Consumer attention and stock returns

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Acknowledgements

Abstract

We investigate whether consumers attention measured by Google searches for company's names and brands can predict stock returns, volatility and trading volume for smartphone and sporting goods manufacturers. Existing research has utilized Google searches mainly as a measure of investor attention (searches for tickers), while we consider two measures of consumer attention: Google searches for company names and brands. We do not find either of these two attention measures to be related to stock returns or volatility. On the other hand, increased attention predicts decreased trading volume in the subsequent week, no matter whether we considered brand or company searches. We further investigate sporting goods companies and smartphone companies separately and find that the conclusions remain similar.

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1. Introduction

Information technology plays an important role in the development of various sectors of the economy. Currently, the internet is utilized extensively by the users for several purposes, for instance, browsing and collecting information, uploading new information, and most importantly, exploring trends. Researchers have found that it is possible to use internet search data to predict economic statistics since 2005 (Ettredge, Gerdes, & Karuga, 2005) and there have been several other studies that have investigated internet searchers data in various fields. The cost associated with obtaining this data is minor, while this data might become increasingly useful and easily accessible. Thus, the number of searching for attention on internet increases day by day. Several search engines are available to users, such as Yahoo, Bing, and Baidu, but the most frequently used search engine is Google.

Google search engine is the most popular search engine (Johnson, 2021). The search engine and its analyzing tool Google Trends allow to access huge collections of various statistical data from searches. Kulkarni, Haynes, Stough, and Paelinck (2009) found that Google data could improve analyzing of economic activities, the level of accuracy and gives a better prediction for financial forecasting. Data from Google Trends may be associated with present values of various economic indicators such as automobile sales, unemployment requirements, travel purpose planning, and consumer confidence (Choi & Varian, 2011) and it can be used for short-term economic forecasts. Preis, Reith, and Stanley (2010) examined the connection between search volume data and market changes. They found that weekly transaction volumes of S&P 500 firms correlate positively with the weekly search volume of the company names and that the price changes influence search volumes in the coming weeks.

In the finance field, Preis, Moat, and Stanley (2013) observed that Google Trend data consider features of the current state of the economy and provide insight into future trends in the behavior of economic aspects. Nevertheless, another research, such as Challet and Ayed (2014), confirmed that random finance-related keywords are not reliable indicators of exploitable predictive information than other random keywords. Da, Engelberg, and Gao (2011), Dimpfl and Jank (2016), and Goddard, Kita, and Wang (2015) all employed multiple search terms such as company name, stock tickers, and other terms used on stock exchanges, during the process of searching data and investigating the attention of investors. Vlastakis and Markellos (2012) found that information demand directly affects the major stock price fluctuations and trading volume of the thirty largest US stocks.

One way to measure investors' attention is to use Google and analyze the top search results. A problem that may occur, is that companies can pay search engine optimization companies to get higher up on search results. For this reason, investors can have excessive attention to the companies who spends money on these activities which are more visible than non-promoted companies. Several studies have been using search volume index (SVI) as a direct measure of investor attention to avoid this problem. In the case of investment decisions and stock returns, the Google search engine grasps the attention of investors, and it reduces the probability of asymmetric information. Since Google Trends can capture real-time search trends, the data has also been used in other various applications, such as influenza surveillance in South China (Kang, Zhong, He, Rutherford, & Yang, 2013) and predicting sales, open numbers for movies, and ranking of songs (Goel, Hofman, Lahaie, Pennock, & Watts, 2010). However, for economic research studies, Da et al. (2011) were among the first to employ SVI as a measure of investor attention. They observe a positive relationship between SVI and stock prices in the following weeks, in line with the results of Preis et al. (2010). Another study by Joseph, Wintoki, and Zhang (2011) also used SVI as a measure of investor sentiment.

Nevertheless, most recent finance literature uses Google Trends as a measure of investor attention, where they often use tickers as keywords. Tickers are the symbol for the publicly traded companies, and sometimes they are not very descriptive. For instance, searching for the ticker "SAN" will give all kinds of search results instead of their company name, Banco Santander. This is because "SAN" has many different meanings. Bijl, Kringhaug, Molnár, and Sandvik (2016) found that a meaningful and negative correlation exists between weekly abnormal search volumes and following stock returns. They assume that company name searches have a more powerful relationship to stock market returns than stock ticker searches. A recent study by Kim, Lučivjanská, Molnár, and Villa (2019) did not find any evidence that Google searches could explain stock returns in the Norwegian stock market. However, they found a relationship between Google searches and volatility and trading volume. We complement the existing literature by using Google Trends to capture consumer attention, and compare this with two consumer-related industries, smartphones, and sporting goods, but not related to each other. We, therefore, use different keywords for the twenty companies we have selected to analyze. For example, we have selected "*Apple*", "*Xiaomi*", "*Adidas*", and "*Nike*." The complete list can be viewed in tables 1 and 2. By this, we study the correlation between consumer attention represented by SVI from Google Trends and stock returns from Yahoo finance.

We chose two groups of companies: smartphone and sporting goods companies, because both of us are interested in these businesses. The group of companies are consumer-related simply because people are purchasing their products for their personal use. Users often like to have the latest technology or latest trend. Moreover, sporting goods companies have different seasons where they

launch new products, like smartphone companies, which launches new models each year. It will be also interesting to see if our research will get similar results when comparing the two groups of businesses, because it looks like there is no relationship between buying a smartphone and shoes.

The whole paper is organized as follows. Section 1, as we stated above, and Section 2 introduces the data used in the paper. The methodology is defined in Section 3. Section 4 presents our findings and a discussion of the results. We conclude in Section 5.

2. Data

In this section, we present our data sources and handling techniques we used. We construct five variables, two attention variables measured by Google search volumes for company names and brand names and volatility, abnormal stock return, abnormal trading volume. The Google search data is representing consumer attention. We collected a dataset covering weekly data over a five-year period from 2016 to 2020. We select two industries where brand names are important: smartphone producers and producers of sport equipment.

