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What makes stocks sensitive to investor sentiment: An analysis based on Google Trends

Adeel Ali Qureshi[1]

Abstract

We capture Google's vast search volume through Google Trends to generate a weekly investor sentiment index (2018–2022) using the most popular keywords (extracted from Google Search) from a keywords collection of 92,000+ words found in business, finance, and common language dictionaries. The results show that Google Trends is an efficient measure of investor sentiment as reflected in relative trading volume. To check what makes stocks sensitive to investor sentiment, 500 randomly selected US firms from various industries are categorised by firm characteristics. We generate two sub-portfolios: large, old, profitable, and dividend-yielding firms versus small, young, unprofitable, and non-dividend-yielding firms—and find the relative trading volume of the latter to be more sensitive to investor sentiment. Our results remain robust when control and autoregressive variables are introduced, in addition to when an alternative measure of sentiment is used, thereby confirming our primary findings.

Keywords

- investor sentiment
- Google Trends
- stock market
- search engine
- firm characteristics

JEL codes: G10, G11, G14, G40, G41

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Introduction

Barber and Odean (2008) suggest that individual investors buy what attracts them, and Baker and Wurgler (2007) refer to the beliefs of investors about future cash flows and investment risks as investor sentiment. These beliefs are generally associated with individual (retail) investors, often treated as "noise traders" (Shleifer & Summers, 1990). While it cannot be measured directly (Duc et al., 2024), studies employ various proxies to measure investor sentiment (Baker & Wurgler, 2006; Haritha & Rishad, 2020). The rise of the internet in recent years has led individual investors to use it when searching for information (Agarwal et al., 2019; Szczygielski et al., 2024; Wang et al., 2015). Therefore, capturing internet searches can be a proxy for investor sentiment. In 2023, 84.7% of all global internet searches were conducted on Google (Statista, 2023). Research shows that individual investors refer to Google to make decisions (Duc et al., 2024), and several researchers use Google Search as a proxy to measure sentiment (Costola et al., 2021; Molnár et al., 2019; Smales, 2021). Observed patterns depict the relationship between searches made on Google and stock movements, such as people searching for "debt" before selling stocks at lower prices (Preis et al., 2013), which suggests the efficacy of the relationship between the Google Search Volume Index (SVI here onwards) and investor sentiment (Da et al., 2011; Salisu et al., 2021).

In their seminal study, Baker and Wurgler (2006) used six proxies to measure investor sentiment and investigate specific characteristics of firms affected by the sentiment. The technological advancements since then have been extraordinary, and many studies on investor sentiment investigate the relationship between Google SVI and the stock markets (Duc et al., 2024; Molnár et al., 2019; Suer & Akarsu, 2021; Swamy & Dharani, 2019), including the impact of the COVID-19 pandemic (Maddodi & Kunte, 2024; Papadamou et al., 2023), or testing relations between stock performance and Google SVI for specific sectors (Challet & Ayed, 2013; Chen & Stejskalova, 2024). Nevertheless, there exists a research gap, as the studies do not explore the relationship of investor sentiment with specific firm characteristics. The motivation for this study is to fulfil the research gap by leveraging technological advancements and providing practical insights into the relationship between investor sentiment and firm characteristics in the context of modern information access. The research problem that we attempt to solve in this study is to identify and investigate the characteristics which make firms sensitive to investor sentiment. Therefore, we ask the following general research questions:

RQ1: Can Google Trends be used to measure investor sentiment?
RQ2: What kind of stocks are most sensitive to investor sentiment?

We elicit firm characteristics (size, age, net income, and whether it yields dividend or not) utilised by Baker and Wurgler (2006) and investigate which are more correlated to the investor sentiment, in addition to finding the dominant characteristics, thus contributing to the literature. We randomly select 500 firms from the US stock markets from several industries where the minimum annual market capitalisation is at least 50 million USD.

We expect to find significant relations between investor sentiment and the trading volume of stocks that we consider sentiment-sensitive. Investor sentiment can be positive or negative. An increase in investor sentiment (towards more positive) should lead to a rise in the trading volume of sentiment-sensitive stocks, as we expect investors to buy more when sentiment is positive. Similarly, extremely negative sentiment should also lead to an increase in the trading volume of sentiment-sensitive stocks, as we expect investors to sell more when sentiment is negative. At the same time, we expect no relations between changes in investor sentiment and trading volume of stocks that we do not consider sentiment-sensitive.

We use Google Trends (GT) to capture Google SVI to calculate investor sentiment. We utilise two open-sourced dictionaries (with over 92,000+ keywords combined) with business and finance, and common language words, attributed with sentimentality. Selecting an equal number of positive and negative keywords, we generate the sentiment[2], and regress it against the change in the trading volume of firms (relative to their annual trading volume mean), separated by their firm characteristics, in the presence of control variables as a proxy to the market movements.

Our findings answer the first question positively. For the second, we investigate separate firms by each characteristic (size, age, income, and dividend) to find that individually, smaller, younger, non-profiting firms which do not yield dividends are positively and significantly sensitive to investor sentiment, while the same characteristics when inversed are not significantly related to investor sentiment. We also generate two portfolios, grouping firms which are simultaneously small, young, non-profiting, and non-dividend-yielding, and those which are at the same time large, old, profiting and dividend-yielding. We find the former rather than the latter to have a positive and statistically significant relationship with investor sentiment. With satisfactory results, we additionally perform further analysis: we regress stock returns and abnormal returns against lagged investor sentiment to investigate whether Google Trends can be used to forecast returns, and if so, which kind of stocks are more forecastable. Our findings show a significant positive relationship between lagged sentiment and next-week stock returns but only for sentiment-sensitive stocks. This also indicates the short-term persistence of investor sentiment.

[2] Details in the methodology section.

The rest of the paper is organised as follows: Section 1 is devoted to the literature review and hypotheses, followed by Section 2, which provides information about data and methodology: data properties and processing, sentiment index, and modelling. In Section 3 and 4, we present our empirical findings (regarding investor sentiment and relative trading volume, and regarding investor sentiment and future stock returns, respectively). Section 4 is devoted to robustness checks (alternative sentiment index), and the last Section comprises a critical summary and conclusions.

1. Literature review and hypotheses development

The emergence of behavioral finance theories[3] has been associated with a scholarly discourse on the influence of investor sentiment on stock returns within the stock market. It has been demonstrated through empirical and theoretical analyses that stock prices are significantly affected by investor sentiment (Barber & Odean, 2008; Da et al., 2015; Tetlock, 2007). Ekinci and Bulut (2021) assert that Google Search plays a crucial role for individual investors in the process of selecting where to invest among the array of available options.

Traditional measures or proxies for investor sentiment include news, returns, and trading volume; however, these indicators are indirect and have certain limitations (Da et al., 2011). With technological advancements, especially the use of online media, internet searches have gained paramount usage globally (Szczygielski et al., 2024), especially among individual investors (Costa et al., 2024; Duc et al., 2024).

