Can attention explain the abnormal dynamics of the stock market?

Google searches as an attention proxy and stock market predictability.

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Abstract

This study investigates the impact of investor attentiveness, measured using Google Trend data, on stock returns, trading volume, and volatility in the US stock market. By analyzing the relationship between Google search volume and market variables, I observe a small positive association between search volume and abnormal returns. Furthermore, I find that Google searches exhibit an even stronger correlation with trading volume and volatility. Granger causality tests reveal a one-way predictive ability from Google search volume to subsequent returns for some companies in the US stock market. Additionally, bidirectional causality is observed when examining the relationship between Google search volume, stock volume, and volatility. These findings provide evidence supporting the presence of market inefficiency to some extent, suggesting that investor attention plays a role in market dynamics. However, the practical implications of these effects are minimal, as they do not offer profitable trading strategies. Furthermore, the study addresses the complex dynamics of the stock market and acknowledges the challenges of endogeneity, emphasizing its significance in evaluating the validity of the analysis results.

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1. Introduction

1.1. Background and motivation

The prediction of stock returns has been extensively studied in the field of finance. Nonetheless, there are two areas where researchers have yet to reach a consensus: the feasibility of predicting stock market movements, and the implications that such predictability may have on our understanding of financial markets. The foundation of asset pricing theory is straightforward: price equals anticipated discounted return. Meaning that the price of an asset today should reflect the expected future cash flows generated by that asset, adjusted for the time value of money and the risks involved.

With the advent of personal computers, the accessibility to stock markets has expanded, and the speed of information sharing has accelerated. This development has empowered individual investors to conduct their own research and engage in stock transactions, consequently enhancing the efficiency of stock markets. As a biproduct, computers have also presented challenges for individual investors in profiting from information, as institutional investors leverage programmed algorithms. The efficient market hypothesis posits that new information is swiftly incorporated into stock prices, leading to infrequent instances of overpriced or underpriced securities. Nonetheless, existing literature extensively discusses a range of contradictory observations that challenge the notion of human error being fully arbitraged away, as suggested by theoretical frameworks. (Poterba & Summers, 1988) (Badrinath & and Wahal, 2002) (Hansen, Lunde, & Nason, 2003) .

Google's search engine stands as the predominant and extensively employed information retrieval platform globally. Nearly 90% of internet searches worldwide are conducted through this influential search giant. Additionally, Google records statistics on various search queries performed on its search engine, making this information publicly accessible through their webpage called Google Trends. (statcounter)

As the price of a stock is determined by the equilibrium of supply and demand at a specific moment, the volume of internet search activity can potentially indicate the level of interest and public sentiment surrounding a stock. Consequently, it may provide insights into the stock's future price prospects.

1.2. Research question

Following the theory and literature review in chapter 2 and 3, I arrived at the following research question:

- Can Google search volume explain the abnormal dynamics of the stock market?

If it is so, the results should suggest informational inefficiency to some extent. It could also be considered a counterargument to efficient market hypothesis and capital asset pricing model[1]. Nevertheless, such arguments will be tested and discussed thoroughly in chapter 7. This paper is a contribution to understanding the stock markets, it's informational efficiency and market participants.

1.3. Methodology

I follow the methods used in Bijl et al. (2016) where they investigate whether Google searches can predict future abnormal returns. By utilizing panel data analysis, I will be observing a large sample of American stocks and the relationship with Google stock ticker searches. Additionally, I base abnormalities observed on predictions made by standard economic theory, namely the capital asset pricing model. The method will be thoroughly explained later in chapter 4.

1.4. Relevance

The world's largest sovereign wealth fund "*The Norwegian Government Pension Fund*" is globally renowned for its influence and professional management. Despite its prestige, there is still disagreement about whether the sovereign wealth fund should engage in active management or not as it is of great interest to the Norwegian population. To actively manage means hiring professional traders to analyze financial assets in an effort to beat the market index. Several Norwegian academics and finance experts have advocated for an absolute passive management of the fund. Other investors argue that the fund should take a more active

[1] Explained in section 2.2.

ownership approach in its positions while facilitating a management strategy that allows for the analysis and evaluation of market prices, in other words managing more attentively. Moreover, a quantitative analysis by (Bauer, Christiansen, & Døskeland, 2022) found a positive, but small surplus by the active management. Nevertheless, theoretical principles indicate that in the long run, it is advantageous to maintain a well-diversified market portfolio. By doing so, one would only be exposed to systemic risk, which affects the entire market. This approach offers the highest achievable return for a given level of risk. Rational investors will naturally aim to position themselves along the tangent line to the efficient set. This point corresponds to the market portfolio. If Google search volume were to demonstrate predictive power for future returns, it could present an argument against passive management strategies.

1.5. Structure

To answer my research question, I will first describe the relevant theory underlying informational efficiency, asset pricing, and the methods I use. I will later explain the methods I use to evaluate "Google search score" predictability for stocks before presenting the results of my analyses. Finally, I summarize the findings of the report and comment on possible implications.

The task is structured as follows:

- *Chapter 2* describes the theoretical basis for informational efficiency. And I explain the capital asset pricing model and what abnormal returns is.
- *Chapter 3* reviews the literature I use in the report.
- *Chapter 4* takes on the methodology framework. I will describe the assumptions I have made and limitations of the models.
- *Chapter 5* deals with the data underlying my analyses.
- *Chapter 6 and 7* present the results of my analyses and answers the research question.
- *Chapter 8* concludes based on the results of the analysis.

2. Theory

2.1. Informational efficiency

2.1.1. Efficient market hypothesis

In traditional finance there is the theory of efficient markets (EMH). According to the theory, market prices "*always reflect all available information*" (Fama E. F., 1970). If investors are to be able to earn money through attentive portfolio management at all, the market cannot be perfectly efficient. Based on the definitions by Fama, certain criteria must be met for a market to be considered efficient:

- The market consists of numerous investors who trade rationally. This means that all information regarding current and future events is interpreted in the same way and is reflected in the stock price.
- Information is available to all market participants at a negligible cost, and stocks can be traded without transaction costs.
- If some investors trade irrationally, the rational and intelligent investor will exploit the arbitrage opportunity. This will eliminate arbitrage, and the market will converge back to equilibrium.
- Future stock prices are not predictable[2], and it is therefore not possible to profit from systematic mispricing.
- The current stock price represents the intrinsic value of the company. In other words, the current price is the future expected cash flow discounted to present value.

Fama divided the EMH into strong, weak, and semi-strong, where the strength reflects how much and what kind of information there is available.

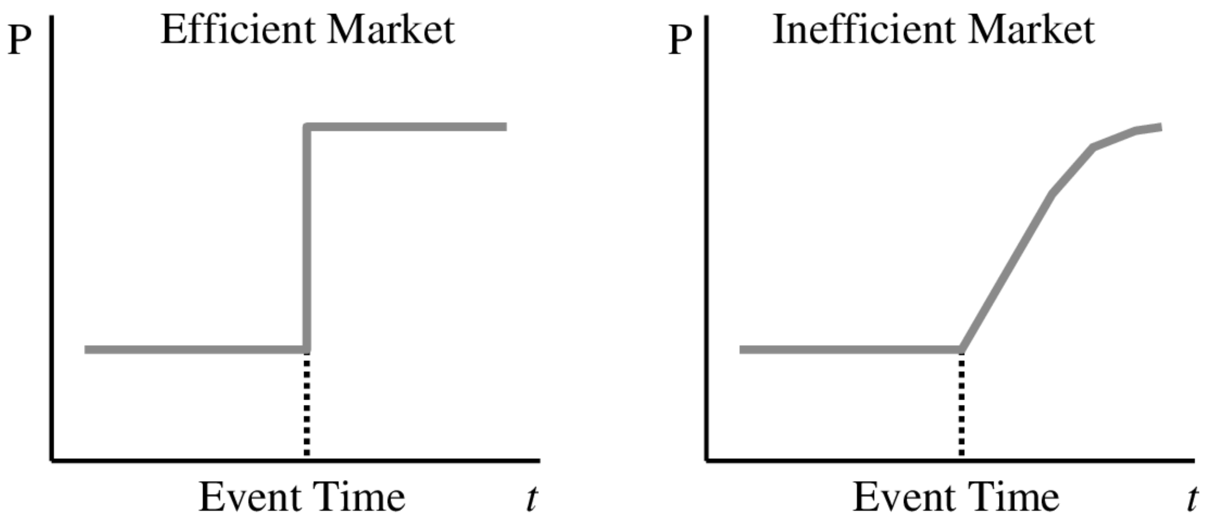
1. *Strong form:* Available information also includes insider information. In other words, information that employees of the company have but which has not been communicated publicly.

[2] Random walk: stock prices move unpredictably, so that past prices cannot be used to predict future prices.

2. *Semi-strong form:* Available information includes, in addition to past prices, other public information such as quarterly reports, news, and market trends.
3. *Weak form:* Available information is information about past price developments.

The markets' reaction to new information can be illustrated as shown below:

Figure 1



Above: Efficient market reaction to favorable news vs. inefficient market reaction. (Chuvakhin)

As the leftmost graph in figure 1 demonstrates, there are no excess return to gain by acting on the event because the market always reflects information in real time. In contrast, inefficient markets are there still possibilities of earning excess return because the market is somewhat slow to react on the information. Both forms of market have empirically been proven by numerous researchers (Malkiel, 2003). Other studies have also demonstrated that stock prices incorporate information prior to its public release (Keown & Pinkerton, 1981).

There has been much criticism of the EMH. It's not surprising considering that there are asset management firms and brokers who make a living selling products based on technical analysis. First and foremost, there have been many questions raised about the assumptions underlying the hypothesis. The criticism revolves around what is defined as information and how to find the causal effect of new information on a stock price. There have also been questions about how market participants interpret information. Emotions and needs can be crucial in how investors interpret new information. The criticism raises questions about how it can be controlled for all investors to trade alike on the same information. Based on this, I will highlight criticism of the assumptions and the ability to test it, on the theory of behavioral finance (Kahneman & Tversky, 1979) and the Grossman-Stiglitz paradox (1980).

2.1.2. Grossman-Stiglitz paradox

Sanford J. Grossman and Joseph Stiglitz (1980) argued that a perfectly efficient market would be impossible because if no one analyzes the market when it is not profitable (*because investors believe the market is efficient*), new information will not be reflected in stock prices. Onward, if some investors start to analyze the market and profit from it, more will follow, and the profit margins will eventually disappear. Noting that a sufficiently large portion of the market participants must believe the market are not efficient for the market to be efficient.

2.1.3. Behavioral finance

Behavioral finance is about how investors' decisions can be influenced by emotions and assumptions. According to professors Barberis and Thaler (2003) from the University of Chicago, the concept can be explained through a model where not all investors act rationally. Behavioral finance consists of two main blocks. Firstly, it can be difficult for rational investors to bring the market into equilibrium as long as there are enough irrational investors. This is because rational investors do not have enough power to bring the market into its intrinsic value. The second block in behavioral finance is psychology. Investor psychology can help explain why investors behave irrationally. Barberis and Thaler (2003) explain that investors' decisions can be influenced by various factors, such as overestimation of their own abilities or a distorted optimistic view of reality.

Barbeis, Shleifer and Vishny conducted a study in 1998 examining investor behavior and reactions to new information. The study is consistent with the representativeness theory of Kahneman and Tversky (1979), meaning that they tested the model on a small sample and assumed that the sample represents the population. They performed statistics on over- and underreactions to earnings announcements and found that investors underreact to positive news in the short term. The model by Barberis et al. (1998) assumes that actual earnings are random, but the results show that investors believe that earnings follow one of two regimes:

Regime 1: Earnings always converge towards their mean, meaning that if earnings are well above average in one period, investors assume that they will be lower in the next period.

Regime 2: Earnings trend positively, meaning that if earnings have had a positive trend in the past two periods, they will continue to do so in the next.

In each period, the investor acquires new earnings information and assesses which regime they are in.

The results of this study show that shareholders absorb information slowly, and this mindset is associated with investor conservatism, but in the longer term (3-5 years), the general investor overreacts to information. This means that a stock with a long positive flow of information tends to become overpriced.

2.1.4. Famas response

In 1998, Fama responded to the studies that attempted to overturn his theory of efficient markets. He emphasizes that behavioral models alone cannot reject EMH. Anomalies in a market may occur and are consistent with EMH. According to Fama (1998), EMH cannot primarily be rejected for two reasons:

Firstly, under- and overreactions to news in an efficient market may occur, but over a long time horizon, there will be as many overreactions as underreactions if the distribution of reaction types is random. This is consistent with EMH.

Secondly, if long-term anomalies in returns are so large that they cannot be attributed, a split between under- and overreactions would be a victory for efficient theory. Anomalies tend to disappear or become marginally small when returns are measured in normal return models or with different statistical approaches.

Fama (1998) emphasizes that most studies do not provide an alternative to EMH and that alternatives must explain how the skewness in information interpretation results in investors underreacting in some cases and overreacting in others.

2.2. Capital asset pricing model

In finance theory the capital asset pricing model (CAPM) models the required rate of return of an asset, that is used to determine a theoretical decision-making about adding an asset to the portfolio. In the mid- 1960s William Sharpe (1994) and John Lintner (1965), individually developed the model. This model considers the assets sensitivity to systematic risk.

There are three main assumptions about investors' behavior behind the CAPM.

I. Investors can buy and sell all assets at competitive market prices (without pay tax and transaction costs) and can borrow and place at a risk-free rent which is the same for everyone.
II. Investors will only hold efficient portfolios, i.e., portfolios that maximize expected return for a given volatility and minimizes volatility for a given expected yield.
III. All investors have homogeneous expectations for volatility, correlation and expected return on all assets.

Figure 2

Investment opportunities

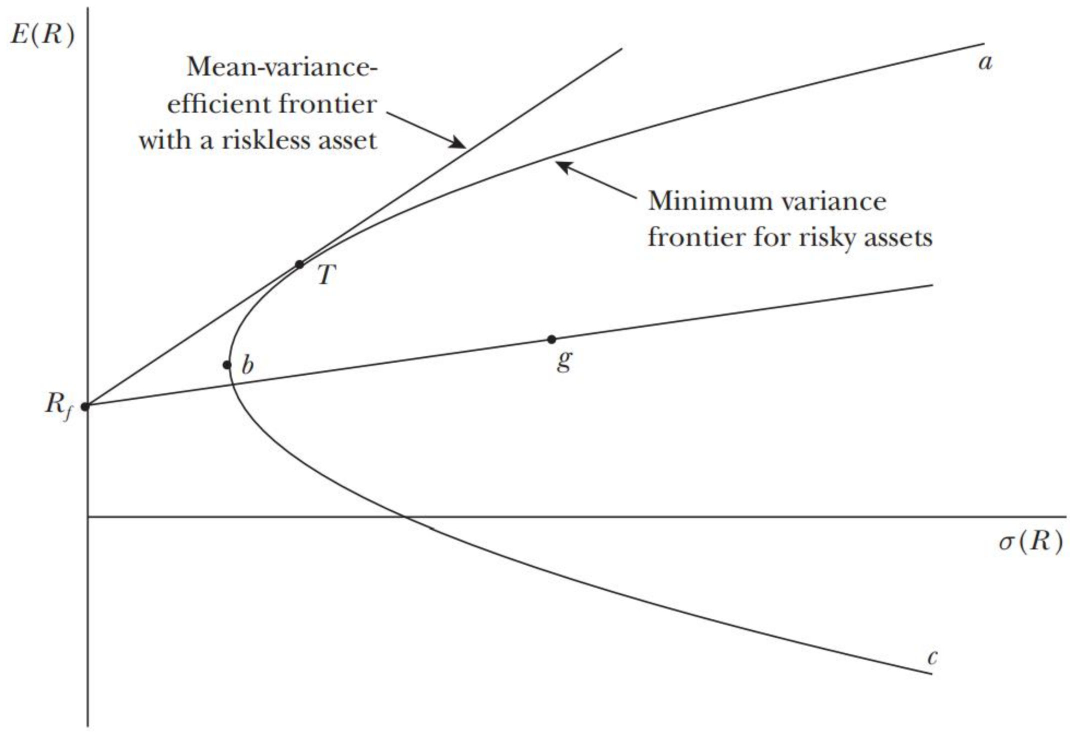


Figure from: (Fama & French, The Capital Asset Pricing Model, 2004)

Figure 2 displays various portfolios ranked by expected return on the vertical axis and the total risk of the portfolio, measured by the standard deviation of the portfolio, on the horizontal axis. The curve a-b-c illustrates the efficient set of portfolios, which are the portfolios that minimize volatility for a given expected return. It is not possible to invest risk-free in this set. Only portfolios above point b (the minimum variance portfolio) along the curve a-b-c are efficient because they maximize expected return for a given level of volatility.

By adding a risk-free borrowing and lending opportunity, the efficient set changes to a straight line (the Capital Market Line (CML)) that starts at the risk-free rate of return (R_f) and passes through the tangency portfolio T. This line represents all efficient combinations of the risk-free asset and the tangency portfolio T. With homogeneous expectations, all investors hold the optimal portfolio T regardless of their risk aversion. The only difference is that more risk-averse investors hold a larger share in the risk-free asset and a smaller share in the tangency portfolio T. A portfolio consisting entirely of the risk-free asset results in the point R_f in the figure, where the return is risk-free.

Because all investors hold the tangency portfolio T, it must be identical to the weighted market portfolio. When the assumptions behind the CAPM hold, the tangency portfolio T is equal to the market portfolio. Because the CML is a straight line, this creates a linear relationship between expected return and market risk (β). Therefore, the CAPM can be used to calculate the expected return on a particular asset by using the market portfolio as a benchmark. The Sharpe-Lintner CAPM formula can be written as:

Equation 1

$$E(R_i) - R_f = \beta\left[R_m - R_f\right]$$

Equation 2

$$E(R_i) = R_f + \beta[R_m - R_f]$$

Where $E(R_i)$ is the expected return of the asset, R_f is the risk-free rate, and $[R_m - R_f]$ is the difference in return between the market portfolio (m) and the risk-free rate (f), often called the market premium. β measures the systematic risk of the asset and is the slope of the CML. From the CAPM formula, the expected return on an asset is determined by the asset's β. $\beta_{i,m}$ is given by:

Equation 3

$$\beta_{i,m} = \frac{Cov(R_i\ ,\ R_m)}{\sigma^2_{R_m}}$$

The numerator is the covariance of the asset's return with the return on the market portfolio. The denominator shows the volatility of the market.

Typical criticism on the CAPM model states that it relies on historical data to predict future outcomes. Specifically, it employs the Beta coefficient to assess the past volatility of a given security in order to anticipate its future volatility. However, it is widely acknowledged that securities are prone to significant deviations from their past behavior. Furthermore, the CAPM framework is based on the assumption that the only risk factor involved in pricing a portfolio or estimating expected returns is systematic risk. There is also no existence of any risk-free asset, i.e., state treasuries still can default. Lastly, CAPM posits that investors are homogeneous in their beliefs, meanwhile many behavioral models discussed previously finds this to not be true.

2.3. Abnormal returns

As to not do a mere “forecasting returns” analysis, more newly research in the field of studying attention on stock market focus on the excess returns. That is, trying to find the missing pieces not explained by standard economic theory[3]. The problem however, rests with what factors that indeed is foundational to estimating returns.

Kim et al. (2019) used their own five-factor model[4] with a one-year-rolling regression[5] to estimate the weekly returns. Their model was based on the Fama & French five-factor model[6], which includes, in addition to the ordinary CAPM, four factors: a company size factor[7], value factor[8], profitability factor[9], and an investment pattern factor[10]. These additional factors were included as to adjust for risk associated with fundamentals. Meanwhile there is an ongoing

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[3] EMH and CAPM
[4] See: https://www.sciencedirect.com/science/article/pii/S1544612317307377#sec0001 (Chapter 2.2)
[5] The beta coefficients are updated every week, using the most recent one year of data.
[6] $r = R_f + \beta(R_m - R_f) + b_s \cdot SMB + b_v \cdot HML + b_h \cdot RMW + b_r \cdot CMA + \alpha$
[7] The size factor SMB stands for "*Small [market capitalization] Minus Big*"
[8] The value factor HML for "*High [book-to-market ratio] Minus Low*"
[9] RMW is the return spread of the most profitable firms minus the least profitable.
[10] CMA is the return spread of firms that invest conservatively minus aggressively.

debate whether the last two additional factors actually improve Fama's model. Blitz et al. (2016) criticizes the 5-factor model stating all these factors interact, which makes it more difficult to summarize the cross section of stock returns. Moreover, they criticize the foundational assumption that CAPM relies on, namely higher returns for higher risk. In other papers the five factor model perform poorly, Foye find mixing results in emerging markets (2018), Kubota & Takehara find no effect in Japan (2018), in Iran, Eyvazloo et al. (2017) found the three-factor model to actually outperform the five-factor. Most supporting research comes from the western hemisphere where Fama and French (2015) leads on with data from NYSE, AMEX, and NASDAQ, and Chiah et. al. finds evidence from Australia (2016). Other researchers like Lee (2020) still uses the simpler three-factor model when studying Google search effects on returns[11]. Bij et al. (2016) subtracted the stock beta multiplied by the market return to find the excess return as shown: $AR_t = R_t - \beta_{52} R_{m,t}$.

Regardless, the favorability of these multi-factorial models mainly rooted in research on portfolio return estimations, not individual stock returns. In the introduction papers by Fama on the three-factor model: it accounted for more than 90% of the returns of diversified portfolios, while the CAPM typically explains an average of 70% of these returns (1992). The empirical tests of the Fama-French three-factor model also face the same problem as ordinary CAPM. Although the Fama-French three-factor model has been successful in explaining the behavior of long-term winners and losers in the stock market, it falls short in explaining the momentum effect. Hence, the continuation of short-term returns is left unexplained by the model. Bartholdy & Peare (2005) finds that the performance of both the ordinary CAPM and three-factor models preform poorly when explaining monthly data. In their analysis CAPM where on average able to explain 3% of differences in returns while the three-factor model did not much better explaining on average 5% of differences in returns on individual stocks.

The efficient market hypothesis posits that future stock prices cannot be predicted due to the immediate and complete disclosure of all relevant information. This paper operates under the assumption that markets are efficient, while simultaneously seeking to test if attention can explain what CAPM cannot[12]. If the observed return deviates from the estimated return by the CAPM, I, like Kim et al (2019), state that the observed deviation is abnormal in that sense. The

[11] Only includes the "size factor" and "value factor" in addition to CAPM.

[12] The CAPM assumes a stable relationship between risk and return over the long term, and therefore is not suitable for predicting short-term returns due to the model's inability to account for short-term market fluctuations and unexpected events.

reasoning behind this is based on that such deviations is caused by unexpected events. Explained in other terms: if we subtract the systematic risk of the asset return, one is left with the “unsystematic” return, or so to speak. In the absence of a multifactorial model similar to that proposed by Kim et al., I intend to also incorporate a Granger causality test to examine the extent to which Google search volume may act as a predictor of log returns in addition as this may be of interest.

Now, as we know the expected return given by CAPM is as shown in equation 2. I define abnormal return (or excess return) as a deviation from the expectation:

Equation 4

$$AR = R_i - E(R_i)$$

To summarize: an abnormal return in finance refers to the deviation between the actual return and the expected return of a security, which can be influenced by various events such as mergers, dividend announcements, company earnings, interest rate fluctuations, lawsuits, among others, that are not yet reflected in the market pricing and are therefore classified as information or occurrences with impact on the return.

3. Literature review

3.1. Stock market anomalies

In 1987, Merton created a model to demonstrate the impact of investor attention on financial markets. According to his model, the value of a company's security increases as its recognition grows, but the expected return decreases as recognition increases. This is intuitive because larger companies have greater recognition and a larger investor base. It is more difficult to gain excess returns from mispricing larger companies compared to less recognized ones. This is because the larger investor base ensures more accurate pricing of the shares. (Merton, 1987)

In the field of finance literature, there is an increasing consensus among scholars that stock prices are influenced by two distinct categories of investors: noise traders and arbitrageurs (Shleifer & Summers, 1990). Arbitrageurs base their trading decisions on fundamental factors, aiming to align prices with the intrinsic "true" value of stocks. In contrast, noise traders rely on pseudo-signals, noise, and popular trading models. The impact of such pseudo-signals, noise, and popular models on altering demand and subsequently affecting prices is well-documented. For instance, Engelberg et al. (2012) find that the attention generated by Jim Cramer, the host of the popular TV show Mad Money, leads to an average abnormal overnight return of over 3%. Additionally, Barber and Odean (2008) demonstrate that individual investors tend to be net buyers of stocks that are in the news. This is much like the phenomenon of information neglect, meaning that humans tend to be too sensitive to the "*telling and retelling of stories*" in the manner of acting upon old news. Enke and Zimmermann (2017) explain that people have problems in identifying and thinking through the correlation of signals.

