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Investor Behaviour and Market Dynamics: A Google SVI Perspective

A Study of the STOXX Europe 600 Index

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ABSTRACT

This thesis explores the relationship of investor attention, as proxied by the Google Search Volume Index (SVI), and stock performance. Using panel data from June 2016 to June 2020, this study evaluates the impact that Google SVI has on both the weekly traded volumes and the weekly returns of 53 selected stocks within the STOXX Europe 600 index.

Key findings indicate a highly significant and positive relationship between the Google SVI and the weekly traded volume, suggesting that increased growth in investor attention could strongly enhance trading activity. In contrast, the Google SVI's relation to weekly returns is negative, revealing that a higher level of investor attention tends to yield lower stock returns.

Keywords: STOXX Europe 600, Google SVI, investor attention, returns

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CHAPTER 1 Introduction

During the COVID-19 pandemic, an observable trend emerged where pharmaceutical companies announced promising vaccine trials, accompanied by surges in Google searches. Khakimova, Abdollahi, Zolotarev, & Rahim (2022) write that ‘’The interest of users in vaccines during the COVID-19 pandemic increases significantly when looking at the Google SVI data’’. Sharp spikes in the global interest in terms like "Pfizer Corona Vaccine" and "COVID-19 virus vaccine" were highly pronounced during these uncertain times. In apparent contradiction, after the announcement of vaccine approvals, Sorvali, J. (2023), found mostly negative stock returns for those companies. This gap might be due to the fact that investors had already taken the vaccine news into account, had doubts about profit margins, distribution challenges, and possible changes in regulation, including excess profits taxes. This curious phenomenon has called for a closer look into the relationship between investor attention and the performance of companies.

A lot of research has been done on how Google searches can affect the performance of different asset classes. Da, Engelberg, and Gao (2011) find that, using a sample of Russell 6000 stocks from 2004 to 2008, Google Search Volume Index (SVI) captures the attention of retail investors. An increase in the SVI for stocks listed on the Russell 6000 predicts higher stock prices for the next two weeks and an eventual price reversal within the year. In addition, the SVI also contributes to large first-day returns and long-run underperformance for a sample of IPO stocks. Salisu, A. A., Ogbonna, A. E., & Adediran, I. (2021) find that both the single-and multiple-factor predictive models, with Google SVI as the predictive variable, consistently outperform the conventional random walk model. Once asymmetry and macroeconomic variables are incorporated, their in-sample predictive model improves even more. The data used in this research covered the period from 2004 to 2017 of the US S&P500, global crude oil prices, the US/Pound exchange rate, and the volume of US stocks' searches on the Google search engine. Swamy, V. and Dharani, M. (2019) find high Google search volumes predict positive and significant excess returns in the subsequent fourth and fifth weeks. The authors use a dataset of NIFTY 50 stocks for the period of 2012-2017 to investigate whether search query data on company names can be used to predict weekly stock returns for individual firms in the Indian stock market. Additionally, they find that investors prefer to trade within their domestic markets, as searches from these domestic investors are associated with greater excess returns compared to worldwide investor searches.

Akarsu, S., & Süer, Ö. (2022) find that the effect of investors' attention on stock returns is not homogenous all over the world. The direction and significance of the effect vary across countries. They observe that investor attention weighs heavier in nations with individualistic cultures, those with a high aversion to uncertainty, and in more developed countries. On the contrary, the effect of abnormal returns on investor attention appears to be more consistent among different countries. One-week lagged absolute abnormal returns are found to be a positive predictor of investor attention in sixteen countries. Further, results on investor attention indicate that in more individualistic nations and those with lower aversion to uncertainty, attention returns to its normal level within three weeks. Costa, Vieira, & Madaleno (2024) investigate the influence of Google search activity on Euronext stock returns and find that the number of Google searches had no significant impact on stock returns. They also find that in 2024, a negative link between investor sentiment and Euronext stock returns existed. According to their research, the best time to invest is at moments of pessimism. These studies give insights into the workings of Google search behaviour and stock returns but leave a window open for research to further explore these mechanisms and possible variations within different market and sector conditions. Therefore, the main research question this thesis aims to answer is: Is there a relationship between investor attention, as measured by the Google Search Volume Index (SVI), and the stock performance of Europe's biggest companies —the STOXX Europe 600?

Additionally, this paper looks at the relationship that exists between stock returns and the traded volume, as trading fluctuations tend to signal changes in investor attention and sentiment. Previous research by Barber and Odean (2008) have shown that trading volume is closely related to investor behavior and stock performance. This study, therefore, intends to answer the sub-question: Is there a relationship between investor attention, as measured by the Google Search Volume Index (SVI), and the traded volume of Europe's biggest companies —the STOXX Europe 600?

From the Google Search Volume Index (SVI), I will collect the weekly Google SVI data for 53 individual stocks. From the financial database Refinitiv DataStream, I will collect the weekly returns of 53 stocks listed in the STOXX Europe 600 that had the relevant data available. Looking at a four-year period from June 2016 to June 2020, trends and patterns may arise and indicate influences on market dynamics. Two regression analyses will be performed, the first of which sets the weekly traded stock volume as the dependent variable and investor attention, as measured by the Google SVI, as the independent variable. The second regression sets weekly returns as the dependent variable and investor attention as the independent variable. Furthermore, realized volatility, market related search volume, market returns, and the lagged variant of the dependent variable will be added to this regression as control factors. To perform this, I would follow much the same methodological framework previous studies have employed.