There exists a strong correlation between Google SVI for keywords and the relative volume volatility of stocks (Dimpfl & Jank, 2016). Preis et al. (2013) conclude similarly with regard to stock returns. The correlation is even stronger when using the corpora of economic and financial words to retrieve the SVI (Da et al., 2015; Zhang et al., 2020). Interestingly, market volatility affects sentiment, rather than sentiment affecting it, particularly as seen in the ESG market (El Oubani, 2024). Regarding which keywords are more effective, negative keywords carry a stronger sentiment (Da et al., 2015; Tetlock, 2007), thus validating Prospect Theory (Kahneman & Tversky, 1979).

Regarding firm characteristics, Baker and Wurgler (2006) focused on size, volatility, profitability, dividend payments, growth and distress. They conclud-

[3] Barberis (2003) proposes that behavioral finance offers solutions to the challenges encountered by traditional financial theories. Ricciardi and Simon (2001) suggest that behavioral finance seeks to understand the thought processes of investors and how much these processes impact their decisions.

ed that smaller, younger, more volatile, and unprofitable firms that do not yield dividends are affected more by investor sentiment. Aboody et al. (2018) used firm size, age and profitability, in addition to earnings-to-price and book-to-market ratio to establish that firm size and age display an inverse U shape relationship to weekly overnight stock returns when factored against investor sentiment. Conversely, Yang et al. (2017) correlated investor sentiment to Korean firms to conclude a stronger relationship of the former with firms which are smaller, low-priced, with more book-to-market ratio, and which are more volatile stocks. For the Tunisian stock market, Hadjmohamed and Bouri (2023) find that the higher the investor sentiment, the lower stock returns are for large, young, least profitable, and lower-dividend-yielding firms, among other characteristics.[4]

Building on the literature, we form intersecting characteristics—size, age, profitability, and dividend-yield—where characteristics may have contrasting values, e.g., whether a firm yields a dividend, or not, or whether or not it is profitable. Therefore, we simplify the remaining two; size divided between large and small, and age between old and young. Drawing on the findings of Baker and Wurgler (2006), we expect small, young, unprofitable, and non-dividend-yielding firms to relate to investor sentiment, as our first hypothesis states. Lee and Kumar (2006) suggest that individual investors buy one group of stocks, followed by more groups of stocks.[5] Therefore, for instance, placing small and young firms together supersedes placing large and young firms together. We additionally expect the trading volume to be directly proportional to sentiment based on the trend-like behavior of similar stocks mentioned by Lee and Kumar (2006), as in our next hypothesis. Nevertheless, we initiate our analysis by investigating each characteristic individually (size; large and small, age; young and old, etc.), followed by characteristics consolidated as explained; dubbing one portfolio comprising small, young, non-profitable, and non-dividend-yielding firms as Sentiment-Sensitive Companies, and the exact opposite attributes (large, old, profitable, and dividend-yielding), naturally, as Sentiment-Resistant Companies. Thus, we hypothesise as follows:

H1: There is a positive relationship between investor sentiment derived from Google Trends and stock trading volume for Sentiment-Sensitive Companies.

H2: Regardless of sentiment directionality, an increase in sentiment magnitude (towards more positive or more negative) is associated with a corresponding increase in stock trading volume for Sentiment-Sensitive Companies.

[4] Least tangible, and lower sales growth.

[5] The same authors also suggest that groups of retail investors follow groups of retail investors buying stocks, signaling a mass movement of individuals in a similar direction.

As an additional contribution, we further investigate the predictability of investor sentiment derived from Google Trends, and in so doing, we leverage the findings of Hadjmohamed and Bouri (2023) and Baker and Wurgler (2006) to formulate an additional hypothesis:

H3: Investor sentiment derived from Google Trends can be used to forecast the future returns of Sentiment-Sensitive Companies

2. Data and methodology

We retrieve and process data from the stock market in addition to Google Trends. Both datasets are processed separately. Data from Google Trends is used to generate a sentiment index. Acquisition and processing methodology is detailed below in corresponding sub-sections.

2.1. Stock market

Researchers vary between choices of data from the stock market to relate to Google SVI. Dimpfl and Jank (2016) opted for Dow Jones Industrial Average (DJIA), Preis et al. (2013) and Zhang et al. (2020) used stock market data of single and multiple countries, respectively. We generate a portfolio of 500 randomly selected companies from the US stock markets with at least 50 million USD market capitalisation from several industries. We retrieve[6] daily trading volume for selected companies for five years from 2018 to 2022 (in addition to stock prices). We also retrieve annual net income, annual market capitalisation, founding year of each company, and dividend paid to shareholders for each company. We separate firms by characteristics based on the following rules:

1. size: large and small (top and bottom 33%, respectively, based on market capitalisation),
2. age: young and old (before and after median age counting from founding year),
3. dividend yield: binary,
4. annual net income: binary for positive or negative.

To narrow the scope of our analysis, we combine opposing attributes per characteristic to generate two sub-portfolios: 1) large, old, positive annual

[6] Stock market data acquired from S&P Capital IQ.

net-income-generating, and dividend-yielding firms (47,350 observations) and 2) small, young, negative annual net-income-generating, and non-dividend-yielding firms (33,180 observations). Intuitively and following Zhang et al. (2020) and Baker and Wurgler (2007), we expect the latter group of firms to be more sensitive to our sentiment index. Thus, we label this group the "Sentiment-Sensitive Companies" portfolio (SSC hereafter) and the other group as "Sentiment-Resistant Companies" portfolio (SRC here onwards). Table 1 presents the summary statistics for the retrieved stock returns and relative trading volume data for all stocks, and stocks characterised by firm characteristics, in addition to the two portfolios (Sentiment-Resistant Companies and Sentiment-Sensitive Companies).

With the definition of firm characteristics being distinctive (specified above), we observe the summary statistics in Table 1 to describe opposing attributes of each characteristic to be particularly different from each other; e.g. large and small having a mean of 51 billion USD and 320 million USD, respectively, while old and young having median ages of 82 and 24, respectively, followed by net income shows 871 billion USD yearly net profit of 347 positive net-income-generating companies and –87 billion USD of yearly net losses of 153 negative net-income-generating companies. We also note that 267 companies yielded 2.24 billion USD in dividends, whereas 233 companies did not yield any dividend. Bringing together companies which are simultaneously large, old, positive net-income-generating companies, which also yield dividend, we account for 97 (or 19.4%) companies, as opposed to small and young companies that generate net losses and do not yield dividend to be 69 (or 13.8%) of total 500 companies.

Additionally, we perform Student's t-test to determine whether the means of each characteristic counterparts are statistically significant, e.g., to compare the mean ages of large companies with the mean ages of small companies, or market capitalisation of old companies with the same of young companies, etc. We also perform the same Student's t-test for SRC versus SSC. We present the results along with the rest of the descriptive statistics in Table 1.