If uninformed investors could identify when other investors possess non-public information by monitoring Google search volumes, they could potentially respond preemptively to public announcements. In the wake of the GameStop short squeeze in 2021, Vasileiou et al. (2021) found that Google search volume was a reliable predictor of GameStop's stock performance. The researchers also noted that the speed with which investors could access this information provided an even greater advantage to faster investors.

Previous literature has extensively discussed various anomalies present in stock markets, including mean reversion (Poterba & Summers, 1988), momentum trading (Badrinath & and

Wahal, 2002), herding behavior (Aloosh, Choi, & Ouzan, 2021), and calendar effects (Hansen, Lunde, & Nason, 2003), which all can be attributed to the psychology of investors.

3.2. Information and attention

In an article discussing attention constraints to fund managers, meaning that the fund manager has a limited amount of attention to allocate among the various assets in their portfolio. The study found that managers who allocate their attention more efficiently, in other words, who focus their attention on the assets that are most likely to generate positive returns, tend to have better performance. Observing that well-performing funds were categorically smaller and more actively managed, suggesting that they are more skillfully managed (Gupta-Mukherjee & Pareek, 2020). Whether a fund's performance is truly consistent or whether it was just a temporary fluke are left unexplained.

Typical parameters used to predict stock returns assume that "*sudden increases in returns*" or "*trading volume*", as well as "*news headlines*", are all indicators that investors are paying attention to a particular stock. However, it is important to note that these returns can also be influenced by factors unrelated to attention. Simply because an article is published in the media does not guarantee that investors will pay attention to it, unless they actually read it. Or as highlighted by Da, Engelberg and Gao in their article "In Search of Attention" (2011): where there is an abundance of information available, there is a scarcity of attention.

Measuring investor attention empirically is challenging due to the absence of an exact measure. As a result, researchers have employed indirect proxies to study the effects of attention. One of the latest proxies for investor attention is the use of internet search queries through search engines like Bing, Yahoo, and Google. Other proxies used to study investor attention include Wikipedia searches, Twitter, and stock forums. Measuring search volume is considered a more direct approach to measuring attention since media coverage does not necessarily translate into attention unless it is read by an investor. Several studies have been conducted using these proxies to study the relationship between attention and stock market behavior. For instance, Moat et al. (2013) find that Wikipedia data provide insights into future trends in market behavior, while Bollen et al. (2011) establish a correlation between public mood states on Twitter and daily changes in the Dow Jones Industrial Average. Additionally, Ackert et al.

(2016) find that influential investors on stock forums tend to target large and liquid firms and prefer local investments in their messages.

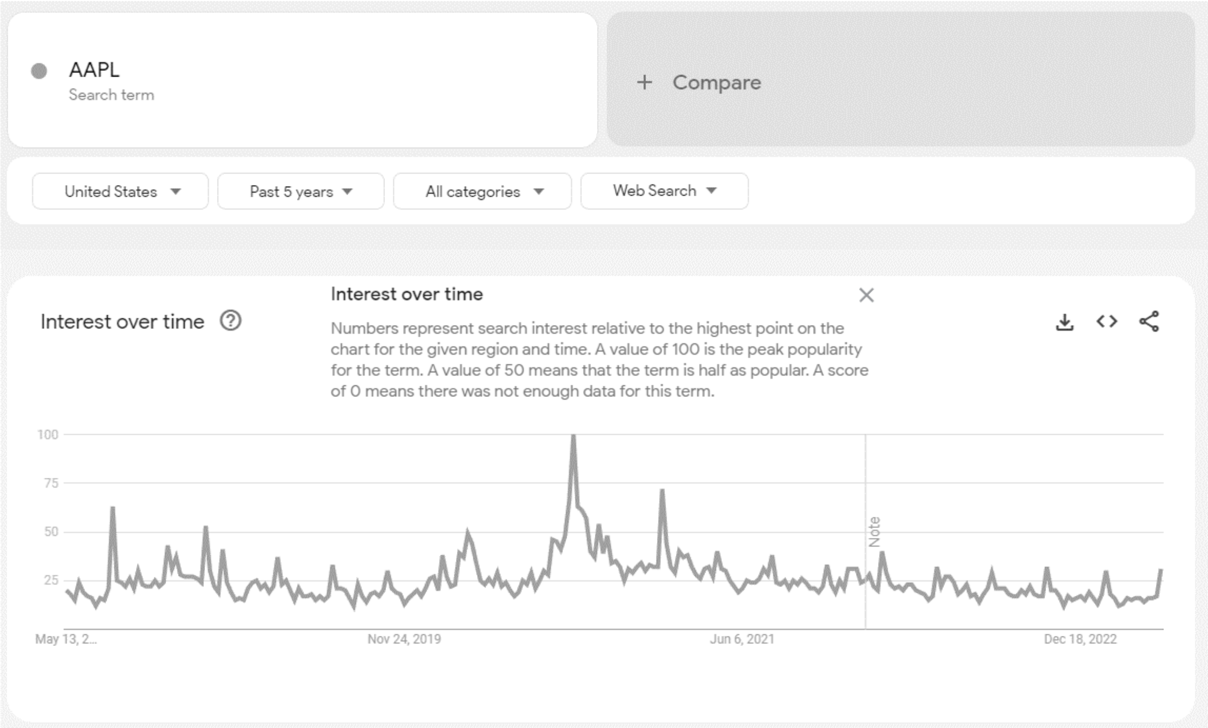
3.3. Google search volume

In 2009, Google's research division published an article on the potential use of Google data for "nowcasting" - explaining real-time developments in different markets. The article, authored by Varian and Choi (2009), highlights four markets that they studied: retail, automotive, housing, and travel. Their findings indicate that models that incorporate variables based on Google search data demonstrate a higher degree of explanatory power than those that exclude such variables for all the markets they examined. In a later study on the stock market, Joseph et al. (2011) discovered that online search intensity can reliably predict abnormal stock returns over a weekly horizon. According to Jun, Yoo, and Choi (2018), the use of Google Trends in research has increased significantly over the past decade, and there has been a noticeable shift from describing research to a greater focus on forecasting ability of Google trends.

Google's publicly available platform for search words historical popularity is named “Google Trends”. Google trends provides various features for analyzing search trends, such as keyword searches, location filters, time range filters, category filters etc. Users can input a keyword or phrase and get results for the search volume of that keyword over a specific period. The platform can be used to track the interest and engagement of people in social movements. As mentioned above, researchers have greatly used this tool to observe how search word interest correlates with the timing of events or media coverage.

Figure 3

The Google trend internet page.



Above: Apple inc. ticker "AAPL" search interest last 5 years (GoogleTrends)

To compare the search data, results in Google Trends are normalized. The term normalized means that sets of search data are divided by a common variable, like total searches, to cancel out the variable's effect on the data. The Google trend scores (GTS) generated are relative to the most popular moment for that specific search word. Meaning, Google trends does not provide the exact number of queries for a specific search term. Instead, a standardized scale ranging from 0 to 100 is used to indicate the highest query volume during a given time period and geographic region. Furthermore, it is important to note that weekly data is only available for a time period of up to 5 years, the week with the highest search count for a search word (ex. "AAPL") is given a score of 100. Then all the following scores are of relative size compared to this week. Consequently, it's not possible to detect comparable differences in search volume between the different individual stock tickers.

Various studies have reached different conclusions regarding the effectiveness of using ticker symbols versus company names in search queries. For instance, Bijl et al. (2016) have found that using the company name yields a stronger relationship with stock market returns than using ticker symbols. However, Da et al. (2011) have put forward two reasons to suggest that it is more beneficial to use searches based on ticker symbols rather than the company name. Firstly, they argue that searches for company names may not necessarily be related to investment. Secondly, different investors may use varying forms of a company's name when conducting a search. In my analysis I will only include search queries for the company ticker symbols[13]. My method of standardizing the raw Google trend scores will be explained in section 4.3.

[13] Reason: Google trends limits the number of requests a user can send in a given amount of time.

4. Research design and method

The analysis will be based on several variables, which will be introduced and explained in this section. Subsequently, the assumptions underlying the regression models will be presented, along with various approaches aimed at observing potential causal effects of investor attention and sentiment on stock prices and market efficiency.

4.1. Regression variables

4.1.1. Return

The adjusted closing price of Yahoo is utilized in calculating returns since it has already undergone adjustments for dividends and stock splits. The percent return can be calculated as follows:

Equation 5

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \Rightarrow R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \Rightarrow R_{i,t} + 1 = \frac{P_{i,t}}{P_{i,t-1}}$$

This is the standard formula for percent change, and simply states the ratio between the change in price from t-1 to t compared to the initial price in t-1. Where t symbols a trading week. Following Kim et. al. (2019) I will be using the log of the returns:

Equation 6

$$r_{i,t} := \ln\left(R_{i,t} + 1\right) = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

There are three main reasons for using the logarithm of returns when doing time series analysis. Firstly, the logarithm of returns is symmetric, meaning negative and positive returns become of equal magnitude. Secondly, the log of returns is time additive, i.e. It’s time consistent. Finally, the log returns show relative change, hence the extreme absolute values are accounted for[14].

[14] Extreme values for return will skew the regression line, biasing coefficient values.

4.1.2. Abnormal return

With inspiration from Bijl et al. (2016) the expected returns are calculated using the formula introduced in chapter 2.2: $E(R_i) = R_f + \beta[R_m - R_f]$ and the abnormal return is then calculated from equation[15]:

Equation 7

$$AR = r_i - (r_f + \beta_{52}[r_m - r_f])$$

The actual return (R_i) is the $r_{i,w}$ introduced in chapter 4.1.1. I will be using the one year rolling beta as in Bijl et al. (2016). The risk-free rate (R_f) is assumed to be the 10-year (US) Treasury yield[16]. Because Treasury bills, notes, and bonds carry the full backing of the U.S. government, they are viewed as one of the safest investments (Treasury Inflation Protected Securities, 2023). Now, the risk-free rate is based on an annual rate, so I estimated the weekly growth rate[17]. I Similarly, I compounded this growth rate $r_f = \log(1 + R_{f,w})$.

Finally, the model utilized the weekly return of the Standard and Poor's 500 index. Standard and Poor's 500 index is seen as a generally good proxy for market return as it tracks the 500 most dominant stocks in the US stock market even though sectoral biases can be observed (Basu & Rizzuto, 1995). Market returns where compounded $r_m = \log(1 + R_{m,w})$. In the end, results will later show that the CAPM model used in this thesis is principally the same as the Bijl et al. equation as the risk-free rate on a weekly basis is negligible.

[15] Similar to Bijl et al. But with the inclusion of the risk-free asset.

[16] Obtained from: https://finance.yahoo.com/quote/%5ETNX/

[17] $R_{f,w} = (1+R_{f,y})^{1/52} - 1$

4.1.3. Volume

Volume is measured as the number of stocks that were traded during a trading day. The simplest and most direct approach measuring abnormal volume involves using the daily volume data for the identified start to end of the week. Following Bijl et al. (2016) I state the total trading volume (TV) as the mean of volumes traded during a week.

Equation 8

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

Where $S_t$is a set of all the trading days during a given week t, and $|S_t|$is the length of that set, in other words number of trading days. I base my formula for abnormal trading volume (ATV) on Bijl et al. (2016) where the average trading volume of the previous year is subtracted from the trading volume of the current week. The resulting value is then divided by the standard deviation of trading volume in the previous year. See the equation below.

Equation 9

$$ATV_t = \frac{TV_t - \frac{1}{n}\sum_{i=1}^{n} TV_i}{\sigma_{TV}}$$

As you see above, the TV is subtracted by the mean TV for the past n periods (12-, 26-, 52-weeks). This deviation is divided by the standard deviation (*52 weeks*) to compensate for stock specific volume variability.

4.1.4. Volatility

Assets that involve risk are typically characterized by a significant degree of price volatility. Compared to calculating stock returns and volume, are analyzing volatility difficult, and people often lack precision while discussing it. I am using the written definition as described by (Mullins, s. 2)

"The degree to which the price of a security, commodity, or market rises or falls within a short-term period."

Previous research has shown a positive relationship between volatility and future stock returns (Bollerslev & Zhou, 2009), which is why I include volatility as a control variable in my regression model to explain returns and volume, as well as a measure of market activity.

In research, the standard deviation is the most prevalent approach for measuring volatility[18]. To compute the standard deviation, you must first specify a timeframe for the returns you want to evaluate. This entails deciding whether you want to assess the volatility of hourly returns, daily returns, monthly returns, and so on. Although standard deviation is a widely used measure of dispersion, it has several limitations. Firstly, it does not measure the actual distance of a data point from the mean, but rather compares the squared differences, which may lead to subtle yet important differences in dispersion. Secondly, outliers have a larger impact on standard deviation since the squared difference is amplified, giving more weight to extreme values. Lastly, for daily volatility one would need multiple measurements throughout the trading day to get a precise measure.

As I have daily trading data from Yahoo, including daily highs, lows, open and closing prices I'll be use the Garman-Klass volatility estimator:

Equation 10

$$Variance = 0.5(H_t - L_t)^2 + (2\ln 2 - 1)(O_t - C_t)^2$$

Equation 11

$$\text{Volatility}_{\ t} = \sqrt{\frac{1}{|S_t|}\sum_{i \in S_t} \text{Variance}_{\ t}}$$

where O_t, C_t, H_t and L_t denote the *opening*, *closing*, *high* and *low* **log prices** of day *t*, respectively (Garman & Klass, 1980). Molnár (2015) suggested that the Garman-Klass estimator is a superior method for measuring volatility when analyzing low-frequency (daily) data, due to its increased precision compared to other measures.

[18] In addition to using Garman-Klass volatility, I test (weekly) standard deviation and high low difference measurements in the Appendix 4:
$\text{Rel. st. dev}_{\ i,t} = \frac{(P_{i,t}+\sigma_{i,t})-P_{i,t}}{P_{i,t}}$ $and \;\; hld_t = \frac{|H_t-L_t|}{(H_t+L_t)\div 2}$

4.1.5. Standardized Google search volume

To capture attention paid towards particular stocks, we examine the search volume for stock ticker symbols (e.g., "AAPL" for Apple Computer and "MSFT" for Microsoft). I will attempt to estimate the abnormal search volume in comparison to time lagged data using the formula presented in Bijl et al. (2016):

Equation 12

$$SGSV = \frac{GTS_t - \frac{1}{n}\sum_{i=1}^{n} GTS_i}{\sigma_{GTS}}$$

The standardization method proposed by Bijl et al. (2016) was chosen for two reasons. The Standardized Google Search Volume (SGSV) measures the degree to which the Google Trends Score (GTS) differs from the mean score of the previous n weeks, divided by the standard deviation of those previous 52 weeks. In essence, this measurement can be defined as "*the extent to which the Google trend score deviates from the norm of the past year.*"

4.1.6. Google search volume correlation

I will also be using an additional measurement which is simply the Google Trends Correlation (GTC), this measurement can be formulated:

Equation 13

$$GTC_i = Corr(Vol_i, GTS_i)$$

Because I suspect some stocks to be more affected by attention, I will be using this measurement to observe stocks where the trading volume correlates more with the Google search score. This will ultimately be used for illustrative purposes[19].

[19] See Appendix C

4.2 Regression assumptions

A1. $E(u_i|x_i) = 0$ The Error Term has Conditional Mean of Zero.

A2. All observations are independent and identically distributed. (IID)

A3. Large outliers are unlikely.

A4. No Perfect Multicollinearity Condition: The regressors are said to be perfectly multicollinear if one of the regressors is a perfect linear function of the other regressor(s).

Assuming these conditions are met, the Ordinary Least Squares (OLS) estimators can be considered unbiased and consistent estimators, with an approximate normal distribution.

For the first assumption to hold it implies that regardless of the value we select for x_i, the error term u_i should not exhibit any consistent pattern and should have an average of zero. The most common violation of this assumption is omitted variable bias. For example, if time was a parameter in our regression analysis, it would be highly correlated to the error term as most stocks are affected by common macroeconomic patterns, leading to an inaccurate estimation. Because of this, it is good to include such influential variables. Additionally, will I be using fixed effects in this paper to control for stock and time specific effects. In a fixed effects panel data regression, individual specific effects are represented as fixed intercepts or dummies. These intercepts or dummies capture any unobserved individual-level characteristics that may influence the outcome variable.

For the second assumption there is the assumption of IID. It states that the observations must be independent from each other and have the same probability distribution. For the sample stocks to be representative for the general population.

It is frequently possible to identify scenarios in which exceptional observations, commonly referred to as outliers, may arise, displaying a marked departure from the typical range of values. Assumption 3 stipulates that both X and Y must exhibit finite kurtosis. I.e., observations cannot overshoot the usual range of data. Such problems are usually solved by exclusion, for example when they arise due to typographical errors, conversion errors, or measurement inaccuracies. Extreme values are a problem because estimation is more sensitive to outliers in OLS. In this paper I handle the extreme values by using the logarithm of returns.

One can expect that the stock return, volatility, or trading volume at any given time will be correlated with their respective past values. Hence, there is a risk for autocorrelation. Consequently, cluster robust standard errors are applied to account for serial both autocorrelation and heteroscedasticity.

4.3. Regression models

The data is organized into panel data to enable control for company- and time-specific effects. Neglecting to account for common time-specific factors can result in underestimation of standard errors and incorrect statistical significance of coefficients. Therefore, I utilize panel data regression[20] with both firm fixed effects, and time fixed effects, as employed by Da et al. (2011), is conducted to avoid this issue. This approach minimizes the risk of omitted variable bias, even in cases where relevant variables are unobserved.

I will use a predictive regression model to examine whether past values of SGSV can be used to predict current values of stock returns, trading volume, and volatility. But first I want to include a descriptive model to observe features present during trading weeks.

4.3.1. Descriptive regression models

The descriptive regression investigates if the market parameters are correlated with the dependent variable in the current period. To improve the accuracy of the model I account for trends over time by including the lagged value for the dependent variable.

Model 1

$$AR_{it} = \lambda_t + \alpha_i + \beta_1 AR_{i,t-1} + \beta_2\, SGSV_{it} + \beta_3 ATV_{it} + \beta_4 \text{ Volatility}_{it} + u_{it}$$

Model 1 describes the correlation between AR and the describing variables: SGSV, ATV and Volatility. Where λ_t is the time fixed effect intercept, and α_i is the stock fixed effect intercept.

Model 2

$$\text{Volatility}_{it} = \lambda_t + \alpha_i + \beta_1 \text{Volatility}_{i,t-1} + \beta_2\, SGSV_{it} + \beta_3 ATV_{it} + \beta_4 \text{ AR}_{it} + u_{it}$$

[20] A panel dataset consists of observations on multiple entities observed over time. Each entity is referred to as a panel, and the data collected for each panel typically includes measurements on multiple variables at different time points. Panel data allows for the analysis of both cross-sectional and time series dimensions.

Model 2 describes the correlation between Volatility and the describing variables: SGSV, ATV and AR.

Model 3

$$ATV_{it} = \lambda_t + \alpha_i + \beta_1 ATV_{i,t-1} + \beta_2\ SGSV_{it} + \beta_3 \mathrm{AR}_{it} + \beta_4\ \mathrm{Volatility}_{it} + u_{it}$$

Model 3 describes the correlation between ATV and the describing variables: SGSV, AR and Volatility.

4.3.2. Predictive regression models

Unlike static panel data models that focus on the current period's relationships, dynamic panel data models consider the lagged values of variables, capturing the dynamics and interdependencies over time. Lagged values of abnormal Google search volume, volatility, volume, and stock returns are included in the predictive model, as they have been found to be correlated with future values of the dependent variables. In line with Kim et al. (2019), only lagged variables are used as explanatory variables in these regressions.

Model 4

$$AR_{it} = \lambda_t + \alpha_i + \beta_1 AR_{i,t-1} + \beta_2\ SGSV_{it-1} + \beta_3 ATV_{it-1} + \beta_4\ \mathrm{Volatility}_{it-1} + u_{it}$$

Model 4 is a predictive model for AR.

Model 5

$$\mathrm{Volatility}_{it} = \lambda_t + \alpha_i + \beta_1 \mathrm{Volatility}_{i,t-1} + \beta_2\ SGSV_{it-1} + \beta_3 ATV_{it-1} + \beta_4\ \mathrm{AR}\ _{it-1} + u_{it}$$

Model 5 is a predictive model for Volatility.

Model 6

$$ATV_{it} = \lambda_t + \alpha_i + \beta_1 ATV_{i,t-1} + \beta_2\ SGSV_{it-1} + \beta_3 \mathrm{AR}_{it-1} + \beta_4\ \mathrm{Volatility}_{it-1} + u_{it}$$

Model 6 is a predictive model for ATV.

4.4. Granger causality test

I am interested in investigating potential causal relationships between Google searches and stock characteristics, and therefore I will be utilizing Granger causality tests in my analysis. The Granger causality test, initially introduced in 1969, is a statistical test that aims to determine the usefulness of one time series in predicting another. While ordinary regressions generally indicate only correlations, Clive Granger proposed that testing for causality in economics involves evaluating the ability to forecast future values of a time series by using prior values of another time series. (Granger, 1969)

To test whether SGSV Granger-causes AR, where both AR and SGSV are stationary time series[21], will I be using the Dumitrescu–Hurlin (DH) test introduced in (2012) by fitting a autoregressive model to the time series for forecasting based solely on the past values in the series (called lags). To determine whether SGSV Granger-causes AR, the next step is to include all the individually significant lagged values of SGSV into an augmented regression model, provided that they collectively contribute to the explanatory power of the model, as determined by an F-test where the null hypothesis is no explanatory power added by the values of SGSV.

Model 7

$$AR_t = \alpha_i + \sum_{k=1}^{K} \gamma_{ik} AR_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} \text{SGSV}_{i,t-k} + \varepsilon_{i,t}$$

$$\text{with } t = 1, \dots, T$$

$$\text{with } i = 1, \dots, N$$

In the model above, T is the total number of weeks in the panel and N is the total number of companies. K is the selected number of lags appropriate for the autoregressive model. This can be used to DH test whether SGSV Granger-Causes AR. Essentially, by evaluating the significance of previous SGSV values as predictors of the current AR value, even when prior AR values have already been incorporated into the model, we can ascertain whether SGSV has a causal impact on AR. The lag order K is assumed to be identical for all companies and the panel is balanced.

---

[21] A stationary time series is one whose properties do not depend on the time at which the series is observed. Thus, time series with trends, or with seasonality, are not stationary. Based on augmented Dickey–Fuller tests AR, SGSV, r, ATV were all tested to be stationary in my sample.

The null hypothesis that SGSV does not Granger-cause AR[22] is accepted if and only if no lagged values of SGSV are retained in the regression. One might easily investigate this causality based on an F-test with the following null-hypothesis:

$$H_0: \beta_{i1} = \cdots = \beta_{iK} = 0 \qquad \forall \;\; i = 1, \dots, N$$

If H_0 is rejected, one can conclude that Granger-causality from SGSV to AR exists. The variables can also be interchanged to test for causality in the opposite direction, if AR also yields Granger-causal impact on SGSV one state that there is bidirectional causality.
The DH test assumes that there can be causality for some companies but not necessarily for all.

DH proposed that to test for Granger causality one should follow this procedure:

1. Run the regressions individually.
2. Perform F tests of the hypothesis to retrieve the individual Wald statistic W.
3. Finally compute the average Wald statistic for the panel data.

Equation 14

$$\bar{W} = \frac{1}{N}\sum_{i=1}^{N} W_i$$

It is important to emphasize that the test I am discussing is specifically designed to detect causality at the panel level. It is worth noting that rejecting the null hypothesis does not necessarily rule out the possibility of noncausality for certain individuals within the panel. However, through Monte Carlo simulations, Dumitrescu and Hurlin (2012) have demonstrated that W exhibits asymptotically reliable behavior, making it a valid tool for investigating panel causality. Under the assumption that the Wald statistic is IID across the companies, a Z-statistic can be made[23].
Granger-causality, as the name suggests, does not necessarily imply a true causal relationship. There may be additional underlying factors that influence both SGSV and AR, such as the flow of information in the context of Efficient Market Hypothesis (EMH). The causal relationship will be thoroughly discussed in chapter 7.

[22] Will also be tested for AR1, ATV, Volatility and Log-return.
[23] See https://journals.sagepub.com/doi/pdf/10.1177/1536867X1801700412 page 974.

5. Data

Based on information obtained from the Nasdaq stock screener (nasdaq, 2023), has it been identified that there is a total of 5116 US / USA[24] labeled stocks as of April 2023. I collected data from March 28th, 2018, to January 15th, 2023. However, data from 2018 are excluded from the analysis because I standardize some of the variables with respect to their past values. All companies in the sample have data on daily open, close, highs, lows, and volumes[25]. Weekly actual returns were calculated from Yahoo Finance's daily adjusted close price, and weekly excess returns were calculated using CAPM where I use the 10-year treasury yield as a proxy for the risk-free rate, and the Standard and Poor's 500 index as a proxy for the market return. Lastly, weekly trading volume and volatility were calculated using daily data from Yahoo Finance. To ensure sufficiently large sample size a web crawler[26] was utilized to collect the data material. The final sample size consists of 959 companies when accounting for time consistency in the period 2018-2023 and identifiability of the sector. The companies were observed over a period of 254 weeks. I used Google Trends to obtain raw internet search volumes for the stock tickers, with a set of five-year continuous data.

