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資訊需求、網路搜尋行為與投機交易活動

Information Demand, Web Search Behavior, and Speculative Trading Activity

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摘要

本研究使用 Google 提供的搜尋量指標（Google Search Volume Index）做爲資訊需求的代理變數，探討投資人的網路搜尋行爲對其股票交易活動的影響，尤其是投機交易活動如融資、融券、當沖等交易活動的影響。實證結果發現：(1)、Google 搜尋量指標與散戶投資人的股票交易量之間具有正向關係，可能因爲散戶投資人具有資訊不足(uninformed)的特性，而造成其使用網路搜尋取得投資相關資訊的需求較高。(2)、隨著 Google 搜尋量指標的增加，融資、當沖等投機交易活動亦增加，顯示管理當局或可透過觀察 Google 搜尋量指標的變動，來預測股票市場上投機交易活動的變化。

關鍵詞：Google 搜尋量指標、資訊需求、投機交易、散戶投資人

Abstract

Investors nowadays can utilize search engines to collect information from Internet before trading. Although prior studies have extensively investigated the impact of information flow on the capital market, the influence of information collected from web sites on stock trading activity is relatively unexplored. Using search volume on Google as a proxy for information demand, this paper aims to fill up the gap. Specifically, this research extends prior studies to investigate the role of information demand in stock trading activities, focusing on speculative ones, such as margin buying, short selling, and day trading. The evidence shows that rises in Google search volume are positively associated with trading volumes by individual investors, margin purchase, and day trading. These findings support the following hypotheses: (1) individuals, being uninformed, have a greater demand for information; (2) with more information collected from web sites, more investors engage in speculative activities. Overall, these findings imply that market

administrators can predict trading activities of individual investors by observing changes in Google search volume.

Keywords: Google Search Volume Index, Information Demand, Speculative Trading Activity, Individual Investors

1. Introduction

Rational investors in the capital market collect information to ensure proper decision-making, and there is a considerable amount of theoretical literature on the importance of information (Kihlstrom, 1974; Grossman & Stiglitz, 1980; Radner & Stiglitz, 1984; Allen, 1990). Different models and hypotheses have been proposed to investigate the role of information in trading activity. Among them, the Mixture of Distributions Hypothesis suggests that trading activity would exhibit observable patterns due to the arrival of information in the capital market (Clark, 1973; Epps & Epps, 1976; Tauchen & Pitts, 1983). The hypothesis imposes a joint dependence of both trading volume and stock returns on a latent information process, thereby providing a theoretical foundation on the link between information flow and trading activity.

Since trading volume can assess the degree of trader participation, empirical studies tend to use it as an essential measure of trading activity (Bessembinder et al., 1996; Ryan & Taffler, 2004). On the other hand, low trading volume implies uncertainty and illiquidity, which limits one's capacity of raising funds. A primary cause of low trading volume would be information asymmetry between sellers and buyers (Akerlof, 1970). Informed traders tend to exploit this asymmetry to gain from trading with the uninformed. To reduce the cost arising from information asymmetry, investors naturally demand more information before they trade. In view of such information demand, market administrators endeavor to improve the quality of information disclosure policy in the hope of reducing information

asymmetry, and in turn promote trading activity. Accordingly, information demand increases with information asymmetry from the perspective of investor rationality.

While many financial economists seem to agree that information plays a critical role in the capital market (Fama et al., 1969; French & Roll, 1986), they face a challenge when studying its effect on capital markets for lack of direct measures of information flow due to its invisibility (Vlastakis & Markellos, 2012). Moreover, since information comes from a wide range of channels, empirical studies use a variety of alternative proxies for information flow.[1] In the modern society, Internet is an important source of information. As Bank et al. (2011) have pointed out that the Internet appears to be the largest pool of information available to almost everyone. The invention of search engine also accelerates the rate of information gathering. In practice, investors may take advantage of search engines to gather information of all sorts, including product announcements, financial news, market information, and so forth. Specifically, they may use company names or stock symbols as keywords to search for related news and recent stock price information. Consequently, internet search activities are expected to possess a certain degree of influence on capital markets. Moreover, investors can collect information through different search engines, among which Da et al. (2011b) suggest that search volume on Google is most likely to be representative of the internet search behavior of the general population.[2] Google also provides Search Volume Index (hereafter SVI) as an indicator of search volume on Google.[3] Due to the popularity of Google search engine, SVI can describe interest of the public and help to predict numerous economic activities (Bank et al., 2011; Da et al., 2011a, 2011b; Mondria & Wu, 2011; Choi & Varian, 2012). However, the effect of information collected from internet on the capital market has not been fully

[1] For example, the number of macroeconomic and firm-specific news announcements (Mitchell & Mulherin, 1994). For a review of related studies, see Vlastakis & Markellos (2012).

[2] For example, Google had a market share close to almost 90% in 2010 in the German search engine market. Moreover, Google accounted for 72.1% of all search queries performed in the United States in 2009. Google is the leading representative of search engines and the search volume it reports is thus likely to be representative of the internet search behavior of the general population.