We retrieve daily trading volume data and calculate daily averages for every week within the time frame analysed. We calculate Relative Trading Volume (from here onwards as RTV): first, for each firm, we individually calculate the weekly change in its trading volume relative to its annual weekly average, based on the following formula:

$$Relative\,Trading\,Volume_{Stock|week} = \frac{\begin{array}{c}Average\ Daily\ Trading\\ Volume\ for\ Given\ Week\end{array}}{\begin{array}{c}Average\ Daily\ Trading\ Volume\ for\\ Given\ Week\text{'}s\ Corresponding\ Year\end{array}}$$

Table 1. Summary statistics

		All	Size		Age		Net income		Dividend yield		SRC	SSC
			large	small	old	young	pos	neg	yes	no		
	N	500	165	165	244	239	347	153	267	233	97	69
Size	$\bar{x}$	17.85	51.03	0.32	19.32	16.43	24.01	3.87	22.95	12.00	44.79	0.31
	t		149.18***		16.26***		126.19***		64.14***		232.50***	
	$\tilde{X}$	2.25	20.88	0.15	3.67	1.23	4.20	0.21	4.46	0.67	21.84	0.13
	σ	72.81	120.05	0.57	48.29	92.47	81.60	44.05	52.67	90.18	69.03	0.49
Age	$\bar{x}$	55.80	73.29	38.51	89.01	22.38	63.88	36.50	74.87	33.25	97.74	16.96
	t		7.64***		26.06***		6.68***		12.09***		17.39***	
	$\tilde{X}$	41.00	65.00	27.00	82.00	24.00	48.00	24.00	68.00	28.00	95.00	14.00
	σ	43.27	45.10	36.01	37.98	11.02	44.15	34.16	46.38	24.63	37.65	9.90
Net income	$\bar{x}$	577.79	1707.16	–18.00	711.96	458.23	871.13	–87.48	827.91	291.18	1751.09	–49.51
	t		7.91***		2.04*		9.14***		4.48**		9.44***	
	$\tilde{X}$	48.56	682.08	–10.30	131.27	5.45	156.94	–30.53	179.64	0.00	812.64	–38.59
	σ	2739.22	4555.60	174.33	2117.27	3318.95	3220.25	607.71	2187.81	3235.90	3013.41	235.24
Dividend yield	$\bar{x}$	1.19	1.76	0.64	1.56	0.88	1.58	0.31	2.24	0.00	2.20	0.00
	t		144.22***		81.6***		177.17***		229.51***		287.33***	
	$\tilde{X}$	0.00	1.39	0.00	1.11	0.00	0.89	0.00	1.64	0.00	1.95	0.00
	σ	2.17	1.81	2.44	1.98	2.34	2.34	1.38	2.55	0.00	0.00	0.00

Note: The table reports statistical information about research sample and the subsample of each firm characteristic, SRC and SSC. Measures shown are count (N), mean ($\bar{x}$), Student's t-test (t), median ($\tilde{X}$), and standard deviation (σ), for each group. Count is the number of firms. Size and net income are in billion USD and million USD, respectively. Age is the number of years. Dividends are in USD. Large and small are 33% of the largest and smallest firms, respectively, by market capitalisation. Young and small are calculated by firms younger and older, respectively, than median age of all 500 firms. Firms with precise median age are excluded from young or small calculation. SRC firms are filtered for each characteristic: large, old, positive net income, and dividend yielding, and vice versa for SSC. For Student's t-test, we present coefficients in numerical format and p-values indicated by asterisks: ***, **, * depicting 1%, 5%, and 10% significance levels, respectively.

Source: own calculations.

Furthermore, we categorise firms according to specific characteristics, such as size and age, and subsequently compute their average relative trading volumes within each category. All stocks carry equal weights during relative volume calculation. Portfolio may refer to grouping of stocks for SSCs, SRCs, or per each firm characteristic as described. We then calculate the average portfolio relative trading volume using the following formula:

$$Relative\ Trading\ Volume_{Portfolio|week} = \frac{RTV_{Stock\,1\ |Week} + RTV_{Stock\,2\ |Week} + \ldots + RTV_{Stock\,N\ |Week}}{N}$$

where:

– N: Number of stocks in the given portfolio

We further employ two control variables to capture volatility, namely, the Chicago Board Options Exchange's VIX index to capture market's general volatility, and the self-calculated volatility of each sub-portfolio. In an additional analysis, we use S&P 500 index to control for market movements and calculate abnormal returns.[7]

2.2. Google Trends

Google Trends is a free-to-use tool developed by Google which allows its users to retrieve Google SVI for required keywords, date range and category of search. The category of search is particularly useful because words may have several meanings. For example, 'Tesla' may be a search for the scientist Nicola Tesla, or the car, or company, or TSLA the stock ticker. Google determines the context (Google Search, 2023) on its own, and allows the users of Google Trends to retrieve SVI per category. We filter each SVI result for the category of finance.

For selecting keywords and segregating positive and negative keywords, we use free-to-use dictionaries. These dictionaries also contain neutral keywords; however, we ignore these to maintain an absolute contrast. Together, these dictionaries contain a pool of more than 92,000 words:

1. Loughran-McDonald Dictionary of business vocabulary from the University of Notre Dame.[8]
2. A common language and internet vocabulary dictionary from the University of Illinois Chicago.[9]

[7] Formula mentioned in the appendix.
[8] https://sraf.nd.edu/loughranmcdonald-master-dictionary/
[9] https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

We retrieve five years of Google SVI for 1,150 randomly chosen keywords along with Google Search's total number of search results per keyword. We filter for geographical location in the United States and results only for Google Search (not for Google Images, Google News, Google Maps, etc.), and only English language-based search results.

The retrieved search volume is an index, not an absolute number and the temporal range may produce variable results. The index is expressed as a percentage, with the highest number of searches for a given keyword within the given date range defined as 100%. An absolute zero denotes no searches made for that iteration. Not being an absolute number resolves the potential issue of comparing frequently searched keywords to those that are less frequently searched. We also include 50 stock market-based words in the pool of dictionary keywords. Since we produce SVI for the same date range, the index is already calculated by Google Trends, making each of the 1,150 keywords comparable to each other.

Google Trends produces daily SVI if the requested date range is less than 9 months, weekly for greater than 9 months but less than 5 years, and monthly for greater than 5 years. Expanding our temporal scope to more than 5 years would decrease the number of observations. In fact, to match the number of monthly observations to the number of weekly observations for 5 years (244) we would have to expand our temporal scope to 20 years (243 observations), which would exceed the temporal range Google Trends offers, if we calculate backwards from our latest temporal range (Rogers, 2021). Therefore, maximising the number of observations, we retrieve weekly Google SVI for a 5 years' temporal range. Google produces weekly results iterated each Sunday. Data acquired for the stock market had the temporal granularity of being daily, therefore, we resample it to weekly to match the retrieved data from Google Trends.

Some keywords may be searched more frequently than others and indices do not reflect this information; therefore, we use each keyword's number of Google Search results to measure the 'popularity' of keywords during our analysis.