[24] Canadian stocks are not included.

[25] Ideally one would need transaction level data on all market participants to make any detailed results in the search for causal effects of attention. If one had data on all daily order book transactions combined with the correct identification of buying (selling) investors, it would be possible to observe the effect of attention more accurately for a particular stock.

[26] A program that automatically scans and indexes web pages on the internet. I used python with the following packages: requests, selenium.

5.1. Sample statistics

The initial dataset comprised 2,514 companies. However, after applying four inclusion criteria, the sample was reduced to 959 companies. Compared to previous research: Bijl et al. (2016) studied 431 companies and Joseph et al. (2011) all 500 of the stocks in the SNP500 index. The criteria for company inclusion in the sample were as follows:

1. $\mathrm{GTS} > 0 \quad \text{for all } t \in T$
2. $\mathrm{Close} > 0 \quad \text{for all } t \in T$
3. $\mathrm{Volume} > 0 \quad \text{for all } t \in T$
4. The company must belong to a clearly defined sector.

The set T represents the weeks for a company, comprising a total of 254 weeks. The incorporation of these four criteria guarantees that all selected firms have met the following requirements: actively traded on the stock exchange, existence throughout the entire sample period, and a sufficiently large Google search base for their ticker.

Table 1

Panel data contents

	N
Companies	959
Industries	133
Sectors	11
Weeks	254
Total Obs.	243,586

Table 2

Foundational variables

	N	Mean	St.dev	Min	Max
Open	243,586	91.76	181.6	0.190	5935
Close	243,586	88.90	181.3	0.180	5936
High	243,586	94.91	187.5	0.220	5982
Low	243,586	88.65	176.0	0.130	5763
Volume	243,586	3,009,000	9,524,000	800	640,000,000
GTS	243,586	50.41	22.47	1	100

The open, close, high, and low values are expressed in US dollars ($). The open price refers to the initial price observed on the first day of the week, while the closing price represents the adjusted closing price recorded at the end of the week. The high price indicates the highest observed price during the week, while the low price represents the lowest observed price during the same period. The volume represents the average number of stocks traded per week[27]. GTS is the weekly Google Trend score for the company ticker.

Table 3

Sample compared to the true population

	Population		Sample	
Sector	N	Proportion	N	Proportion
Basic Materials	28	1 %	7	1 %
Consumer Discretionary	744	15 %	251	26 %
Consumer Staples	98	2 %	29	3 %
Energy	153	3 %	24	3 %
Finance	1313	26 %	143	15 %
Health Care	1012	20 %	94	10 %
Industrials	726	14 %	147	15 %
Miscellaneous	30	1 %	4	0 %
Real Estate	241	5 %	93	10 %
Technology	597	12 %	113	12 %
Telecommunications	42	1 %	13	1 %
Utilities	132	3 %	41	4 %
Total	5116	100 %	959	100 %

My sample is dominated by companies in the consumer discretionary[28], industry, and finance sectors. Compared to the total population as of April 2023 are there some noticeable differences. Firstly, the proportion of consumer discretionary is 11 percentage points higher than the general population in the sample, and vice versa for the financial sector. Secondly, the healthcare sector proportion is 10 percentage points lower than the general population. This is due to the fact that healthcare firms have a shorter lifespan, which resulted in the exclusion of many such firms during the data preprocessing phase because of time inconsistencies. It is possible that an

[27] Volume = TV. Explained in section 4.1.3.

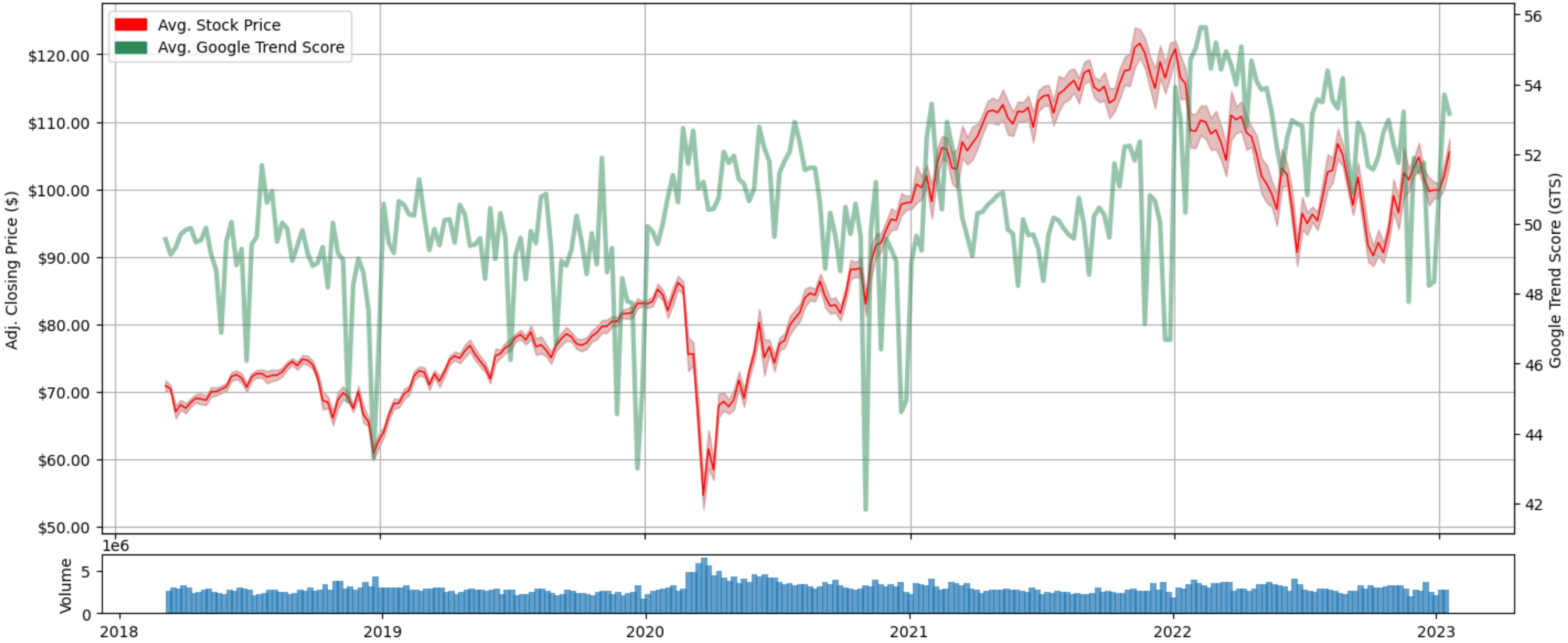
[28] consumer discretionary sector encompasses those industries that tend to be the most sensitive to economic cycles. Its manufacturing segment includes automotive, household durable goods, textiles & apparel and leisure equipment.

analysis may result in a biased representation of the total population. However, in order to examine any potential differences between companies in terms of the attention effect, Appendix E will provide Granger-causality tests for each one of the firms.

I found the Google search engine market share using the website statcounter. Over the past five years, Google has maintained a global market share of more than 85%, which closely aligns with the overall search behavior of the US population. For the United States Google search engine market share stood around 88% for the entire period (statcounter, 2018 - 2023).

Figure 4

Price and Google trend development during sample period. *(Includes avg. weekly standard deviation shown as fill around the red line)*



5.2. Summary statistics

Table 4

Short definitions for included regression variables

Variable	Name	Definition
r	log-return	The logarithm of the adjusted closing price change from t-1 to t.
AR	Abnormal Return	The diffrence between "r" and the expected return derived from the Capital Asset Pricing Model. With the Standard and Poor's 500 index as a proxy for the market rate and the 10-year (US) Treasury yield as a proxy for the risk-free rate.
ATV	Abnormal Trading Volume	The extent to which the average volume deviates from the norm of the past year
Volatility	Garman-Klass Volatility	Is the jump-adjusted garman-klass volatility estimator.
SGSV	Stantarized Google Search Volume	The extent to which the Google Trend score deviates from the norm of the past year
GTC	Google Trend Correlation	The correlation coefficient between trading volume and Google Trend Score.

The table below displays the summary statistics for the variables generated from the data collected. When requesting data from Google trends I filtered the data on the geographic location of USA.

Table 5

Descriptive statistics for included regression variables

	N	Mean	St.dev	Min	Max	Skew	Kurtosis
R	242,627	0.00307	0.0684	-0.832	3.806	3.102	113.3
r	242,627	0.000832	0.0668	-1.784	1.570	-0.359	24.85
AR_{CAPM}	192,759	-0.00183	0.0563	-1.020	1.442	0.0489	25.34
AR_{Bijl}	192,759	-0.00186	0.0563	-1.020	1.441	0.0443	25.32
ATV	194,520	-0.00203	1.082	-2.905	7.065	1.740	7.794
Volatility	242,627	0.0661	0.0833	0	2.272	4.382	52.19
SGSV	194,520	0.0593	1.090	-4.802	7.072	0.878	5.627
GTC	194,520	0.0515	0.236	-0.789	0.970	0.429	3.562

The variable SGSV were calculated using the formula proposed by Bijl et al. (2016) with a 52-week time horizon, as discussed in section 4.1.5.

The variable AR represents the abnormal returns presented in section 4.1.2. The variable ATV was standardized according to the discussion in section 4.1.3. Finally, the variable "Volatility" was calculated using the weekly Garman-Klass estimator discussed in section 4.1.4. All variables that will be included in the analysis show a tendency to be positively skewed.

To avoid multicollinearity[29] a correlation matrix is added.

Table 6

Correlation matrix for included regression variables

	R	r	AR	ATV	Volatility	SGSV	GTC
R	1	0.984	0.822	-0.0229	-0.00270	0.0196	0.00320
r	0.984	1	0.827	-0.0703	-0.00730	0.0128	-0.00400
AR	0.822	0.827	1	-0.0100	-0.0210	0.0123	-0.00660
ATV	-0.0229	-0.0703	-0.0100	1	0.0604	0.0823	0.0414
Volatility	-0.00270	-0.00730	-0.0210	0.0604	1	0.00800	0.00370
SGSV	0.0196	0.0128	0.0123	0.0823	0.00800	1	0.0280
GTC	0.00320	-0.00400	-0.00660	0.0414	0.00370	0.0280	1

Based on my analysis of the data presented in Table 2, it can be inferred that the variables exhibit a correlation coefficient that is in close proximity to zero, indicating that they are largely uncorrelated. Nevertheless, it is noteworthy that a moderate positive correlation of 0.82 exists between the variables AR and r, as AR is dependent on r. However, this issue does not pose a problem since these two variables will not be incorporated in the same regression model.

[29] Multicollinearity is a problem as it can lead to inflated standard errors, which in turn can cause the regression model to underestimate the significance of the independent variables. As a result, the model may not accurately reflect the true relationship between the independent and dependent variables.

Table 7

Correlation matrix for AR based on different beta estimates

	AR	AR6	AR1
AR	1	0.986	0.816
AR6	0.986	1	0.830
AR1	0.816	0.830	1

In contrast with CAPM theory, the different rolling beta measurements yield different abnormal return measures. Here: AR6 means 6-month rolling beta and AR1 means a 1-month rolling beta. AR is the 12-month rolling beta.

6. Results

The regression models underwent testing using both fixed and random effects. Based on the results of the Hausman test, which compared the two models, it was found that the fixed-effect model was supported. As a result, the subsequent presentation of results will focus on the fixed effects model.

The tables in this study are presented with clustered standard errors, specifically clustered around the company level. Additionally, supplementary tables featuring clustering based on industry and sector are included in the appendix section. The utilization of clustered standard errors accounts for potential heterogeneity and dependence within the respective clustering units, ensuring robust statistical inference.

6.1. Regression results

Table 8

Descriptive and predictive models for Anormal return ($\beta_{12\text{-month}}$) with company-clustered standard errors and fixed effects

	Abnormal Return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AR_{t-1}	-0.0233***	-0.0234***	-0.0235***	-0.0237***	-0.0236***	-0.0239***	-0.0238***	-0.0244***	-0.0243***	-0.0171**	-0.0174***
	(-4.40)	(-4.43)	(-4.46)	(-4.38)	(-4.39)	(-4.49)	(-4.47)	(-4.49)	(-4.53)	(-3.25)	(-3.35)
$SGSV$		0.000681**						0.000723***		0.000836***	
		(3.23)						(3.63)		(4.12)	
$SGSV_{t-1}$			0.000948***						0.00109***		0.000966***
			(4.46)						(5.09)		(4.44)
ATV				-0.000471				-0.000450		0.000643	
				(-1.39)				(-1.37)		(1.59)	
ATV_{t-1}					-0.00162***				-0.00165***		-0.000308
					(-9.76)				(-10.06)		(-1.74)
$Volatility$						-0.0325***		-0.0318***		-0.0297***	
						(-6.50)		(-6.76)		(-4.22)	
$Volatility_{t-1}$							-0.0279***		-0.0252***		-0.0130***
							(-9.14)		(-8.75)		(-3.43)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	191800	191649	191648	191649	191648	191800	191800	191649	191648	191649	191648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.002	0.073	0.073
adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.072	0.072

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table above provides a summary of my regression results for the descriptive and predictive models of abnormal returns. The analysis indicates that the SGSV variable is statistically significant in both the descriptive and predictive regression models, and the R2 values are found to be very low. Hence, the findings suggest that search volume can only explain a small portion of the variation in stocks returns but cannot effectively predict its movements, i.e., it's not a good model for reliably forecasting stock movements on a weekly basis. The sample size for each model is large[30], comprising approximately 191,000 observations. It is worth noting that while several explanatory variables exhibit high statistical significance, their practical effects are minimal. For instance, in Model 9, a 1% increase in SGSV is associated with a marginal 0.1% increase in AR for the following week.

Table 9

Descriptive and predictive models for Anormal return ($\beta_{1\text{-month}}$) with company-clustered standard errors and fixed effects

	Abnormal Return (One month β)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AR1_{t-1}$	0.0938***	0.0937***	0.0936***	0.0921***	0.0924***	0.0926***	0.0928***	0.0910***	0.0913***	0.0993***	0.0995***
	(9.12)	(9.10)	(9.09)	(8.88)	(8.97)	(8.98)	(9.03)	(8.73)	(8.84)	(9.20)	(9.28)
$SGSV$		0.000575**						0.000701***		0.000791***	
		(2.79)						(3.53)		(3.90)	
$SGSV_{t-1}$			0.000532*						0.000706**		0.000744***
			(2.45)						(3.27)		(3.40)
ATV				-0.00148***				-0.00143***		-0.000236	
				(-5.09)				(-5.07)		(-0.72)	
ATV_{t-1}					-0.00205***				-0.00202***		-0.000367
					(-10.56)				(-10.89)		(-1.96)
$Volatility$						-0.0439***		-0.0416***		-0.0424***	
						(-8.00)		(-8.04)		(-5.62)	
$Volatility_{t-1}$							-0.0357***		-0.0324***		-0.0208***
							(-8.64)		(-8.43)		(-4.38)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	191800	191649	191648	191649	191648	191800	191800	191649	191648	191649	191648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.009	0.009	0.009	0.010	0.010	0.010	0.010	0.011	0.011	0.080	0.080
adj. R^2	0.009	0.009	0.009	0.010	0.010	0.010	0.010	0.011	0.011	0.079	0.079

t statistics in parentheses

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 9 presents similar findings to Table 8, with the exception that the beta used in the CAPM model transitions from a 52-week rolling beta to a 5-week rolling beta. Notably, the variable SGSV demonstrates even smaller coefficient values, indicating a diminished impact.

[30] With a larger sample size, statistical tests are more likely to detect even small differences or relationships, leading to higher statistical significance. The standard errors of the estimated coefficients tend to decrease, making it easier to reject the null hypothesis and obtain significant results.

Furthermore, in Model 3, the significance levels decrease from a 99.9% level to a 95% level, suggesting a slightly less robust relationship.

Table 10

Descriptive and predictive models for Anormal volume with company-clustered standard errors and fixed effects

	Abnormal Volume										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ATV_{t-1}	0.484***	0.481***	0.474***	0.485***	0.485***	0.483***	0.484***	0.480***	0.474***	0.439***	0.436***
	(128.89)	(133.63)	(131.48)	(127.86)	(128.43)	(129.33)	(129.28)	(133.01)	(131.68)	(106.41)	(104.36)
SGSV		0.0526***						0.0525***		0.0417***	
		(13.01)						(13.31)		(12.02)	
$SGSV_{t-1}$			0.124***						0.125***		0.0966***
			(21.06)						(21.12)		(17.33)
AR				0.130				0.139		0.235*	
				(1.19)				(1.32)		(2.17)	
AR_{t-1}					-0.848***				-0.880***		-0.627***
					(-14.51)				(-15.79)		(-11.12)
Volatility						1.406***		1.430***		1.674***	
						(8.18)		(8.21)		(7.49)	
$Volatility_{t-1}$							0.0823		0.0202		-0.0346
							(1.02)		(0.24)		(-0.30)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	193543	193543	193543	192587	191630	193543	193543	192587	191630	192587	191630
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.235	0.238	0.250	0.235	0.237	0.238	0.235	0.241	0.253	0.400	0.406
adj. R^2	0.235	0.238	0.250	0.235	0.237	0.238	0.235	0.241	0.253	0.400	0.405

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The presented table provides findings regarding the effect of SGSV, controlling for other variables. The analysis reveals that the inclusion of ATV from the previous week and SGSV from the current week accounts for 23.8% of the variability in the current week's ATV. Moreover, the combination of ATV and SGSV from the previous week proves predictive for the variability in the current week's trading volume. Among models 8, 9, 10, and 11, SGSV consistently exhibits the most robust coefficient values compared to volatility and AR, indicating its influential role in explaining the observed patterns. Thus, my study suggests that Google Search Volume can be used to both describe and predict trading volume in companies trading on the US stock market. This observed relationship highlights the potential of SGSV as a valuable indicator of investor sentiment and attention.

Table 11

Descriptive and predictive models for Volatility with company-clustered standard errors and fixed effects

	Garman-Klass Volatility										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Volatility_{t-1}	0.966*** (340.25)										
SGSV		0.000175 (0.67)						-0.0000351 (-0.14)		0.000122 (0.56)	
SGSV_{t-1}			0.000516 (1.94)						0.000443 (1.66)		0.000583** (2.68)
AR				-0.0174*** (-6.36)				-0.0170*** (-6.73)		-0.0109*** (-4.25)	
AR_{t-1}					-0.0183*** (-8.57)				-0.0183*** (-8.87)		-0.00773*** (-3.95)
ATV						0.00267*** (9.96)		0.00265*** (9.90)		0.00244*** (8.93)	
ATV_{t-1}							0.00109*** (4.44)		0.00104*** (4.26)		0.000523* (2.06)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	241668	194520	193562	192759	191800	194520	193562	192606	191648	192606	191648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.939	0.000	0.000	0.001	0.001	0.005	0.001	0.005	0.002	0.346	0.342
adj. R^2	0.939	0.000	0.000	0.001	0.001	0.005	0.001	0.005	0.002	0.345	0.341

t statistics in parentheses

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 11[31] reveals the impact of SGSV on Garman-Klass volatility, which is observed to be insignificant. However, it is important to note that the tests proved significant for other volatility measures included in the appendix[32]. And when time fixed effects were included, there is observed a positive relationship between Garman-Klass volatility and lagged-SGSV.

[31] Excluded lagged values of volatility due to high correlation. This is because a strong correlation may make it difficult to disentangle the individual effects of each variable on the dependent variable.

[32] A marginal increase in SGSV results in a significant 0.00126% increase in the weekly standard deviation, as observed at a 99.9% significance level. Similarly, a marginal increase in SGSV leads to a 0.000863% increase in the high-low difference, also found to be statistically significant at a 99.9% confidence level.

Table 12

Descriptive and predictive models for log-return with company-clustered standard errors and fixed effects

	Log Return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
r_{t-1}	-0.0490***	-0.0521***	-0.0523***	-0.0491***	-0.0490***	-0.0605***	-0.0545***	-0.0608***	-0.0546***	-0.0413***	-0.0420***
	(-8.46)	(-9.49)	(-9.52)	(-8.48)	(-8.46)	(-9.99)	(-9.67)	(-10.07)	(-9.71)	(-6.99)	(-7.15)
$SGSV$		0.000871***						0.00129***		0.000889***	
		(3.50)						(5.42)		(4.19)	
$SGSV_{t-1}$			-0.0000637						0.000109		0.00103***
			(-0.25)						(0.43)		(4.48)
$Volatility$				-0.00948**				-0.00112		-0.0399***	
				(-3.03)				(-0.24)		(-4.94)	
$Volatility_{t-1}$					-0.00256				0.00292		-0.0158***
					(-1.29)				(1.00)		(-3.84)
ATV						-0.00495***		-0.00505***		0.00105*	
						(-12.15)		(-12.85)		(2.46)	
ATV_{t-1}							-0.00206***		-0.00208***		-0.000193
							(-10.82)		(-11.14)		(-1.04)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	241668	194520	193562	241668	241668	194520	193562	194520	193562	194520	193562
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.002	0.003	0.003	0.002	0.002	0.008	0.004	0.009	0.004	0.334	0.335
adj. R^2	0.002	0.003	0.003	0.002	0.002	0.008	0.004	0.009	0.004	0.333	0.334

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The presented models focus exclusively on predicting log-returns, revealing a notable positive descriptive correlation between returns and SGSV. However, it is important to note that the significance of SGSV's predictive power diminishes when time fixed effects are not considered, rendering it statistically insignificant. Nevertheless, once time effects are controlled for, SGSV emerges as a significant predictor of log-returns.

6.2. Granger causality results

As suggested by Lopez and Weber (2017), the decision to reject the null hypothesis is based on the $\tilde{Z}$ statistic because N is large, and T is relatively small. All tests were performed using the lag order of 2. For company-level Wald statistics for SGSV on log-returns see Appendix E.

Table 13

Abnormal return ($\beta_{12\text{-month}}$) and standardized Google search volume Granger causality

Dumitrescu and Hurlin test		
H_0	SGSV⇏AR	AR⇏SGSV
H_a	SGSV does Granger-cause AR for at least one panel	AR does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\bar{W}$	3.333	2.102
$\bar{Z}$	20.65	1.579
$\tilde{Z}$	19.91	1.231
Decision	Reject***	Accept

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Only the first null hypothesis was rejected suggesting there is Granger Causality from SGSV to AR for some of the firms in the sample. It appears that AR has no ability to forecast future values of SGSV.

Table 14

Abnormal return ($\beta_{1\text{-month}}$) and standardized Google search volume Granger causality

Dumitrescu and Hurlin test

H_0	SGSV⇏AR1	AR1⇏SGSV
H_a	SGSV does Granger-cause AR1 for at least one panel	AR1 does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\bar{W}$	3.238	2.117
$\bar{Z}$	19.18	1.806
$\tilde{Z}$	18.46	1.453
Decision	Reject***	Accept

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

When the CAPM model transitions from a 52-week rolling beta to a 5-week rolling beta I observe similar results as in the previous table, but with somewhat higher uncertainty.

Table 15

Abnormal volume and standardized Google search volume Granger causality

Dumitrescu and Hurlin test

H_0	SGSV⇏ATV	ATV⇏SGSV
H_a	SGSV does Granger-cause ATV for at least one panel	ATV does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\bar{W}$	27.19	3.234
$\bar{Z}$	390.1	19.11
$\tilde{Z}$	381.7	18.40
Decision	Reject***	Reject***

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Both null hypotheses gave statistically significant results suggesting there is bi-directional Granger Causality. Suggesting the variables correlate to a higher degree compared to the variable AR.

Table 16

Volatility and standardized Google search volume Granger causality

Dumitrescu and Hurlin test		
H_0	SGSV⇏Volatility	Volatility⇏SGSV
H_a	SGSV does Granger-cause Volatility for at least one panel	Volatility does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\bar{W}$	6.968	2.751
$\bar{Z}$	76.92	11.63
$\tilde{Z}$	75.02	11.07
Decision	Reject***	Reject***

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Both null hypotheses gave statistically significant results suggesting there is bi-directional Granger Causality. Similar to ATV, SGSV is a predictor for Volatility and vice versa.

Table 17

Log-return and standardized Google search volume Granger causality

Dumitrescu and Hurlin test		
H_0	SGSV$\nRightarrow$return	return$\nRightarrow$SGSV
H_a	SGSV does Granger-cause return for at least one panel	return does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\bar{W}$	3.140	2.065
$\bar{Z}$	17.66	1.004
$\tilde{Z}$	16.98	0.667
Decision	Reject***	Accept

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Only the first null hypothesis was rejected suggesting there is Granger Causality from SGSV to log-return for some of the firms in the sample. It appears that log-return has no ability to forecast future values of SGSV. Wald statistics for specific companies are included in Appendix E for SGSV on log-return. Of the 959 companies the test was based on, only 106 yielded significant forecasting ability of SGSV on log-return at a 95% confidence level.

