Google Trends and Cognitive Finance: Lessons Gained from the Taiwan Stock Market

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Abstract. We investigate the relationship between Google Trends Search Volume Index (SVI) and the average returns of Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). In particular, we used the aggregate SVI searched by a company's abbreviated name and by its ticker symbol to conduct our research. The results are very different. While the aggregate SVI of abbreviated names is significantly and positively correlated to the average returns of TAIEX, the aggregate SVI of ticker symbols is not. This gives strong evidence that investors in the Taiwan stock market normally use abbreviated names, not ticker symbols, to conduct Google search for stock information. Additionally, we found the aggregate SVI of small–cap companies has a higher degree of impact on the TAIEX average returns than that of the mid–cap and large–cap companies. Finally, we found the aggregate SVI with an increasing trend also has a stronger positive influence on the TAIEX average returns than that of the overall aggregate SVI, while the aggregate SVI with a decreasing trend has no influence on the TAIEX average returns. This supports the attention hypothesis of Odean [12] in that the increased investors attention, which is measured by the Google SVI, is a sign of their buying intention, hence caused the stock prices to increase while decreased investors attention is not connected to their selling intention or the decrease of stock prices.

Keywords: Google Trends · Investors attention · TAIEX
Cognitive finance · Search volume index · Attention hypothesis
Stock returns

1 Introduction

Investors' attention plays an important role in their buying decisions [12] and in stock pricing [11]. When buying a stock, investors are faced with a large number of choices. Since human beings have bounded rationality [14], the cognitive and temporal abilities of an investor to process stocks related information are limited. To manage this problem of choosing among many possible stocks to purchase,

E. Bucciarelli et al. (Eds.): DCAI 2018, AISC 805, pp. 114–124, 2019.
https://doi.org/10.1007/978-3-319-99698-1_13

Odean [12] proposed that investors limit their choices to stocks that have recently caught their attention. When selling stocks, however, attention has no effect, because investors tend to sell stocks that they own. In [3], Barber and Odean validated this attention hypothesis empirically using indirect attention measures, including news, high abnormal trading volume, and extreme one–day returns.

When attention–grabbing stocks are the subjects of buying interests, the buying pressure would drive these stocks' prices upward. Using Google Trends Search Volume Index (SVI) as a direct measure of investors' attention, Da, Engelberg and Gao [7] sampled Russell 3000 stocks and found that the increase in the SVI could predict higher stock prices in the short term and price reversals in the long run. The positive correlation between Google SVI and stock returns has also been observed in the S&P 500 stocks [8], and the stocks traded in the German [2] and the Japan [16] stock markets.

In this paper, we investigate the relationship between Google SVI and the average returns of *Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX)*. Unlike previous works which first modeled the relationship between Google SVI and an individual stock's returns and then aggregated the results, we first aggregated the SVI of all companies included in TAIEX and then modeled the relationship between the aggregate SVI and the TAIEX average returns. Since TAIEX is a capitalization weighted index, we used capitalization as the weight to aggregate the SVI of each company.

In our study, we used the aggregate SVI of a company's abbreviated name and of its ticker symbol to conduct our research. We found they give different results. The aggregate SVI of abbreviated names is significantly and positively correlated to the average returns of TAIEX, which is similar to that reported in previous works [2,7,8] and [16]. By contrast, the aggregate SVI of ticker symbols has no impact on the TAIEX average returns. This gives strong evidence that investors in the Taiwan stock market normally use abbreviated names, not ticker symbols, to conduct Google search for stock information.

Additionally, we found the aggregate SVI of small–cap companies has a higher degree of impact on the TAIEX average returns than that of the mid–cap and large–cap companies. This result is similar to that of Russell 300 stocks [7] but is different from the result of stocks traded in the German stock market [2].