2.3. Sentiment Index

We use popularity, the retrieved number of search results for Google Search per keyword, to choose top 30 keywords (15 positive, 15 negative) from the total 1,150 randomly chosen keywords (575 positive, 575 negative) to calculate the weekly investor sentiment index. We count only non-zero values because zero denotes no searches. We average each week's positive and negative keywords separately, building two time series, and use the following formula to produce the Google Trends-based investor sentiment:

$$Standardised\ Sentiment_w = \frac{Sentiment_w - AVG(Sentiment)}{STDEV(Sentiment)}$$

where:

– $Sentiment_w = \frac{AVG(+SVI_{k,w})}{AVG(-SVI_{k,w})} - 1$,
– w = week,
– k = keyword,
– $+SVI_{k,w}$ = Weekly Search Volume Index per positive keywords,
– $-SVI_{k,w}$ = Weekly Search Volume Index per negative keywords,
– $AVG(Sentiment)$ = Average sentiment index for the whole 5-year period,
– $STDEV(Sentiment)$ = Standard deviation of the weekly sentiment index for the whole 5-year period.

In our analyses, we always use what is called standardised sentiment, which is essentially the Z-score normalised sentiment. Having a mean of zero and standard deviation of 1 ensures the entire sentiment time series to be scaled, and specifically, fit for linear regression models (Anggoro & Supriyanti, 2019). We observe a pre-modeling improvement—a more balanced sentiment index with 127 observations below zero as opposed to 5 previously. Nevertheless, in selective models, we additionally use absolute (standardised) sentiment to capture the relationship of the stock market data with only the magnitude of the investor sentiment, rather than the directionality of it, to record the impact of sentiment magnitude on the variations in the dependent variable. We also employ another sentiment index from the American Association of Individual Investors for a robustness check.

3. Empirical findings: Investor sentiment and stock trading volume

We start our analysis by presenting the standardised sentiment and absolute standardised sentiment, noting the maximum and minimum of the former as +3.03 and –2.63, respectively. We observe that sentiment was highest on 27th June 2021 and lowest on 15th April 2018.

Figure 1 displays this sentiment with variations over an almost five-year temporal range within our research scope. We also present the sentiment without directional bias. We note how 2018 and 2019 were more intense, especially negatively, than the subsequent couple of years.

In Figure 2, inspecting the data, we eliminate directional bias, thereby facilitating a visual pattern comparison between sentiment (standardised absolute

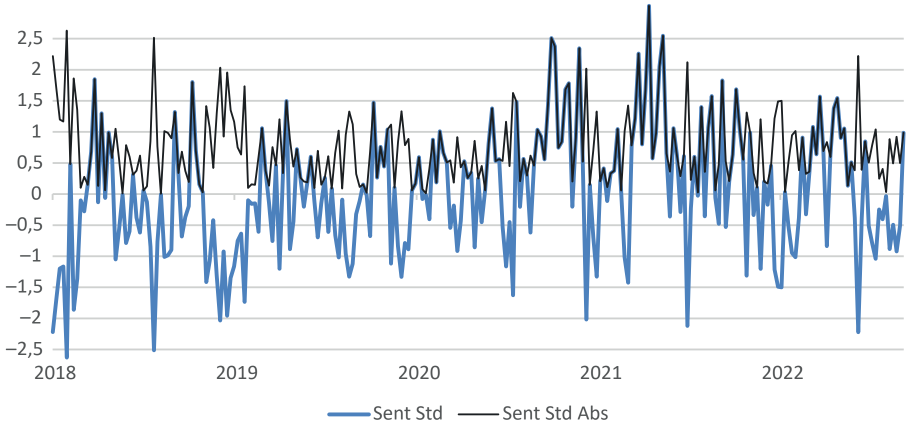

Figure 1. Sentiment standardised, and absolute sentiment standardised

Source: own work.

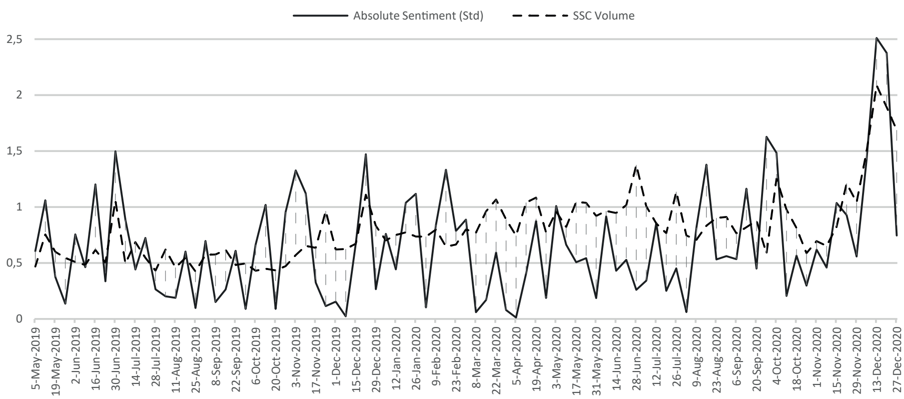

Figure 2. Sentiment without directional bias and relative trading volume of Sentiment-Sensitive Companies during COVID-19

Source: own work.

sentiment) and the relative trading volume of Sentiment-Sensitive Companies (SSCs) during the initial year of the COVID-19 pandemic. In Figure 1, we observe more negative sentiment than positive during the second half of 2019, while in Figure 2 during the same temporal range, we observe low and less varied movements in SSCs' relative trading volume, supporting Kahneman and Tversky's (1979) prospect theory's loss aversion concept, where a negative sentiment slows down stock trade of Sentiment-Sensitive Companies. We observe the peaks and dips in both time series in coherence with each other. We then begin to model the data for further investigation. For each subsample of stocks grouped by their characteristics we regress their relative trading volume on sentiment.

Table 2. Regression results of relative trading volume of stocks by characteristics against sentiment

	Size		Age		Net income		Dividend yield	
	large	**small**	**old**	**young**	**positive**	**negative**	**yes**	**no**
Const	0.989***	0.843***	0.968***	0.913***	0.970***	0.866***	0.965***	0.908***
	(31.35)	(24.35)	(34.72)	(32.26)	(34.93)	(25.87)	(34.68)	(31.50)
Std Sent	–0.008	0.082***	0.013	0.044***	0.008	0.076***	0.011	0.049***
	(–0.763)	(3.848)	(1.139)	(3.237)	(0.728)	(3.693)	(1.014)	(3.005)
Abs Std Sent	–0.004	0.080***	0.018	0.044**	0.017	0.066**	0.017	0.050**
	(–0.184)	(2.634)	(0.803)	(2.011)	(0.813)	(2.237)	(0.789)	(2.019)
Adjusted R^2 (%)	–0.06	13.33	0.01	6.6	–0.02	11.9	–0.03	7.3

Note: This table presents the results of eight regression analyses performed separately and displayed in one table. For each analysis, we use the mean relative volume of stocks (firms) grouped for the corresponding characteristic (size, age, profitability, dividend yield) as the dependent variable, and use sentiment and absolute sentiment as explanatory variables. We estimate t-statistics (in parentheses) using robust standard errors. We present coefficients in numerical format and p-values indicated by asterisks: ***, ** depicting 1%, and 5% significance levels, respectively, observations: 244.