2.1 Keyword sample selection

First, we have looked at sales statistics and found some of the top smartphone and sporting goods companies globally. These companies are some of the more popular in the world. This means they will get attention from consumers and investors all over the world. If we would have selected smaller companies, they might only sell their products in their local market. This could mean they would not get the same attention from consumers abroad. We have selected the following twenty companies: Apple, an American company, Blackberry from Canada, Nokia from Finland, LG and Samsung from South Korea, Sony from Japan, ASUSTeK (Asus) and HTC from Taiwan, and Lenovo and Xiaomi from China. We have selected these sporting goods companies: Nike, Lululemon, Under Armour, Skechers, and Columbia from the United States, Adidas and Puma from Germany, Fila from South Korea, and Anta from China.

The search categories we selected were company and brand categories. It is more likely consumers know the company names and products, than company's stock ticker. For example, for Blackberry, searching for the ticker name "BB" would give to many results not related to the company Blackberry. Most consumers are not professional investors who knows the different ticker names. With the help of Google AdWords, we figured out which keywords are most relevant in the brand categories we selected. The way Google AdWords keyword platform works, is that we input the company name that we want to investigate, and it displays all relevant keywords with the time horizon and location

we selected. Since the companies are located all over the world, we focus on search results from worldwide Google search results. We reduced the number of keywords manually down to 10-15 most relevant words per company. The reason for the reduction of the brand keywords is that including keywords that are not very relevant would create too much noise.

We have the following two categories:

1. Brand-related: incorporates the keywords by their brand names. For example, a brand name for Apple and Nike will have keywords which is constructed by their products and services, "*iPhone 11*", "*Apple Watch*", "*Nike Air*", "*Jordan 1*". This will be referred to as SVI^B.
2. Company-related: incorporates their company names as keywords. "*Apple*", "Puma", "*Xiaomi*" will be referred to as SVI^C.

The complete list can be found in the Appendix A.

2.2 Google Trends

Google Trends is an analyzing website created by Google to rank the most popular search queries worldwide. It displays the search term frequency based on keywords and a given period called search volume index (SVI). Each search is divided by total search for geography and time range. And then normalized on a scale of 0-100.

The first step is to enter the brand name we have selected on a website called Google AdWords. Here it is possible to see which other keywords are relevant for the brand name entered and it is ranked by popularity. Then we reduced the relevant keyword sample from the Google AdWords platform to around 10-15 brand-related keywords per company and used Google Trends to see how many search hits each keyword has, and this is the raw SVI from Google Trends. To make the data clean as possible, we exclude the keywords irrelevant for the companies and keywords with zero hits. (Preis et al., 2013) mentioned that local investors prefer domestic market, and that global search volume data are less successful than U.S. searches for the U.S. markets. The search results we have are based on worldwide Google searches since the companies we have selected are located all over the world and their products are being sold worldwide.

2.3 Search volume index construction

The SVI from Google Trends is an index with a scale from 0 to 100. The 100 represents the largest share of the total queries in the chosen region for a search term (Choi & Varian, 2011). We standardize SVI, to abnormal search volume index (ASVI) due to the nature of the type of regression and because the companies in our sample vary a lot concerning trading volumes and the SVI. The two figures below are graphs of SVI which shows the search trend for some of the company names we have selected over the time period 2016-2020.
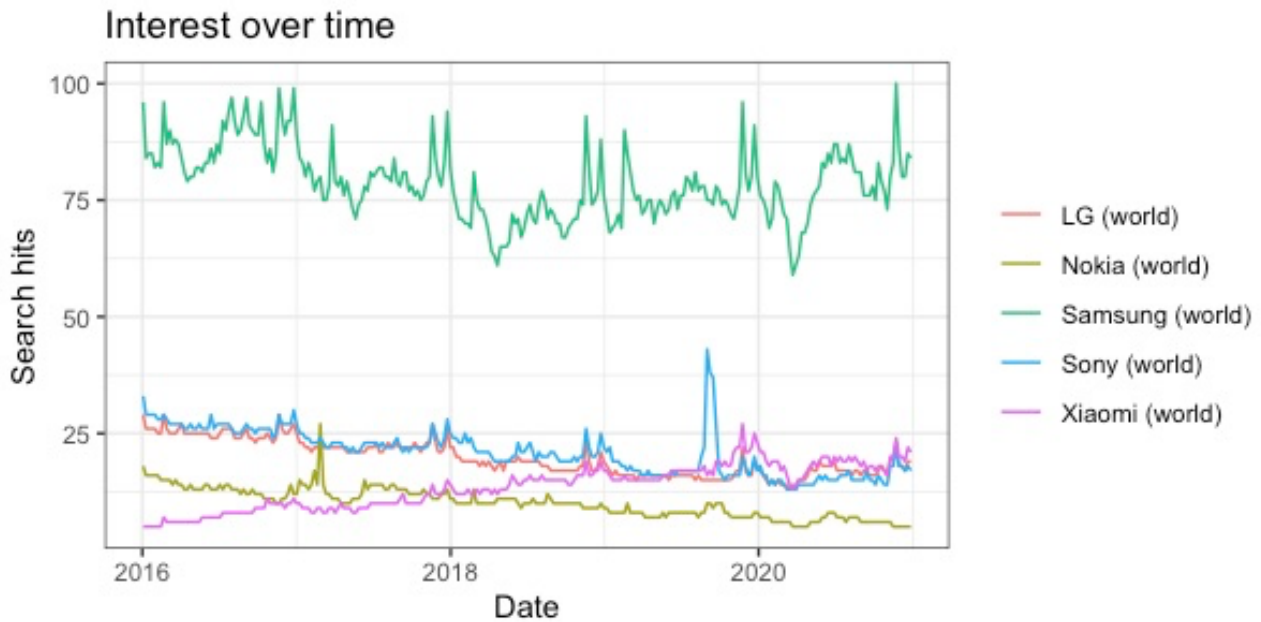
Figure 1. Google Search Volume index for LG, Nokia, Samsung, Sony, Xiaomi between 2016 and 2020.

We focus on specific company names and brands as search terms but select the top-rated words to fit more efficiently. Preis et al. (2010) found a relationship between Google Trend data for company names and the transaction volumes of the identical stock on a weekly time range. All the company names, and brands we search for, and keyword lists from Google AdWords are attached in the appendix. To achieve more comparability among the companies we converted the raw SVI data to an abnormal SVI (ASVI).