Finally, we found the aggregate SVI with an increasing trend, i.e. $SVI_t > SVI_{t-1}$, has more positive impact on the TAIEX average returns than the overall aggregate SVI has. Moreover, the aggregate SVI with a decreasing trend, i.e. $SVI_t \leq SVI_{t-1}$, has no effect on the TAIEX average returns. These combined results support the attention hypothesis of Odean [12], which states that investors' attention only influences their stock buying decisions, not stock selling decisions. Using Google SVI as a proxy of investors' attention, an increased SVI is a sign of buying intention, which would lead to possible stock prices increase. By contrast, selling intention has no influence on the Google SVI, hence, a decreased SVI is not directly connected to the decrease of stock returns.

The rest of the paper is organized as follows. Section 2 summarizes related works. Section 3 explains the data and methods used to conduct our research.

The results are then presented and analyzed in Sect. 4. Finally, Sect. 5 gives our concluding remarks.

2 Related Works

Google Trends (`trends.google.com/trends/`) provides data on search term frequency dating back to January of 2004. The search frequency is normalized to an index called *Search Volume Index* (SVI) such that the highest search frequency within the search period has index value 100 and the rest of the frequencies have index between 0 and 100. To search information about a stock on Google, a user can enter either its ticker symbol or the company name. In [7], Da, Engelberg, and Gao used ticker symbols of Russell 3000 stocks as search keywords to obtain their SVIs for the period of 2004–2008. They then ran Vector Autoregression (VAR) model for each stock's *abnormal SVI* on the stock's following week *abnormal returns*. After that, they averaged the VAR coefficients across all stocks. The p–value is also computed using a block bootstrap procedure under the null hypothesis that all VAR coefficients are zero. Their results showed that the abnormal SVI can positively and significantly predict the abnormal returns over the next two weeks and the predictive power of abnormal SVI is stronger among smaller stocks.

Joseph, Babajide Wintoki and Zhang also used the ticker symbols of S&P 500 stocks to obtain their SVIs from 2005–2008 to conduct research [8]. They first sorted these SVIs into 5 portfolios, from the highest SVI to the lowest SVI. They then compared the stocks' following week's *abnormal returns* in the 5 portfolios. They found that there is a monotonic increase of abnormal stock returns from the lowest SVI portfolio to the highest SVI portfolio.

While SVI based on the ticker symbol of a stock might reveal investors' attention on the stock more closely, Bank, Larch, and Peter [2] are interested in the question of how public interest in a firm influences stock market activity. For that purpose, they studied the stocks traded in the German stock market by using their company names given by the Thomson Reuters Datastream as the search keywords to obtain their SVIs from 2004 to 2010. Using a similar portfolio–based analysis in [8] with 3 portfolios, they found a moderate relation between the *change of SVI* and the stock's next month *excess returns*. However, after incorporating market capitalization of the stock to refine the original 3 portfolios into 9 portfolios, they found that the portfolio of stocks with a large *change of SVI* and large market capitalization has much higher next month returns than that of the portfolio of stocks with a small *change of SVI* and small market capitalization.

For the Japan stock market, Takeda and Wakao [16] also used company names as keywords to obtain the SVIs of 189 stocks included in the Nikkei 225 from 2008 to 2011. They divided the SVIs into 4 portfolios using three criteria: SVI in [8], *change of SVI* in [2] and *abnormal SVI* in [7]. They observed that the *change of SVI* values can be positive or negative while the *abnormal SVI* values are more stable and smooth. Their analysis showed that under the grouping strategies of [2] and [7], the portfolio with the highest SVI has the largest next week abnormal returns.

Similar researches have also been conducted for stocks traded in other stock markets, such as NASDAQ & NYSE [18], France [1] and Turkey [17].