Source: own calculations.

Referring to the results displayed in Table 2 the relative trading volume of firms which are large, or old, or generate positive net income, or yield dividends do not display any significant relationship with sentiment, whereas firms comprising the exact opposite of these attributes for each firm characteristic (i.e. firms which are small, or young, or generate losses, or do not yield dividend) depict a highly statistically significant relationship with sentiment. Removing directional bias, we also use absolute sentiment to find that firms with the same characteristics respond significantly to it, although the relation seems to be less significant.

The results for each characteristic confirm our expectations based on hypotheses H1 and H2: we observe high trading volumes in weeks with both abnormally high or low investor sentiment but only for certain group of companies (small, young, generating losses and those not paying dividends).

We also consider each regression model's adjusted R-squared value to determine the explainability of the variance in relative trading volume of the stocks corresponding to the particular firm characteristic, based on the explanatory variables (sentiment and absolute sentiment in our case). We observe size to be the most significant proxy for sentiment sensitivity, followed by net income, dividend yield, and age, in that order. We note a significant difference in each characteristic's division. We observe the t-statistic indicating that sentiment consistently outperforms absolute sentiment; specifically, sentiment is the strongest predictor for smaller stocks, among other characteristics.

These results motivate our next step, which involves summing the hypothesised firm characteristics together and regressing the mean relative trading volume of Sentiment-Resistant Companies and Sentiment-Sensitive Companies on sentiment and absolute sentiment. It is, nevertheless, worth remembering that the number of firms which simultaneously satisfy all characteristics to qualify for one portfolio or another is fewer than those per separate characteristics. While the characteristics for size, age, net income, and dividend yield are non-mutually exclusive (e.g., a firm may be large and old, while another may be large and young), firm characteristics for Sentiment-Resistant Companies and Sentiment-Sensitive Companies are mutually exclusive.

Figure 3 shows the number of stocks per characteristic. It also emphasises the reduction in the number of stocks, as the same are filtered for simultaneously comprising of corresponding characteristics per SRC or SSC.

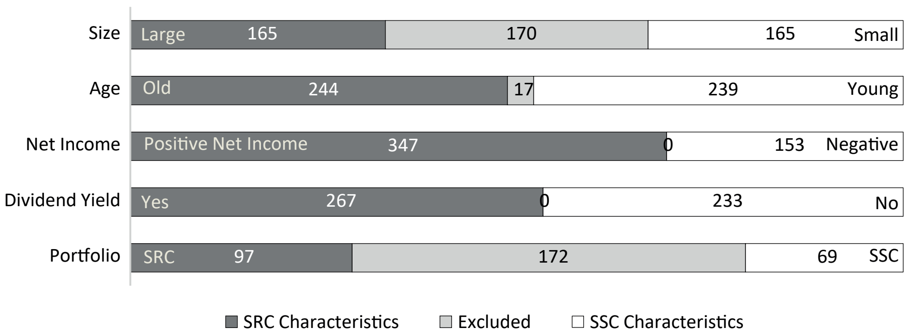

Figure 3. Breakdown of number of firms forming portfolios

Source: own work.

We regress the relative trading volume of Sentiment-Resistant Companies against sentiment and absolute sentiment, and separately, the same of Sentiment-Sensitive Companies against sentiment and absolute sentiment. Regression results are presented in Table 3.

We start with Model 1, regressing the relative trading volume of portfolios against sentiment; we observe it to be statistically significant for the relative trading volume of Sentiment-Sensitive Companies but not for Sentiment-Resistant companies. In Model 2, replacing sentiment with absolute sentiment to capture only the sentiment magnitude and not the directional bias, we observe the same results as Model 1. We find absolute sentiment to be statistically significant for the relative trading volume of Sentiment-Sensitive Companies only. Next, we introduce both explanatory variables together in Model 3. The findings indicate that the trading volume of Sentiment-Resistant Companies exhibits no correlation with sentiment, whereas the relative trading volume of Sentiment-Sensitive Companies demonstrates a statistically sig-

Table 3. Regression results of relative trading volume of portfolios against sentiment

	Model 1		Model 2		Model 3	
	SRC	SSC	SRC	SSC	SRC	SSC
Const	0.979***	0.849***	0.982***	0.752***	0.982***	0.764***
	(52.42)	(21.15)	(32.05)	(14.33)	(31.710)	(15.690)
Std Sent	–0.007	0.127***	–	–	–0.007	0.122***
	(–0.647)	(3.953)	–	–	(–0.620)	(4.094)
Abs Std Sent	–	–	–0.005	0.125**	–0.004	0.109***
	–	–	(–0.217)	(2.203)	(–0.172)	(2.772)
Adjusted R^2 (%)	–0.3	12	–0.4	3.8	–0.06	14

Note: This table presents the results of 6 regression analyses performed for 3 comparative models, displayed in one table. For each analysis, we use the mean relative volume of firms grouped for the corresponding portfolio (i.e. Sentiment-Resistant Companies, and Sentiment-Sensitive Companies) as the dependent variable, and for explanatory variables, in Model 1 we take sentiment, in Model 2, we take absolute sentiment, and in Model 3 we take both. We estimate t-statistics (in parentheses) using robust standard errors. We present coefficients in numerical format and p-values indicated by asterisks: ***, ** depicting 1%, and 5% significance levels, respectively, observations: 244.

Source: own calculations.

nificant and robust relationship with both sentiment and absolute sentiment. Specifically, the coefficient for sentiment is +0.122, suggesting that for each one-unit increase in sentiment, the relative trading volume is expected to increase by +0.122 units, holding all other factors constant. The same holds true for absolute sentiment as well. This strong evidence allows us to reject the null hypothesis that the coefficients are equal to zero, suggesting that both sentiment and absolute sentiment have a meaningful impact on the relative trading volume of Sentiment-Sensitive Companies. A key factor to note here is the adjusted R-squared, which for the model regarding Sentiment-Resistant Companies is –0.06%, suggesting that Google Trends-based sentiment explains no variance in the relative trading volume of these set of companies, while the same for Sentiment-Sensitive Companies is 14%. Similarly, we observe the high t-statistic for sentiment and nearly half for the sentiment when directional bias is removed, in the case of SSCs, providing evidence in favor of sentiment being a strong predictor in the equation. In the case of SRCs, we observe neither of the explanatory variables to be explainable of the waves or patterns of the relative trading volume of SRC stocks.

Overall, these results underscore the importance of sentiment in influencing the trading behavior of the (retail) investors of companies which are simultaneously small, young, and do not generate profit or yield dividend.