The method we used to standardize the SVI into ASVI, is taking the log of current week minus the log median SVI during the previous eight weeks. We used the following formula for abnormal SVI (Da et al., 2011):

$$ASVI_t = \log SVI_t - \log \left[Median\left(SVI_{t-1,\ldots} SVI_{t-8} \right) \right] \qquad (1)$$

2.4 Financial data

To study if there is a relationship between stock trading activity and consumer attention, we used Yahoo Finance to download stock data for our selected companies, as well as their benchmark indexes to calculate abnormal returns. Yahoo Finance provide Open, High, Low, Close, Adjusted Close and Volume as daily data. We gathered data for five years. Furthermore, financial data are converted to weekly data to match the data from Google Trends. For the risk-free rate calculations, we are using the 10-year US Treasury constant maturity rate, which is used for the abnormal return calculations based on Capital Asset Pricing Model (CAPM). The period is the same 2016-2020 and we are using the average rate. The stock data downloaded is used to find abnormal trading volume, volatility, stock prices, and index prices. The companies we have selected in our study are publicly traded companies in stock markets around the world. We have used the following ten stocks and indexes for a period of five years from 2016 to 2020:

Table 1. List of smartphone companies and their benchmark indices.

Company name	Stock ticker	Index name	Index ticker
Apple Inc.	AAPL	S&P 500	^GSPC
Samsung Electronics Co Ltd	005930.KS	Kospi Composite Index	^KS11
Xioami Corp.	1810.HK	Hang Seng Index	^HSI
Sony Group Corp.	6758.T	Nikkei 225	^N225
ASUSTeK Computer Inc. (ASUS)	2357.TW	TSEC weighted index	^TWII
Blackberry Limited	BB.TO	S&P/TSX Composite index	^GSPTSE
Lenovo Group Limited	0992.HK	Hang Seng Index	^HSI
LG Electronic Inc.	066570.KS	Kospi Composite Index	^KS11
Nokia Corporation	Nokia.HE	OMX Helsinki 25 index	^OMXH25
HTC Corp	2498.TW	TSEC weighted index	^TWII

Table 2. List of sporting goods companies and their benchmark indices.

Company name	Stock ticker	Index name	Index ticker
Nike Inc.	NKE	Dow Jones Industrial Average	^DJI
Adidas AG	ADS.DE	DAX Performance Index	^GDAXI
Puma SE	PUM.DE	DAX Performance Index	^GDAXI
Asics Corp	7936.T	Nikkei 225	^N225
Under Armour Inc.	UA	Dow Jones Industrial Average	^DJI
Lululemon Athletica Inc	LULU	NASDAQ 100 Index	NDX
Columbia Sportswear Company	COLM	NASDAQ 100 Index	NDX
FILA Holdings Corporation	081660.KS	Kospi Composite Index	^KS11
Skechers U.S.A., Inc.	SKX	Dow Jones Industrial Average	^DJI
ANTA Sports Products Limited	2020.HK	Hang Seng Index	^HSI

2.4.1 Stock return

We use the adjusted return calculated from Yahoo Finance, since it is adjusted for stock splits and dividend distributions calculated the following way:

$$r_t = \log\left(\frac{adjprice_t}{adjprice_{t-1}}\right) \tag{2}$$

where r_t is the stock return and $adjprice_t$ is adjusted stock price for the week t.

2.4.2 Abnormal stock return

For finding the abnormal return, we are use Capital Asset Pricing model (CAPM):

$$Abnormal\ Return_i = r_i - \beta_i * (r_m - r_f) - r_f \tag{3}$$

Where r_i is the stock return of company i, r_f is the risk-free rate calculated as a mean of 2016-2020 of the US 10-Year Treasury Constant Maturity Rate and β_i is the company's beta.

2.4.3 Volatility and variance

Volatility is a standard measure to evaluate how stock returns fluctuate over time. (Parkinson, 1980) was the first to improve this method by implementing high and low price instead of closing price. But then Garman and Klass (1980) improved it again by adding opening and close price. We use one with a further improvement for estimating volatility utilizing volatility estimator adjusted for the opening jump, as discussed by Molnár (2012) The information used from Yahoo Finance is the open, high,

low, close, and adjusted close prices during a trading day t to calculate the volatility for the current day in the following way:

$$c_t = \log(closing\ price) - \log(opening\ price) \tag{4}$$

$$l_t = \log(lowest\ price) - \log(opening\ price) \tag{5}$$

$$h_t = \log(highest\ price) - \log(opening\ price) \tag{6}$$

$$j_t = \log(opening\ price) - \log(closing\ price)_{t-1} \tag{7}$$

Opening jump adjusted equation:

$$r_t = \log(closing\ price) - \log(closing\ price)_{t-1} \tag{8}$$

$$radj_t = \log(adj.\,closing\ price) - \log(adj.\,closing\ price)_{t-1} \tag{9}$$

$$jadj_t = j_t * \frac{radj_t}{r_t} \tag{10}$$

First, we calculate the daily variance with following formula:

$$Variance_t = \frac{1}{2}(h_t - l_t)^2 - (2\log 2 - 1)c_t{}^2 + jadj_t^2 \tag{11}$$

The next step is calculating the weekly volatility as a square root of average daily variance from a specific week:

$$Volatility_t = \sqrt{\frac{1}{|S_t|}\sum_{i \in S_t} Variance_t} \tag{12}$$

Where S is the set of trading days in a specific week t.

2.4.4 Trading Volume

The weekly trading volume is calculated as an average of daily trading volumes from a specific week:

$$TV_t = \frac{1}{|S_t|}\sum_{i \in S_t} TV_t \tag{13}$$

Where S is the set of trading days in a specific week t.

The abnormal weekly trading volume is calculated as follows:

$$ATV_t = \frac{TV_t - \frac{1}{52}\sum_{i=1}^{52} TV_{t-i}}{\sigma_{TV_t}} \tag{14}$$

Where ATV_t is abnormal trading volume, TV_t is trading volume and σ_{TV_t} is the standard deviation of the trading volume.