7. Discussion

7.1. Trading strategy

My findings regarding the impact of $SGSV_{t-1}$ on log-return contradict those of Bijl et al. (2016). Specifically, I observe a positive effect on log-return, in contrast to their reported negative effect. This could be attributed to differences in our time periods. I conducted an analysis specifically during a period characterized by high market uncertainty, which was marked by significant events such as the global stock market downturn caused by the COVID-19 pandemic and the Russian-Ukrainian war. Another reason may be due to the use of different Google search-words[33]. Kim et al. (2019) conducted a comprehensive examination encompassing both types of search-words and discovered that ticker-based search-words produced outcomes comparable to those reported in this paper while name-based produced a negative relation as reported by Bijl et al. (2016). And my results are also strikingly similar to those of Da et al. (2011), which reviled a positive significant effect the first two weeks with SGSV on log-return.

Both my analysis and the study by Bijl et al. (2016) yielded similarly significant results for the first lags t-1, t-2, and t-3, indicating a consistent influence of attention across these three weeks. However, I opted to restrict the analysis to a maximum of two weeks prior, considering that the impact of attention beyond this timeframe is likely to be negligible on stock demand and supply. This decision was based on the observation that the effects of attention diminished over time.

The observed effects, as determined in both Bijl et al. (2016) and my analyses, are minimal. In my analysis, a one-unit increase in $SGSV_{t-1}$ is projected to result in a 0.001 unit increase in the log-return, corresponding to a 0.1% increase in return. For instance, consider a stock with an initial price of 100 and a revealed return of 2% in the current week. If SGSV = 1 one week prior, these returns would be augmented to 2.002%, resulting in adjusted earnings of 2.002 instead of 2. Despite being statistically significant, these findings indicate that the influence of SGSV on return is small. In my samples most extreme cases the SGSV score reached as high as ≈7, following the equation above this would yield 2.012 instead of 2, a total additional SGSV earning of 1.2 pennies. As previously noted by Bijl et al. (2016), the profitability of the observed

[33] Bijl et al. Used company-name in contrast to ticker-name used in this paper.

relationship between SGSV and returns appears that, without accounting for transaction costs, there may be potential profitability in utilizing SGSV as a predictor of returns. However, when transaction costs are taken into account, the profitability becomes non-existent. This is also not accounting for the costs related to getting the information from Google.

It is worth noting that in the context of a large sample size, even small differences or effects can reach statistical significance. However, it is crucial to assess the practical significance of these effects in order to determine their meaningfulness. It appears that the observed effects in this study are indeed quite small, to the extent that their practical relevance may be negligible. Nevertheless, the results still indicate that there is relationship between $SGSV_{t-1}$ and the other variables, and the directions of this relationships still remains relevant.
In the Granger-causality tests, the analysis revealed a distinctive pattern when using SGSV as a forecasting variable for log-returns. It exhibited an initial upward swing followed by a subsequent downward swing, reminiscent of the mean reversion theory. It would be interesting to explore these effects in the context of herding mechanisms and investigate whether Google Trends data could be utilized to detect such deviations from the intrinsic value.

Returning to the initial idea of developing a trading strategy based on Google Trends, there is evidence suggesting that, under certain circumstances, it is possible to derive profitability from utilizing search volume data. Vasileiou et al. (2021) demonstrate that investors would have had the potential to profit on information derived from search volume and Google searches during the GameStop hype. This is to highlight a special case scenario but proves Googles potential usefulness.

All the models discussed so far assumes a linear relationship exists between Google Trends and price movements, meanwhile there is a wealth of research exploring the predictive power of Google Trends in financial markets using non-linear models, such as machine learning. Sudies by Hu et al. (2018) and Pyo et al. (2017), have demonstrated higher variance explained by their non-linear models compared to our linear models. These models generally exhibit proficiency in forecasting market directions but exhibit mixed results in predicting precise returns. Suggesting uncertainty around the validity of the linearity assumption. However, as machine learning is considered good for forecasting, it falls short in explaining the relationship between the independent and dependent variable. Additionally, using weekly data is considered too low frequent to precisely predict future returns.

Another consideration is that if an investor is seeking to profit from these models, assuming there is no omitted variable bias, they may find it more interesting to focus on observing the volatility of the stock rather than internet search traffic. This is because volatility is likely to have a more pronounced impact on post-returns, potentially leading to more substantial negative consequences for the investment outcome.

7.2. CAPM

In addition to examining the excess return using a 52-week rolling beta, I also analyzed the results based on a 5-week rolling beta. Interestingly, my findings indicate that the beta does not remain constant as theory suggests. There is, however, a lesser degree of discrepancy between the 52-week and 26-week betas, as shown in appendix D. It is noteworthy that the significance level decreases when the beta is estimated using the data from the 5 prior weeks.

I have already identified several issues with CAPM, including the presence of taxes, the absence of a truly risk-free asset, and the limited precision of the S&P 500 as a proxy of the overall market. Another concern is that CAPM relies on historical price movements to determine its value. This argument is closely related to the debate on whether beta is an effective measure of capturing systematic risk.

It is important to recognize that beta provides a simplified measure of systematic risk, representing an average relationship between an asset and the market. However, it fails to account for specific factors that can impact an asset's risk profile, including industry-specific risks, company-specific events, and changing market conditions. Furthermore, I extended the analysis by conducting regression with sectorial and industry clustering, which is included in appendix D. This additional analysis revealed less- to non-significant effects of SGSV.

Market conditions and correlations can change over time, potentially making beta estimates less relevant and accurate. Moreover, beta assumes a linear relationship between the returns of the asset and the market, but market dynamics are often more complex and nonlinear, especially during periods of extreme market conditions like the events mentioned in the previous section.

Consequently, my beta may not fully capture the extent of systematic risk in such situations. For example, the healthcare sector would to a larger degree be asymmetric to the other sectors during the pandemic. Considering the issues mentioned, am I unable to assert with certainty that the CAPM model utilized in this paper accurately assesses the systematic risk.

7.3. Market efficiency

The same patterns were observed for all dependent variables: log-return, AR, ATV and volatility, with the explanatory variable SGSV. They all exhibited positive correlation in both the same week and followed by a another upward swing the next week. The Granger-causality models and regression models employed in the analysis consistently indicate a significant relationship: a higher Google search volume is on average predictive of a higher value for all the dependent variables. For the market to be truly efficient, that is, the information is incorporated instantly, my results in the Granger-causality test would yield insignificant causal effects on returns. Contrary to this expectation, the obtained results reveal a significant outcome. A tempting rationale behind this observation might be that if SGSV demonstrates forecasting ability for returns, it implies that the information from a week prior is not entirely assimilated into the stock price until the following week. However, there exists a notion supported by Keown & Pinkerton (1981) that the information may incorporated before its official release. For instance, investors may exhibit herding behavior around companies prior to the publication of public earnings reports, and Google's search data could potentially capture some of this pre-release traffic.
Another notion is that one might expect that interest around a stock ticker might increase more as to bad news compared to good news. Also, I do observe in figure 4 in section 5 that under the market uncertainty pre covid lockdowns and its market implications, there is an increase in the average Google search score for the included firms. However, the regressions show that on a weekly basis Google searches correlate positively with the returns. A possible explanation might be that Google searches on specifically “stock tickers” is not utilized by the majority population that is interested in such news. And the Granger causality tests show that returns cannot predict Google search volume, that is, even if a stock has a significant downturn a week, the search traffic remains unexplained.

The results of my analysis suggest a correlation between attention and price movements, particularly in relation to abnormal stock volume. This finding is intuitive, as larger groups of investors who show interest in a stock are likely either interested in buying or selling it, leading to a higher number of stocks changing hands. One could argue for a potential causal relationship as follows: "*Investors **search** for information about a particular stock before deciding to **buy or sell** it.*" In this sense, attention leads to increased trading volume like observed. However, it is essential to recognize that it is the underlying information that influences investors' decisions, not merely their level of attentiveness. Conversely, if there is information available but no corresponding attention from market participants, it is less likely to be reflected in the stock price. Therefore, in the stock market, one could argue that the existence of a stock is largely dependent on human attention. Assuming that all traders are rational humans, and neglecting the presence of automated trading, liquidation due to other factors, and various other influencing factors.

The correlation discovered in my analysis supports a clear linkage between attention and volume. I will also highlight the one-way Granger causal impact of search volume on returns that could be used as an argument against EMH if one where to assume the attention reflects underlying information. However, the analysis falls short of directly proving that markets are indeed inefficient.

7.4. Issues

I have already mentioned some different issues with the study, among them: the linearity assumption, misrepresentation of the population, Google trend bias, choice of search-word, and the assumption that SGSV has the same effect on all companies in the regressions. There is also a possibility of omitted variable bias. A significant challenge in studying stock markets arises from their inherent complexity, as the equilibrium prices at any given moment are typically influenced by interconnected determining processes. This implies a bidirectional relationship between the dependent and independent variables involved. In my analysis, the Granger causality test consistently demonstrated a bidirectional correlation among most variables, except for SGSV in relation to AR and log-return. Additionally, the Granger causality model encounters its own challenges due to the limitations of only one explanatory variable.

All analysis in this paper is based on OLS, meanwhile the intricate dynamics of stock markets often lead to omitted variable bias in OLS regressions. While most studies, including this paper, incorporate time and entity fixed effects to address this issue, it is important to acknowledge that the omitted variables are likely to be non-constant. Consequently, these variables are not adequately captured in an OLS regression with firm and time fixed effects. There is a chance that the strict exogeneity assumption is violated. It's also possible that there are complex dynamics and feedback loops between search volume and stock returns that are not fully captured in the panel data models. Therefore, I cannot be confident in the effects observed in the regressions interpreting the results. However, it does make sense that search volume can explain the abnormal volume of stocks.

On the other hand, when it comes to forecasting returns one week into the future, the practical significance of these observed effects is minimal. Furthermore, only a small portion (11%) of the stocks demonstrated Granger-causal effects in this scenario. This raises questions regarding whether these effects are merely due to chance rather than indicating true causality on a broader scope. Moreover, the applicability of assuming such effects exist across the entire sample becomes problematic. Furthermore, Bijl et al. (2016) observe that the relationship between Google search volume and stock return undergoes changes over time. The last notion being important when discussing the volatile period, the results are from. And that search volume may be a better indicator in scenarios of stock hypes, like the mentioned GameStop scenario.

When comparing earlier reports, the effects appear to be sporadic, meaning that researchers report different results depending on three factors: the period they measure, the stock exchange they observe, and the search words they use. Some concluding that Google search capture the attention of irrational retail investors leading to an arbitrage opportunity that does not mean revert before the third week (Da, Engelberg, & Gao, 2011). In the other hand Kim et al. (2019) concludes that their measured insignificant effects make sense as this is in line with EMH. In Bijl et al. (2016), it is explained that the reported negative effects may be inherent to the rapid incorporation of underlying information in the first week, with the weekly data only capturing subsequent negative returns. Nevertheless, there is agreement on one aspect of Google search volume and that is its inherited correlation with stock volume.

8. Conclusion

The aim of this paper is to investigate whether Google search activity can explain and predict activity in the stock market, in particular, the dynamics of stock returns, trading volume, and volatility. In terms of stock returns I observe a positive relationship and a predictive ability of Google searches on stock returns as is in line with previous findings from the US market (Da, Engelberg, & Gao, 2011).

Google searches demonstrate the capacity to both explain and forecast trading volume in the US stock market. This suggests that investors in the market utilize information from Google, in conjunction with other channels, when making investment decisions, aligning with the findings of Da et al. (2011), Bijl et al. (2016) and Kim et al. (2019). Additionally, while Google search activity does not exhibit a contemporaneous relationship with volatility, it exhibits the ability to predict future volatility. In summary, Google searches not only exhibit associations with trading activity, as measured by both volatility and trading volume, but also possess predictive capabilities. Interestingly, the predictive power of Google searches proves to be even stronger than their contemporary explanatory power for all variables: return, volatility, and trading volume.

CAPM seems to unreliably explain the systematic risk and expected return based on what length of historical data to include. Another finding is that Google searches can predict stock returns contradicts the Efficient Market Hypothesis when the associated costs of acquiring information and conducting transactions are disregarded and one assumes that attention-level reflects the underlying information. However, even if the assumptions were to hold, these predictive effects are practically negligible of magnitude, thereby limiting the meaningful conclusions that can be drawn. And the other studies mentioned above indicate that when transaction costs are taken into account, the profitability of utilizing Google searches diminishes. Meanwhile, the results seem to indicate that stock returns are not as perfectly random as proposed by EMH.

This thesis has made attempts to mitigate the presence of omitted variable bias by incorporating time and entity fixed effects in the analysis. However, it is important to acknowledge the possibility that the strict exogeneity assumption may still be violated. Nevertheless, one of the most significant findings from the results is the clear correlation between search volume and trading volume, which highlights a linkage between these two variables. In conclusion, these findings underscore the importance of including attentiveness when predicting outcomes in financial markets as it still remains a viable explanatory variable in complex financial markets.

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APPENDIX A

Python packages

Name	Definition
requests	HTTP library for Python.
selenium	Used to carry out automated test cases for browsers or web applications.
pandas	Data analysis and manipulation tool.
math	Mathematical functions defined by the C standard.
statistics	Functions for calculating mathematical statistics of numeric data.
matplotlib	Library for creating static, animated, and interactive visualizations.

Stata commands

Name	Definition
sum	Used for summary statistics
pvcorr	Used for panel data correlation diagrams
xtset	Used to set Stata up for panel data analysis
xtreg	Panel data regression
xtgcause	Dumitrescu and Hurlin granger causality test
xtserial	Woolridge test for autocorrelation in panel data.
xtunitroot	Dickey–Fuller tests for stationarity.

Data reliability

All the data in the thesis is collected with the use of webcrawler bots, crawling the following websites: trends.Google.com and finance.yahoo.com.

The reliability of data material is contingent on the foundational assumption that webpages are accurate and trustworthy. Determining the credibility of a website is a complex matter with no universally accepted criteria. It is considered a philosophical question, as the perception of trustworthiness is subjective and can vary from person to person. However, there is some degree of consensus around the concept of a website's ethos, or perceived credibility for these webpages.

Other volatility measures

Weekly "*relative*" standard deviations by prices, illustrated by these formulas:

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{n-1}}, \qquad 3 \le n \le 5$$

$$\text{Rel. st. dev}_{\,i,t} = \frac{(P_{i,t} + \sigma_{i,t}) - P_{i,t}}{P_{i,t}}$$

This way it becomes possible to compare different assets in different price classes. Note, the standard deviation is based on a small sample comprising of 3 to 5 observations per week, as these are the included weekly trading days.

Additionally, the average difference between the weekly high and lows is also estimated.

$$hld_t = \frac{|H_t - L_t|}{(H_t + L_t) \div 2}$$

APPENDIX B

Wooldridge test for autocorrelation in panel

Number of panels	959

H0: No first-order autocorrelation
Ha: There exists autocorrelation in panel

Regression model	F(1, 958)	Prob > F
AR = SGSV ATV Volatility	2.516	0.1130
ATV = SGSV AR Volatility	4791.005	0.0000
Volatility = SGSV ATV AR	96.811	0.0000
Log-return = SGSV ATV Volatility	200.563	0.0000

Fisher-type unit-root test for variables

Based on augmented Dickey–Fuller tests

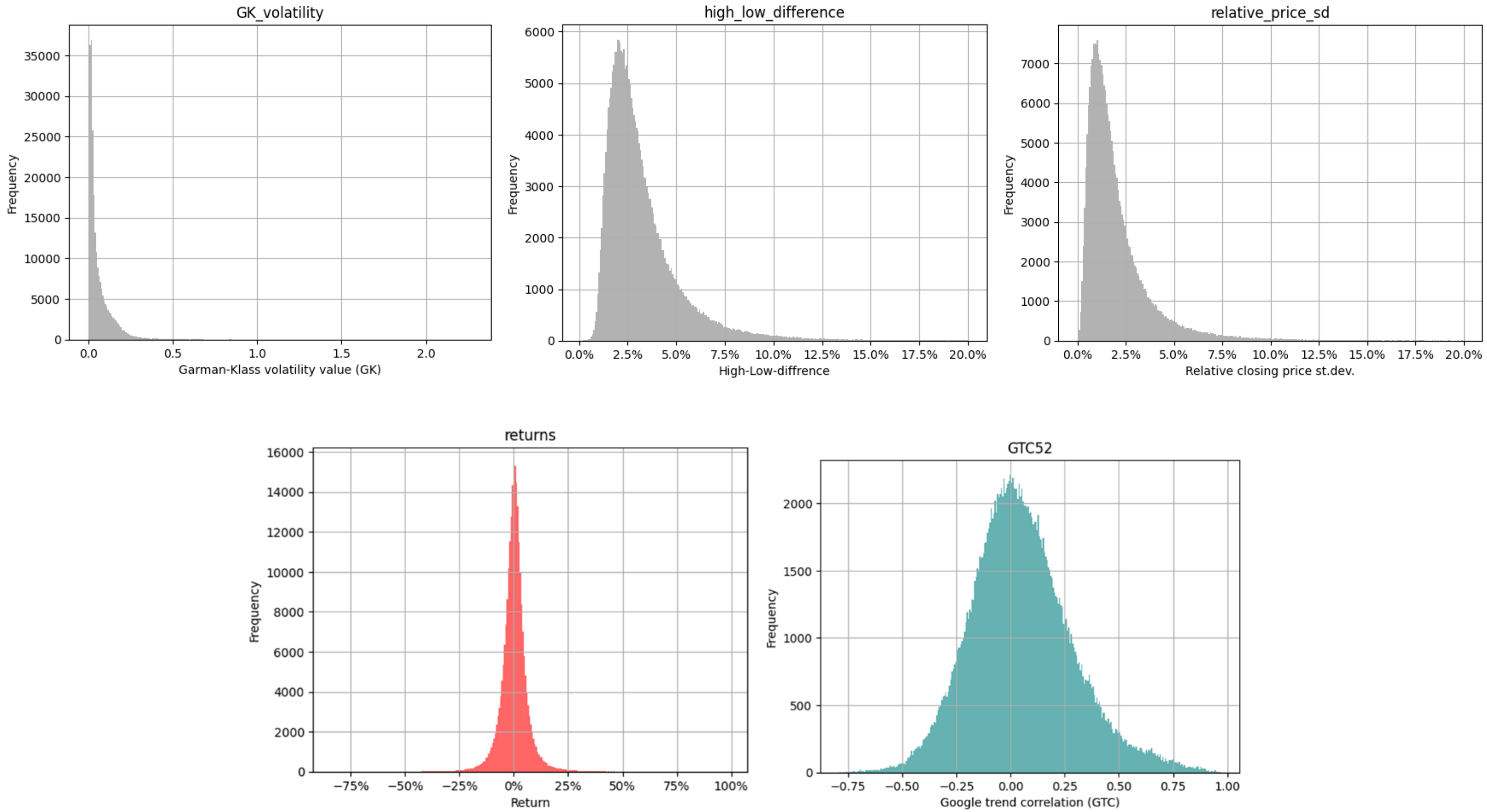
Number of panels	959
ADF regressions	1 lag

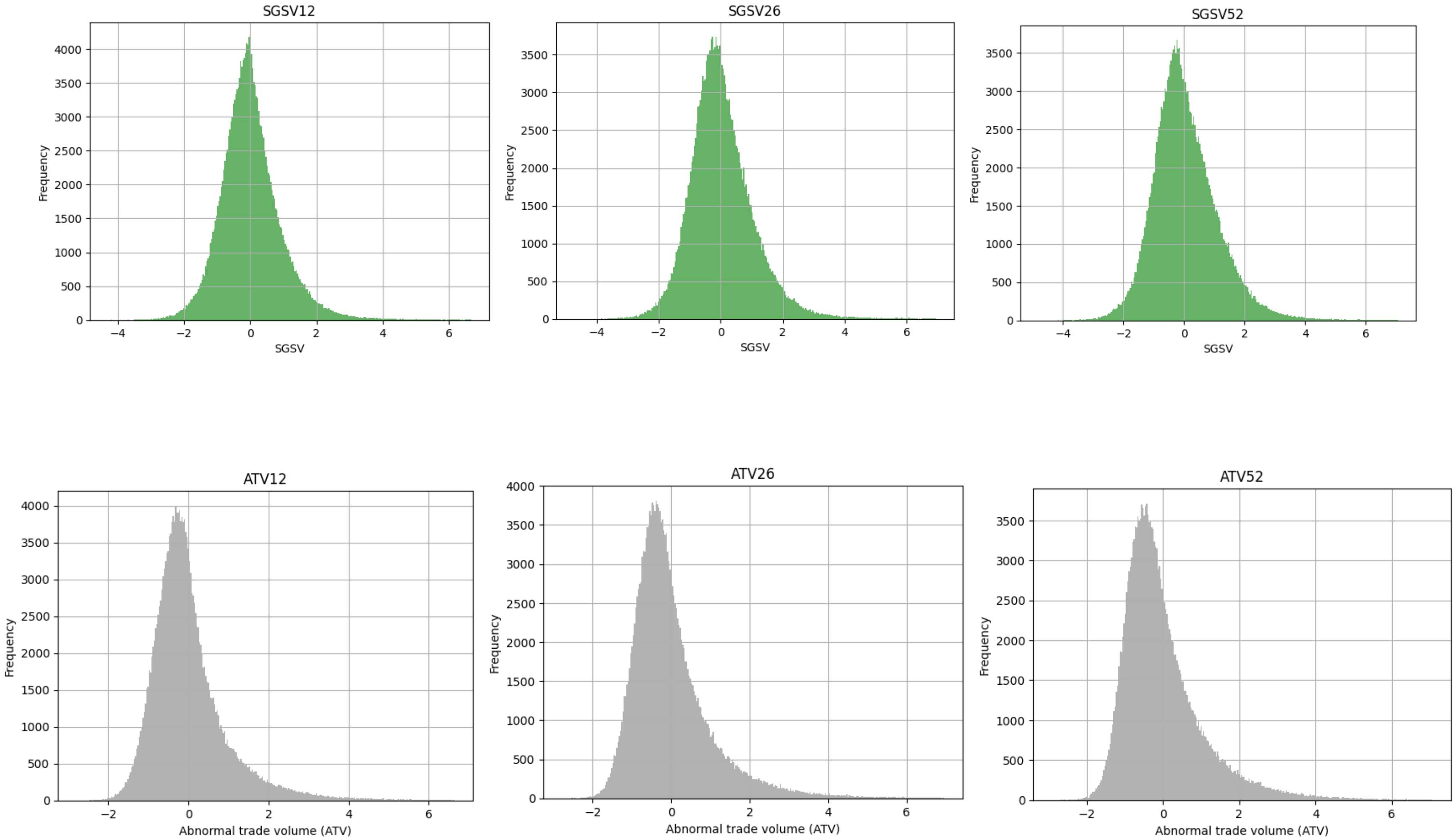
H0: All panels contain unit roots
Ha: At least one panel is stationary

Variable	Modified inv. chi-squared statistic	p-value
Price	0.4163	0.3386
log-return	1044.9917	0.0000
AR	1071.3357	0.0000
SGSV	487.7449	0.0000
ATV	530.8391	0.0000
Volatility	247.5499	0.0000

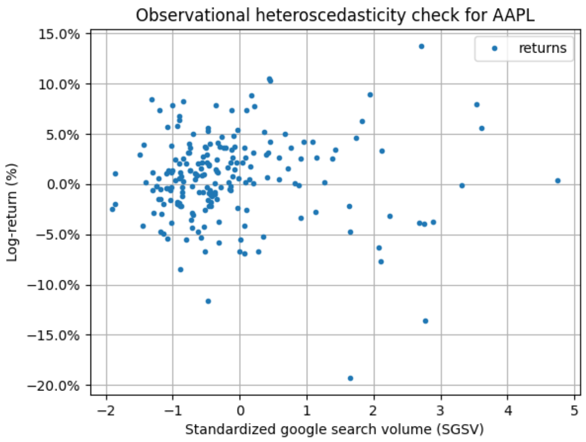
APPENDIX C

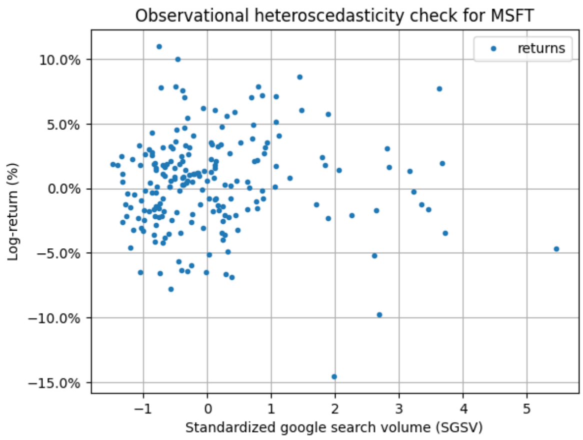
Histograms for included regression variables

