume index (SVI) and the return volatility is 0.4333, which is significantly positive at 1% significance level. The result indicates that the variation of logarithm of search volume index (SVI) is significantly positively correlated with the return volatility. In the regression (2), in which we add market return at the previous period as one of the controlling variables, the variation of logarithm of search volume index (SVI) is still significantly positively correlated with the return volatility. In the regressions (3) and (4), we add the lagged return volatility as one of the regressors and redo the above procedure. The results in the regression (3) and (4) also indicate that the variation of logarithm of search volume index (SVI) is significantly positively correlated with the return volatility. Besides, we adopt the variable, the variation of the return volatility, as the dependent variable in the regressions (5) and (6). Consistent with our expectation, the variation of logarithm of SVI is significantly positively correlated with the variation of the return volatility at 1% significance level as well. Thus, the empirical results in Table 5 indicate that the large amount of change on logarithm of SVI should be accompanied with the high return volatility.

From the above analysis, we show that the variation of logarithm of Google search volume index (SVI), as a direct proxy for investors' attention, is significantly positively correlated with the trading volume, the turnover ratio, and stock return volatility, respectively. The findings indicate that online search activities are highly associated with financial markets since online search activities reflect individual investors' attention and thus are associated with investors' investment behaviors.

5. Concluding remarks

The paper explores whether online search activities are able to forecast stock trading volume, stock turnover and stock volatility on Taiwan stock markets. Da et al. (2011) propose that Google search volume could be a direct measure of investor attention. We construct the Google search volume index (SVI) by companies' Chinese character symbol, a direct proxy for individual/retail investors' attention in Taiwan stock markets. As individual investors pay attention on a certain stock in Taiwan markets, they usually search for company's Chinese name at Google search engine. Hence, we claim that constructing the search volume index (SVI) by companies' Chinese name should be a direct proxy for individual/retail investors' attention in Taiwan markets.

Following the previous studies (Da et al., 2011), we investigate the correlation between online search activities and several important indicators in financial markets. We show that the variation of logarithm of SVI is significantly positively correlated with the trading volume, the turnover ratio, and stock return volatility, respectively. Our findings indicate that online search activities are highly associated with financial markets since online search activities reflect individual investors' attention and thus are associated with investors' investment behaviors.

Appendix. Variable Definitions

Appendix presents detailed definitions of the variables used in the analyses and regressions.

Variables	Definitions
$SVI_{i,t}$	The search volume index for stock i in month t, which is obtained from Google Trends by using the stock ticker as the keyword. All of search volume indexes are adjusted by the search volume index of a common keyword of "Taiwan 50".
$\Delta\ln(SVI_{i,t-1,t})$	The variation of Logarithm of the search volume index for stock i in month t, which is defined as $\ln(SVI_{i,t}) - \ln(SVI_{i,t-1})$.
$\text{Volume}_{i,t}$ ($mil.)	Trading volume for stock i in month t.
$\Delta\text{Volume}_{i,t-1,t}$ ($mil.)	The variation of trading volume for stock i in month t, which is defined as $\text{Volume}_{i,t} - \text{Volume}_{i,t-1}$.
$\text{Volatility}_{i,t}$ (%)	Monthly volatility for stock i in month t, which is defined as the standard deviation of the daily rate of returns during the month times square root of number of days in the month.
$\Delta\text{Volatility}_{i,t-1,t}$ (%)	The variation of monthly volatility for stock i in month t, which is defined as $\text{Volatility}_{i,t} - \text{Volatility}_{i,t-1}$.
$\text{Turnover}_{i,t}$ (%)	Monthly turnover ratio for stock i in month t, which is defined as the monthly trading volume divided by the market capitalization at the end of month.
$\Delta\text{Turnover}_{i,t-1,t}$ (%)	The variation of trading volume for i in month t, which is defined as $\text{Turnover}_{i,t} - \text{Turnover}_{i,t-1}$.
$\text{Return}_{i,t}$ (%)	Rate of return for stock i in month t.
Market Return_t (%)	Monthly return in month t.
$\text{Size}_{i,t}$ ($mil.)	Market capitalization for stock i in month t, which is defined as the price at the end of month times the number of shares outstanding at the end of month.
$\ln(\text{Size}_{i,t})$	Logarithm of the market capitalization for stock i in month t.

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