2.5 Summary statistics

Table 3. Descriptive statistics for all variables

Descriptive Statistics

	N	Mean	St. dev.	Min	Max	Skew	Kurtosis
r^{abn}	4675.00	0.00	0.04	-0.35	0.35	0.00	7.58
$ASVI_t^B$	4675.00	-0.01	0.20	-2.06	1.12	-1.80	15.23
$ASVI_t^C$	4675.00	-0.00	0.13	-1.59	1.14	-0.38	22.95
ATV_t	4675.00	-4.54	4.00	-53.03	5.25	-2.78	22.30
VOL_t	4675.00	0.08	0.13	0.01	2.34	6.04	60.16

In table 3 we present the summary table for all the variable that we created from our raw data. The abnormal stock returns are calculated from the CAPM addressed in section "stock return" The ASVI is based on search terms calculated using Da et al. (2011) formula with an eight-week median time horizon explained in the section "Google Trend." Volatility is constructed by using the weekly Jump adjusted Garman-Klass. The abnormal trading volume is calculated from the formula Zheng (2007) as we addressed in "Trading volume."

Table 4. Correlation Matrix for variables

Correlation Matrix

	r_t^{abn}	$ASVI_t^B$	$ASVI_t^C$	ATV_t	VOL_t
r_t^{abn}	1				
$ASVI_t^B$	0.003	1			
$ASVI_t^C$	-0.004	0.558	1		
ATV_t	0.001	-0.094	-0.058	1	
VOL_t	0.005	-0.041	-0.023	0.117	1

In table 4 we study the correlation between the variables to evaluate whether consumer attention (company and brand) can provide additional information to the information provided by the other variables. The correlation matrix reported in table 4 shows a small correlation coefficient among the consumer attention (ASVI) and the other variables, as the correlation coefficients are all close to zero. When comparing both ASVI together, there is a correlation at 0.558. Which means they have a connection with some search words.

3. Methodology

In this section, we will describe the models and equations used to investigate our main research, whether there is a relation between consumer attention and stock returns. Simultaneously, we examined the other variables: abnormal trading volume and volatility. We present the panel data regression model in 3.1, the descriptive model in 3.2, and lastly, the predictive model in 3.3.

3.1 Panel data regression model and examining predictive power of SVIs.

We investigate whether stock returns are explained or predicted by an ASVI, volatility, or abnormal trading volume utilizing the panel data regressions with fixed effects. All regression models included a lagged dependent variable. Since we want to examine which ASVI variable is more significant in the explaining and predicting return, we estimate the descriptive and predictive models with both ASVI against with other variables.

3.2 Descriptive models

We estimate the following regression:

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \varepsilon_t \tag{15}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ASVI_t^B + \varepsilon_t \tag{16}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ASVI_t^C + \varepsilon_t \tag{17}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 Volatility_t + \varepsilon_t \tag{18}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ATV_t + \varepsilon_t \tag{19}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ASVI_t^B + \beta_3 Volatility_t + \beta_4 ATV_t + \varepsilon_t \tag{20}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ASVI_t^C + \beta_3 Volatility_t + \beta_4 ATV_t + \varepsilon_t \tag{21}$$

$$r_t^{abn} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ASVI_t^B + \beta_3 ASVI_t^C + \beta_4 Volatility_t + \beta_5 ATV_t + \varepsilon_t \tag{22}$$

Previous studies and results by Da et al. (2011) motivated us to investigate and create a descriptive model of trading volume on whether ASVI as a measurement of consumer attention can explain or predict abnormal return since their study was focused on investor attention. The weekly abnormal trading volume is used as a dependent variable to examine changes in trading volume are explained by changes in search interest. We additionally include volatility, abnormal return, and lagged abnormal trading volume as control variables. This results in the following regression model.

$$ATV_t = \alpha + \beta_1 ATV_{t-1} + \beta_2 ASVI_t^B + \beta_3 ASVI_t^C + \beta_4 Volatility_t + \beta_5 r_t^{abn} + \varepsilon_t \qquad (23)$$

Next, we study whether there is an additional association between ASVI and volatility. We have used the descriptive model below:

$$Volatility_t = \alpha + \beta_1 volalitiy_{t-1} + \beta_2 ASVI_t^B + \beta_3 ASVI_t^C + \beta_4 r_t^{abn} + \beta_5 ATV_t + \varepsilon_t \qquad (24)$$

3.3 Predictive models

To see if is possible to forecast or predict abnormal return, we have created several models. In these models, all explanatory variables are lagged from the previous week. These models are estimated as panel data regressions with fixed effects. We first estimate them for the group of all companies together, and later separately for smartphone companies and for sports equipment companies.

$$r_t^{abn\ all} = \alpha + \beta_1 r_{t-1}^{abn} + \beta_2 ASVI_{t-1}^B + \beta_3 ASVI_{t-1}^C + \beta_4 volatility_{t-1} + \beta_5 ATV_{t-1} + \varepsilon_t \qquad (25)$$

$$ATV_t^{all} = \alpha + \beta_2 ASVI_{t-1}^B + \beta_3 ASVI_{t-1}^C + \beta_4 r_{t-1}^{abn} + \beta_5 Volatility_{t-1} + +\varepsilon_t \qquad (26)$$

$$Volatility_t^{all} = \alpha + +\beta_2 ASVI_{t-1}^B + \beta_3 ASVI_{t-1}^C + \beta_4 ATV_{t-1} + \beta_5 r_{t-1}^{abn} + \varepsilon_t \qquad (27)$$

4. Results

We used Heteroscedasticity-consistent standard errors in our models to control for possible heteroskedasticity. All the results are presented with robust standard error. We organize this section by presenting and discussing the results for both sporting goods companies and smartphones companies together in section 4.1. We compare the regression results for sporting goods companies and one for smartphone companies separately in section 4.2.

4.1 Regression model results for ASVI search terms

4.1.1 Abnormal return

Table 5. Explanatory model

				Dependent variable: Abnormal Return				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_{t-1}^{abn}	-0.052**					-0.052**	-0.052**	-0.052**
	(0.019)					(0.019)	(0.019)	(0.019)
$ASVI_t^B$		0.001				0.003		0.004
		(0.003)				(0.003)		(0.004)
$ASVI_t^C$			-0.001				0.0003	-0.003
			(0.005)				(0.005)	(0.006)
VOL_t				0.001		0.002	0.002	0.002
				(0.004)		(0.004)	(0.004)	(0.004)
ATV_t					0.00001	-0.00001	-0.00001	-0.00001
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	4,657	4,675	4,675	4,675	4,675	4,657	4,657	4,657
R^2	0.003	0.00001	0.00001	0.00002	0.00000	0.003	0.003	0.003
Adjusted R^2	0.003	-0.0002	-0.0002	-0.0002	-0.0002	0.002	0.002	0.002