There are also works investigating the relationship between asset indexes performance and Google SVI, searched by the index names. For example, Vozlyublennaia [19] studied a set of six asset indexes, including Dow Jones Industrial Average (DJIA) index, NASDAQ index, S&P 500 index, the 10 year Treasury index, the Chicago Board Options Exchange Gold index and the West Texas Intermediate crude oil index. He found the increased attention to an index has a significant short-term effect on the index's return. However, the price pressure can be either positive or negative, depending on the nature of the information uncovered by the Google search. This result is different from that of previously mentioned works [2,7,8,16], which endorsed Odean's attention hypothesis that retail investors are more likely to buy than sell a security that attracts their attention, hence investors' attention normally creates positive price pressures.

Another work is by Latoeiro, Ramos and Veiga [10], who studied the EURO STOXX 50 index performance related to the Google SVI searched by EURO STOXX. Their results show that an increase in SVI for the index predicts a drop in the market index, which is different from that of the U.S. market indexes reported in [19]. Also, the SVI with an increasing trend is statistically significant in impacting the index returns but the SVI with a decreasing trend is not.

In addition to stock prices, Google SVI has also been used to predict the prices of digital currencies. In [9], Krištoufek reported that there is a very strong bidirectional positive correlation between the price of BitCoin and the SVI searched by "BitCoin". He found that when the interest in the BitCoin currency, measured by the Google SVI, increases, so does its price. Similarly, when the BitCoin price increases, it generates more interest of the currency not only from investors but also from the general public. This is not surprising since there is no macroeconomic fundamentals for the digital currency and the market is filled with short-term investors, trend chasers, noise traders and speculators. Additionally, it is quite easy to invest in BitCoin as the currency does not need to be traded in large bundles. Consequently, the Google SVI of the digital currency influences the price of the digital currency and vice visa. However, these bidirectional effects are short-lived for two periods (weeks) only.

Google SVI has also been used to build currency exchange rate models to perform forecasting. The key ingredients of these models are macroeconomic fundamentals, such as inflation, which are normally released by government with a monthly time lag. In [4], Bulut used Google SVI of related keywords to nowcast these fundamentals to built two currency exchange rate models. The results indicate that inclusion of the Google Trends-based nowcasting values of macro fundamentals to the current set of government released-macro-economic variables improve the out-of-sample forecast of Purchasing Power Parity model in seven currency pairs and of Monetary model in four currency pairs.