[3] SVI for a particular term is the number of queries for that term in a specific time and space, normalized by the highest volume over the time-series.

explored.

Information demand is probably the main motivation behind these internet search activities. Accordingly, internet search volume might serve as a direct measure of information demand. Recognizing the fact, Vlastakis & Markellos (2012) employ SVI to proxy information demand and find strong links of SVI to market volatility and to trading volume. Likewise, using SVI as a proxy for investors' speculative demand, Gwilym et al. (2012) find that market returns and trading volume of Chinese stock indices increased with SVI. Bank et al. (2011) also document a significant and positive association between SVI and stock liquidity. Da et al. (2011b) find that SVI can predict IPO returns.[4]

These above-mentioned studies generally confirm the predictive power of SVI for stock return, market volatility, and trading volume. However, research on whether SVI can predict other kinds of stock trading activities is quite limited, not to mention speculative ones − such as margin buying, short selling, and day trading.[5] Since speculative trading activities involve substantial risks, investors who engage in these activities need more information to lower risks. Therefore, one would expect that speculators demand more information than regular investors. However, the question as to whether speculators utilize search engines to collect information remains unclear. To fill up the gap in prior studies, this paper endeavors to investigate the relationship between information demand and speculative trading activity. This study also sheds light on how web search behavior influences primary trading activities in the stock market.

Additionally, primary market participants are either individual investors or institutional investors. The present study seeks the answer to which type of investors mainly use the Google search engine to collect information. Literature on investor types suggests that individual investors are disposed to trade out of speculative motives (Kumar & Lee, 2006; Dorn et al., 2008; Kaniel et al., 2008; Foucault et al., 2011). Accordingly, individual investors would be the principal

[4] Da et al. (2011b) claimed that SVI is a revealed attention measure, holding that "if you search for a stock in Google, you are undoubtedly paying attention to it."

[5] Day trading refers to buying and selling the same stocks within a single trading day. It has been regarded as a quick but speculative way to acquire wealth with limited funds.

participants of speculative activities. On the other hand, financial economists tend to view individuals as uninformed or noise traders, but believe institutions to have an information advantage (Kyle, 1985; Kaniel et al., 2008), so information asymmetry is particularly severe between individual and institutional investors (Odean, 1999; Grinblatt & Keloharju, 2000; Barber et al., 2009). To prevent the losses arising from information asymmetry, individual investors might ask for more information inflows. In a similar spirit, Da et al. (2011b) argue that individual investors are more likely to search financial information than institutional investors, holding that the latter have access to more sophisticated information services.

Focusing on the speculative trading activity, we endeavor to investigate the predictive power of SVI in the Taiwan stock market. Our reasons for selecting the Taiwan stock market are as follows. First and foremost, Taiwan is a densely populated country with extremely high internet penetration rate.[6] As a result, information can quickly disperse and be accessible to investors via internet, which in turn contributes to an efficient market. In addition, information demand varies across regions (Huberman, 2001; Coval & Moskowitz, 2002). Taiwan, being a small island, can minimize the variation in interest across regions and helps contribute to less heterogeneous beliefs. The last but most important reason is a high proportion of individual investors trading in the Taiwan stock market.[7]Owing to the above-mentioned reasons, Taiwan provides a nature environment to explore the link between internet search activities and the trading activities dominated by individual investors.

Taking a panel regression approach, we find that an increase in SVI is positively related to the number of shares traded by individual investors. The evidence supports the hypothesis that individual investors have a greater information demand and thus tend to use search engines more frequently, consistent with the finding of Da et al. (2011b). We then explore the subsequent

[6] According to Internet World Stats, there were 17,530,000 internet users in Taiwan, representing 75.4% of the population, at mid-year 2012. The Council for Economic Planning and Development (CEPD) also noted that Taiwan's Internet penetration rate is the fourth highest in Asia.

[7] Barber et al. (2009) document that individual investors, occupying about one-third of Taiwan's population and holding more than half of total stock ownership in 2000, dominate the Taiwan market.

trading strategies of individual investors after their collecting information from Internet. We find that changes in SVI are related to a variety of trading activities. Both trading volumes and turnover increase after SVI rises, confirming an increased willingness to trade. These findings are consistent with those of prior empirical studies (Bank et al., 2011; Vlastakis & Markellos, 2012). Moreover, trading volumes of margin purchase and those of day trading also increase after SVI rises, implying that more speculative activities appear after a series of internet search activity. This evidence supports our hypothesis that investors get compelled to conduct risky strategies after obtaining more information about their investment. However, we fail to identify the link between information demand and short selling. One possible reason may lie in the short-selling restraints (Barber & Odean, 2008). Overall, our findings indicate that search volumes on Google can reflect investors' demand for information, and that SVI can predict future trading activities. These results provide some implications for market administrators who need to govern and monitor the trading activity in capital markets.