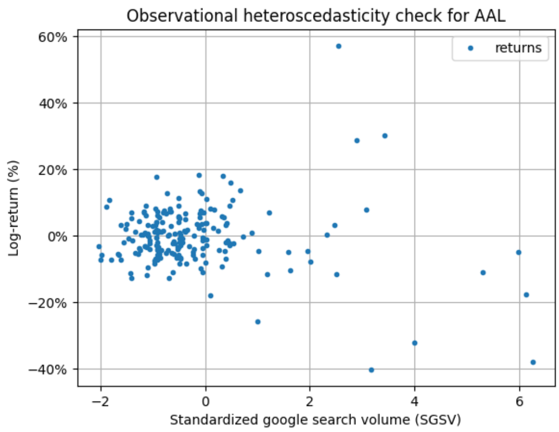


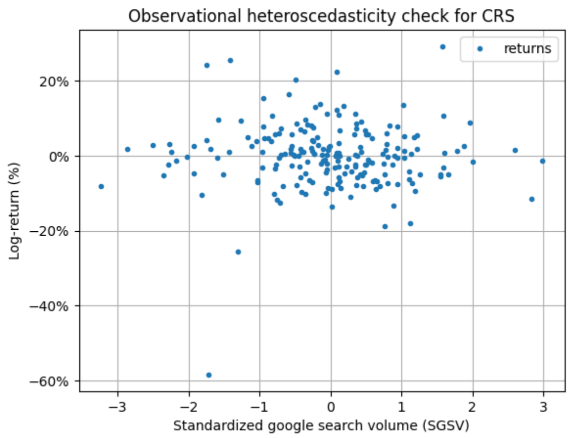

SGSV12
SGSV26
SGSV52
Frequency
SGSV
ATV12
ATV26
ATV52
Frequency
Abnormal trade volume (ATV)

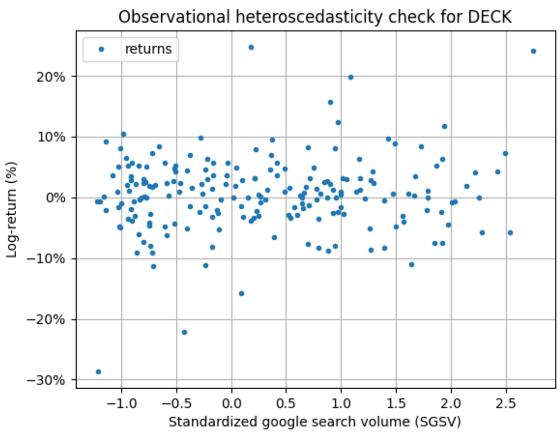
Random sample check for heteroscedasticity

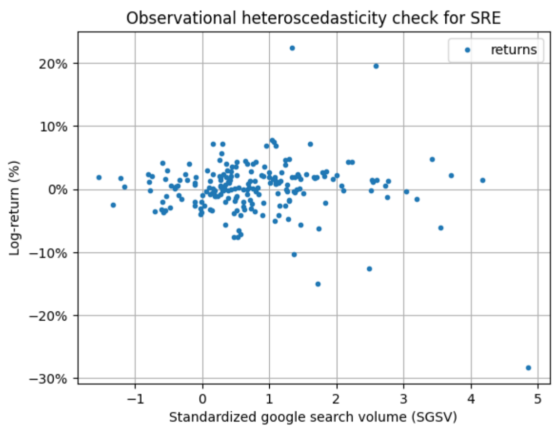


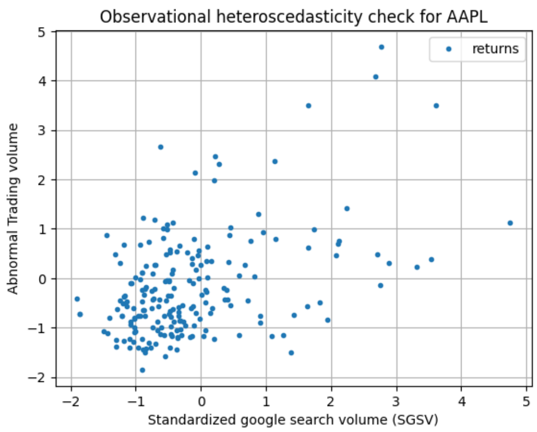


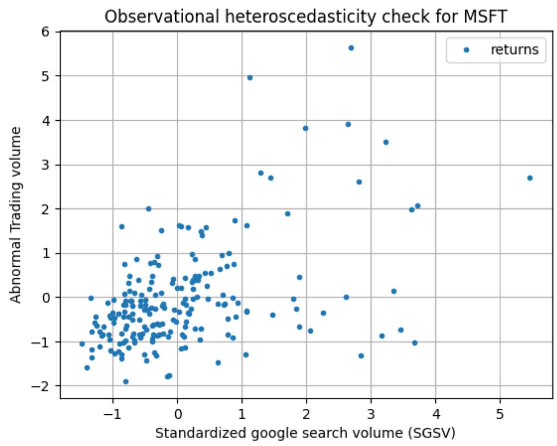


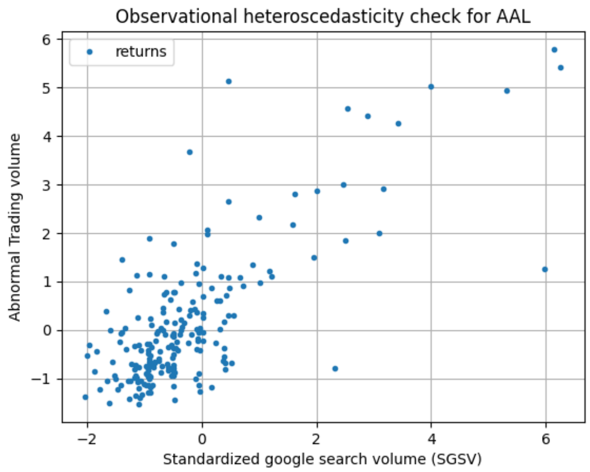


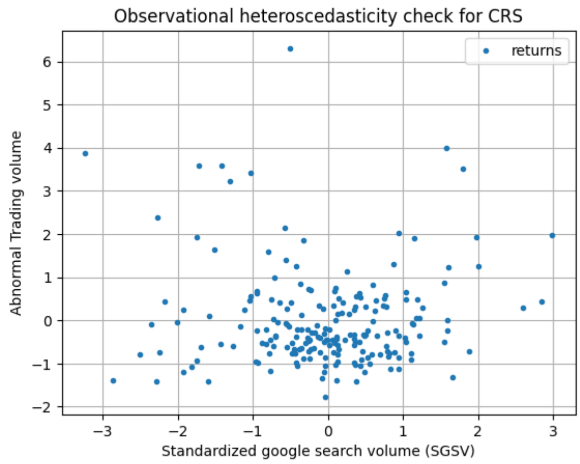


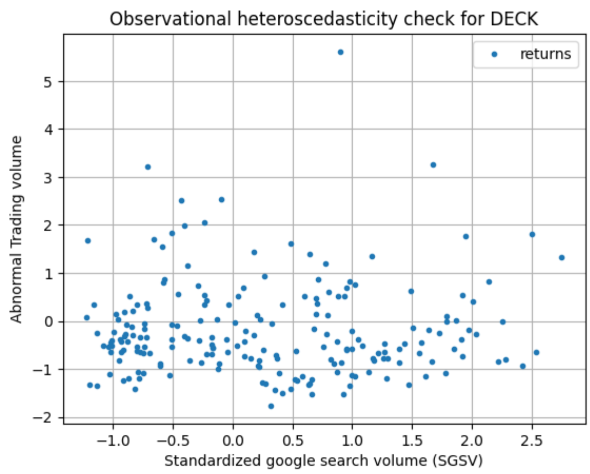


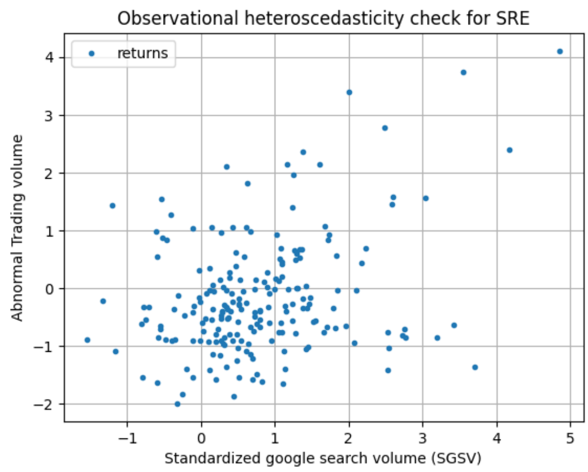

Observational heteroscedasticity check for AAPL
returns
Abnormal Trading volume
Standardized google search volume (SGSV)

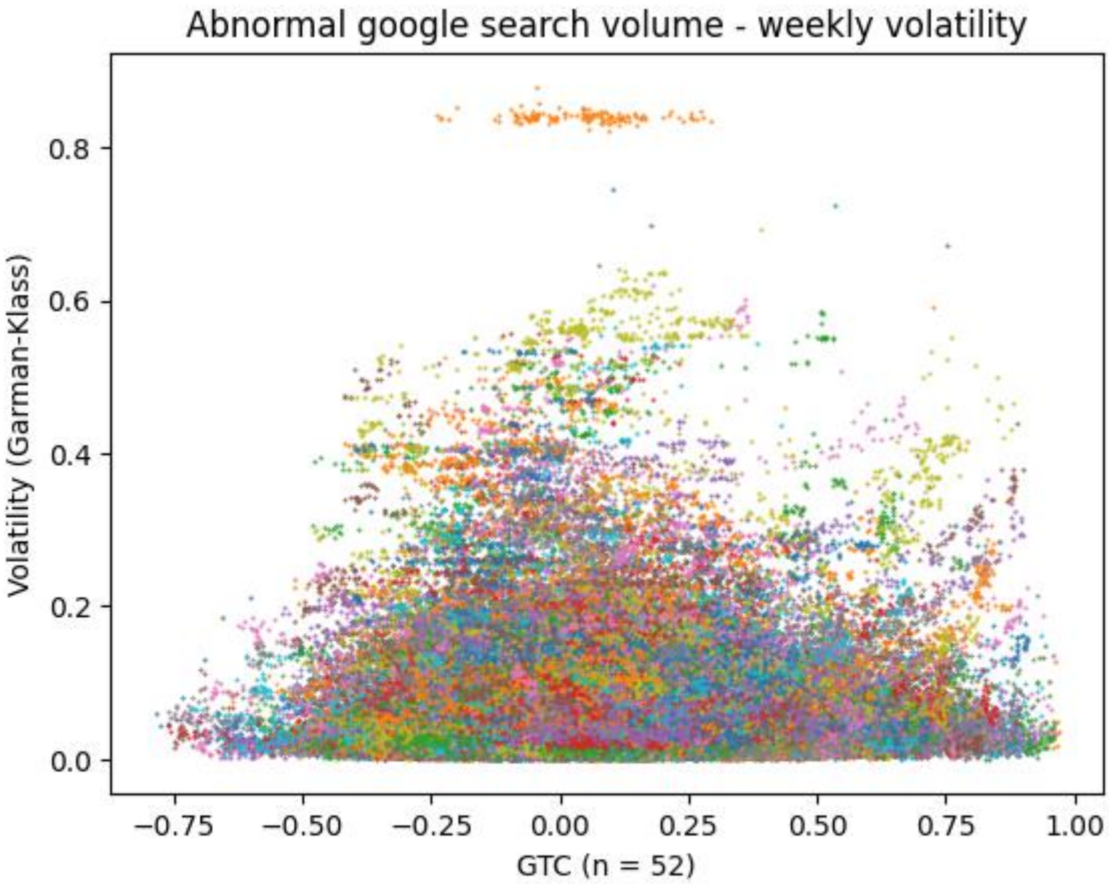

Observational heteroscedasticity check for MSFT
returns
Abnormal Trading volume
Standardized google search volume (SGSV)


Observational heteroscedasticity check for AAL
returns
Abnormal Trading volume
Standardized google search volume (SGSV)


Observational heteroscedasticity check for CRS
returns
Abnormal Trading volume
Standardized google search volume (SGSV)


Observational heteroscedasticity check for DECK
returns
Abnormal Trading volume
Standardized google search volume (SGSV)


Observational heteroscedasticity check for SRE
returns
Abnormal Trading volume
Standardized google search volume (SGSV)



Each dot represents a trading week. The colors are grouped weeks by their unique ticker names. For example, orange dots in the upper middle are the trading weeks for the stock ticker "LAUR". Even though there are around 1600 unique tickers, the number of colors is limited to far less, so do not get distracted by the same colors appearing on different sectors of the diagram. Notice the curvature that can be observed by the plot-groups. As you see, the right-most stocks are generally increasing in weekly volatility as the stock volume is increasingly correlated with Google trends. The same can be observed to a smaller degree on the left side when the correlation is negative.

APPENDIX D

Additional regression models

Industry clustered abnormal return

	Abnormal Return (Six month β)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AR6_{t-1}$	-0.0188***	-0.0189***	-0.0190***	-0.0194***	-0.0192***	-0.0194***	-0.0193***	-0.0201***	-0.0198***	-0.0137**	-0.0139**
	(-3.50)	(-3.53)	(-3.56)	(-3.49)	(-3.50)	(-3.60)	(-3.57)	(-3.61)	(-3.63)	(-2.81)	(-2.89)
$SGSV$		0.000552						0.000607*		0.000810**	
		(1.76)						(2.13)		(2.74)	
$SGSV_{t-1}$			0.000811**						0.000957**		0.000891**
			(2.67)						(3.18)		(2.85)
ATV				-0.000621				-0.000591		0.000497	
				(-1.27)				(-1.24)		(1.10)	
ATV_{t-1}					-0.00170***				-0.00171***		-0.000363
					(-6.01)				(-6.25)		(-1.64)
$Volatility$						-0.0322***		-0.0313***		-0.0300***	
						(-5.89)		(-5.90)		(-4.07)	
$Volatility_{t-1}$							-0.0274***		-0.0246***		-0.0136**
							(-5.82)		(-5.48)		(-2.74)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	190800	190649	190648	190649	190648	190800	190800	190649	190648	190649	190648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.000	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.002	0.073	0.073
adj. R^2	0.000	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.002	0.072	0.072

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Company clustered abnormal return

	Abnormal Return (Six month β)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$AR6_{t-1}$	-0.0189***	-0.0190***	-0.0191***	-0.0195***	-0.0193***	-0.0195***	-0.0194***	-0.0201***	-0.0199***	-0.0138*	-0.0140**
	(-3.56)	(-3.58)	(-3.60)	(-3.60)	(-3.59)	(-3.66)	(-3.64)	(-3.71)	(-3.71)	(-2.58)	(-2.64)
$SGSV$		0.000560**						0.000614**		0.000811***	
		(2.76)						(3.20)		(4.16)	
$SGSV_{t-1}$			0.000814***						0.000959***		0.000893***
			(3.94)						(4.62)		(4.26)
ATV				-0.000621				-0.000591		0.000483	
				(-1.87)				(-1.84)		(1.23)	
ATV_{t-1}					-0.00169***				-0.00170***		-0.000364*
					(-10.11)				(-10.38)		(-2.08)
$Volatility$						-0.0323***		-0.0314***		-0.0302***	
						(-6.59)		(-6.80)		(-4.36)	
$Volatility_{t-1}$							-0.0275***		-0.0246***		-0.0137***
							(-9.02)		(-8.67)		(-3.67)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	191800	191649	191648	191649	191648	191800	191800	191649	191648	191649	191648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.073	0.073
adj. R^2	0.000	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.002	0.072	0.072

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regressions without lagged values of AR

	Abnormal Return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AR_{t-1}	-0.0233***										
	(-4.40)										
$SGSV$		0.000672**						0.000711***		0.000825***	
		(3.26)						(3.63)		(4.12)	
$SGSV_{t-1}$			0.000931***						0.00107***		0.000949***
			(4.47)						(5.09)		(4.42)
ATV				-0.000427				-0.000402		0.000659	
				(-1.30)				(-1.27)		(1.67)	
ATV_{t-1}					-0.00161***				-0.00164***		-0.000332
					(-9.99)				(-10.26)		(-1.91)
$Volatility$						-0.0318***		-0.0311***		-0.0283***	
						(-6.56)		(-6.82)		(-4.11)	
$Volatility_{t-1}$							-0.0274***		-0.0247***		-0.0116**
							(-9.21)		(-8.82)		(-3.18)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	191800	192606	192605	192606	192605	192759	192759	192606	192605	192606	192605
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.001	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.002	0.073	0.073
adj. R^2	0.001	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.002	0.072	0.072

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Sector clustered abnormal return

	Abnormal Return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AR_{t-1}	-0.0232*	-0.0233*	-0.0234*	-0.0236*	-0.0234*	-0.0238*	-0.0237*	-0.0243*	-0.0242*	-0.0170*	-0.0173*
	(-2.44)	(-2.46)	(-2.48)	(-2.41)	(-2.42)	(-2.52)	(-2.50)	(-2.50)	(-2.52)	(-2.48)	(-2.54)
$SGSV$		0.000674						0.000716		0.000833	
		(1.74)						(1.99)		(2.04)	
$SGSV_{t-1}$			0.000946*						0.00109**		0.000964*
			(2.81)						(3.23)		(2.46)
ATV				-0.000470				-0.000447		0.000658	
				(-0.70)				(-0.68)		(1.74)	
ATV_{t-1}					-0.00163**				-0.00166**		-0.000305
					(-3.34)				(-3.52)		(-0.98)
$Volatility$						-0.0324**		-0.0317**		-0.0295**	
						(-4.13)		(-4.09)		(-3.34)	
$Volatility_{t-1}$							-0.0279**		-0.0251**		-0.0128*
							(-4.39)		(-4.22)		(-2.44)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	190800	190649	190648	190649	190648	190800	190800	190649	190648	190649	190648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.002	0.073	0.073
adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.072	0.072

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry clustered abnormal return

	Abnormal Return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AR_{t-1}	-0.0232***	-0.0233***	-0.0234***	-0.0236***	-0.0234***	-0.0238***	-0.0237***	-0.0243***	-0.0242***	-0.0170**	-0.0173**
	(-3.85)	(-3.89)	(-3.93)	(-3.80)	(-3.82)	(-3.93)	(-3.91)	(-3.91)	(-3.96)	(-3.16)	(-3.26)
$SGSV$		0.000674*						0.000716*		0.000833**	
		(2.09)						(2.44)		(2.73)	
$SGSV_{t-1}$			0.000946**						0.00109***		0.000964**
			(3.00)						(3.48)		(2.99)
ATV				-0.000470				-0.000447		0.000658	
				(-0.93)				(-0.92)		(1.40)	
ATV_{t-1}					-0.00163***				-0.00166***		-0.000305
					(-5.89)				(-6.16)		(-1.43)
$Volatility$						-0.0324***		-0.0317***		-0.0295***	
						(-5.94)		(-6.00)		(-4.05)	
$Volatility_{t-1}$							-0.0279***		-0.0251***		-0.0128*
							(-5.94)		(-5.60)		(-2.60)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	190800	190649	190648	190649	190648	190800	190800	190649	190648	190649	190648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.002	0.073	0.073
adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.072	0.072

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Company clustered high-low-difference volatility

	HLD Volatility										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
HLD_{t-1}	0.669***	0.672***	0.670***	0.673***	0.672***	0.576***	0.679***	0.576***	0.675***	0.429***	0.500***
	(32.51)	(35.88)	(35.16)	(37.23)	(40.32)	(27.18)	(42.10)	(27.78)	(47.81)	(19.10)	(29.41)
SGSV		0.000514**						0.000104		0.000130	
		(4.22)						(1.13)		(1.70)	
$SGSV_{t-1}$			0.000968***						0.000995***		0.000863***
			(6.12)						(6.06)		(6.39)
AR				-0.000188				-0.000622		0.00221	
				(-0.04)				(-0.15)		(0.60)	
AR_{t-1}					-0.0186**				-0.0189**		-0.00955*
					(-4.35)				(-4.52)		(-2.62)
ATV						0.00589***		0.00590***		0.00437***	
						(17.38)		(17.23)		(11.17)	
ATV_{t-1}							-0.000194		-0.000236		-0.000707***
							(-1.17)		(-1.31)		(-7.16)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	241362	193505	192552	191754	190800	193505	192552	191601	190648	191601	190648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.447	0.455	0.457	0.454	0.457	0.555	0.454	0.556	0.460	0.714	0.672
adj. R^2	0.447	0.455	0.457	0.454	0.457	0.555	0.454	0.556	0.460	0.713	0.672

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

clustered standard deviation volatility

	Price Standard Deviation (RPSD) Volatility										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$RPSD_{t-1}$	0.313***	0.323***	0.321***	0.325***	0.330***	0.212***	0.289***	0.211***	0.291***	0.0886***	0.144***
	(13.05)	(11.85)	(11.69)	(13.55)	(13.64)	(8.00)	(10.10)	(8.88)	(11.54)	(5.33)	(8.51)
SGSV		0.000790***						0.000256**		0.000255**	
		(5.08)						(2.68)		(2.78)	
$SGSV_{t-1}$			0.00154***						0.00147***		0.00126***
			(7.84)						(7.86)		(7.18)
AR				-0.0427***				-0.0433***		-0.0413***	
				(-11.03)				(-13.61)		(-12.37)	
AR_{t-1}					-0.000196				-0.00219		-0.00387
					(-0.08)				(-0.92)		(-1.57)
ATV						0.00766***		0.00762***		0.00627***	
						(17.93)		(18.87)		(13.98)	
ATV_{t-1}							0.00145***		0.00134***		-0.0000154
							(8.67)		(9.69)		(-0.13)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	241362	193505	192552	191754	190800	193505	192552	191601	190648	191601	190648
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.098	0.107	0.114	0.123	0.109	0.259	0.112	0.277	0.119	0.418	0.328
adj. R^2	0.098	0.107	0.114	0.123	0.109	0.259	0.112	0.277	0.119	0.418	0.328

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry clustered abnormal volume

	Abnormal Volume										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ATV_{t-1}	0.485***	0.481***	0.474***	0.485***	0.485***	0.483***	0.484***	0.480***	0.475***	0.439***	0.436***
	(76.35)	(79.91)	(78.96)	(76.53)	(78.37)	(76.06)	(77.04)	(79.81)	(82.83)	(84.55)	(85.97)
SGSV		0.0525***						0.0524***		0.0414***	
		(8.63)						(9.07)		(8.44)	
$SGSV_{t-1}$			0.124***						0.125***		0.0965***
			(12.78)						(12.86)		(10.02)
AR				0.132				0.142		0.238	
				(0.89)				(0.99)		(1.93)	
AR_{t-1}					-0.851***				-0.883***		-0.630***
					(-8.54)				(-9.73)		(-8.03)
Volatility						1.407***		1.430***		1.670***	
						(4.26)		(4.30)		(4.40)	
$Volatility_{t-1}$							0.0839		0.0213		-0.0409
							(0.82)		(0.20)		(-0.30)
Cross sections	959	959	959	959	959	959	959	959	959	959	959
N	192533	192533	192533	191582	190630	192533	192533	191582	190630	191582	190630
Time fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
R^2	0.235	0.238	0.251	0.235	0.238	0.238	0.235	0.241	0.253	0.401	0.407
adj. R^2	0.235	0.238	0.251	0.235	0.238	0.238	0.235	0.241	0.253	0.400	0.406

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Granger causality with 6-month rolling beta

Dumitrescu and Hurlin test

H_0	SGSV⇏AR6	AR6⇏SGSV
H_a	SGSV does Granger-cause AR6 for at least one panel	AR6does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\overline{W}$	3.300	2.115
$\bar{Z}$	20.13	1.787
$\tilde{Z}$	19.40	1.434
Decision	Reject***	Accept

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Granger causality with high-low-difference volatility

Dumitrescu and Hurlin test

H_0	SGSV⇏Volatility	Volatility⇏SGSV
H_a	SGSV does Granger-cause Volatility for at least one panel	Volatility does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\overline{W}$	9.160	3.202
$\bar{Z}$	110.9	18.62
$\tilde{Z}$	108.3	17.92
Decision	Reject***	Reject***

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Granger causality with high-low-difference volatility

Dumitrescu and Hurlin test

H_0	SGSV⇏Volatility	Volatility⇏SGSV
H_a	SGSV does Granger-cause Volatility for at least one panel	Volatility does Granger-cause SGSV for at least one panel
N	959	959
T	202	202
$\bar{W}$	11.19	2.892
$\bar{Z}$	142.2	13.81
$\tilde{Z}$	139.0	13.21
Decision	Reject***	Reject***

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

APPENDIX E

Companies, sectors, and Wald statistics

Companies where SGSV Granger-causes log-return according to the Dumitrescu–Hurlin test