In [13], Preis, Moat & Stanley incorporated Google search volume to devise the following trading strategies:

```
if ΔSVI(t − 1, Δt) > 0
    sell at the closing price p(t) on the first
    trading day of week t and buy at price p(t − 1) at the end
    of the first trading day of the following week
if ΔSVI(t − 1, Δt) < 0
    buy at the closing price p(t) on the first trading day
    of week t and sell at price p(t+1) at the end of the
    first trading day of the coming week
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where $\Delta SVI(t-1, \Delta t) = SVI(t-1) - MA_{SVI}(t-2, \Delta t)$, $MA_{SVI}(t-2, \Delta t)$ is the Δt weeks moving average of Google SVI between weeks $t-2$ and $t-2-\Delta t$.

They tested the strategies using a set of 98 search keywords on the DJIA index from 2004 to 2011 under $\Delta t = 3$. They found that the overall returns from the strategies are significantly higher than the returns from the random strategies. Among them, the SVI of the search keyword *debt* gives the best performance of 326% profit, which is much higher than the 33% profit yield by the historical pricing strategy (replacing SVI with the DJIA prices in the above strategies) and the 16% profit produced by the "buy and hold" strategy.

The predictive power of Google Trends data for the future stock returns has also been challenged. In [6], Challet and Ayed applied non-linear machine learning methods and a backtest procedure to examine if the Google SVI data contain more predictive information than the historical price returns data. They downloaded SVI data searched by company tickers and names from 2004 to 2013-04-21. They also obtained historical pricing data for the same testing period. After processing the two sets of data, their backtest system shows that both data give similar accumulative returns, after transaction costs. The authors believe that SVI data share many similar properties with the price returns: (1) both are aggregate signals created by many individuals; (2) they reflect something related to the underlying assets, (3) both are very noisy. Consequently, the backtest system found them contain about the same amount of predictive information.

3 Research Methods

3.1 TAIEX Weekly Average Open Prices

TAIEX is the capitalization–weighted index of companies that are traded in the *Taiwan Stock Exchange (TWSE)*. From the website of *Taiwan Economic Journal (TEJ)*, a database that contains historical financial data and information of the major financial markets in Asia, we downloaded TAIEX *weekly average opening prices* between January 5, 2014 and November 6, 2016.

3.2 Aggregate Google SVI Variable

Two sets of SVI data were downloaded from Google Trends using two sets of search terms. The first set consists of the *abbreviated names* of 849 companies traded on TWSE and the second set contains the *ticker symbols* of these companies. The following subsections explain the data processing procedures.

Abbreviated Names. A stock traded on TWSE has an abbreviated name to represent the company. For example, 台積電 is the abbreviated name for 台灣積體電路製造股份有限公司. We retrieved the SVI in the Taiwan region using the abbreviated name of each company traded on TWSE from January 5, 2014 to November 6, 2016. However, we found some small-cap companies have some weekly SVI data missing. In addition, some abbreviated names are common terms that may be used by non-investors to conduct Google search for non-investment related information. In these two situations, we replaced the search results with the results obtained using their ticker symbols. The total number of stocks whose SVI have been replaced under this process is 49.

To aggregate the 849 SVIs into a single index, we used a weighted sum approach, where the weight is the company size, represented by its relative percentage of market value on November 18, 2016. The information was obtained from the website of *Taiwan Futures Exchange*. This approach is based on the following assumptions:

- Each search volume is independent. Increased attention on one stock will not influence others.
- The higher a company's market value is, the more attention the company receives and hence the higher the search volume.
- The companies that constitute TAIEX remain unchanged.

The aggregate SVI time series contains 146 weeks of data.

Ticker Symbols. A stock traded on TWSE also has a ticker symbol. For example, the ticker symbol of 台積電 is 2330. We first used the ticker symbol of each stocks to retrieve their SVIs. Next, we used the same procedures described in the previous section to obtain the aggregate SVI. The time series also has 146 weeks of data.

3.3 Econometric Method