The rest of the paper is organized as follows. Section 2 presents literature review. Section 3 describes data and sample construction. Section 4 examines whether individual investors have a greater information demand, and explores a wide range of trading activities after internet search activity. Section 5 concludes the paper.

2. Literature Review

Information plays a critical role in the stock trading activity as it influences investors' decision-making, and in turn affects their investment performance (Fama et al., 1969; Akerlof, 1970; Kihlstrom, 1974; Grossman & Stiglitz, 1980; French & Roll, 1986; Allen, 1990). As mentioned above, the Mixture of Distributions Hypothesis (MDH) provides a theoretical foundation on the link between information flow and trading activity such as stock return, market volatility, and

trading volume. Among various measures for trading activity, empirical studies tend to use trading volume as a basic one, because it can directly reflect the degree of investor participation (Karpoff, 1987; Lo & Wang, 2000; Chordia et al., 2001; Chordia et al., 2007). Bessembinder et al. (1996), for instance, have examined the impacts of idiosyncratic and market information using trading volume as a proxy for trading activity. Ryan & Taffler (2004) also find a strong link between firm-specific information releases and trading volume.

Information asymmetry is an important determent that deeply affects trading activity (Akerlof, 1970). Due to information asymmetry, uninformed investors tend to lose wealth in the stock market. The issue has been extensively discussed. Since individual investors have limited accesses to information, they are often viewed as uninformed or noise investors (Kaniel et al., 2008; Foucault et al., 2011). Using account data from a large U.S. brokerage firm, Odean (1999) find that stocks purchased by individual investors generally underperform those they sell. Grinblatt & Keloharju (2000) find similar evidence and suggest that individual investors perform worse than institutional investors because the latter might possess private information. A recent study by Foucault et al. (2011) confirm the poor performance of individual investors and suggested that they tend to trade based on non-informational reasons such as misperception of future returns, shifts in risk aversion, or hedging needs. These findings support the views that individuals are uninformed investors. In contrast, having an information advantage, institutions tend to exploit this asymmetry to gain from uninformed individuals. For example, in a study of the Taiwan market, Barber et al. (2009) find that individual investors are losers whose wealth flows into their informed counterparts, institutional investors, including corporations, dealers, foreign investors, and mutual funds. They conclude that the profits of institutional investors originate from an information advantage over the uniformed.

To reduce information asymmetry, investors naturally demand more information. Uninformed investors, especially individuals, have a greater information demand. Da et al. (2011b) argue that individual investors are more likely to search financial information. Since internet is source of information, individual investors can utilize search engines to collect information from web sites.

Based on the reasoning, Da et al. (2011b) document a strong and direct link between changes in Google search volume and trading by retail investors. Owing to this finding, they conclude that individual investors use Google search engines more frequently than institutional investors, because institutions have access to more sophisticated information services. Similarly, Bank et al. (2011) document a positive relationship between search queries and trading activity and suggest that using search engines helps reduce information asymmetry, resulting in increased individuals' willingness to invest. Their findings indicate that the entry of these individual investors not only contributes to a broader ownership of a firm but also improves the liquidity of its stock, as predicted by Amihud & Mendelson (2006). Vlastakis & Markellos (2012) also document a positive link between Google search volume and trading volume after studying 30 stocks traded on the NYSE. Put together, individual investors are found to be the main users of Google search engines, when compared with other types of investors. One possible reason is to reduce the information asymmetry. Trading volume and liquidity were also found to increase after SVI rises. However, the link between SVI and other types of trading activities, such as regular cash trading, margin buying, short selling, and day trading has not yet been investigated. Therefore, this study aims to fill the gap.

In addition, information demand varies across regions. People living in different regions have a variety of interests and thus ask for miscellaneous kinds of information. For example, Grinblatt & Keloharju (2001) and Huberman (2001) find that investors prefer to invest in local companies because of their general familiarity with these firms. Likewise, Coval & Moskowitz (2002) document that U.S. portfolio fund managers tend to invest in locally headquartered firms. In a word, investors are found to have a home bias – a preference for the familiar – and are thus inclined to buy their familiar stocks. Investors also prefer to the stocks whose products are commonly seen around them. Driven by home bias, investors are inclined to search for relevant information that exhibits strong locality of reference.

3. Data and Sample Construction

To measure a wide range of stock trading activities, we collect all relevant data from the Taiwan Economic Journal database (TEJ). Since data on margin purchase, short sales, and day trading is not available prior to 2008 from TEJ, the sample is limited to the period from January 2008 to October 2012. We focus on all listed common stocks ever traded on the Taiwan Stock Exchange (TWSE) during this period and thus obtain a sample of 834 common stocks.

Following prior studies (Karpoff, 1987; Lo & Wang, 2000; Chordia et al., 2001; Chordia et al., 2007), we use trading volume in dollars and stock turnover rate as our basic measures for trading activity in the capital market. Specifically, the former is the natural logarithm of the number of shares traded volume multiplied by the respective price, while the latter is the fraction of shares traded relative to the number shares outstanding. Moreover, since investors can trade using either regular cash accounts or brokerage margin accounts, we also consider the ratios of trading volume using cash account and using margin account, respectively, to total trading volume.