While our first research question investigates the potential of Google Trends as a tool for measuring investor sentiment, the findings support this inquiry, demonstrating that Google Trends can indeed serve as a reliable indicator of investor sentiment. The second research question explores which firm characteristics are sensitive to investor sentiment. Our findings indicate that our Sentiment-Sensitive Companies portfolio comprises firms with characteristics that are sensitive to investor sentiment: they are small, young, with negative annual net profit, and those which do not yield dividends.

Our first hypothesis posits a positive and linear relationship between investor sentiment derived from Google Trends, and stock trading volume for Sentiment-Sensitive Companies. The analysis confirms this hypothesis revealing a significant positive correlation between the two variables. Following suit, our second hypothesis asserts that, irrespective of the directionality of sentiment, an increase in sentiment magnitude is associated with a corresponding increase in stock trading volume for Sentiment-Sensitive Companies. The results substantiate this hypothesis, indicating that greater sentiment magnitude consistently correlates with increased relative trading volume in the stocks with the same firm characteristics, as exhibited visually in Figure 4. These findings are in alignment with Das and Chen (2007), who found a strong relationship between the trading volume and sentiment. Loss aversion theory seemed in place during COVID-19 era between the trading volume of SSCs and negative sentiment, the volatility may also be explained by the disposition effect (Weber & Camerer, 1998). This posits that investors may desire to avoid risk and hence sell stocks more in response to negative news (greater negative sentiment), naturally attracting further investors, and continuing the volatility.

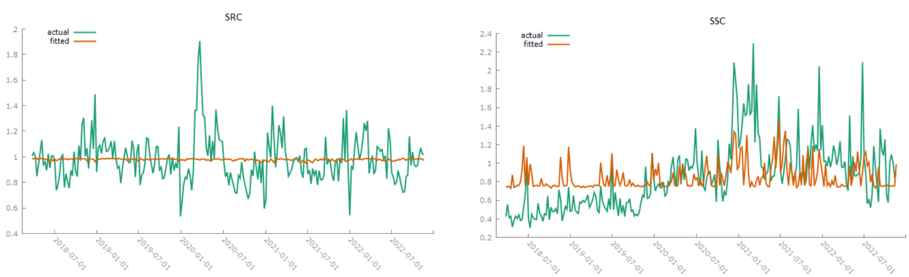

Figure 4. Actual versus fitted relative trading volume of SRCs and SSCs based solely on sentiment and absolute sentiment

Source: own work.

Overall, the successful validation of the research questions and confirmation for hypotheses provides empirical evidence of the association between investor sentiment and stock trading volume.

To verify whether the observed results are not driven by other factors we expand our models by adding control variables. We added VIX index as previous studies reveal strong correlations between stock market volatility and stock trading volume (regardless of investor sentiment). We also added lagged relative trading volume. These results are presented in Table 4.

Table 4. Regression results of relative trading volume of SRC and SSC against sentiment with control variables

	SRC		SSC	
Const	0.426***	(7.168)	0.138***	(3.076)
Std Sent	–0.01	(–1.200)	0.062***	(4.002)
Abs Std Sent	0.015	(1.081)	0.087***	(3.475)
VIX	0.007***	(3.524)	0.005***	(2.907)
Vol L1	0.390***	(5.208)	0.626***	(10.95)
Adjusted R^2 (%)	38.9		56.7	

Note: This table presents two regression analyses performed separately and displayed together. For each analysis, we use the mean relative volume of firms grouped for the corresponding portfolio (i.e. Sentiment--Resistant Companies, and Sentiment -Sensitive Companies) as the dependent variable, and use sentiment, absolute sentiment, CBOE's VIX index, and the one-iteration lagged (abbreviated to L1) relative trading volume of the corresponding portfolio, as explanatory variables. We estimate t-statistics (in parentheses) using robust standard errors. We present coefficients in numerical format and p-values indicated by asterisks: *** depicting a 1% significance level, observations: 243.

Source: own calculations.

Regarding sentiment, our findings remain consistent with the previous findings of the two portfolios (SRC and SSC). The newly introduced variables in our models—the VIX index and the one-week lagged relative trading volume of the respective portfolios—are statistically significant and positively correlated with each portfolio. The analyses conducted are auto-regressive, indicating that while both portfolios exhibit a strong correlation with the newly added variables, investor sentiment remains a significant determinant of

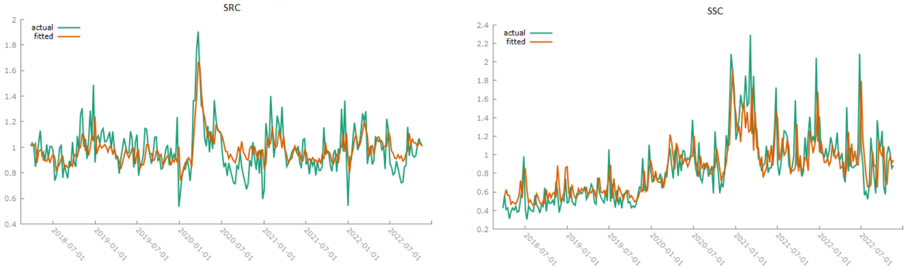

Figure 5. Actual versus fitted relative trading volume of SRCs and SSCs based on sentiment, absolute sentiment, and control variables

Source: own work.

the relative trading volume of the stocks comprising the firm characteristics peculiar to Sentiment-Sensitive Companies. We observe the improvement in both models due to the additional variables in Figure 5.

It is important to highlight the high t-statistic associated with sentiment and absolute sentiment in both the SRC and SSC models. Additionally, we observe a significantly higher adjusted R-squared value in the SSC model compared to the SRC model, indicating that the explanatory variables account for 18% more variance in the relative trading volume of the SSC. This observation necessitates a critical comparison between Table 3 and Table 4. The inclusion of control variables leads to an improvement in the adjusted R-squared value, with the new explanatory power being particularly significant for the VIX and the latent relative trading volume, as evidenced by the t-statistics and p-values. A similar enhancement is indeed noted in the SSC models when comparing Table 3 and Table 4. In both cases, the market volatility index (VIX) is expected to display a strong correlation, since all stocks in SRCs and SSCs are chosen from the list of S&P 500, comprising the largest and most liquid companies in the United States (Kenton, 2024). Adding lagged relative trading volume as the strongest predictor (with the highest t-statistic), due to its auto-regressive nature, sufficiently supports the adjusted R-squared explainability power of the models. Consequently, we focus on investor sentiment, in line with our scope, to conclude that small and young companies that generate losses and do not yield dividends are most sensitive to investor sentiment derived from Google Trends. Our findings are in line with Ferguson et al. (2015), who used sentiment based on news media, or Oliveira et al. (2017) using Twitter. As we observed the standardised sentiment overperforming the directionless sentiment, this is indeed the case with the findings of Aysan et al. (2024).