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 6. Predictive model

				Dependent variable: Abnormal Return				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_{t-1}^{abn}	-0.052**					-0.052**	-0.052**	-0.052**
	(0.019)					(0.019)	(0.019)	(0.019)
$ASVI_{t-1}^B$		0.003				0.003		0.004
		(0.003)				(0.003)		(0.004)
$ASVI_{t-1}^C$			-0.0001				-0.001	-0.004
			(0.005)				(0.005)	(0.006)
VOL_{t-1}				-0.009*		-0.008*	-0.009*	-0.008*
				(0.004)		(0.004)	(0.004)	(0.004)
ATV_{t-1}					-0.0001	-0.0001	-0.0001	-0.0001
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	4,657	4,657	4,657	4,657	4,657	4,657	4,657	4,657
R^2	0.003	0.0002	0.00000	0.001	0.0001	0.004	0.004	0.004
Adjusted R^2	0.003	-0.00003	-0.0002	0.001	-0.0001	0.003	0.003	0.003

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Tables 5 and 6 present the results from the regressions on abnormal return using the weekly ASVI company and brand as independent variables, together with volatility and abnormal trading volume. With these models, we want to investigate the impact of consumer attention and the difference between ASVI company and the ASVI brand, to see which one has stronger impact on abnormal returns. We conclude that the weekly ASVI for both company and brand can neither explain nor predict the abnormal return. However, there is a negative association between previous abnormal return and current abnormal return in both models. For table 6, the lagged volatility can predict the abnormal return in the single and all three multiple regressions. The magnitude of this relationship is very small, as documented by small regression coefficient and low regression's R^2.

4.1.2 Abnormal trading volume

Table 7. Explanatory model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Abnormal trading volume							
ATV_{t-1}	0.841**					0.837**	0.838**	0.837**
	(0.033)					(0.033)	(0.033)	(0.033)
$ASVI_t^B$		-1.895**				-0.297*		-0.210
		(0.236)				(0.143)		(0.168)
$ASVI_t^C$			-1.748**				-0.411	-0.239
			(0.437)				(0.218)	(0.256)
VOL_t				3.586**		0.694*	0.694*	0.692*
				(0.424)		(0.288)	(0.288)	(0.288)
r_t^{abn}					0.059	0.931	0.916	0.926
					(1.281)	(0.811)	(0.812)	(0.811)
Observations	4,657	4,675	4,675	4,675	4,675	4,657	4,657	4,657
R^2	0.702	0.009	0.003	0.014	0.0000	0.703	0.703	0.703
Adjusted R^2	0.702	0.009	0.003	0.013	-0.0002	0.703	0.703	0.703

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 8. Predictive model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Abnormal trading volume							
ATV_{t-1}	0.841**					0.834**	0.836**	0.834**
	(0.033)					(0.033)	(0.033)	(0.033)
$ASVI_{t-1}^B$		-2.253**				-0.645**		-0.548**
		(0.240)				(0.146)		(0.173)
$ASVI_{t-1}^C$			-2.178**				-0.717**	-0.261
			(0.421)				(0.199)	(0.235)
VOL_{t-1}				3.885**		0.904**	0.922**	0.904**
				(0.452)		(0.272)	(0.271)	(0.272)
r_{t-1}^{abn}					-1.178	-1.137	-1.155	-1.141
					(1.223)	(0.633)	(0.635)	(0.634)
Observations	4,657	4,675	4,675	4,675	4,675	4,657	4,657	4,657
R^2	0.702	0.009	0.003	0.014	0.0000	0.703	0.703	0.703
Adjusted R^2	0.702	0.009	0.003	0.013	-0.0002	0.703	0.703	0.703

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

We did not find any relationship between stock returns and ASVI. Next, we look further at the impact of ASVI on other variables. We conduct similar regressions as we did with the abnormal return. Tables 7 and 8 present the results from the abnormal trading volume with the same explanatory variables. Since there is a positive relationship between volatility and abnormal trading volume, therefore abnormal trading volume has the highest impact on volatility. These results are similar to the results from the predictive model. We further observe a positive association between current and previous abnormal trading volume in both regression models, and the two different ASVI can predict abnormal trading volume.

4.1.3 Volatility

Table 9. Explanatory model

					Dependent variable: Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL_{t-1}	0.268**					0.259**	0.259**	0.259**
	(0.034)					(0.034)	(0.034)	(0.034)
$ASVI_t^B$		-0.027*				-0.004		0.0002
		(0.012)				(0.009)		(0.011)
$ASVI_t^C$			-0.023				-0.012	-0.012
			(0.014)				(0.015)	(0.017)
r^{abn}				0.014		0.038	0.038	0.038
				(0.035)		(0.033)	(0.033)	(0.033)
ATV_t					0.004**	0.002**	0.002**	0.002**
					(0.0005)	(0.0004)	(0.0004)	(0.0004)
Observations	4,657	4,675	4,675	4,675	4,675	4,657	4,657	4,657
R^2	0.077	0.002	0.001	0.00002	0.014	0.084	0.084	0.084
Adjusted R^2	0.077	0.001	0.0003	-0.0002	0.013	0.083	0.083	0.083

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 10. Predictive model

					Dependent variable: Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL_{t-1}	0.268**					0.260**	0.259**	0.260**
	(0.034)					(0.034)	(0.034)	(0.034)
$ASVI_{t-1}^B$		-0.011				0.001		0.004
		(0.009)				(0.009)		(0.010)
$ASVI_{t-1}^C$			-0.015				-0.005	-0.008
			(0.015)				(0.015)	(0.018)
r_{t-1}^{abn}				-0.014		-0.017	-0.017	-0.017
				(0.036)		(0.035)	(0.035)	(0.035)
ATV_{t-1}					0.003**	0.002**	0.002**	0.002**
					(0.001)	(0.0005)	(0.0005)	(0.0005)
Observations	4,657	4,657	4,657	4,657	4,657	4,657	4,657	4,657
R^2	0.077	0.0003	0.0002	0.012	0.00002	0.083	0.083	0.083
Adjusted R^2	0.077	0.0001	0.00002	0.012	-0.0002	0.083	0.083	0.082

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

In tables 9 and 10 the regression is done to see if there is any relationship between stock price volatility with the ASVI for brand and company, together with the other variables. In table 9 the results show that there is not an association between both company and brand with stock price volatility. Similar results are obtained in the predictive models reported in table 10. Therefore, we conclude that the search volume for company and brand cannot predict the stock price volatility. We also observe significant autocorrelation in volatility.