	N	(%) of total
Companies	959	100 %
p < 0.05	106	11 %
p < 0.001	23	2 %
p < 0.0001	13	1 %

Index	Ticker	Name	Sector	Wald statistic	p-value
1	A	Agilent Technologies Inc	Industrials	4,573	0,104
2	AAL	American Airlines Group Inc	Consumer Discretionary	3,328	0,192
3	AAON	AAON, Inc.	Industrials	1,963	0,377
4	AAP	Advance Auto Parts, Inc.	Consumer Discretionary	0,189	0,910
5	AAPL	Apple Inc	Technology	1,611	0,448
6	AAT	American Assets Trust, Inc	Real Estate	0,875	0,646
7	ABBV	AbbVie Inc	Health Care	2,542	0,283
8	ABC	AmerisourceBergen Corp.	Health Care	2,718	0,259
9	ABG	Asbury Automotive Group, Inc.	Consumer Discretionary	0,101	0,951
10	ABM	ABM Industries, Inc.	Consumer Discretionary	1,099	0,578
11	ABT	Abbott Laboratories	Health Care	2,188	0,337
12	ACCO	ACCO Brands Corporation	Consumer Discretionary	2,313	0,317
13	ACLS	Axcelis Technologies Inc	Technology	0,763	0,683
14	ACM	Aecom	Consumer Discretionary	8,495	0,016*
15	ADBE	Adobe Inc	Technology	14,33	0,001**
16	ADC	Agree Realty Corporation	Real Estate	2,768	0,253
17	ADEA	Adeia Inc	Technology	1,942	0,380
18	ADES	Advanced Emissions Solutions Inc	Industrials	7,96	0,020*
19	ADI	Analog Devices, Inc.	Technology	3,696	0,160
20	ADMA	ADMA Biologics Inc	Health Care	11,89	0,003*
21	ADP	Automatic Data Processing Inc	Consumer Discretionary	2,693	0,263
22	ADT	ADT Inc	Consumer Discretionary	1,692	0,431
23	AEL	American Equity Investment Life Holding	Finance	7,254	0,028*
24	AEO	American Eagle Outfitters Inc	Consumer Discretionary	0,228	0,892
25	AFG	American Financial Group Inc	Finance	0,197	0,906
26	AFL	AFLAC Incorporated	Finance	1,43	0,490
27	AGCO	AGCO Corporation	Industrials	0,224	0,894
28	AGNC	AGNC Investment Corp	Real Estate	4,269	0,121

29	AGR	Avangrid Inc	Utilities	0,407	0,816
30	AGS	Playags Inc	Consumer Discretionary	1,777	0,413
31	AHT	Ashford Hospitality Trust, Inc.	Real Estate	6,687	0,037*
32	AIG	American International Group Inc	Finance	2,6	0,275
33	AIN	Albany International Corp.	Consumer Discretionary	0,0655	0,968
34	AIR	AAR Corp.	Industrials	0,937	0,627
35	AIRG	Airgain Inc	Technology	0,712	0,701
36	AIT	Applied Industrial Technologies Inc	Industrials	1,696	0,430
37	AKAM	Akamai Technologies, Inc.	Consumer Discretionary	2,42	0,300
38	AKR	Acadia Realty Trust	Real Estate	1,113	0,574
39	AL	Air Lease Corp	Consumer Discretionary	1,932	0,382
40	ALB	Albemarle Corporation	Industrials	3,217	0,203
41	ALEX	Alexander & Baldwin, Inc.	Real Estate	3,017	0,224
42	ALK	Alaska Air Group, Inc.	Consumer Discretionary	3,372	0,188
43	ALL	Allstate Corp	Finance	0,0258	0,987
44	ALLE	Allegion Public Limited	Consumer Discretionary	0,378	0,828
45	ALLY	Ally Financial Inc	Finance	4,404	0,113
46	ALRM	Alarm.com Holdings, Inc.	Technology	3,05	0,220
47	ALT	Altimmune Inc	Health Care	0,0489	0,976
48	ALTO	Alto Ingredients Inc	Industrials	4,355	0,116
49	ALX	Alexander's, Inc.	Real Estate	2,584	0,277
50	AM	Antero Midstream Partners LP	Utilities	4,009	0,137
51	AMAT	Applied Materials, Inc.	Technology	7,682	0,023*
52	AMBA	Ambarella Inc	Technology	2,923	0,234
53	AMD	Advanced Micro Devices, Inc.	Technology	1,349	0,511
54	AME	AMETEK, Inc.	Consumer Discretionary	0,907	0,636
55	AMED	Amedisys Inc	Health Care	4,132	0,129
56	AMG	Affiliated Managers Group, Inc.	Finance	3,872	0,147
57	AMGN	Amgen, Inc.	Health Care	0,328	0,849
58	AMN	AMN Healthcare Services, Inc.	Health Care	3,762	0,155
59	AMP	Ameriprise Financial, Inc.	Finance	0,108	0,948
60	AMRS	Amyris Inc	Industrials	14,57	0,001**
61	AMT	COMMON STOCK USD.01	Real Estate	2,663	0,266
62	AMZN	Amazon.com, Inc.	Consumer Discretionary	0,192	0,909
63	AN	AutoNation, Inc.	Consumer Discretionary	0,0391	0,981
64	ANDE	Andersons Inc	Consumer Staples	1,253	0,536
65	ANGI	Angie's List, Inc.	Technology	1,451	0,485
66	AON	Aon PLC	Finance	1,528	0,467
67	AOS	Smith (A.O.) Corp.	Industrials	5,62	0,063
68	APD	Air Products & Chemicals, Inc.	Industrials	2,93	0,234
69	APH	Amphenol Corporation	Technology	2,047	0,361
70	APLE	Apple Hospitality REIT Inc	Real Estate	0,887	0,642
71	APLS	Apellis Pharmaceuticals Inc	Health Care	1,248	0,537

72	APPS	Digital Turbine Inc	Technology	2,192	0,336
73	AQUA	Evoqua Water Technologies Corp	Industrials	2,642	0,269
74	ARCC	Ares Capital Corporation	Finance	0,342	0,843
75	ARE	Alexandria Real Estate Equities Inc	Real Estate	0,299	0,861
76	ARI	Apollo Commercial Real Est. Finance Inc	Real Estate	8,322	0,017*
77	AROW	Arrow Financial Corporation	Finance	0,0923	0,955
78	ARR	ARMOUR Residential REIT, Inc.	Real Estate	0,487	0,784
79	ARW	Arrow Electronics, Inc.	Technology	5,301	0,073
80	ARWR	Arrowhead Pharmaceuticals Inc	Health Care	4,09	0,132
81	ASB	Associated Banc-Corp.	Finance	12,76	0,002*
82	ASH	Ashland Global Holdings Inc.	Industrials	0,706	0,703
83	ASRT	Assertio Holdings Inc	Health Care	4,984	0,085
84	ASTE	Astec Industries, Inc.	Industrials	2,234	0,329
85	ATEC	Alphatec Holdings Inc	Health Care	0,652	0,722
86	ATI	Allegheny Technologies Incorporated	Industrials	5,227	0,076
87	ATO	Atmos Energy Corporation	Utilities	3,295	0,195
88	ATR	AptarGroup, Inc.	Industrials	1,833	0,402
89	ATRA	Atara Biotherapeutics Inc	Health Care	4,99	0,085
90	ATVI	Activision Blizzard, Inc.	Technology	4,953	0,087
91	AUB	Atlantic Union Bankshares Corp	Finance	3,905	0,145
92	AVA	Avista Corp	Utilities	0,825	0,663
93	AVB	AvalonBay Communities Inc	Real Estate	2,244	0,328
94	AVD	American Vanguard Corp.	Industrials	1,958	0,378
95	AVGO	Broadcom Inc	Technology	5,093	0,081
96	AVY	Avery Dennison Corp	Industrials	1,517	0,470
97	AWK	American Water Works Company Inc	Utilities	2,914	0,236
98	AX	Axos Financial Inc	Finance	5,841	0,056
99	AXL	American Axle & Manufact. Holdings, Inc.	Consumer Discretionary	0,27	0,874
100	AXON	Axon Enterprise Inc	Consumer Discretionary	2,72	0,259
101	AXP	American Express Company	Finance	4,387	0,114
102	AZZ	AZZ Inc	Industrials	0,285	0,867
103	B	Barnes Group Inc.	Industrials	1,786	0,411
104	BAC	Bank of America Corp	Finance	0,396	0,821
105	BAH	Booz Allen Hamilton Holding Corporation	Consumer Discretionary	3,856	0,148
106	BALL	Ball Corp.	Industrials	2,474	0,293
107	BAND	Bandwidth Inc	Technology	1,321	0,518
108	BANF	BancFirst Corporation	Finance	3,51	0,176
109	BAX	Baxter International Inc	Health Care	7,81	0,022*
110	BBSI	Barrett Business Services, Inc.	Consumer Discretionary	0,252	0,882
111	BBY	Best Buy Co Inc	Consumer Discretionary	0,0551	0,973
112	BC	Brunswick Corporation	Consumer Discretionary	0,525	0,769
113	BCO	Brink's Company	Technology	2,008	0,368
114	BDC	Belden Inc.	Telecommunications	9,449	0,010*

115	BDN	Brandywine Realty Trust	Real Estate	0,0551	0,973
116	BDX	Becton Dickinson and Co	Health Care	1,784	0,412
117	BEN	Franklin Resources, Inc.	Finance	3,272	0,197
118	BERY	Berry Plastics Group, Inc.	Industrials	10,1	0,007*
119	BFS	Saul Centers Inc	Real Estate	0,4	0,819
120	BG	Bunge Ltd.	Industrials	0,898	0,639
121	BGS	B&G Foods, Inc.	Consumer Staples	0,587	0,746
122	BH	Biglari Holdings Inc	Consumer Discretionary	0,697	0,706
123	BIG	Big Lots, Inc.	Consumer Discretionary	9,788	0,008*
124	BIIB	Biogen Inc	Health Care	1,87	0,394
125	BIO	Bio-Rad Laboratories, Inc.	Industrials	1,922	0,384
126	BK	Bank of New York Mellon Corp	Finance	90,29	0,000
127	BKD	Brookdale Senior Living, Inc.	Health Care	0,756	0,686
128	BKE	Buckle Inc	Consumer Discretionary	0,749	0,688
129	BKNG	Booking Holdings Inc	Consumer Discretionary	0,2	0,905
130	BL	Blackline Inc	Technology	1,782	0,412
131	BLD	TopBuild Corp	Industrials	5,3	0,073
132	BLUE	bluebird bio Inc	Health Care	2,33	0,314
133	BMI	Badger Meter, Inc.	Industrials	0,483	0,786
134	BMY	Bristol-Myers Squibb Co	Health Care	0,441	0,802
135	BOH	Bank of Hawaii Corporation	Finance	0,436	0,804
136	BOOT	Boot Barn Holdings Inc	Consumer Discretionary	0,148	0,929
137	BOX	Box Inc	Technology	4,28	0,120
138	BR	Broadridge Financial Solutions, Inc.	Consumer Discretionary	4,433	0,112
139	BRC	Brady Corp	Technology	2,81	0,248
140	BRO	Brown & Brown, Inc.	Finance	1,521	0,469
141	BSX	Boston Scientific Corporation	Health Care	2,285	0,321
142	BW	Babcock & Wilcox Enterprises Inc	Technology	2,988	0,227
143	BWA	BorgWarner Inc.	Consumer Discretionary	1,852	0,398
144	BX	Blackstone Group L.P. (The)	Finance	1,338	0,513
145	BY	Byline Bancorp Inc	Finance	2,586	0,277
146	BYD	Boyd Gaming Corporation	Consumer Discretionary	1,743	0,420
147	C	Citigroup Inc	Finance	3,114	0,213
148	CABO	Cable One Inc	Consumer Discretionary	0,329	0,848
149	CACC	Credit Acceptance Corp.	Finance	4,768	0,095
150	CACI	CACI International Inc	Technology	6,863	0,034*
151	CADE	Cadence Bancorporation	Finance	2,679	0,264
152	CAG	ConAgra Foods, Inc.	Consumer Staples	0,0941	0,954
153	CAH	Cardinal Health, Inc.	Health Care	1,007	0,605
154	CAKE	Cheesecake Factory Incorporated (THE)	Consumer Discretionary	0,246	0,884
155	CAL	Caleres Inc	Consumer Discretionary	4,691	0,099
156	CALM	Cal-Maine Foods Inc	Consumer Staples	2,185	0,337
157	CAR	Avis Budget Group Inc.	Consumer Discretionary	3,846	0,149

158	CASY	Casey's General Stores Inc	Miscellaneous	1,832	0,402
159	CAT	Caterpillar Inc.	Industrials	2,951	0,231
160	CATY	Cathay General Bancorp	Finance	5,626	0,063
161	CBRE	CBRE Group Inc	Finance	0,778	0,678
162	CBT	Cabot Corp	Industrials	2,109	0,350
163	CBU	Community Bank System, Inc.	Finance	1,111	0,575
164	CC	Chemours Co	Industrials	0,566	0,754
165	CCK	Crown Holdings, Inc.	Industrials	2,156	0,342
166	CCL	Carnival Corp	Consumer Discretionary	0,973	0,616
167	CCO	Clear Channel Outdoor Holdings Inc	Consumer Discretionary	0,0924	0,955
168	CCS	Century Communities Inc	Consumer Discretionary	0,124	0,940
169	CDE	Coeur Mining Inc	Basic Materials	9,899	0,008*
170	CDNA	CareDx Inc	Health Care	2,984	0,227
171	CDW	CDW Corp	Consumer Discretionary	0,505	0,777
172	CE	Celanese Corporation	Industrials	1,421	0,493
173	CF	CF Industries Holdings, Inc.	Industrials	4,208	0,125
174	CFG	Citizens Financial Group Inc	Finance	3,542	0,173
175	CFR	Cullen	Finance	1,199	0,550
176	CG	Carlyle Group Inc	Finance	0,58	0,749
177	CHE	Chemed Corporation	Health Care	3,136	0,211
178	CHH	Choice Hotels International Inc	Consumer Discretionary	0,944	0,624
179	CI	Cigna Corp	Health Care	0,654	0,722
180	CIEN	Ciena Corporation	Utilities	0,364	0,834
181	CIM	Chimera Investment Corp.	Real Estate	15,14	0,001**
182	CL	Colgate-Palmolive Company	Consumer Discretionary	0,0338	0,983
183	CLW	Clearwater Paper Corp	Basic Materials	0,959	0,620
184	CLX	Clorox Co	Consumer Discretionary	1,561	0,460
185	CMA	Comerica Incorporated	Finance	1,105	0,576
186	CMC	Commercial Metals Company	Industrials	2,009	0,368
187	CME	CME Group Inc	Finance	5,41	0,069
188	CMG	Chipotle Mexican Grill, Inc.	Consumer Discretionary	1,524	0,468
189	CMI	Cummins Inc.	Industrials	6,129	0,049*
190	CMP	Compass Minerals International, Inc.	Basic Materials	3,829	0,150
191	CMS	CMS Energy Corporation	Utilities	0,545	0,762
192	CNA	Cna Financial Corp	Finance	1,116	0,573
193	CNO	CNO Financial Group Inc	Finance	2,304	0,318
194	CNP	CenterPoint Energy Inc	Utilities	2,893	0,238
195	CNS	Cohen & Steers, Inc.	Finance	1,604	0,450
196	COF	Capital One Financial Corp.	Finance	1,802	0,408
197	COKE	Coca-Cola Bottling Co. Consolidated	Consumer Staples	1,028	0,599
198	COLD	AmeriCold Realty Trust	Finance	3,349	0,190
199	COLM	Columbia Sportswear Company	Consumer Discretionary	10,03	0,008*
200	COMM	Commscope Holding Company Inc	Technology	2,35	0,311

201	COO	Cooper Companies Inc	Health Care	1,914	0,386
202	COOP	Mr. Cooper Group Inc	Finance	1,93	0,383
203	COP	ConocoPhillips	Energy	4,049	0,135
204	CORT	Corcept Therapeutics Incorporated	Health Care	5,134	0,079
205	COST	Costco Wholesale Corporation	Consumer Discretionary	12,38	0,002*
206	COTY	Coty Inc	Consumer Discretionary	1,019	0,602
207	CPB	Campbell Soup Company	Consumer Staples	1,201	0,550
208	CPE	Callon Petroleum Company	Energy	1,167	0,559
209	CPK	Chesapeake Utilities Corporation	Utilities	0,561	0,756
210	CPT	Camden Property Trust	Real Estate	1,184	0,554
211	CRAI	CRA International, Inc.	Consumer Discretionary	0,249	0,883
212	CRI	Carter's, Inc.	Consumer Discretionary	0,754	0,686
213	CRL	Charles River Laboratories Intl. Inc	Consumer Discretionary	0,483	0,786
214	CRM	salesforce.com, inc.	Technology	4,106	0,131
215	CROX	Crocs, Inc.	Consumer Discretionary	10,38	0,006*
216	CRS	Carpenter Technology Corporation	Industrials	4,86	0,091
217	CRUS	Cirrus Logic, Inc.	Technology	5,764	0,058
218	CSCO	Cisco Systems, Inc.	Telecommunications	3,679	0,162
219	CSR	Centerspace	Real Estate	2,754	0,255
220	CSV	Carriage Services, Inc.	Consumer Discretionary	1,213	0,546
221	CSX	CSX Corporation	Industrials	5,031	0,084
222	CTAS	Cintas Corporation	Consumer Discretionary	1,316	0,519
223	CTS	CTS Corporation	Technology	4,469	0,110
224	CTSH	Cognizant Technology Solutions Corp	Technology	5,267	0,074
225	CUBE	CubeSmart	Real Estate	0,934	0,628
226	CUTR	Cutera, Inc.	Health Care	0,79	0,674
227	CUZ	Cousins Properties Inc	Real Estate	3,926	0,143
228	CVI	CVR Energy, Inc.	Energy	2,472	0,293
229	CVNA	Carvana Co	Consumer Discretionary	1,306	0,522
230	CVS	CVS Health Corp	Health Care	2,494	0,290
231	CVX	Chevron Corporation	Energy	0,721	0,698
232	CWT	California Water Service Group	Utilities	3,851	0,149
233	D	Dominion Resources, Inc.	Utilities	4,306	0,119
234	DAL	Delta Air Lines, Inc.	Consumer Discretionary	0,0131	0,993
235	DAN	Dana Holding Corp.	Consumer Discretionary	0,288	0,866
236	DAR	Darling Ingredients Inc	Consumer Staples	0,613	0,736
237	DBD	Diebold, Inc.	Technology	7,427	0,026*
238	DBI	Designer Brands Inc	Consumer Discretionary	2,388	0,305
239	DCI	Donaldson Company, Inc.	Industrials	4,609	0,103
240	DCO	Ducommun Incorporated	Industrials	10,27	0,007*
241	DCOM	Dime Community Bancshares, Inc.	Finance	0,406	0,816
242	DDD	3D Systems Corporation	Technology	0,469	0,791
243	DDS	Dillard's, Inc.	Consumer Discretionary	0,688	0,709

244	DE	Deere & Co.	Industrials	1,543	0,464
245	DECK	Deckers Outdoor Corp	Consumer Discretionary	13,02	0,002*
246	DEI	Douglas Emmett, Inc.	Real Estate	5,747	0,059
247	DFS	Discover Financial Services	Finance	4,395	0,114
248	DG	Dollar General Corp.	Consumer Discretionary	3,416	0,184
249	DGX	Quest Diagnostics Inc	Health Care	0,0268	0,987
250	DHC	Diversified Healthcare Trust of Beneficial Interest	Real Estate	6,309	0,045*
251	DHR	Danaher Corporation	Health Care	1,678	0,434
252	DIN	DineEquity, Inc.	Consumer Discretionary	5,986	0,053
253	DINO	HF Sinclair Corporation Common Stock	Energy	0,269	0,874
254	DIS	Walt Disney Co	Consumer Discretionary	2,298	0,319
255	DISH	DISH Network Corp	Telecommunications	0,464	0,793
256	DK	Delek US Holdings Inc	Energy	3,12	0,213
257	DKS	Dick's Sporting Goods, Inc.	Consumer Discretionary	2,607	0,274
258	DLB	Dolby Laboratories, Inc.	Technology	0,481	0,786
259	DLR	Digital Realty Trust, Inc.	Real Estate	0,589	0,745
260	DLX	Deluxe Corporation	Consumer Discretionary	5,12	0,080
261	DOC	Physicians Realty Trust	Real Estate	2,552	0,281
262	DORM	Dorman Products Inc.	Consumer Discretionary	2,19	0,337
263	DOV	Dover Corp	Industrials	0,668	0,716
264	DRI	Darden Restaurants, Inc.	Consumer Discretionary	0,0096	0,995
265	DVA	DaVita HealthCare Partners Inc.	Health Care	1,478	0,479
266	DVAX	Dynavax Technologies Corporation	Health Care	0,668	0,716
267	DY	Dycom Industries, Inc.	Industrials	5,392	0,070
268	EA	Electronic Arts Inc.	Consumer Discretionary	1,925	0,384
269	EAT	Brinker International, Inc.	Consumer Discretionary	26,32	0,000***
270	EBAY	eBay Inc	Consumer Discretionary	0,28	0,870
271	EBS	Emergent Biosolutions Inc	Health Care	0,577	0,750
272	ECL	Ecolab Inc.	Consumer Discretionary	3,023	0,223
273	ED	Consolidated Edison, Inc.	Utilities	9,508	0,010*
274	EDIT	Editas Medicine Inc	Health Care	0,935	0,627
275	EFX	Equifax Inc.	Finance	7,346	0,027*
276	EGP	Eastgroup Properties Inc	Real Estate	0,9	0,638
277	EHC	Encompass Health Corp	Health Care	1,995	0,371
278	EIG	Employers Holdings, Inc.	Finance	2,481	0,291
279	EL	Estee Lauder Companies Inc	Consumer Discretionary	2,918	0,235
280	ELF	e.l.f. Beauty Inc	Consumer Discretionary	0,745	0,690
281	EME	Emcor Group Inc	Industrials	1,835	0,401
282	EMN	Eastman Chemical Company	Industrials	1,217	0,545
283	EMR	Emerson Electric Co.	Industrials	0,65	0,723
284	ENPH	Enphase Energy Inc	Technology	3,515	0,175
285	ENR	Energizer Holdings Inc	Industrials	0,0309	0,985
286	ENS	EnerSys	Consumer Discretionary	1,478	0,479

287	ENV	Envestnet Inc	Technology	0,86	0,651
288	EOG	EOG Resources Inc	Energy	18,55	0,000**
289	EPR	EPR Properties	Real Estate	6,767	0,036*
290	EQC	Equity Commonwealth	Real Estate	1,879	0,393
291	ES	Eversource Energy	Utilities	1,599	0,451
292	ESE	ESCO Technologies Inc.	Telecommunications	0,632	0,729
293	ESI	Element Solutions Inc	Industrials	3,861	0,148
294	ESS	Essex Property Trust, Inc.	Real Estate	2,992	0,227
295	ETD	Ethan Allen Interiors Inc	Consumer Discretionary	1,191	0,552
296	ETR	Entergy Corporation	Finance	3,578	0,170
297	ETSY	Etsy Inc	Consumer Discretionary	0,84	0,658
298	EVH	Evolent Health Inc	Health Care	2,566	0,280
299	EVR	Evercore Partners, Inc.	Finance	2,06	0,359
300	EW	Edwards Lifesciences Corp	Health Care	1,488	0,477
301	EXAS	EXACT Sciences Corporation	Health Care	5,097	0,081
302	EXC	Exelon Corporation	Utilities	0,321	0,852
303	EXEL	Exelixis, Inc.	Health Care	1,326	0,516
304	EXP	Eagle Materials, Inc.	Industrials	2,542	0,283
305	EXPE	Expedia Group Inc	Consumer Discretionary	5,131	0,080
306	EXPI	eXp World Holdings Inc	Finance	0,23	0,892
307	EXPO	Exponent, Inc.	Consumer Discretionary	3,154	0,209
308	EXR	Extra Space Storage, Inc.	Real Estate	0,394	0,821
309	EYE	National Vision Holdings Inc	Health Care	12,19	0,003*
310	F	Ford Motor Company	Consumer Discretionary	20,92	0,000***
311	FAF	First American Financial Corp	Finance	1,273	0,530
312	FARO	FARO Technologies, Inc.	Industrials	0,772	0,680
313	FAST	Fastenal Company	Basic Materials	5,455	0,068
314	FATE	Fate Therapeutics Inc	Health Care	2,404	0,303
315	FC	Franklin Covey Co.	Consumer Discretionary	0,748	0,688
316	FCEL	FuelCell Energy Inc	Utilities	0,195	0,907
317	FCF	First Commonwealth Financial Corp	Finance	0,397	0,820
318	FCN	FTI Consulting, Inc.	Consumer Discretionary	6,041	0,051
319	FDS	FactSet Research Systems Inc.	Finance	4,48	0,109
320	FDX	FedEx Corporation	Consumer Discretionary	45,97	0,000***
321	FET	Forum Energy Technologies Inc	Industrials	1,789	0,410
322	FFIN	First Financial Bankshares Inc	Finance	0,245	0,885
323	FHB	First Hawaiian Inc	Finance	3,889	0,146
324	FHI	Federated Hermes Inc	Finance	6,478	0,041*
325	FHN	First Horizon Corp (Tennessee)	Finance	2,604	0,274
326	FICO	Fair Isaac Corporation	Technology	0,887	0,642
327	FIS	Fidelity National Information Servcs Inc	Consumer Discretionary	0,238	0,888
328	FIVE	Five Below Inc	Consumer Discretionary	0,961	0,619
329	FIX	Comfort Systems USA, Inc.	Industrials	6,445	0,042*