4. Empirical findings: Investor sentiment and stock returns

In the next step, we extend our analysis towards stock returns to investigate the predictability potential of investor sentiment derived by Google Trends. Table 5 presents the results of the analysis between stock returns and sentiment.

Initially, we perform a regression analysis of portfolio stock returns using explanatory variables that include sentiment, the VIX index, relative trading volume, and the stock returns of the corresponding portfolio. All explanatory variables are lagged by one week. Subsequently, we calculate abnormal returns by subtracting the change in the S&P 500 from the stock returns of each portfolio, thereby mitigating the impact of market movements. We then

Table 5. Regression results of returns of SRC and SSC against sentiment with other variables

Table 5-A			Table 5-B		
	Ret SRC	**Ret SSC**		**Abn Ret SRC**	**Abn Ret SSC**
Const	–0.003	–0.013	Const	0.000	–0.008
Sent Std L1	0.002	0.006**	Sent Std L1	–0.001	0.004*
VIX L1	0.000	0.001*	VIX L1	0.000	0.001*
Vol L1	–0.002	–0.017*	Vol L1	0.001	–0.013*
Ret L1	–0.076	0.093	Abn Ret L1	–0.092	0.054
Adjusted R^2 (%)	0.30	3.90	Adjusted R^2 (%)	–0.06	2.50

Note: This table presents two sub-tables, each with results of two regression analyses performed separately and displayed together. For the two models in Table 5-A, we use the mean stock returns of firms grouped for the corresponding portfolio (SRC or SSC) as the dependent variable, and use sentiment, CBOE's VIX index, relative volume (abbreviated to Vol) of the corresponding portfolio, and mean stock returns (abbreviated to Ret) of the corresponding portfolio. For Table 5-B, we replace dependent variables with abnormal stock returns (abbreviated to Abn Ret) of firms grouped for the corresponding portfolios, and among the explanatory variables, we replace mean stock returns with abnormal returns of the corresponding portfolio. It must be noted that in all Table 5 models, all explanatory variables are lagged for one iteration, i.e. one week in this case (abbreviated to L1). We present coefficients in numerical format and p-values indicated by asterisks: **, * depicting 5%, and 10% significance level, respectively, observations: 243.

Source: own calculations.

replace the dependent variable with the abnormal returns of each portfolio and regress these against the same explanatory variables, substituting stock returns with abnormal returns, while maintaining the one-week lag for all explanatory variables.

Our findings indicate that for stock returns, the sentiment from the previous week exhibits a strong and significant positive relationship with the next-week stock returns of SSCs. Additionally, the lagged VIX index and lagged relative trading volume are statistically significant for SSCs, whereas none of these variables demonstrate any correlation with stock returns of SRCs. Notably, in the case of lagged relative trading volume, we observe an inversely proportional relationship with sentiment; specifically, for every increase of 0.017 units in relative trading volume, there is a corresponding decrease of one unit in the stock returns of SSCs. In the analysis of abnormal returns, a similar pattern emerges, with SSCs showing a strong significant relationship with lagged sentiment, the lagged VIX index, and lagged relative trading volume. We again observe the inversely proportional relationship with lagged relative trading volume, quantified at –0.013. Thus, our findings provide statistically significant evidence for the potential to forecast stock returns of small, young, unprofitable firms which do not yield dividends through investor sentiment derived from Google Trends, thus also satisfying our additional hypothesis (H3) that investor sentiment derived from Google Trends can be used to forecast the future returns of Sentiment-Sensitive Companies. Our findings coincide with those of Berger (2022), who also used Google Trends' data to conclude that small, young, and volatile firms are sensitive to investor sentiment, as in our findings. However, we expand on the volatility separately by observing the trading volume (described in the previous chapter), and we include profitability (through the use of net income), and dividend yield to further narrow down the investigation for both relative trading volume and stock returns.

5. Robustness check with Alternate Sentiment Index

There are various ways to measure investor sentiment. Tetlock (2007) used print media, ISEE by NASDAQ uses ratios of long call and put options by retail investors, CNN's sentiment index known as the Fear & Greed Index relies on several proxies such as put and call options, market volatility, junk bond demand, etc., and we captured internet searches. Next, we use an investor sentiment index from the American Association of Individual Investors.[10] This organisation conducts a survey every week to measure investor sentiment based on responses of whether investors believe the market is going to be bullish, neutral, or bearish. Responses from investors are recorded for the upcoming week, and a sentiment is calculated as a bull–bear spread. We use the AAII

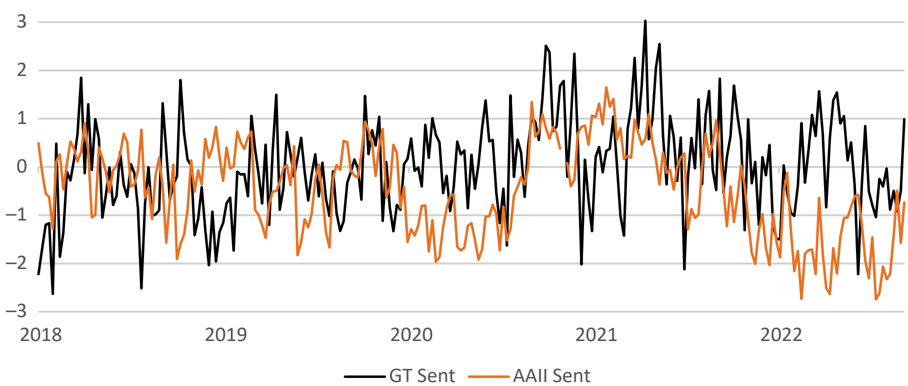

Figure 6. AAII sentiment and Google Trends-based sentiment indices

Source: own work.

[10] https://www.aaii.com/sentimentsurvey

sentiment index as a robustness check for the baseline results from our regression models. Figure 6 presents both sentiment indices (AAII sentiment and Google Trends-based sentiment) in the same scope for visual inspection of the waves and patterns.

We regress the relative trading volumes of SRCs and SSCs against AAII sentiment and Google Trends-based sentiment and compare the results. AAII conducts an expansive survey involving thousands of respondents to gauge investor sentiment, whereas the Google Trends-based measure is free, fast, and adds practical efficiency.

Table 6. Regression analyses of relative trading volume against sentiment – AAII Sentiment versus GT Sentiment

Table 6-A			Table 6-B		
	Ret SRC	**Ret SSC**		**Abn Ret SRC**	**Abn Ret SSC**
Const	0.953***	0.681***	Const	0.982***	0.764***
	(40.54)	(11.34)		(37.310)	(15.690)
AAII Sent Std	–0.030	0.134**	GT Sent Std	–0.007	0.122***
	(–1.437)	(2.537)		(–0.620)	(4.094)
AAII Sent Std Abs	0.013	0.270***	GT Send Std Abs	–0.004	0.109***
	(0.508)	(4.239)		(–0.172)	(2.772)
Adjusted R^2 (%)	3.12	10.12	Adjusted R^2 (%)	–0.06	14

Note: This table presents results of separate regression models in one uniform structure. We regress the relative trading volume of each portfolio with sentiment and absolute sentiment. We replace Google Trends-based sentiment with one acquired from the American Association of Individual Investors, and compare the significance levels of variables, thus concluding our robustness check. We estimate t-statistics (in parentheses) using robust standard errors. We present coefficients in numerical format and p-values indicated by asterisks: ***, **, * depicting 1%, 5%, and 10% significance level, respectively, observations: 243 (6-A), 244 (6-B).