In the next section, we consider estimate the same models separately one for smartphone companies and for sporting goods companies to see if there is difference between them and the results of smartphone and sporting goods together as above.

4.2 Regression model results for ASVI for smartphone and sporting goods companies

We tested the impact of consumer attention from sporting goods companies and smartphones companies separately towards returns, trading volume, and volatility, as shown respectively in tables from 11 to 22.

4.2.1 Abnormal return

Table 11. Explanatory model - Smartphone companies

	Dependent variable: Abnormal return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_{t-1}^{abn}	-0.020					-0.020	-0.020	-0.020
	(0.025)					(0.025)	(0.025)	(0.025)
$ASVI_t^B$		-0.002				0.001		-0.0001
		(0.005)				(0.005)		(0.005)
$ASVI_t^C$			0.003				0.005	0.005
			(0.007)				(0.007)	(0.008)
VOL_t				0.007		0.009	0.009	0.009
				(0.005)		(0.005)	(0.005)	(0.005)
ATV_t					-0.00001	-0.0001	-0.0001	-0.0001
					(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	2,315	2,324	2,324	2,324	2,324	2,315	2,315	2,315
R^2	0.0004	0.0001	0.0001	0.001	0.00000	0.001	0.002	0.002
Adjusted R^2	-0.00004	-0.0003	-0.0003	0.0003	-0.0004	-0.0003	-0.0002	-0.001

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 12. Explanatory model – Sporting goods companies

	Dependent variable: Abnormal return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_{t-1}^{abn}	-0.063**					-0.064**	-0.064**	-0.064**
	(0.024)					(0.024)	(0.024)	(0.024)
$ASVI_t^B$		0.003				0.003		0.007
		(0.004)				(0.004)		(0.006)
$ASVI_t^C$			-0.003				-0.003	-0.009
			(0.007)				(0.007)	(0.009)
VOL_t				-0.004		-0.002	-0.003	-0.003
				(0.006)		(0.007)	(0.007)	(0.007)
ATV_t					-0.0004	-0.0004	-0.0005	-0.0004
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	2,591	2,601	2,601	2,601	2,601	2,591	2,591	2,591
R^2	0.004	0.0002	0.0001	0.0001	0.001	0.005	0.005	0.006
Adjusted R^2	0.004	-0.0002	-0.0003	-0.0003	0.001	0.004	0.004	0.004

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Tables 11 and 12 shows a comparison of the explanatory regression models for smartphone and sporting goods companies. Table 12 explains the negative relationship between lagged abnormal return and abnormal return.

Table 13. Predictive model – Smartphone companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Dependent variable: Abnormal return				
r^{abn}_{t-1}	-0.020					-0.019	-0.019	-0.019
	(0.025)					(0.025)	(0.025)	(0.025)
$ASVI^B_{t-1}$		0.008				0.007		0.006
		(0.005)				(0.005)		(0.005)
$ASVI^C_{t-1}$			0.008				0.007	0.003
			(0.007)				(0.007)	(0.008)
VOL_{t-1}				-0.008		-0.006	-0.006	-0.006
				(0.004)		(0.004)	(0.004)	(0.004)
ATV_{t-1}					-0.0003	-0.0002	-0.0003	-0.0002
					(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	2,315	2,315	2,315	2,315	2,315	2,315	2,315	2,315
R^2	0.0004	0.001	0.0005	0.001	0.001	0.003	0.002	0.003
Adjusted R^2	-0.00004	0.001	0.00004	0.0004	0.001	0.001	0.001	0.001

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 14. Predictive model – Sporting goods companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Dependent variable: Abnormal return				
r^{abn}_{t-1}	-0.063**					-0.063**	-0.063**	-0.063**
	(0.024)					(0.024)	(0.024)	(0.024)
$ASVI^B_{t-1}$		-0.002				-0.002		0.00002
		(0.004)				(0.004)		(0.006)
$ASVI^C_{t-1}$			-0.003				-0.004	-0.004
			(0.006)				(0.006)	(0.009)
VOL_{t-1}				-0.008		-0.008	-0.008	-0.008
				(0.007)		(0.007)	(0.007)	(0.007)
ATV_{t-1}					-0.0002	-0.0002	-0.0002	-0.0002
					(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591
R^2	0.004	0.00005	0.0001	0.0003	0.0002	0.005	0.005	0.005
Adjusted R^2	0.004	-0.0003	-0.0003	-0.0001	-0.0002	0.003	0.003	0.003

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

The results from the previous explanatory models are similar for the predictive model in table 13 and 14.

4.2.2 Abnormal trading volume

Table 15. Explanatory model – Smartphone companies

	Dependent variable: Abnormal trading volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATV_{t-1}	0.793**					0.787**	0.787**	0.786**
	(0.052)					(0.054)	(0.053)	(0.054)
$ASVI_t^B$		-2.602**				-0.228		-0.138
		(0.408)				(0.326)		(0.331)
$ASVI_t^C$			-2.379**				-0.449	-0.363
			(0.825)				(0.507)	(0.512)
VOL_t				4.647**		1.184**	1.188**	1.186**
				(0.667)		(0.458)	(0.460)	(0.459)
r^{abn}					-0.103	2.501	2.513	2.511
					(1.981)	(1.411)	(1.407)	(1.407)
Observations	2,315	2,324	2,324	2,324	2,324	2,315	2,315	2,315
R^2	0.628	0.011	0.003	0.026	0.00000	0.630	0.630	0.630
Adjusted R^2	0.628	0.011	0.003	0.025	-0.0004	0.629	0.629	0.629

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 16. Explanatory model – Sporting goods companies

	Dependent variable: Abnormal trading volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATV_{t-1}	0.904**					0.903**	0.903**	0.903**
	(0.020)					(0.020)	(0.020)	(0.020)
$ASVI_t^B$		-1.333**				-0.313**		-0.252
		(0.264)				(0.115)		(0.145)
$ASVI_t^C$			-1.322**				-0.361*	-0.142
			(0.432)				(0.177)	(0.224)
VOL_t				2.682**		0.205	0.201	0.201
				(0.466)		(0.225)	(0.224)	(0.224)
r^{abn}					-2.202	-1.345	-1.374	-1.352
					(1.514)	(0.879)	(0.881)	(0.881)
Observations	2,591	2,601	2,601	2,601	2,601	2,591	2,591	2,591
R^2	0.805	0.007	0.003	0.006	0.001	0.805	0.805	0.805
Adjusted R^2	0.805	0.006	0.003	0.006	0.001	0.805	0.805	0.805

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 16 shows that the association between the abnormal trading volume and volatility is no longer significant in multiple regression models. However, these results are different in table 15, where the relationship between volatility and abnormal trading volume are significant.