330	FIZZ	National Beverage Corp.	Consumer Staples	1,053	0,592
331	FL	Foot Locker, Inc.	Consumer Discretionary	1,786	0,411
332	FLO	Flowers Foods, Inc.	Consumer Staples	0,361	0,835
333	FLS	Flowserve Corp	Industrials	1,823	0,404
334	FLT	FleetCor Technologies, Inc.	Technology	4,755	0,096
335	FMC	FMC Corp	Industrials	1,845	0,399
336	FNB	F.N.B. Corp	Finance	0,621	0,734
337	FOLD	Amicus Therapeutics, Inc.	Health Care	0,569	0,753
338	FORM	FormFactor, Inc.	Technology	0,0147	0,993
339	FORR	Forrester Research, Inc.	Consumer Discretionary	0,0087	0,996
340	FR	First Industrial Realty Trust, Inc.	Real Estate	0,407	0,816
341	FRC	First Republic Bank	Finance	1,445	0,487
342	FRT	Federal Realty Investment Trust	Real Estate	1,927	0,383
343	FSP	Franklin Street Properties Corp.	Real Estate	0,425	0,809
344	FSS	Federal Signal Corporation	Technology	0,757	0,686
345	FUL	Fuller (H.B.) Co.	Industrials	6,846	0,035*
346	FWRD	Forward Air Corporation	Consumer Discretionary	1,264	0,533
347	GBX	Greenbrier Companies Inc	Industrials	1,87	0,394
348	GD	General Dynamics Corporation	Industrials	0,422	0,810
349	GDOT	Green Dot Corporation	Finance	0,717	0,699
350	GE	General Electric Company	Consumer Discretionary	1,967	0,376
351	GGG	Graco Inc.	Industrials	5,444	0,068
352	GHC	Graham Holdings Co	Consumer Discretionary	2,723	0,259
353	GILD	Gilead Sciences, Inc.	Health Care	8,1	0,019*
354	GIS	General Mills, Inc.	Consumer Staples	3,815	0,151
355	GL	Globe Life Inc	Finance	1,154	0,564
356	GLT	Glatfelter Corp	Basic Materials	3,308	0,194
357	GLW	Corning Incorporated	Technology	6,066	0,051
358	GM	General Motors Company	Consumer Discretionary	0,497	0,780
359	GOLF	Acushnet Holdings Corp	Consumer Discretionary	1,013	0,604
360	GOOG	Alphabet Inc. Class C	Technology	1,589	0,453
361	GPC	Genuine Parts Company	Consumer Discretionary	0,191	0,909
362	GPI	Group 1 Automotive, Inc.	Consumer Discretionary	0,747	0,689
363	GPRO	GoPro Inc	Consumer Discretionary	1,889	0,391
364	GPS	Gap Inc	Consumer Discretionary	2,513	0,287
365	GS	Goldman Sachs Group Inc	Finance	3,08	0,217
366	GT	Goodyear Tire & Rubber Co	Consumer Discretionary	2,147	0,344
367	GTN	Gray Television, Inc.	Industrials	5,699	0,060
368	GTY	Getty Realty Corp.	Real Estate	0,619	0,734
369	GVA	Granite Construction Inc.	Industrials	0,876	0,646
370	H	Hyatt Hotels Corporation	Consumer Discretionary	4,287	0,120
371	HA	Hawaiian Holdings, Inc.	Consumer Discretionary	1,824	0,403
372	HAE	Haemonetics Corporation	Health Care	2,617	0,273

373	HAIN	Hain Celestial Group Inc	Industrials	8,095	0,019*
374	HAL	Halliburton Company	Energy	3,136	0,211
375	HALO	Halozyme Therapeutics, Inc.	Health Care	1,858	0,397
376	HAS	Hasbro, Inc.	Consumer Discretionary	0,63	0,730
377	HBAN	Huntington Bancshares Incorporated	Finance	0,626	0,732
378	HBI	Hanesbrands Inc.	Consumer Discretionary	1,631	0,444
379	HCA	HCA Holdings Inc.	Health Care	1,427	0,491
380	HD	Home Depot Inc	Consumer Discretionary	2,39	0,305
381	HE	Hawaiian Electric Industries, Inc.	Utilities	2,621	0,272
382	HEAR	Turtle Beach Corp	Consumer Staples	0,49	0,783
383	HEI	Heico Corp	Industrials	1,501	0,474
384	HES	Hess Corp.	Energy	1,753	0,418
385	HHC	Howard Hughes Corp	Real Estate	0,677	0,713
386	HI	Hillenbrand, Inc.	Consumer Discretionary	4,565	0,105
387	HIG	Hartford Financial Services Group Inc	Finance	2,193	0,336
388	HIW	Highwoods Properties Inc	Real Estate	1,468	0,481
389	HNI	HNI Corp	Consumer Discretionary	8,41	0,016*
390	HOG	Harley-Davidson Inc	Consumer Discretionary	8,684	0,014*
391	HOPE	Hope Bancorp Inc	Finance	0,553	0,759
392	HOV	Hovnanian Enterprises, Inc.	Consumer Discretionary	1,835	0,401
393	HP	Helmerich & Payne, Inc.	Energy	0,421	0,811
394	HPE	Hewlett Packard Enterprise Co	Telecommunications	2,326	0,315
395	HPP	Hudson Pacific Properties Inc	Real Estate	1,302	0,523
396	HPQ	HP Inc	Technology	2,296	0,319
397	HR	Healthcare Realty Trust Inc	Real Estate	7,09	0,031*
398	HRB	Block (H.&R.), Inc.	Consumer Discretionary	3,088	0,216
399	HRL	Hormel Foods Corp	Consumer Staples	2,502	0,289
400	HSC	Harsco Corp	Industrials	0,36	0,835
401	HST	Host Hotels and Resorts Inc	Real Estate	1,084	0,582
402	HSY	Hershey Co	Consumer Staples	1,779	0,412
403	HT	Hersha Hospitality Trust	Real Estate	0,725	0,696
404	HTH	Hilltop Holdings Inc.	Finance	3,094	0,216
405	HUBB	Hubbell Incorporated	Technology	0,199	0,905
406	HUBS	HubSpot Inc	Technology	1,669	0,436
407	HUM	Humana Inc	Health Care	0,924	0,631
408	HUN	Huntsman Corporation	Industrials	3,57	0,171
409	HURN	Huron Consulting Group Inc	Consumer Discretionary	1,314	0,519
410	HVT	Haverty Furniture Companies, Inc.	Consumer Discretionary	0,0149	0,993
411	HWC	Hancock Whitney Corp	Finance	1,242	0,538
412	HY	Hyster-Yale Materials Handling Inc	Industrials	1,129	0,570
413	IAC	IAC	Consumer Discretionary	1,66	0,438
414	IBM	International Business Machines Corp.	Technology	1,528	0,467
415	ICE	Intercontinental Exchange Inc	Finance	2,276	0,323

416	IDT	IDT Corporation	Telecommunications	0,737	0,692
417	IEX	IDEX Corporation	Industrials	3,819	0,151
418	IFF	International Flavors & Fragrances Inc	Industrials	0,878	0,645
419	IGT	International Game Technology PLC	Consumer Discretionary	1,94	0,381
420	INDB	Independent Bank Corp.	Finance	0,399	0,819
421	INN	Summit Hotel Properties Inc	Real Estate	0,31	0,857
422	INO	Inovio Pharmaceuticals Inc	Health Care	4,431	0,112
423	INT	World Fuel Services Corp	Energy	2,279	0,322
424	INTC	Intel Corporation	Technology	0,536	0,765
425	INTU	Intuit Inc.	Technology	2,469	0,293
426	IONS	Ionis Pharmaceuticals Inc	Health Care	54,43	0,000
427	IP	International Paper Co	Industrials	4,154	0,128
428	IPG	Interpublic Group of Companies Inc	Consumer Discretionary	8,684	0,014*
429	IPI	Intrepid Potash Inc	Industrials	1,081	0,583
430	IR	Ingersoll-Rand plc	Industrials	1,196	0,551
431	IRM	Iron Mountain Incorporated. (REIT)	Real Estate	5,456	0,068
432	IRT	Independence Realty Trust Inc	Real Estate	4,35	0,116
433	ISEE	IVERIC bio Inc	Health Care	7,798	0,022*
434	ISRG	Intuitive Surgical, Inc.	Health Care	0,985	0,612
435	IT	Gartner Inc	Finance	1,556	0,461
436	ITT	ITT Inc	Industrials	2,577	0,278
437	ITW	Illinois Tool Works Inc.	Industrials	18,13	0,000**
438	IVR	Invesco Mortgage Capital Inc	Real Estate	0,653	0,722
439	JACK	Jack in the Box Inc.	Consumer Discretionary	5,449	0,068
440	JBL	Jabil Circuit, Inc.	Technology	3,011	0,224
441	JBT	John Bean Technologies Corp	Industrials	4,689	0,099
442	JEF	Jefferies Group Inc	Finance	5,146	0,079
443	JLL	Jones Lang LaSalle Inc	Finance	2,068	0,358
444	JNJ	Johnson & Johnson	Health Care	0,263	0,877
445	JOE	St. Joe Co	Real Estate	0,346	0,841
446	JPM	JPMorgan Chase & Co.	Finance	1,466	0,482
447	JWN	Nordstrom, Inc.	Consumer Discretionary	1,433	0,490
448	K	Kellogg Company	Consumer Staples	1,855	0,397
449	KAI	Kadant, Inc.	Technology	4,815	0,093
450	KALU	Kaiser Aluminum Corp.	Industrials	4,626	0,102
451	KBR	KBR, Inc.	Industrials	0,667	0,717
452	KDP	Keurig Dr Pepper Inc	Consumer Staples	0,662	0,719
453	KEX	Kirby Corporation	Consumer Discretionary	0,858	0,652
454	KEY	KeyCorp	Finance	2,016	0,367
455	KEYS	Keysight Technologies Inc	Industrials	0,269	0,874
456	KHC	Kraft Heinz Co	Consumer Staples	0,889	0,642
457	KIDS	Orthopediatrics Corp	Health Care	0,0733	0,964
458	KIM	Kimco Realty Corporation	Real Estate	8,071	0,019*

459	KKR	KKR & CO. L.P.	Finance	9,703	0,009*
460	KMB	Kimberly-Clark Corp.	Consumer Discretionary	1,627	0,445
461	KMI	Kinder Morgan Inc	Utilities	0,621	0,734
462	KMT	Kennametal Inc.	Industrials	6,373	0,044*
463	KNX	Knight Transportation, Inc.	Industrials	0,511	0,775
464	KO	Coca Cola Co.	Consumer Staples	2,672	0,265
465	KOP	Kopper Holdings, Inc.	Industrials	3,108	0,214
466	KR	Kroger Co	Consumer Staples	3,5	0,177
467	KRC	Kilroy Realty Corp	Real Estate	1,34	0,513
468	KRG	Kite Realty Group Trust	Real Estate	0,836	0,659
469	KSS	Kohl's Corporation	Consumer Discretionary	6,315	0,045*
470	KW	Kennedy-Wilson Holdings Inc	Real Estate	0,301	0,860
471	L	Loews Corporation	Finance	0,999	0,608
472	LAD	Lithia Motors Inc	Consumer Discretionary	3,163	0,208
473	LANC	Lancaster Colony Corp.	Consumer Staples	0,705	0,703
474	LAUR	Laureate Education Inc	Consumer Discretionary	0,93	0,629
475	LC	LendingClub Corp	Finance	0,284	0,868
476	LE	Lands' End, Inc.	Consumer Discretionary	2,664	0,266
477	LEA	Lear Corporation	Consumer Discretionary	1,639	0,442
478	LECO	Lincoln Electric Holdings, Inc.	Industrials	2,92	0,235
479	LEG	Leggett & Platt, Inc.	Consumer Discretionary	1,642	0,441
480	LEN	Lennar Corporation	Real Estate	1,038	0,596
481	LH	Laboratory Corp. of America Holdings	Health Care	5,614	0,063
482	LII	Lennox International Inc.	Industrials	3,464	0,180
483	LILA	Liberty Latin America Ltd Class A	Telecommunications	4,655	0,100
484	LITE	Lumentum Holdings Inc	Technology	0,96	0,620
485	LKQ	LKQ Corporation	Consumer Discretionary	2,945	0,232
486	LL	Lumber Liquidators Holdings Inc	Consumer Discretionary	2,229	0,330
487	LLY	Eli Lilly And Co	Health Care	2,915	0,235
488	LNC	Lincoln National Corporation	Finance	7,272	0,028*
489	LNG	Cheniere Energy, Inc.	Utilities	0,815	0,666
490	LOB	Live Oak Bancshares Inc	Finance	0,233	0,890
491	LOPE	Grand Canyon Education Inc	Consumer Discretionary	1,781	0,412
492	LOW	Lowe's Companies, Inc.	Consumer Discretionary	4,662	0,100
493	LRCX	Lam Research Corporation	Technology	5,436	0,069
494	LSI	Life Storage Inc	Real Estate	1,199	0,550
495	LTC	LTC Properties Inc	Real Estate	2,648	0,268
496	LUNA	Luna Innovations Incorporated	Health Care	2,412	0,302
497	LUV	Southwest Airlines Co	Consumer Discretionary	1,223	0,544
498	LVS	Las Vegas Sands Corp.	Consumer Discretionary	3,333	0,192
499	M	Macy's Inc	Consumer Discretionary	0,216	0,898
500	MA	Mastercard Inc	Consumer Discretionary	0,354	0,838
501	MAC	Macerich Co	Real Estate	0,605	0,739

502	MAN	ManpowerGroup Inc.	Consumer Discretionary	6,079	0,050
503	MANH	Manhattan Associates, Inc.	Technology	0,757	0,685
504	MAR	Marriott International Inc	Consumer Discretionary	0,185	0,912
505	MARA	Marathon Digital Holdings Inc.	Finance	0,404	0,817
506	MAS	Masco Corp	Industrials	0,636	0,728
507	MASI	Masimo Corporation	Health Care	2,373	0,307
508	MAT	Mattel Inc	Consumer Discretionary	2,27	0,323
509	MATX	Matson Inc	Consumer Discretionary	9,601	0,009*
510	MBI	MBIA Inc.	Finance	0,522	0,771
511	MCD	Mcdonald's Corp	Consumer Discretionary	3,944	0,142
512	MCHP	Microchip Technology Inc.	Technology	3,85	0,149
513	MCK	McKesson Corporation	Health Care	0,28	0,869
514	MCO	Moody's Corporation	Finance	0,471	0,791
515	MD	MEDNAX Inc	Health Care	1,939	0,381
516	MDB	Mongodb Inc	Technology	4,206	0,125
517	MDC	M.D.C. Holdings, Inc.	Consumer Discretionary	1,035	0,597
518	MDT	Medtronic PLC	Health Care	3,236	0,201
519	MDU	Mdu Resources Group Inc	Industrials	2,915	0,235
520	MED	Medifast Inc	Consumer Discretionary	0,011	0,994
521	MEI	Methode Electronics Inc.	Technology	0,257	0,880
522	MET	Metlife Inc	Finance	0,521	0,771
523	META	Meta Platforms Inc	Technology	6,705	0,037*
524	MFA	MFA Financial, Inc.	Real Estate	1,35	0,510
525	MGI	Moneygram International Inc	Consumer Discretionary	0,196	0,907
526	MGM	MGM Resorts International	Consumer Discretionary	2,924	0,234
527	MHK	Mohawk Industries, Inc.	Consumer Discretionary	5,118	0,080
528	MIDD	Middleby Corp	Industrials	5,799	0,057
529	MKC	McCormick & Co., Inc.	Consumer Staples	26,58	0,000***
530	MKL	Markel Corporation	Finance	8,079	0,019*
531	MLI	Mueller Industries, Inc.	Industrials	12,13	0,003*
532	MLM	Martin Marietta Materials, Inc.	Industrials	1,764	0,416
533	MMC	Marsh & McLennan Companies, Inc.	Finance	3,583	0,169
534	MMM	3M Co	Industrials	0,055	0,973
535	MMS	MAXIMUS, Inc.	Consumer Discretionary	3,038	0,222
536	MMSI	Merit Medical Systems, Inc.	Health Care	0,484	0,785
537	MOD	Modine Manufacturing Co.	Consumer Discretionary	0,0492	0,976
538	MOH	Molina Healthcare, Inc.	Health Care	12,93	0,002*
539	MORN	Morningstar, Inc.	Finance	1,872	0,394
540	MOS	Mosaic Co	Industrials	10,11	0,007*
541	MOV	Movado Group, Inc	Consumer Discretionary	3,543	0,173
542	MPC	Marathon Petroleum Corp	Energy	3,947	0,142
543	MPW	Medical Properties Trust, Inc.	Real Estate	0,751	0,688
544	MRC	MRC Global Inc	Industrials	0,925	0,630

545	MRK	Merck & Co., Inc.	Health Care	1,788	0,411
546	MRVL	Marvell Technology Group Ltd.	Technology	0,289	0,866
547	MS	Morgan Stanley	Finance	6,274	0,046*
548	MSA	MSA Safety Inc	Technology	0,218	0,897
549	MSCI	Msci Inc	Finance	0,105	0,949
550	MSFT	Microsoft Corporation	Technology	5,518	0,066
551	MSGS	Madison Square Garden Sports Corp	Consumer Discretionary	2,045	0,362
552	MSI	Motorola Solutions Inc	Technology	2,209	0,334
553	MSM	MSC Industrial Direct Co Inc	Industrials	0,705	0,703
554	MTB	M & T Bank Corp.	Finance	0,254	0,881
555	MTCH	Match Group Inc	Technology	1,951	0,379
556	MTG	MGIC Investment Corp.	Finance	0,371	0,831
557	MTH	Meritage Homes Corp	Consumer Discretionary	1,319	0,518
558	MTN	Vail Resorts, Inc.	Consumer Discretionary	0,144	0,930
559	MTW	Manitowoc Company Inc	Industrials	6,897	0,034*
560	MTX	Minerals Technologies Inc	Industrials	0,359	0,836
561	MTZ	MasTec, Inc.	Industrials	0,908	0,636
562	MU	Micron Technology, Inc.	Technology	0,196	0,907
563	MUSA	Murphy USA Inc	Energy	1,147	0,565
564	MWA	Mueller Water Products, Inc.	Industrials	3,365	0,189
565	MXL	MaxLinear, Inc.	Technology	0,001	0,999
566	MYE	Myers Industries, Inc.	Consumer Discretionary	0,672	0,715
567	NATI	National Instruments Corp	Technology	3,473	0,179
568	NCR	NCR Corporation	Miscellaneous	0,905	0,637
569	NEE	NextEra Energy Inc	Utilities	0,595	0,743
570	NEM	Newmont Mining Corp.	Basic Materials	2,414	0,301
571	NEO	NeoGenomics, Inc.	Health Care	2,528	0,285
572	NEP	Nextera Energy Partners LP	Utilities	3,999	0,138
573	NEU	NewMarket Corporation	Industrials	0,0154	0,992
574	NEWR	New Relic Inc	Technology	2,619	0,272
575	NFG	National Fuel Gas Co.	Energy	1,26	0,534
576	NFLX	Netflix Inc	Consumer Discretionary	1,98	0,373
577	NHI	National Health Investors Inc	Real Estate	0,3	0,861
578	NI	NiSource Inc.	Utilities	0,444	0,801
579	NKE	Nike Inc	Consumer Discretionary	0,514	0,774
580	NLY	Annaly Capital Management, Inc.	Real Estate	32,66	0,000***
581	NMFC	New Mountain Finance Corp.	Finance	1,187	0,553
582	NNN	National Retail Properties, Inc.	Real Estate	1,444	0,487
583	NOV	National Oilwell Varco, Inc.	Industrials	4,067	0,134
584	NOW	ServiceNow Inc	Technology	15,93	0,000**
585	NPK	National Presto Industries Inc.	Consumer Discretionary	0,195	0,907
586	NR	Newpark Resources Inc	Industrials	2,947	0,232
587	NSC	Norfolk Southern Corp.	Industrials	2,676	0,265

588	NSP	Insperity Inc	Consumer Discretionary	0,228	0,893
589	NUE	Nucor Corporation	Industrials	0,387	0,824
590	NUS	Nu Skin Enterprises, Inc.	Health Care	0,78	0,677
591	NUVA	NuVasive, Inc.	Health Care	5,85	0,056
592	NVAX	Novavax, Inc.	Health Care	14,41	0,001**
593	NVDA	NVIDIA Corporation	Technology	4,904	0,089
594	NVR	NVR, Inc.	Consumer Discretionary	0,0414	0,980
595	NWE	NorthWestern Corp	Utilities	0,384	0,826
596	NWL	Newell Brands Inc	Industrials	36,45	0,000***
597	NX	Quanex Building Products Corporation	Industrials	6,124	0,049*
598	NYCB	New York Community Bancorp, Inc.	Finance	2,149	0,343
599	NYT	New York Times Co	Consumer Discretionary	0,119	0,942
600	O	Realty Income Corp	Real Estate	0,662	0,719
601	OCN	Ocwen Financial Corp	Finance	0,0424	0,979
602	ODFL	Old Dominion Freight Line Inc	Industrials	0,221	0,895
603	ODP	Office Depot, Inc.	Miscellaneous	0,866	0,649
604	OFC	Corporate Office Properties Trust	Real Estate	3,734	0,157
605	OGE	OGE Energy Corp.	Utilities	1,411	0,495
606	OHI	Omega Healthcare Investors Inc	Real Estate	0,81	0,668
607	OI	Owens-Illinois, Inc.	Consumer Discretionary	3,851	0,149
608	OIS	Oil States International, Inc.	Industrials	0,0947	0,954
609	OKE	ONEOK, Inc.	Utilities	1,269	0,531
610	OKTA	Okta Inc	Technology	6,793	0,036*
611	OLED	Universal Display Corporation	Technology	0,844	0,656
612	OLLI	Ollie's Bargain Outlet Holdings Inc	Consumer Discretionary	0,342	0,843
613	OLN	Olin Corporation	Industrials	4,973	0,086
614	OMC	Omnicom Group Inc.	Consumer Discretionary	5,874	0,055
615	OMI	Owens & Minor, Inc.	Health Care	1,451	0,485
616	ON	ON Semiconductor Corp	Technology	10,66	0,006*
617	ONB	Old National Bancorp	Finance	1,016	0,603
618	OPI	Office Properties Income Trust	Real Estate	1,752	0,418
619	ORA	Ormat Technologies, Inc.	Utilities	4,139	0,129
620	ORCL	Oracle Corporation	Technology	0,429	0,807
621	ORI	Old Republic International Corporation	Finance	2,462	0,294
622	ORLY	O'Reilly Automotive Inc	Consumer Discretionary	1,521	0,469
623	OSIS	OSI Systems, Inc.	Technology	1,423	0,492
624	OSK	Oshkosh Corp	Consumer Discretionary	7,067	0,031*
625	PAG	Penske Automotive Group, Inc.	Consumer Discretionary	12,2	0,003*
626	PANW	Palo Alto Networks Inc	Technology	4,144	0,129
627	PARR	Par Pacific Holdings Inc	Energy	2,483	0,291
628	PATK	Patrick Industries, Inc.	Consumer Discretionary	0,123	0,940
629	PB	Prosperity Bancshares, Inc.	Finance	1,333	0,515
630	PBF	PBF Energy Inc	Energy	3,113	0,213