Source: own calculations.

Neither of the investor sentiments exhibits statistical significance concerning the relative trading volume of SRC; however, both investor sentiments are significantly correlated with the relative trading volume of SSCs. Comparing SSCs for sentiments derived from AAII and Google Trends (Panel A of Table 6), we observe that both models have positive coefficients suggesting that the waves and patterns between either sentiment would resonate similarly with the relative trading volume of SSCs. We observe the t-statistic for Google Trends-based sentiment (Panel B of Table 6) to be higher than that of AAII-based sentiment, indicating that the former is a stronger predictor of relative trading volume of SSCs. Comparing the results, we observe the Google

Trends-based sentiment index to be a stronger determinant of the relative trading volume of SSCs in comparison to when the directional bias is removed from it. Quite the contrary, for SSCs' relative trading volume being determined through AAII sentiment, this effect is switched: sentiment magnitude regardless of directionality is a stronger determinant than directional sentiment. Nonetheless, the adjusted R-squared for AAII-based model for SSCs is lower than that of the Google Trends-based model for SSCs, suggesting that Google Trends-based sentiment explains a greater portion of the variance in relative trading volume of SSCs compared to the AAII sentiment model. The findings indicate a more pronounced relationship with sentiment derived from Google Trends compared to that from the American Association of Individual Investors. This further substantiates the notion that the characteristics of firms included in the portfolio of Sentiment-Sensitive Companies (small, young, unprofitable, and non-dividend-yielding) exhibit a strong relationship with investor sentiment, regardless of how it is measured. It is pertinent to note that the investor sentiment derived from Google Trends is more effective in explaining the variance for SSCs' relative trading volumes.

Conclusions

This study focuses on the relationship between the stock market, specifically trading volume, and investor sentiment. We formulate a novel approach involving implementing Google SVI-based investor sentiment (based on positive/negative word classification) and find the specific firm characteristics which resonate with the waves and patterns of the sentiment. Our findings affirmatively address the first research question, demonstrating that Google Trends can serve as a reliable proxy for measuring investor sentiment, consistent with the suggestions made by Duc et al. (2024) and other researchers who have utilised Google Search as a sentiment indicator (Costola et al., 2021; Smales, 2021).

Baker and Wurgler (2007) utilised market proxies to generate a sentiment index, the American Association of Individual Investors runs a survey to acquire this knowledge, and we used Google Trends to generate an index to measure investor sentiment and investigate its relationship with the stock market performance of companies and assess which characteristics (size, age, dividend policy, and profitability) make them more sensitive to investor sentiment. Using a sample of 500 US companies, we created two distinct portfolios of Sentiment-Resistant Companies, and Sentiment-Sensitive Companies, expecting large, old, profitable and dividend-yielding companies to be resistant to investor sentiment and the exact opposite characteristics to be sensitive to investor sentiment. The analysis reveals that the said firm characteristics do indeed influence a firm's sensitivity to investor sentiment. Specifically, our results indicate that smaller and younger companies that generate losses and do not yield dividends exhibit a strong and positive correlation with investor sentiment. This finding aligns with the notion that individual investors, often characterised as "noise traders" (Shleifer & Summers, 1990), are more likely to react to sentiment changes in firms that are perceived as riskier or less established. Conversely, larger and older companies which generate profits and yield dividends show no significant relationship with sentiment, suggesting that established firms may be less susceptible to the fluctuations of investor sentiment, as posited by Baker and Wurgler (2006). This distinction emphasises the critical role of firm characteristics in understanding the dynamics of sentiment-driven trading behavior.

Moreover, our investigation into the forecasting potential of investor sentiment reveals a significant and positive relationship between lagged sentiment derived from Google Trends and next-week stock returns for the firms identified as Sentiment-Sensitive Companies, but not for the same of Sentiment-Resistant Companies. This finding not only contributes to the literature on investor behavior (Baker & Wurgler, 2006; Duc et al., 2024) but also offers practical implications for retail investors and market participants seeking to leverage sentiment analysis in their decision-making processes. In conclusion, this study fills a significant gap in the literature by linking investor sentiment to specific firm characteristics, thereby providing a nuanced understanding of how sentiment influences trading volume and stock returns. Our findings are equally useful for researchers and retail investors in repeating or enhancing the methodology of using the free-to-tool Google Trends tool to generate a sentiment index through the use of random keywords from dictionaries available for everyone. They can also capitalise on the firm characteristics which we have shown to be statistically significant with this sentiment. Future research could expand upon these findings by exploring additional firm characteristics or examining the impact of sentiment in diverse market conditions.

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Appendix

Abbreviations

Abs	Absolute	$\bar{x}$	Mean
AVG	Average	t	Student's t-test
Std	Standardised	$\tilde{X}$	Median
Sent	Sentiment	σ	Standard deviation
Vlt	Volatility	STDEV	Standard deviation
Vol	Relative volume	Ret	Returns
SRC	Sentiment-Resistant Companies	SSC	Sentiment-Sensitive Companies
Const	Constant	GT	Google Trends
Pos	Positive	Neg	Negative
L1	Lag 1 (1 week here)		

Formulae

Stock Returns

$$Returns_{Stock\ |Week} = \frac{P_w - P_{w-1}}{P_{w-1}}$$

$$Returns_{Portfolio|week} = \frac{Returns_{Stock\ 1\ |Week} + Returns_{Stock\ 2\ |Week} + \ldots + Returns_{Stock\ N\ |Week}}{N}$$

$$Returns\ S\&P\ 500_{week} = \frac{S\&P\ 500\ Index\ Value_w - S\&P\ 500\ Index\ Value_{w-1}}{S\&P\ 500\ Index\ Value_{w-1}}$$

$$Abnormal\ Returns_{Stock\ |week} = Returns_{Stock\ |Week} - Returns\ S\&P\ 500_{Week}$$

$$Abnormal\ Returns_{Portfolio|week} = \frac{AbnRet_{Stock\ 1\ |Week} + AbnRet_{Stock\ 2\ |Week} + \ldots + AbnRet_{Stock\ N\ |Week}}{N}$$

where:
- P_w: Adjusted closed price of last trading day of week,
- P_{w-1}: Adjusted closed price of last trading day of the previous week,
- $AbnRet$: Abnormal Returns,
- N: Number of stocks.

All stocks carry equal weights during stock returns calculation. Portfolio may refer to grouping of stocks for SSC, SRC, or per each firm characteristic as described.

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