Newey–West correction of standard error is a method to estimate the coefficients of a linear regression model applied to time series data. It is used to correct *autocorrelation* (also called serial correlation) and *heteroskedasticity* in the error terms in the regression model. We applied the method implemented in the statistical software SAS to generate our linear regression models.

Following [7], we first converted all time series data into natural logarithm (ln). In this way, coefficients on the natural–log scale are directly interpretable as approximate proportional changes. For example, with a coefficient of 0.06, a change of 1 in the independent variable corresponds to an approximate 6% change in the dependent variable. Moreover, the transformation reduces the scale difference of the variables, hence increases model prediction accuracy.

The linear regression model is as follows:

$$R_t = \beta_0 + \beta_1 \Delta svi_{t-1} + \epsilon_t \tag{1}$$

where $R_t = ln(p_t) - ln(p_{t-1})$, p_i is the TAIEX price on week i, and $\Delta svi_{t-1} = ln(SVI_{t-1}) - ln(SVI_{t-2})$, which is the *change of SVI* in [8]. We used the aggregate SVI of abbreviated names and of ticker symbols to run the regression. The results are compared in Sect. 4.1.

Next, we are interested in knowing if the Δsvi of companies with different capitalization has a different degree of impact on the TAIEX average returns. To answer that question, we ran the following four linear regression models:

$$\begin{aligned} R_t &= \beta_0 + \beta_1 \Delta svi_{large,t-1} + \epsilon_t \\ R_t &= \beta_0 + \beta_2 \Delta svi_{middle,t-1} + \epsilon_t \\ R_t &= \beta_0 + \beta_3 \Delta svi_{small,t-1} + \epsilon_t \\ R_t &= \beta_0 + \beta_4 \Delta svi_{rest,t-1} + \epsilon_t \end{aligned} \tag{2}$$

where the subscript *large* stands for *large–cap* (top-50 companies), *middle* stands for *mid–cap* (top–51 to top–150 companies), *small* stands for *small–cap* (top–151 to top–450 companies) [15] and *rest* stands for the rest 399 companies. We also used both aggregate SVI of abbreviated names and of ticker symbols to run the regression. The results are presented in Sect. 4.2.

According to Odean [12], investors' attention only impacts their stock buying decisions, not stock selling decisions. Using Google SVI as a proxy of investors' attention, this means that an increased SVI is a sign of buying intention, which leads to possible stock prices increase. By contrast, selling intention has no impact on the Google SVI. Hence, a decreased SVI is not directly connected to the decrease of stock returns.

To test this hypothesis, we divided the aggregate SVI into two groups: one with an increasing trend, i.e. $SVI_t > SVI_{t-1}$, and the other with a decreasing trend, i.e. $SVI_t \leq SVI_{t-1}$. We then used the two aggregate SVIs to run the linear regression model of Eq. 1. The results are analyzed in Sect. 4.3.

4 Results and Analysis

4.1 Abbreviated Names vs. Ticker Symbols

Table 1 shows that the Δsvi of abbreviated names is statistically significant in impacting TAIEX average returns while the Δsvi of ticker symbols is not. This suggests that investors in the Taiwan stock market normally use abbreviated names, not ticker symbols, to conduct Google search for stock information. This makes sense, as the ticker symbols of Taiwanese stocks are 4–digit numerical values, which could be confused as product numbers, specific year, phone extension or other meaning by the Google search engine, hence produces irrelevant search results. By contrast, abbreviated names are less ambitious and are easily linked to the company stocks that a Google user is searching for. Consequently, investors are more likely to use abbreviated names, rather than ticker symbols, to search for stock information to obtain relevant results. This discovery of investors' behaviors supports the belief that Google search data have the potentials to reveal people's interests, intentions and possible future actions [5].

Table 1. Δsvi (Abbreviated Names & Ticker Symbols) on TAIEX Average Returns

	Abbreviated Names				Ticker Symbols			
Parameter	Estimate	Std Err	t	p-value	Estimate	Std Err	t	p-value
Intercept	0.001057	0.000646	1.64	0.1039	0.001099	0.000652	1.69	0.0940
Δsvi	0.037486	0.0186	2.02	0.0454*	0.011643	0.0136	0.86	0.3922

Notes: $***$, $**$ and $*$ indicate statistical significance at the 0.1%, 1% and 5% levels.

The Δsvi of abbreviated names is positively related to the TAIEX average returns, which is similar to that reported in previous works [2,7,8] and [16].

4.2 Large vs. Middle vs. Small Capitalization

Table 2 shows the aggregate SVI of *abbreviated names* for *large–cap*, *mid–cap* and *small–cap* companies are all significant in impacting the TAIEX average returns. Additionally, their coefficients show the aggregate SVI of *small–cap* companies has a larger impact on the TAIEX average returns than that of the *mid–cap* and the *large–cap* companies: increasing the value of Δsvi_{small}, Δsvi_{mid} and Δsvi_{large} by 1 will increase the TAIEX average returns by 0.075961, 0.072652 and 0.062965 respectively. This result is similar to that of the Russell 300 stocks [7] but is different from the stocks traded in the German stock market [2].