To quantify the speculative trading, we primarily employ measures of margin buying, short selling, and day trading. They are ratios of trading volume using margin purchases, short sales, day trading strategies, respectively, to the total trading volume. When examining whether individuals are the main part of investors sending search queries, we employ the ratio of individual trading volume to total trading volume as our dependent variable. However, data about individual trading is unavailable from TEJ. Therefore, we obtain individual trading volume by subtracting institutional trading volume from total trading volume. We convert these measures for daily trading activity into a weekly frequency so as to match the frequency of Google search volume data. Table 1 provides definitions for all variables used in this paper, and Table 2 presents the summary statistics.

For each stock in our sample, we draw the corresponding time series of SVI data from Google Insights for Search.[8] To avoid arbitrariness and assure the

[8] See http://www.google.com.tw/trends/?hl=fil.

reliability of the analysis, we employ each firm's abbreviated name, given by Taiwan Stock Exchange Corporation (TWSE), as the keyword.[9] These abbreviated company names are commonly seen on mass media and official websites, so they are quite recognizable to investors. Since Google Insights designates a certain threshold of traffic for search terms, we obtain SVI data only on 781 common stocks, of which 533 are at weekly frequency.[10] We remove stocks whose abbreviated firm names have a generic meaning or sound indistinguishable.[11] Finally, we collect a total of 119,712 firm-week observations.

In this study, SVI is a primary variable used to measure information demand. In the literature on adaptive expectations, unexpected changes or abnormal deviations have long been considered to possess a greater influence on economic activities. Therefore, we employ ASVI to examine the influence of abnormal changes in SVI on stock trading activities. For comparison purpose, we follow Da et al. (2011b) and define ASVI as the log SVI during the current week minus the log median SVI during the previous 8 weeks. It can be mathematically expressed as

$$ASVI_{it} = log\left(SVI_{it}\right) - log\left[Med\left(SVI_{it\text{-}1}, \cdots, SVI_{it\text{-}8}\right)\right] \tag{1}$$

The median value of SVI during the prior 8 weeks, *Med* ($SVI_{it\text{-}1}$,...,$SVI_{it\text{-}8}$) represents the regular level of information demand during a period. As such, Da et al. (2011b) argue that deviation from the median, or a jump, naturally reflects a surge in SVI. In addition, Da et al. (2011b) suggested that ASVI has some advantages over SVI: it is robust to recent jumps and excludes the influence of time trends and other low-frequency seasonality.

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[9] See http://www.twse.com.tw/en/.

[10] Those with low volume might be inaccessible or might appear in the form of monthly frequency. Moreover, Google Insights does not return a valid SVI for some of our queries. If a term is rarely searched, Google Insights will return a zero value for that ticker's SVI.

[11] Due to ambiguity, SVIs for these stocks are likely to be higher than they should be. For example, the abbreviated firm name for stock code 9928 is "Greater Taipei", which exhibits a geographical meaning. Another example is "Elite" for stock code 2331, which also possesses multiple meanings.

Table 1: Variable Definitions

Variable	Definition
Variables related to Investor Attention	
SVI	Aggregate search frequency from Google Trends based on official abbreviation of company name
ASVI	The log of SVI during the week minus the log of median SVI during the previous 8 weeks
Variables related to Stock Characteristics	
FirmRet	The return of the stock during week t
Volatility	The standard deviation of the daily stock returns of the current week t
LnMV	The natural logarithm of the market capitalization in million
Variables related to Trading Activities	
indTrades	The ratio of individual trading volume to total trading volume
LnVolNTD	Trading volume in NT Dollars; the natural logarithm of the number of shares traded volume multiplied by the respective price
Turnover	The fraction of shares traded relative to the number shares outstanding
TypicalTrading	The ratio of trading volume using cash account to total trading volume
MarginTrading	The ratio of trading volume using margin account to total trading volume
BuyonMargin	The ratio of trading volume using margin purchase to total Trading volume
ShortSelling	The ratio of shorted shares to total trading volume
DayTrading	The ratio of trading volume by day traders to total trading volume

Table 2: Descriptive Statistics of Firm Characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
		Panel A: Stock Characteristics			
LnRet	119712	-0.0506	6.2013	-40.5466	103.2052
Volume	119712	11.8920	2.2043	0.0000	18.0010
Turnover	119712	3.7124	5.1057	0.0010	109.0219
LnMV	119712	8.8810	1.5403	4.3279	14.6737
Volatility	119712	1.9781	1.2512	0.0000	52.2554
		Panel B: Proxy for Attention			
SVI	119712	26.4745	16.4263	0.0000	100.0000
ASVI	119712	0.0176	0.5432	-4.4543	4.6151
		Panel C: Trading Activities			
indTrades	119712	86.6409	15.6959	0.0000	100.0000
MarginTrading	119712	27.7115	17.5474	0.0000	100.0000
TypicalTrading	119712	58.9295	19.7681	0.0000	100.0000
BuyonMargin	115609	18.4179	16.9093	0.0000	100.6400
ShortSelling	115609	0.6709	1.9390	0.0000	70.5900
DayTrading	115609	5.0355	7.4747	0.0000	82.6400