Table 17. Predictive model – Smartphone companies

	Dependent variable: Abnormal trading volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATV_{t-1}	0.793**					0.782**	0.784**	0.782**
	(0.052)					(0.054)	(0.053)	(0.054)
$ASVI_{t-1}^{B}$		-3.091**				-1.004**		-0.848**
		(0.417)				(0.308)		(0.313)
$ASVI_{t-1}^{C}$			-3.083**				-1.202*	-0.681
			(0.791)				(0.476)	(0.480)
VOL_{t-1}				4.822**		1.161**	1.210**	1.169**
				(0.716)		(0.438)	(0.438)	(0.437)
r_{t-1}^{abn}					-0.746	-0.615	-0.541	-0.592
					(2.033)	(1.179)	(1.186)	(1.181)
Observations	2,315	2,324	2,324	2,324	2,324	2,315	2,315	2,315
R^2	0.079	0.003	0.0001	0.001	0.026	0.093	0.093	0.093
Adjusted R^2	0.079	0.003	-0.0004	0.0003	0.025	0.092	0.092	0.091

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 18. Predictive model – Sporting goods companies

	Dependent variable: Abnormal trading volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATV_{t-1}	0.904**					0.900**	0.901**	0.900**
	(0.020)					(0.020)	(0.020)	(0.020)
$ASVI_{t-1}^{B}$		-1.574**				-0.355**		-0.286*
		(0.269)				(0.120)		(0.156)
$ASVI_{t-1}^{C}$			-1.588**				-0.406*	-0.150
			(0.425)				(0.161)	(0.210)
VOL_{t-1}				3.307**		0.920**	0.916**	0.916**
				(0.449)		(0.187)	(0.189)	(0.187)
r_{t-1}^{abn}					-3.177*	-1.164	-1.196	-1.173
					(1.298)	(0.641)	(0.640)	(0.641)
Observations	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591
R^2	0.805	0.009	0.005	0.009	0.002	0.806	0.806	0.806
Adjusted R^2	0.805	0.009	0.004	0.009	0.002	0.806	0.806	0.806

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

All together the results in table 18 are similar to table 17.

4.2.3 Volatility

Table 19. Explanatory model – Smartphone companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Dependent variable: Volatility				
VOL_{t-1}	0.267**					0.250**	0.250**	0.250**
	(0.042)					(0.041)	(0.041)	(0.041)
$ASVI_t^B$		-0.048				-0.002		-0.003
		(0.025)				(0.016)		(0.017)
$ASVI_t^C$			-0.012				0.002	0.004
			(0.031)				(0.032)	(0.035)
r^{abn}				0.105		0.137*	0.137*	0.137*
				(0.066)		(0.062)	(0.062)	(0.062)
ATV_t					0.006**	0.004**	0.004**	0.004**
					(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,315	2,324	2,324	2,324	2,324	2,315	2,315	2,315
R^2	0.079	0.003	0.0001	0.001	0.026	0.093	0.093	0.093
Adjusted R^2	0.079	0.003	-0.0004	0.0003	0.025	0.092	0.092	0.091

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 20. Explanatory model – Sporting goods companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Dependent variable: Volatility				
VOL_{t-1}	0.255**					0.250**	0.250**	0.250**
	(0.060)					(0.060)	(0.060)	(0.060)
$ASVI_t^B$		-0.012				-0.005		0.002
		(0.010)				(0.010)		(0.011)
$ASVI_t^C$			-0.023				-0.014	-0.016
			(0.012)				(0.013)	(0.013)
r^{abn}				-0.018		-0.005	-0.005	-0.005
				(0.030)		(0.030)	(0.030)	(0.030)
ATV_t					0.002**	0.002**	0.001**	0.001**
					(0.0005)	(0.0004)	(0.0004)	(0.0004)
Observations	2,591	2,601	2,601	2,601	2,601	2,591	2,591	2,591
R^2	0.065	0.001	0.001	0.0001	0.006	0.068	0.068	0.068
Adjusted R^2	0.065	0.0003	0.001	-0.0003	0.006	0.067	0.067	0.067

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

The results from table 19 and 20 are similar. However, in table 9, there is an association between abnormal returns and volatility in the multiple regressions, where this does not exist in table 20.

Table 21. Predictive model – Smartphone companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Volatility							
VOL_{t-1}	0.267**					0.252**	0.251**	0.252**
	(0.042)					(0.041)	(0.041)	(0.041)
$ASVI_{t-1}^{B}$		-0.006				0.016		0.016
		(0.015)				(0.015)		(0.015)
$ASVI_{t-1}^{C}$			-0.004				0.007	-0.003
			(0.037)				(0.037)	(0.039)
r_{t-1}^{abn}				-0.011		-0.036	-0.036	-0.035
				(0.065)		(0.063)	(0.063)	(0.063)
ATV_{t-1}					0.005**	0.004**	0.004**	0.004**
					(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,315	2,315	2,315	2,315	2,315	2,315	2,315	2,315
R^2	0.079	0.0001	0.00001	0.022	0.00001	0.091	0.091	0.091
Adjusted R^2	0.079	-0.0004	-0.0004	0.022	-0.0004	0.090	0.089	0.089

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

Table 22. Predictive model – Sporting goods companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Volatility							
VOL_{t-1}	0.255**					0.251**	0.251**	0.251**
	(0.060)					(0.060)	(0.060)	(0.060)
$ASVI_{t-1}^{B}$		-0.014				-0.008		-0.007
		(0.010)				(0.010)		(0.010)
$ASVI_{t-1}^{C}$			-0.016				-0.008	-0.002
			(0.013)				(0.013)	(0.013)
r_{t-1}^{abn}				0.012		0.021	0.020	0.021
				(0.034)		(0.033)	(0.033)	(0.033)
ATV_{t-1}					0.002**	0.002**	0.002**	0.002**
					(0.0005)	(0.0004)	(0.0004)	(0.0004)
Observations	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591
R^2	0.065	0.001	0.001	0.006	0.00003	0.069	0.069	0.069
Adjusted R^2	0.065	0.0004	0.0002	0.006	-0.0004	0.068	0.068	0.067

Note: Column (6) presents results from regression including all variables except ASVI Company, and column (7) presents results from regression including all variables except ASVI Brand. And column (8) presents results from regression including all variables. Robust standard errors are in parentheses. The sample period covers weekly data from 2016 to 2020. The symbols ** and * denote significance at the 1% and 5% levels, respectively.