Table 2. Δsvi for Companies of Different Capitalization on TAIEX Average Returns

	Abbreviated Names				Ticker Symbols			
Parameter	Estimate	Std Err	t	p-value	Estimate	Std Err	t	p-value
Intercept	−0.00087	0.00102	−0.85	0.3982	0.000398	0.00106	0.38	0.7074
Δsvi_{large}	0.062965	0.0125	5.05	<.0001***	0.028567	0.0104	2.74	0.0079**
Intercept	−0.00051	0.00123	−0.41	0.6813	0.000661	0.00134	0.49	0.6231
Δsvi_{mid}	0.072652	0.0202	3.60	0.0006***	0.014188	0.0208	0.68	0.4978
Intercept	−0.00126	0.00120	−1.05	0.2969	−0.00063	0.00125	−0.50	0.6157
Δsvi_{small}	0.075961	0.0226	3.36	0.0013**	0.027574	0.0139	1.99	0.0502
Intercept	0.001918	0.00168	1.14	0.2578	0.002607	0.00147	1.78	0.0802
Δsvi_{rest}	0.048907	0.0440	1.11	0.2705	0.008281	0.0243	0.34	0.7345

Notes: $***$, $**$ and $*$ indicate statistical significance at the 0.1%, 1% and 5% levels.

The aggregate SVI of *ticker symbols* for the *large–cap* companies is also significant in impacting the TAIEX average returns, although the degree (coefficient) of its impact is much lower than that of the aggregate SVI of *abbreviated names*. This means that investors also use the ticker symbols of large–cap companies to conduct Google search for large–cap companies stock information. This also makes sense because stocks of large–cap companies are traded more often; hence their ticker symbols are easily associated with their companies by the Google search engine to generate relevant search results. Furthermore, investors tend to remember the tickle symbols of more frequently traded stocks. These explain why the aggregate SVI of ticker symbols for the large–cap companies is significantly correlated to the TAIEX average returns.

4.3 Validation of the Attention Hypothesis

Section 4.1 shows the aggregate SVI of abbreviated names is positively and significantly correlated to the TAIEX average returns. In this section, we used this SVI data to validate the attention hypothesis of Odean [12]. As shown in Table 3, there are 66 weeks of data in this aggregate SVI that have an increasing trend. Similar to the entire 146 weeks of data, these increasing trend data are also positively and significantly correlated to the TAIEX average returns. However, the increasing trend data have more positive impact (larger coefficient) and more significant impact (smaller p–value) on the TAIEX average returns. By contrast, the 80 weeks of decreasing trend data have no impact on the average returns of TAIEX. The combination of these results supports the attention hypothesis of Odean [12] in that increased investors' attention, which is measured by the Google SVI, is connected to the increased stock prices while decreased attention is not connected to the decrease of stock prices.

Table 3. Δsvi with Increasing/Decreasing Trends on TAIEX Average Returns

	Increasing Trend Data (66 weeks)				Decreasing Trend Data (80 weeks)			
Parameter	Estimate	Std Err	t	p-value	Estimate	Std Err	t	p-value
Intercept	−0.00237	0.00282	−0.84	0.4045	0.004747	0.00269	1.76	0.0818
Δsvi	0.083459	0.0253	3.29	0.0016**	0.037635	0.0244	1.54	0.1265

Notes: $***$, $**$ and $*$ indicate statistical significance at the 0.1%, 1% and 5% levels.

5 Concluding Remarks

Google Trends data have been linked to various economic indicators, including automobile sales, unemployment claims, travel destination planning and consumer confidence [5]. In this study, we investigate the relationship between Google Trends SVI and the average returns of TAIEX. In addition to identifying their significant and positive correlation, similar to that reported in previous works, we also discover that Taiwan investors normally use a company's abbreviated name, rather than its ticker symbol, to conduct Google search for stock related information. We will continue exploring other investors' buying and selling intentions/behaviors by evaluating expanded Google search keywords using other tools such as Google Correlate.

Google SVI of small–cap companies is found to have a stronger impact on the TAIEX average returns than that of the mid–cap and the large–cap companies. This result is similar to that of the Russell 300 stocks but is different from the stocks traded in the German stock market. Why this difference? Is it due to the differences of the two different stock market structures or is it due to other factors? We will address this question in the future.

Acknowledgement. The authors are grateful for the research support in the form of Ministry of Science and Technology (MOST) Grants, MOST 106-2410-H-004-006-MY2.

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