Notes: This table depicts firm characteristics. *LnRet* is the one-week stock return in percent, *Volume* is the trading volume in dollars, *Turnover* is the turnover rate, *LnMV* is the market capitalization in billions of the previous week, and, *Volatility* gives the weekly standard deviation of daily stock returns. *ASVI* is the log of *SVI* during the week minus the log of median *SVI* during the previous 8 weeks. *indTrades* is trading volume by individual investors divided by total trading volumes. *TypicalTrading* and *MarginTrading* are trading volume using cash or margin account, respectively. Both are divided by total trading volumes. *BuyonMargin*, *ShortSelling*, and *DayTrading* are ratios of trading volume of margin purchase, short sales, and day trading to total trading volumes. The estimated panel models employ the within estimator and time-fixed effects for different model specifications.

4. EMPIRICAL RESULTS

4.1 Web Search Behavior and Individual Investors

In this section, we explore what kind of users send queries for abbreviated company names, contributing to the considerable growth in Google search volume (SVI). Since individual investors are constrained to access inside information, in order to ensure better decision making in investment, they need to acquire information from other possible channels. In the so-called information explosion era, rational investors naturally utilize the search engine to gather information. Based on the general observation, an intuitive conjecture is that individual investors are more likely to send these queries than institutional investors, for the later have access to more sophisticated information services (Da et al., 2011b).

To explore whether the SVI for abbreviated firm names reflects the information demand of individual investors in the Taiwan stock market, we examine the relation between internet search activity and trading volume by individual investors. Specifically, we derive weekly trading data of individual investors from TEJ by subtracting institutional trading volume from total trading volume. Then, we use the ratio of shares traded by individual investors to total trading volume as an indicator of individual trading. By observing its variation, we can know the degree of individual investors' market participation. If the ratio rises after an increase in SVI, SVI probably reveals some degrees of information demand of individual investors.

However, individual investors' trading behavior is also affected by many other factors. For example, investors, particularly those employing feedback trading strategies, may make decisions based on past stock performance. For trend chasers, positive price changes are often a buying signal that attracts them to trade. Therefore, past stock performance or expected returns, is a determinant of investors' behavior. The next important consideration is risk, usually measured by stock return volatility. Risk-averse investors prefer to invest in stocks with low volatilities, while others tend to buy highly risky securities for the underlying risk premium. As a result, whether risk attracts or discourages an investor depends on

the attitude and preference. Nevertheless, risk is an essential factor of investors' behavior. The third factor is firm size. Stocks with large market capitalization may inhibit individual investors with limited endowment. Nevertheless, possessing a greater visibility, they may also attract more investors to buy. Therefore, the effect of size on individual investor is ambiguous but can be expected.

To explore whether internet search activity contributes to more shares traded by individual investors, we take a panel regression approach after controlling the above-mentioned factors.[12] Specifically, we include weekly and firm fixed effects in all panel regressions and apply the following model:

$$\begin{aligned} indTrades_{it} &= b_0 + b_1 SVI_{it-1} + b_2 LnRet_{it-1} + b_3 Volatility_{it-1} + b_4 LnMV_{it-1} \\ &\quad + c_i + u_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where $indTrades_{it}$ is the ratio of shares traded by individual investors to total trading volume. $SVI_{it\text{-}1}$ is the proxy for information demand. $LnRet_{it\text{-}1}$, $Volatility_{it\text{-}1}$, and $LnMV_{it\text{-}1}$ are control variables representing stock returns, risk (i.e., standard deviation of stock returns), and firm size for firm *i* at week *t-1*, respectively. Since abnormal changes in SVI has been viewed as a better predictor than SVI (Da et al., 2011b), we also examine $ASVI_{it\text{-}1}$.

Table 3 sets out the estimation results of the eight specifications. Specifications (1)-(4) explain the $indTrades_{it}$ as a function of the lagged Google search volume, and the gradually included control variables: $LnRet_{it\text{-}1}$, $Volatility_{it\text{-}1}$, and $LnMV_{it\text{-}1}$. The coefficients on $SVI_{it\text{-}1}$ are insignificant till all these control variables are included in specification (4). Specifications (5)-(8) include $ASVI_{it\text{-}1}$ instead of using $SVI_{it\text{-}1}$. When we measure the influence of information demand on individual trading without considering other factors, we find that a 1% increase in $ASVI_{it\text{-}1}$ leads to a 0.184% increase in individual investor trading (regression 5). The results are quite robust even after we control for other related variables, as shown in specifications (6)-(8). In sum, these empirical results support the hypothesis that SVI measures the information demand of individual investors. We

[12] Trading volume and turnover rate also play an important role in investors' decisions in investment. Both are found affected by SVI in section VI. For clarity, we do not show results including these variables in this section.

infer that internet search volume is positively related to individual investor trading. The rise in individual trading is most likely due to a reduction in asymmetric information costs. The results of the panel regressions confirm prior findings (Bank et al., 2011; Da et al., 2011b).