There is no notable difference in tables 21 and 22 when compared to tables 19 and 20.

We compared the two different groups of companies by estimating the same regression models. We wanted to see whether there was a difference between the results we got from all companies together, compared to smartphone companies and sporting goods companies separately. We conclude that there is still not a relationship between abnormal return and ASVI. Overall, the results are similar for both groups of companies.

5. Conclusion

Predicting stock returns is a popular topic, and the recent years there has been considerable research on investors' attention and stock returns. We investigate whether consumers attention measured by Google searches for company's names and brands can predict stock returns, volatility and trading volume for smartphone and sporting goods manufacturers. Therefore, we selected large publicly traded smartphone companies and sporting goods companies and investigated whether abnormal search volume indexes (ASVI) can explain and predict the following three market variables: stock returns, trading volume, and volatility of these companies. We did not find a relation between the different companies' consumer attention and stock returns or volatility. Despite this, there is a relation between past and the current abnormal returns; past stock price volatility can predict the abnormal returns; and lastly, the trading volume can explain and predict the stock price volatility and vice versa.

Since we did not find any significant relationship between ASVI and abnormal returns in the predictive model nor the explanatory models for the two groups of companies together. We did the same calculations again, but this time for sporting goods and smartphone companies separately to discover any distinction between these two groups. Hence, the main conclusion remains. On the other hand, we did discover some differences between sporting goods and smartphone companies. Previous lagged abnormal return can no longer explain abnormal return for the smartphone companies. Furthermore, abnormal trading volume can no longer explain volatility and vice versa for sporting goods companies.

As for future research, there could be other industries worth looking into to investigate if there is a relationship between consumer attention SVI and stock return. It would also be interesting to examine if smaller, less known companies would get a higher return when they get more attention than larger companies. Alternatively, it is also possible to include the investors' attention. A more extensive approach would be to investigate who the consumers are for a specific business. And then further investigate how the consumers search for stock information and use that information to create search terms instead of using the top ranked words on Google Trends. In addition, if the final findings are significant, one could develop a strategy for abnormal stock return.

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APPENDIX

Appendix A: Keywords

Table 23. *Company names*

apple	adidas
asus	anta
blackberry	asics
htc	columbia
lenovo	fila
lg	lululemon
nokia	nike
samsung	puma
sony	skechers
xiaomi	under armour

Table 24. *Brand specific keywords*

apple	asus	blackberry	htc
Iphone	asusus	blackberry phone	incredible s
Airpods	asus laptop	blackberry key	wildfire s
Macbook	asus vivobook	blackberry mobile	htc viva
Apple watch	asus zenbook	blackberry passport	htc u11
Ios	rog phone	blackberry priv	htc phones
Ipad	rog	blackberry z10	htc 10
Facetime	asus phone	blackberry classic	desire s
Icloud	asus tablet	blackberry bold	htc one
Itunes		blackberry curve	htc desire
ipod		blackberry key3	htc u12
		blackberry q10	
		blackberry torch	
		blackberry smartphone	

lenovo	lg mx	nokia	samsung
lenovo laptop	lg v30	nokia 3310	samsung galaxy
ideapad	lg stylo	nokia 6	samsung note
lenovo yoga	lg velvet	nokia phone	samsung watch
thinkpad	lg wing	nokia 8	samsung fold
lenovo legion	lg g6	nokia 7.1	galaxy note
lenovo chromebook	lg v60	nokia 5.3	galaxy watch
lenovo smart clock	lg k40	nokia 7.2	
lenovo x1 carbon	lg g8	nokia mobile	
lenovo tab	lg g7	nokia 2.3	
lenovo flex 5	lg smartwatch	nokia 8.3	
	lg phones	nokia smartphone	

sony	**xiaomi**	**adidas**	**anta**
playstation	redmi	yeezy	anta kt5
ps5	mi band	adidas shoes	anta klay thompson
ps3	xiaomi poco	yeezy	anta salehe bembury
xperia	xiaomi mi	adidas originals	anta gh1
sony alpha	pocophone	stan smith	anta kt
ps vita	mihome	terrex	anta gh2
sony phone	xiaomi home	ultra boost	anta basketball
		adidas nmd	anta rr6
		adidas predator	anta dragon ball
		ozweego	anta running

asics	**columbia**	**fila**	**lululemon**
asics gel	columbia jackets	fila disruptor	lululemon outlet
asics shoe	columbia outlet	filas shoes	lululemons leggings
asics running	columbia clothing	fila bts	canada lululemon
asics kayano gel	columbia usa	fila trainers	lululemon leggings
asics outlets	columbia store	fila ray tracer	lululemon shorts
asics novablast	columbia canvas	fila india	lululemon we made too
asics gt 2000	columbia titanium	fila sandals	much
asics nimbus	columbia rain jackets	grant hill shoes	lululemon mirror
onitsuka tiger	mycolumbia	fila slides	lululemon black friday
asics trainers	columbia coupons	fila ray	lululemon yoga mat
			athleta lululemon

nike	**puma**	**skechers**	**under armour**
jordan 1	tenis puma	workshire	curry 8
nike air forces 1	puma suede	dynamight	project rock
air max 90	puma cali	skechers outlets	curry 7
airmax	puma shoes	sketcher go walk	under armour hovr
kobes	pumas rs x	sketchers for girls	curry 6
air nike	pumas sneakers	shoe skechers	kevin plank
jordans 4	puma store	sketure	cubrebocas under
air max nike	puma future rider	skechers ultra flex	armour
airforce1	puma trainers	skechers go walk 5	heatgear
nike outlets	neymar puma	skechers shape ups	under armour charged
			coldgear