631	PBI	Pitney Bowes Inc.	Consumer Discretionary	1,097	0,579
632	PCG	PG&E Corporation	Utilities	2,066	0,358
633	PCH	Potlatch Holdings, Inc.	Real Estate	4,408	0,113
634	PCTI	PC-Tel, Inc.	Technology	0,765	0,683
635	PDFS	PDF Solutions, Inc.	Technology	1,248	0,537
636	PDM	Piedmont Office Realty Trust, Inc.	Real Estate	1,799	0,408
637	PEG	Public Service Enterprise Group Inc.	Utilities	3,31	0,194
638	PEGA	Pegasystems Inc.	Technology	3,889	0,146
639	PENN	Penn National Gaming, Inc	Consumer Discretionary	0,318	0,853
640	PEP	PepsiCo, Inc.	Consumer Staples	1,456	0,484
641	PFE	Pfizer Inc.	Health Care	0,809	0,668
642	PFS	Provident Financial Services, Inc.	Finance	3,509	0,176
643	PG	Procter & Gamble Co	Consumer Discretionary	0,398	0,820
644	PGR	Progressive Corp	Finance	2,107	0,351
645	PH	Parker-Hannifin Corp	Industrials	0,14	0,932
646	PI	IMPINJ Inc	Utilities	1,304	0,522
647	PII	Polaris Industries, Inc	Consumer Discretionary	4,725	0,097
648	PK	Park Hotels & Resorts Inc	Real Estate	0,361	0,835
649	PKG	Packaging Corp. of America	Basic Materials	1,723	0,424
650	PKI	PerkinElmer, Inc.	Health Care	3,709	0,159
651	PLAB	Photronics, Inc.	Technology	0,0944	0,954
652	PLAY	Dave & Buster's Entertainment Inc	Consumer Discretionary	0,82	0,664
653	PLCE	Children's Place Inc	Consumer Discretionary	0,183	0,913
654	PLD	Prologis Inc	Real Estate	0,42	0,811
655	PLNT	Planet Fitness Inc	Consumer Discretionary	1,792	0,410
656	PLUG	Plug Power Inc	Consumer Discretionary	1,688	0,432
657	PLUS	ePlus Inc.	Technology	2,165	0,341
658	PMT	Penny Mac Mortgage Investment Trust	Real Estate	0,953	0,622
659	PNC	PNC Financial Services Group Inc	Finance	3,003	0,225
660	PNFP	Pinnacle Financial Partners Inc	Finance	2,217	0,332
661	PNW	Pinnacle West Capital Corporation	Utilities	0,418	0,812
662	POOL	Pool Corporation	Consumer Discretionary	0,878	0,645
663	POR	Portland General Electric Company	Utilities	2,31	0,317
664	POST	Post Holdings Inc	Consumer Discretionary	0,991	0,610
665	PPC	Pilgrim's Pride Corporation	Consumer Staples	1,605	0,450
666	PPG	PPG Industries, Inc.	Consumer Discretionary	2,362	0,309
667	PPL	PPL Corp	Utilities	3,384	0,187
668	PRA	ProAssurance Corporation	Finance	0,0865	0,958
669	PRG	PROG Holdings Inc	Consumer Discretionary	4,142	0,129
670	PRI	Primerica, Inc.	Finance	0,481	0,787
671	PRIM	Primoris Services Corp	Industrials	11,31	0,004*
672	PRO	PROS Holdings, Inc.	Technology	0,39	0,823
673	PRTS	Carparts.Com Inc	Consumer Discretionary	1,75	0,419

674	PRU	Prudential Financial, Inc.	Finance	4,56	0,105
675	PSA	Public Storage	Real Estate	0,71	0,702
676	PSX	Phillips 66	Energy	2,473	0,293
677	PTC	PTC Inc	Technology	19,97	0,000***
678	PUMP	Propetro Holding Corp	Energy	2,013	0,367
679	PWR	Quanta Services Inc	Industrials	0,43	0,807
680	PYPL	Paypal Holdings Inc	Consumer Discretionary	0,571	0,752
681	PZZA	Papa John's Int'l, Inc.	Consumer Discretionary	2,776	0,252
682	QCOM	QUALCOMM, Inc.	Technology	5,253	0,075
683	R	Ryder System, Inc.	Consumer Discretionary	0,723	0,697
684	RAMP	Liveramp Holdings Inc	Technology	0,865	0,649
685	RARE	Ultragenyx Pharmaceutical Inc	Health Care	1,978	0,374
686	RCL	Royal Caribbean Cruises Ltd.	Consumer Discretionary	27,9	0,000***
687	RCM	R1 RCM Inc	Consumer Discretionary	1,007	0,605
688	RDFN	Redfin Corp	Finance	0,0106	0,995
689	RDN	Radian Group Inc	Finance	1,736	0,421
690	REG	Regency Centers Corp	Real Estate	11,66	0,003*
691	REGN	Regeneron Pharmaceuticals Inc	Health Care	4,004	0,138
692	RES	RPC, Inc.	Energy	2,542	0,283
693	RETA	Reata Pharmaceuticals Inc	Health Care	0,839	0,658
694	RF	Regions Financial Corp	Finance	3,248	0,200
695	RGA	Reinsurance Group of America Inc	Finance	13,08	0,002*
696	RH	RH	Consumer Discretionary	2,429	0,299
697	RHI	Robert Half International Inc.	Consumer Discretionary	4,243	0,123
698	RHP	Ryman Hospitality Properties Inc	Real Estate	4,325	0,118
699	RIOT	Riot Blockchain Inc	Technology	0,571	0,752
700	RL	Ralph Lauren Corp	Consumer Discretionary	1,066	0,588
701	RLI	RLI Corp	Finance	0,534	0,766
702	RMD	ResMed Inc.	Health Care	0,108	0,947
703	RMR	RMR Group Inc	Finance	2,115	0,349
704	ROG	Rogers Corporation	Technology	3,133	0,211
705	ROIC	Retail Opportunity Investments Corp	Real Estate	1,417	0,494
706	ROK	Rockwell Automation	Industrials	0,817	0,665
707	ROKU	Roku Inc	Telecommunications	6,087	0,050
708	ROL	Rollins, Inc.	Consumer Discretionary	1,844	0,399
709	ROP	Roper Technologies Inc	Technology	0,715	0,700
710	ROST	Ross Stores, Inc.	Consumer Discretionary	3,119	0,213
711	RPD	Rapid7 Inc	Technology	2,173	0,339
712	RPM	RPM International Inc.	Consumer Discretionary	14,14	0,001*
713	RPT	Ramco-Gershenson Properties Trust	Real Estate	1,656	0,438
714	RRR	Red Rock Resorts Inc	Consumer Discretionary	8,769	0,014*
715	RS	Reliance Steel & Aluminum Co	Industrials	0,359	0,836
716	RSG	Republic Services, Inc.	Utilities	0,794	0,673

717	RTX	Raytheon Technologies Corp	Industrials	0,806	0,669
718	RUN	Sunrun Inc	Industrials	1,185	0,554
719	RYAM	Rayonier Advanced Materials Inc	Industrials	0,0493	0,976
720	RYN	Rayonier, Inc. (REIT)	Real Estate	2,657	0,267
721	SABR	Sabre Corp	Consumer Discretionary	0,302	0,860
722	SAFT	Safety Insurance Group, Inc.	Finance	0,068	0,967
723	SAGE	SAGE Therapeutics Inc	Health Care	3,693	0,161
724	SAH	Sonic Automotive Inc	Consumer Discretionary	5,051	0,083
725	SAIA	Saia Inc	Industrials	0,238	0,888
726	SAM	Boston Beer Company Inc	Consumer Staples	3,7	0,160
727	SATS	EchoStar Corp.	Technology	6,24	0,046*
728	SAVE	Spirit Airlines Incorporated	Consumer Discretionary	7,055	0,031*
729	SBAC	SBA Communications Corp.	Real Estate	2,677	0,265
730	SBH	Sally Beauty Holdings, Inc.	Miscellaneous	1,309	0,521
731	SBUX	Starbucks Corporation	Consumer Discretionary	6,987	0,032*
732	SCHW	Schwab Charles Corp	Finance	1,198	0,551
733	SCI	Service Corp. International	Consumer Discretionary	0,674	0,714
734	SCL	Stepan Company	Industrials	0,172	0,918
735	SCOR	COMSCORE, Inc.	Consumer Discretionary	13,77	0,001*
736	SCS	Steelcase Inc.	Consumer Discretionary	3,907	0,145
737	SCU	Sculptor Capital Management Inc	Finance	0,687	0,710
738	SE	Sea Ltd	Technology	0,0222	0,989
739	SEAS	SeaWorld Entertainment Inc	Consumer Discretionary	0,115	0,944
740	SEE	Sealed Air Corp	Industrials	0,142	0,931
741	SEEL	Seelos Therapeutics Inc	Health Care	4,795	0,094
742	SEM	Select Medical Holdings Corporation	Health Care	0,525	0,769
743	SENS	Senseonics Holdings Inc	Health Care	5,965	0,053
744	SF	Stifel Financial Corp	Finance	4,41	0,113
745	SFIX	Stitch Fix Inc	Consumer Discretionary	9,443	0,010*
746	SFM	Sprouts Farmers Market Inc	Consumer Discretionary	0,17	0,919
747	SGH	Smart Global Holdings Inc	Technology	27,7	0,000***
748	SHAK	Shake Shack Inc	Consumer Discretionary	1,543	0,464
749	SHEN	Shenandoah Telecommunications Company	Telecommunications	2,333	0,314
750	SHO	Sunstone Hotel Investors Inc	Real Estate	1,474	0,480
751	SHOO	Steven Madden, Ltd.	Consumer Discretionary	0,395	0,821
752	SHW	Sherwin-Williams Co	Consumer Discretionary	2,862	0,242
753	SIGA	SIGA Technologies, Inc.	Health Care	0,196	0,907
754	SIGI	Selective Insurance Group Inc	Finance	3,137	0,211
755	SIRI	Sirius XM Holdings Inc	Consumer Discretionary	1,397	0,499
756	SIX	Six Flags Entertainment Corp	Consumer Discretionary	1,969	0,376
757	SJM	Smucker (J.M.) Co.	Consumer Staples	33,22	0,000***
758	SJW	SJW Corp.	Utilities	2,944	0,232
759	SKT	Tanger Factory Outlet Centers Inc.	Real Estate	6,446	0,042*

760	SKX	Skechers U.S.A. Inc.	Consumer Discretionary	1,006	0,606
761	SKY	Skyline Corp.	Consumer Discretionary	0,828	0,662
762	SLAB	Silicon Laboratories Inc	Technology	0,247	0,884
763	SLG	SL Green Realty Corp	Real Estate	0,693	0,707
764	SLM	SLM Corp	Finance	2,83	0,245
765	SM	SM Energy Co	Energy	1,033	0,597
766	SMG	Scotts Miracle-Gro Co	Industrials	0,723	0,697
767	SMP	Standard Motor Products, Inc.	Consumer Discretionary	4,694	0,098
768	SNA	Snap-on Incorporated	Consumer Discretionary	2,277	0,322
769	SNAP	Snapchat, Inc.	Technology	2,009	0,368
770	SNPS	Synopsys, Inc.	Technology	0,684	0,711
771	SO	Southern Co	Utilities	0,381	0,827
772	SOI	Solaris Oilfield Infrastructure Inc	Industrials	3,627	0,166
773	SON	Sonoco Products Co	Industrials	2,516	0,287
774	SP	SP Plus Corp	Consumer Discretionary	1,809	0,407
775	SPG	Simon Property Group Inc	Real Estate	0,424	0,809
776	SPR	Spirit AeroSystems Holdings, Inc.	Industrials	1,622	0,446
777	SPWR	SunPower Corporation	Technology	1,371	0,505
778	SQ	Block Inc	Technology	15,85	0,000**
779	SR	Spire Inc	Utilities	2,148	0,344
780	SRC	Spirit Realty Capital Inc	Real Estate	0,0114	0,994
781	SRE	Sempra Energy	Utilities	35,22	0,000***
782	SRG	Seritage Growth Properties	Real Estate	1,373	0,504
783	SRI	Stoneridge, Inc.	Consumer Discretionary	1,269	0,531
784	SRPT	Sarepta Therapeutics Inc	Health Care	1,411	0,495
785	SSB	South State Corp	Finance	3,415	0,184
786	SSYS	Stratasys Ltd	Technology	11,05	0,005*
787	STAG	Stag Industrial Inc	Real Estate	0,208	0,901
788	STC	Stewart Information Services Corp	Finance	24,47	0,000***
789	STE	Steris PLC	Health Care	0,685	0,710
790	STRA	Strayer Education, Inc.	Consumer Discretionary	8,732	0,014*
791	STT	State Street Corp	Finance	0,889	0,642
792	STZ	Constellation Brands, Inc.	Consumer Staples	1,153	0,563
793	SUI	Sun Communities Inc	Real Estate	0,509	0,775
794	SUM	Summit Materials Inc	Industrials	0,43	0,807
795	SUP	Superior Industries International Inc	Consumer Discretionary	0,537	0,765
796	SWK	Stanley Black & Decker, Inc.	Consumer Discretionary	1,37	0,505
797	SWKS	Skyworks Solutions Inc	Technology	0,503	0,778
798	SWX	Southwest Gas Corp.	Utilities	1,126	0,570
799	SXT	Sensient Technologies Corporation	Industrials	0,421	0,810
800	SYF	Synchrony Financial	Finance	6,634	0,038*
801	SYK	Stryker Corporation	Health Care	0,834	0,660
802	SYY	SYSCO Corporation	Consumer Discretionary	1,119	0,572

803	T	AT & T, Inc.	Consumer Discretionary	0,401	0,819
804	TA	Travelcenters of America Inc	Energy	1,63	0,444
805	TBI	Trueblue Inc	Consumer Discretionary	1,545	0,463
806	TDC	Teradata Corporation	Technology	4,865	0,091
807	TDOC	Teladoc, Inc.	Health Care	1,084	0,582
808	TDS	Telephone and Data Systems, Inc.	Telecommunications	1,893	0,390
809	TDY	Teledyne Technologies Incorporated	Industrials	2,505	0,288
810	TECH	BIO-TECHNE Corp	Health Care	6,799	0,035*
811	TELL	Tellurian Inc	Energy	9,102	0,012*
812	TER	Teradyne, Inc.	Industrials	3,753	0,156
813	TEX	Terex Corporation	Industrials	5,414	0,069
814	TFC	Truist Financial Corp	Finance	4,537	0,106
815	TFX	Teleflex Incorporated	Health Care	0,0244	0,988
816	TGI	Triumph Group Inc	Industrials	0,107	0,948
817	TGT	Target Corporation	Consumer Discretionary	1,476	0,479
818	TGTX	TG Therapeutics Inc	Health Care	7,971	0,020*
819	THC	Tenet Healthcare Corp	Health Care	1,483	0,478
820	THG	Hanover Insurance Group Inc	Finance	0,241	0,887
821	THO	Thor Industries, Inc.	Industrials	0,0503	0,975
822	THR	Thermon Group Holdings Inc	Consumer Discretionary	18,68	0,000**
823	THRM	Gentherm Inc	Consumer Discretionary	0,327	0,849
824	THS	TreeHouse Foods Inc.	Consumer Staples	2,044	0,362
825	TJX	TJX Companies Inc	Consumer Discretionary	2,126	0,347
826	TKR	Timken Co	Industrials	3,468	0,179
827	TMO	Thermo Fisher Scientific Inc.	Industrials	1,93	0,383
828	TMP	Tompkins Financial Corporation	Finance	6,957	0,033*
829	TMUS	T-Mobile Us Inc	Telecommunications	8,529	0,015*
830	TNC	Tennant Company	Industrials	4,258	0,122
831	TOL	Toll Brothers Inc	Consumer Discretionary	1,29	0,526
832	TOWN	Towne Bank (Portsmouth, VA)	Finance	1,693	0,430
833	TPB	Turning Point Brands Inc	Consumer Discretionary	24,95	0,000***
834	TPC	Tutor Perini Corp	Industrials	1,261	0,533
835	TPH	Tri Pointe Homes, Inc.	Consumer Discretionary	3,852	0,149
836	TPR	Tapestry Inc	Consumer Discretionary	0,722	0,698
837	TPX	Tempur Sealy International Inc	Consumer Discretionary	0,556	0,758
838	TR	Tootsie Roll Industries, Inc.	Consumer Staples	5,915	0,054
839	TRC	Tejon Ranch Company	Finance	1,108	0,575
840	TREE	Lendingtree Inc	Finance	1,92	0,385
841	TRN	Trinity Industries Inc	Industrials	4,538	0,106
842	TROW	Price (T.) Rowe Group, Inc.	Finance	0,495	0,781
843	TRS	TriMas Corp	Technology	0,0916	0,955
844	TRST	TrustCo Bank Corp NY	Finance	0,767	0,682
845	TRU	TransUnion	Finance	0,248	0,883

846	TRUE	TrueCar Inc	Technology	5,216	0,076
847	TRUP	Trupanion Inc	Health Care	5,018	0,084
848	TRV	Travelers Companies Inc	Finance	1,33	0,515
849	TSCO	Tractor Supply Company	Consumer Discretionary	2,251	0,327
850	TSLA	Tesla Motors, Inc.	Consumer Discretionary	1,959	0,377
851	TSN	Tyson Foods, Inc.	Consumer Staples	3,861	0,148
852	TTC	Toro Co	Consumer Discretionary	0,125	0,940
853	TTD	Trade Desk Inc	Technology	1,012	0,604
854	TTEC	TeleTech Holdings, Inc.	Technology	0,29	0,865
855	TTWO	Take-Two Interactive Software Inc	Technology	1,481	0,478
856	TUP	Tupperware Brands Corporation	Industrials	0,133	0,936
857	TUSK	Mammoth Energy Services Inc	Industrials	5,413	0,069
858	TWLO	Twilio Inc	Industrials	1,631	0,444
859	TWO	Two Harbors Investment Corp	Real Estate	0,189	0,910
860	TXN	Texas Instruments Incorporated	Technology	0,0988	0,952
861	TYL	Tyler Technologies, Inc.	Technology	0,435	0,805
862	UA	Under Armour, Inc., Class C	Consumer Discretionary	1,405	0,497
863	UAA	Under Armour Inc	Consumer Discretionary	0,399	0,819
864	UAL	United Continental Holdings, Inc.	Consumer Discretionary	2,546	0,282
865	UBA	Urstadt Biddle Properties Inc	Real Estate	2,308	0,318
866	UCBI	United Community Banks, Inc.	Finance	0,189	0,910
867	UDR	UDR, Inc.	Real Estate	3,434	0,182
868	UE	Urban Edge Properties	Real Estate	5,135	0,079
869	UGI	UGI Corp	Utilities	1,133	0,568
870	UHAL	AMERCO	Consumer Discretionary	2,752	0,255
871	UHS	Universal Health Services, Inc.	Health Care	0,607	0,739
872	UHT	Universal Health Realty Income Trust	Real Estate	0,488	0,784
873	UI	Ubiquiti Inc	Technology	0,159	0,923
874	UNF	UniFirst Corp	Consumer Discretionary	1,361	0,507
875	UNFI	United Natural Foods Inc	Consumer Discretionary	2,47	0,293
876	UNH	UnitedHealth Group Inc	Health Care	3,054	0,220
877	UNIT	Uniti Group Inc	Real Estate	7,556	0,025*
878	UNM	Unum Group	Finance	7,176	0,030*
879	UNP	Union Pacific Corporation	Industrials	0,68	0,712
880	UPS	United Parcel Service, Inc.	Consumer Discretionary	0,0431	0,979
881	URBN	Urban Outfitters, Inc.	Consumer Discretionary	0,974	0,615
882	URI	United Rentals, Inc.	Consumer Discretionary	2,509	0,288
883	USB	U.S. Bancorp	Finance	0,465	0,793
884	USM	United States Cellular Corp	Telecommunications	0,789	0,674
885	V	Visa Inc	Consumer Discretionary	1,816	0,405
886	VAC	Marriott Vacations Worldwide Corp	Consumer Discretionary	1,7	0,429
887	VFC	V.F. Corp.	Consumer Discretionary	0,342	0,843
888	VIRT	Virtu Financial Inc	Finance	1,736	0,421

889	VLO	Valero Energy Corporation	Energy	2,267	0,324
890	VLY	Valley National Bancorp	Finance	8,458	0,016*
891	VMI	Valmont Industries, Inc.	Industrials	2,738	0,257
892	VMW	VMware, Inc.	Technology	0,0805	0,961
893	VOYA	Voya Financial Inc	Finance	0,338	0,845
894	VRAY	Viewray Inc	Health Care	2,928	0,234
895	VRE	Veris Residential Inc	Real Estate	0,66	0,719
896	VRTX	Vertex Pharmaceuticals Incorporated	Technology	0,405	0,817
897	VSAT	ViaSat, Inc.	Technology	4,945	0,087
898	VTR	Ventas, Inc.	Real Estate	3,291	0,196
899	VVV	Valvoline Inc	Industrials	1,097	0,579
900	VZ	Verizon Communications Inc.	Telecommunications	0,279	0,870
901	W	Wayfair Inc	Consumer Discretionary	7,511	0,025*
902	WAB	Wabtec Corp.	Industrials	4,861	0,091
903	WABC	Westamerica Bancorporation	Finance	0,761	0,684
904	WAL	Western Alliance Bancorporation	Finance	11,91	0,003*
905	WASH	Washington Trust Bancorp Inc	Finance	10,29	0,007*
906	WAT	Waters Corporation	Health Care	0,0575	0,972
907	WBA	Walgreens Boots Alliance Inc	Consumer Staples	1,306	0,522
908	WBS	Webster Financial Corporation	Finance	0,668	0,716
909	WCC	WESCO International, Inc.	Consumer Discretionary	0,19	0,909
910	WD	Walker & Dunlop, Inc.	Finance	1,212	0,546
911	WDAY	Workday Inc	Technology	2,907	0,236
912	WDC	Western Digital Corp	Technology	0,383	0,826
913	WELL	Welltower Inc	Real Estate	13,47	0,001*
914	WEN	The Wendy's Company	Consumer Discretionary	0,0133	0,993
915	WEX	WEX Inc	Technology	19,17	0,000**
916	WFC	Wells Fargo & Co	Finance	3,771	0,155
917	WGO	Winnebago Industries, Inc.	Industrials	0,784	0,676
918	WHR	Whirlpool Corporation	Consumer Discretionary	0,481	0,786
919	WING	Wingstop Inc	Consumer Discretionary	1,433	0,490
920	WIRE	Encore Wire Corporation	Industrials	6,138	0,049*
921	WK	Workiva Inc	Technology	2,323	0,315
922	WLK	Westlake Chemical Corporation	Industrials	2,155	0,342
923	WM	Waste Management, Inc.	Utilities	0,259	0,879
924	WMB	Williams Companies Inc	Utilities	2,396	0,304
925	WMS	Advanced Drainage Systems Inc	Industrials	0,6	0,741
926	WMT	Walmart Inc	Consumer Discretionary	2,955	0,231
927	WNC	Wabash National Corporation	Industrials	0,295	0,863
928	WOR	Worthington Industries, Inc.	Consumer Discretionary	2,927	0,234
929	WPC	W.P. Carey Inc.	Real Estate	0,986	0,612
930	WRB	Berkley (W.R.) Corp.	Finance	2,025	0,365
931	WSC	Willscot Mobile Mini Holdings Corp	Consumer Discretionary	1,364	0,507

932	WSFS	WSFS Financial Corporation	Finance	2,723	0,259
933	WSM	Williams-Sonoma, Inc.	Consumer Discretionary	1,023	0,600
934	WSO	Watsco Inc	Consumer Discretionary	1,654	0,439
935	WST	West Pharmaceutical Services Inc.	Health Care	0,772	0,680
936	WTM	White Mountains Insurance Group Ltd	Finance	0,0773	0,962
937	WTS	Watts Water Technologies Inc	Industrials	2,196	0,336
938	WU	The Western Union Company	Consumer Discretionary	0,0832	0,959
939	WWD	Woodward Inc	Industrials	5,399	0,070
940	WWE	World Wrestling Entertainment, Inc.	Consumer Discretionary	2,525	0,285
941	WWW	Wolverine World Wide, Inc.	Consumer Discretionary	1,709	0,427
942	WY	Weyerhaeuser Co	Real Estate	0,367	0,832
943	WYNN	Wynn Resorts, Limited	Consumer Discretionary	1,263	0,533
944	X	United States Steel Corporation	Industrials	1,731	0,422
945	XOM	Exxon Mobil Corporation	Energy	0,457	0,796
946	XPO	XPO Logistics Inc	Industrials	0,0862	0,958
947	XRAY	DENTSPLY SIRONA Inc	Health Care	13,81	0,001*
948	XRX	Xerox Corp.	Technology	0,946	0,624
949	YELL	Yellow Corporation	Industrials	7,81	0,022*
950	YELP	Yelp Inc	Technology	1,612	0,448
951	YEXT	Yext Inc	Technology	3,861	0,148
952	YUM	Yum! Brands, Inc.	Consumer Discretionary	0,557	0,757
953	ZEUS	Olympic Steel, Inc.	Industrials	1,72	0,425
954	ZG	Zillow Group Inc	Consumer Discretionary	3,777	0,154
955	ZION	Zions Bancorporation	Finance	2,553	0,281
956	ANF	Abercrombie & Fitch Co.	Consumer Discretionary	0,253	0,881
957	AWR	American States Water Co	Utilities	2,616	0,273
958	BLK	BlackRock, Inc.	Finance	1,157	0,562
959	ELS	Equity Lifestyles Properties, Inc.	Real Estate	3,717	0,159