With regard to the control variables, as shown in Table 3, the row labeled $LnRet_{it\text{-}1}$ indicates a significant interdependence between lagged stock returns and individual trading. This suggests that individual investors on average are positive feedback traders. The finding is quite robust in all reported specifications. However, past stock performance alone is not a decisive factor. Risk also plays an important part, for $Volatility_{it\text{-}1}$, the lagged standard deviation of returns, has significantly positive explanatory power for the individual trading measure. Finally, the estimation results suggest a negative relationship between market capitalization ($LnMV_{it\text{-}1}$) and individual trading. Accordingly, individual investors are more likely to buy smaller stocks. One possible reason may be limited endowment of individual investors. Moreover, as shown in specifications (4) and (8), inclusion of $LnMV_{it\text{-}1}$ dramatically increases the explanatory power (see R-square), suggesting that market capitalization is a crucial factor in affecting individual investors' security selection.

4.2 Web Search Behavior and Trading Activities

In this section, we examine whether internet search behavior possesses an effect on trading activity. Particularly, we focus our empirical analysis on speculative activities such as margin trading, short selling, and day trading. To conduct such risky strategies, risk-averse investors need information to ensure their analyses and to strengthen their expectations. Moreover, calibration literature has found that individuals tend to overestimate the precision of their information.[13] In the sense, more investors are expected to trade in the stock market after they collect information from web sites regardless of the validity of information. With search volume on Google (SVI), we obtain the opportunity to examine the relation between information demand and speculation.

[13] See Lichtenstein et al. (1977).

Table 3: Panel Estimations of Individual Trading Volume Controlling for Firm Characteristics

VARIABLES	*indTrades*$_{it}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	86.57***	86.60***	85.99***	113.70***	86.76***	86.77***	86.11***	113.70***
	(0.60)	(0.60)	(0.62)	(2.29)	(0.54)	(0.54)	(0.57)	(2.30)
SVI_{it-1}	0.01	0.01	0.00	0.02***				
	(0.01)	(0.01)	(0.01)	(0.01)				
$ASVI_{it-1}$					0.18***	0.15***	0.13***	0.13***
					(0.05)	(0.05)	(0.05)	(0.05)
$LnRet_{it-1}$		0.09***	0.09***	0.10***		0.09***	0.09***	0.10***
		(0.00)	(0.00)	(0.01)		(0.01)	(0.01)	(0.01)
$Volatility_{it-1}$			0.33***	0.15***			0.33***	0.16***
			(0.05)	(0.04)			(0.05)	(0.04)
$LnMV_{it-1}$				-3.14***				-3.09***
				(0.27)				(0.27)
Observations	119,189	119,189	119,189	119,189	119,189	119,189	119,189	119,189
Clusters (firms)	523	523	523	523	523	523	523	523
Prob > chi2	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00
σ_e	9.53	9.51	9.50	9.44	9.53	9.51	9.50	9.44
σ_u	12.37	12.31	12.15	6.71	12.38	12.32	12.15	6.70
rho	0.63	0.63	0.62	0.34	0.63	0.63	0.62	0.34

Notes: This table depicts the coefficients of weekly panel regressions of individual trading on lagged Google search volume and selected control variables. The dependent variables are $indTrades_{it}$. The estimated panel models employ the within estimator and time-fixed effects for different model specifications. SVI_{it} shows the weekly value of the Google Insights search volume, $ASVI_{it}$ is the log of SVI_{it} during the week minus the log of median SVI during the previous 8 weeks, $LnRet_t$ is the one-week stock return in percent, $Volatility_{it}$ is the weekly standard deviation of daily stock returns, and $LnMV_{it}$ is the natural logarithm of the market capitalization in thousands at week-end. P-values based on robust standard errors are given in parentheses. *, **, *** denote 10%, 5% and 1% significance levels.

Following prior studies, we first adopt weekly trading volume and share turnover as primary measures of trading activity (Karpoff, 1987; Lo & Wang, 2000; Chordia et al., 2001; Chordia et al., 2007). To observe speculative activities, we consider margin buying, short selling, and day trading. For comparison purpose, we also examine typical cash trading and margin trading. The number of searches for abbreviated company names on Google serves as a proxy for information demand (or web search behavior) in this study. To investigate the relation between information demand and stock trading activities, we take a panel regression approach, controlling for other well-known determinants.

Specifically, we model trading activity as a function of information demand and other control variables, as shown in Equation (3),

$$\begin{aligned} TradingActivity_{it} &= c + b_1 ASVI_{it-1} + b_2 LnRet_{it-1} + b_3 Volatility_{it-1} + b_4 LnMV_{it-1} \\ &\quad + c_i + u_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where the dependent variable *TradingActivity* may represent trading volume in dollars (*Volume*), turnover rate (*Turnover*), cash trading (*TypicalTrading*), margin trading (*MarginTrading*), margin buying (*BuyonMargin*), short selling (*ShortSelling*), and day trading (*DayTrading*). One independent variable of main interest is $ASVI_{it\text{-}1}$, which represents a surge in information demand. The control variables are all one-week lagged and include the weekly stock return in percent $LnRet_{it\text{-}1}$, the weekly standard deviation of daily returns $Volatility_{it\text{-}1}$, and the week-end natural logarithm of the market value $LnMV_{it\text{-}1}$. c_i stands for entity-fixed effects (i.e., the within estimator), which account for unknown time-constant firm-specific factors, while the time-fixed effects u_t control for macroeconomic influences.

As trading volume in dollars has been a very obvious and basic measure for trading activity (Karpoff, 1987; Lo & Wang, 2000; Chordia et al., 2001; Chordia et al., 2007), we first explore how trading volume in dollars varies with SVI. Reduction in information asymmetry tends to result in improved liquidity. Accordingly, we expect an increase in trading volume after SVI rises. Specification (1) in Table 4 shows a significantly positive relation between *Volume* and *ASVI*. Therefore, abnormal rises in information demand is associated with increases in

trading volume. This implies: with more information, investors are more willing to trade. We attribute the increased trading volume to a reduction in uncertainties due to more information. The evidence supports that of Bank et al. (2011).

The other basic but important measure of trading activity is the stock turnover rate, which is also commonly employed by Lo & Wang (2000) and Chordia et al. (2007). Intuitively, turnover can be interpreted as the reciprocal of the average holding period, implying that stocks with a higher turnover rate are on average held for shorter time intervals. Granger & Morgenstern (1970) consider share turnover to be a proxy of speculative activity. Specification (2) shows that greater increases in SVI significantly help improve the turnover rate. In other words, the liquidity of stocks with a large signed change in attention improves significantly. The links of SVI to trading volume and turnover rate found here are consistent with Bank et al. (2011).

Trading through cash and stocks is a typical way. In addition, investors can trade using brokerage margin accounts. Margin trading or leveraged trading exogenously supplies liquidity and, with the additional liquidity, accelerates price discovery process, which in turn promotes market efficiency. Consequently, accurate and continuous price discovery generally makes resource and risk reallocation efficient. However, trading using leverage is risky and costs much. A rational investor requires more information to conduct leveraged trading strategies. Therefore, he might collect relevant information from internet so as to make accurate decisions. Accordingly, we expect more shares traded through margin accounts after SVI increases. Specifications (3)-(4) show changes in volume through cash trading (*TypicalTrading*) and leverage trading (*MarginTrading*), respectively. The coefficient on *ASVI* in specification (4) is found positive and significant, while that in (3) is insignificant. Therefore, we find that investors tend to trade using margin accounts after they collect information from the internet. This suggests that with more information, investors are more willing to perform risky strategies using leverage.

Moreover, margin trading includes buying on margin (*BuyonMargin*) and short selling (*ShortSelling*), which are shown in specifications (5) and (6), respectively. *BuyonMargin* (*ShortSelling*) is computed through dividing the volume

of margin purchase (short sales) by total trading volume of stock *i*. Buying on margin (i.e., borrowing money from a broker to purchase stock) allows investors to buy more than his capacity but is associated with interest payments. As debt increases, the interest charges increase. So, it is mainly used for short-term investments and can be viewed as a sign of speculative activity. In comparison, short selling can be interpreted as a proxy for investor sentiment, since higher values are associated with more pessimism. According to the attention theory of Barber & Odean (2008), stocks with more investor attention are likely to experience positive price pressures. Therefore, we expect more trading volume of margin purchase than short sales. Comparing specifications (5) and (6), we find that more investors buying on margin than selling short, consistent with the attention theory of Barber & Odean (2008).

Day trading refers to buying and selling the same stocks within a single trading day. Since it has been regarded as a quick way to acquire wealth with limited funds, and promoted by numerous books and advertisements as a shortcut to early retirement, day trading gains noticeable popularity among speculators and attracts many individual investors to engage in such a speculative practice. In Taiwan, day trading is prevalent as well. Specification (7) shows the relation between day trading and SVI. Since the coefficient on *ASVI* is significantly positive at the 1% level, we find that an increase in search queries is associated with a rise in day trading. In other words, intense day trading activity tends to emerge after a series of internet search activities. Although it may be risky, information collected from Google strengthen day traders' belief which drives them to trade in uncertainties.

In summary, we find that internet search behavior contributes to the rise in the volume of speculation. Therefore, we conclude that SVI not only captures Internet user attention, but is also related to a variety of trading activities.

Table 4: Panel Estimations of Trading Activities Controlling for Firm Characteristics

SPECIFICATIONS	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	$Volume_{it}$	$Turnover_{it}$	$TypicalTrading_{it}$	$MarginTrading_{it}$	$BuyonMargin_{it}$	$ShortSelling_{it}$	$DayTrading_{it}$
Intercept	-1.17***	-12.74***	106.00***	6.58	-26.80***	-4.05***	-8.71***
	(0.44)	(1.21)	(4.36)	(4.65)	(5.66)	(0.64)	(1.21)
$ASVI_{it-1}$	0.05***	0.31***	-0.08	0.21**	0.20***	0.044	0.12***
	(0.00)	(0.04)	(0.08)	(0.08)	(0.07)	(0.03)	(0.04)
$LnRet_{it-1}$	0.02***	0.13***	0.00	0.10***	-0.01*	0.01***	0.05***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
$Volatility_{it-1}$	0.21***	0.76***	-1.30***	1.46***	0.61***	0.15***	0.76***
	(0.01)	(0.03)	(0.11)	(0.11)	(0.08)	(0.01)	(0.04)
$LnMV_{it-1}$	1.43***	1.70***	-4.92***	1.96***	4.94***	0.50***	1.38***
	(0.05)	(0.14)	(0.49)	(0.52)	(0.66)	(0.07)	(0.14)
Observations	119,189	119,189	119,189	119,189	115,172	115,172	115,172
Clusters (firms)	523	523	523	523	515	515	515
Prob > chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
σe	0.91	4.08	13.50	12.92	9.03	1.62	6.43
σu	0.86	2.34	10.76	11.86	12.71	1.05	2.66
rho	0.47	0.25	0.39	0.46	0.66	0.29	0.15

Notes: This table depicts the coefficients of weekly panel regressions of $TradingActivity_{it}$ on lagged Google search volume and selected control variables. The dependent variables include $Volume_{it}$, the trading volume in dollars, $Turnover_{it}$, the turnover rate. Moreover, $TypicalTrading_{it}$ and $MarginTrading_{it}$ are trading volume using cash or margin account, respectively. Both are divided by total trading volumes. $BuyonMargin_{it}$, $ShortSelling_{it}$, and $DayTrading_{it}$ are ratios of trading volume of margin purchase, short sales, and day trading to total trading volumes. The estimated panel models employ the within estimator and time-fixed effects for different model specifications. $ASVI_{it-1}$ is the log of *SVI* during the week minus the log of median *SVI* during the previous 8 weeks, $LnRet_{it}$ is the one-week stock return in percent, $Volatility_{it}$ is the weekly standard deviation of daily stock returns, and $LnMV_{it}$ is the natural logarithm of the market capitalization in thousands at week-end. P-values based on robust standard errors are given in parentheses. *, **, *** denote 10%, 5% and 1% significance levels.

5. Conclusions

To conclude, the present study has investigated the relationship between information demand and stock trading activity, but its relevance to web search behavior of individual investors can also be seen. When examining the effect of information demand, prior studies encounter difficulties in measuring the invisible information demand. To overcome the problem, this study uses Google Search Volume Index (SVI) as a proxy for information demand.

Our findings as to the role of information in trading activities are consistent with prior studies (Bank et al., 2011; Da et al., 2011a, 2011b; Mondria & Wu, 2011; Choi & Varian, 2012). Specifically, we find SVI exhibits significant and positive associations with trading volume, turnover rate, individual trading, margin trading, and day trading. The finding that trading volume of individual investors increases after SVI rises indicates that individuals might be the primary investors who utilizes search engines to collect information. This finding also supports the hypothesis that individual investors have a greater demand for information in order to reduce information asymmetry. Meanwhile, speculative activities such as margin trading, and day trading also increases after SVI rises, implying that individual investors tend to conduct speculative trading strategies after collecting information. The evidence supports the general observation that individual investors are disposed to trade out of speculative motives (Kumar & Lee, 2006; Dorn et al., 2008; Kaniel et al., 2008; Foucault et al., 2011).

Trading activity in capital markets affect asset allocation as well as fund flows, and thus plays a critical role in a nation's economic development. Accordingly, how to monitor the trading activity has been a concern for market administrators, particularly when individual investors dominate the capital market, as they tend to engage in the speculative trading activities that deeply influence market stability (Kumar & Lee, 2006; Dorn et al., 2008; Kaniel et al., 2008; Foucault et al., 2011). However, market administrators might lack an efficient indicator that can predict the trading activities by individual investors. Our findings demonstrate that SVI is linked with individual trading, leverage trading, and day trading. These results indicate that SVI can be considered in monitoring the stock trading activities.

This study has explored main issues concerning the relationship between information demand and primary stock trading activities. However, much remains to be answered because of several limitations to this study. First, SVI may reflect only parts of the aggregate demand for information because investors have other sources of information in addition to Internet. Therefore, the influence of SVI on stock trading activities might be somewhat related to the popularity of Google search engines. Second, as SVI is a relatively novel variable, related knowledge and researches are quite limited. Although this study follows Da et al. (2011b) and Vlastakis & Markellos (2012) to treat this new variable, the our results largely depend on the validity of the SVI-based measures. Therefore, more future researches on the nature of SVI should be helpful.

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