I am expecting to identify similar patterns and trends observed by Da et al. (2011) in the U.S. Russell 6000 Index. Like the comprehensive and heterogeneous representation of stocks in this U.S. Index, the STOXX Europe 600 Index is likely to yield a strong relationship between increased search activity and heightened investor attention, leading to greater stock volatility. This would agree with the results of Da et al. (2011) and allow us to conclude that investor behaviour is not restricted to the markets in the United States but applicable in other markets as well, specifically, European markets.

The paper proceeds as following: Section II is the literature review. Section III explains the data used to answer the main research question. Section IV describes the methods applied in the analysis of the data. Results from the regression analyses are presented in Section V. Section VI contains the discussion of the findings in order to provide conclusions. Finally, Section VIII contains the references and the appendix.

CHAPTER 2 Theoretical Framework

Existing financial research asserts that investor attention has a significant impact on market activity. However, the magnitude of these findings varies and the impact of negative and positive trading behaviours differs significantly across different countries and markets. For example, Barber et al. (2008) find that individual investors are net buyers of high-attention-grabbing, extreme one-day return, and abnormal trading volume stocks. They formulate a hypothesis that investors mainly think of buying stocks that have first captured their attention. Threshold-setting studies paved the way for more research that can seek to understand the complex relationship between investor attention and market activity.

2.1 Google SVI use in Financial Forecasting

The Google SVI has been used in many ways to predict real-time economic activity. According to Choi and Varian (2009), Google search data is a good source for the forecasting of a series of economic indices such as unemployment rate, automobile sales, and vacation destinations. Joseph, Wintoki, and Zhang (2011) use the Google SVI to predict abnormal stock returns and trading volumes. Their research on S&P 500 firms between 2005 and 2008 show that search intensity could predict abnormal stock returns and trading volume at a weekly frequency. They also noted that stock returns were more sensitive to search intensity for volatile stocks, which in turn demonstrates that the Google SVI is a useful instrument to capture investor sentiment. Adachi, Masuda, and Takeda (2017) examine the relationship between investor attention and the startup stock exchange on the Tokyo Stock Exchange. Search intensity is found to be positively correlated with stock returns and liquidity. Contrary to previous studies that identified stock prices declining after a quick rise in stock prices, this study finds that startups which experience sudden surges in stock prices, might not experience a rapid reversal and could even maintain these higher prices over the long term.

A myriad of factors might be influencing market and trading activities, from macroeconomic determinants, to company-specific news. A more traditional financial theory, the Efficient Market Hypothesis (EMH), states that markets are always efficient and that stock prices fully reflect all information available. This notion is opposed by behavioural finance, which suggests that cognitive biases and investor sentiment causes mispricing and market anomalies.

Research by Preis, Moat, and Stanley (2013) indicate that the Google SVI data may reflect not only the current state of the economy but also be predictive of future trends in investor behaviour. In their study, using data ranging from January 2004 to February 2011, the Google search volumes for financial keywords significantly increase before major drops in the stock market. This indicates that intensified search activity may also be used as an early-warning indicator for stock market downturns. The authors interpret increased search activity through the Herbert Simon model of decision-making and consider it is a phase of information gathering that precedes market actions, such as selling stocks.

In another study, Perlin, Caldeira, Santos and Pontuschka (2016) examine the frequency with which individuals search for words related to finance and the subsequent effects of this upon their respective financial markets. They focused on volatility, return, and traded volume in four countries where English is the primary language. Their results show that social data — in this case, the internet query — predicts some aspects of financial markets. They find an increase in the frequency of the term 'stock' predicts future volatility and return negative future returns. That is, investors search for stock-related queries a few weeks before important downturns of financial markets. This is a cyclical tendency, important for understanding and predicting market movements in financial markets. Their empirical application show that portfolios generated from search frequency predictions outperformed the benchmark strategies, mainly during crises, indicating the usefulness of search data in constructing early warning systems for financial markets.

This study is relevant as it investigates a period of relative economic stability in Europe, leading up to 2020, followed by a more volatile period as the COVID-19 pandemic emerged. By means of panel data regression models, that include data from one of the biggest indices across Europe, the STOXX Europe 600, insights will be gained. This approach might provide a more nuanced exploration of the relationship between investor attention and stock market performance, contributing to current economic theory and practice of modern European stock markets at the onset of the 2020 crisis.

CHAPTER 3 Data

This study uses the STOXX Europe 600 index financial data obtained from Refinitiv DataStream during the period of June 2016 to June 2020 and Google Search Volume Index (SVI) downloaded from Google's database.

3.1 Google Search Volume Index

The Google SVI is a measure used to obtain the relative search frequency for a company's ticker symbol. This number scales from 0 to 100, where 100 equals the peak search volume for the term in the specified period and location. This normalization process explains the relative popularity of the search term over time and through geographic regions. Depending on the specified time range, the output may be displayed daily, weekly, or monthly. This information essentially provides a proxy for investor attention in this paper, the central focus of this analysis. If an observation results in a missing value for one or more important variables, the observation is removed from the database. This way, the integrity of the analysis is safeguarded, leaving just those observations that can be used in a statistically valid and reliable manner.

From June 2016 to June 2020, Google SVI data on stocks in the STOXX Europe 600 index is used. However, since the stock market is closed on weekends, the weekend search activity is removed from the search volume data in order to maintain consistency in trading activity and thereby investor behaviour.

Da et al. (2009) recommend using the stock ticker as the search term in the first place to filter out irrelevant components from the SVI. Since Google does not always provide results for stock tickers, company names are used as search terms, as specified in Table 9 of the appendix. To preserve both accuracy and efficiency in the sample estimates, I follow Chen, S. (2011) and exclude from the sample stocks that a) have been included in the STOXX Europe 600 for less than three years, and b) have a value of 0 for more than two consecutive months in the sample period. Table 1 presents the list of the 53 remaining stocks and their respective search queries after purification of the sample.

3.2 Financial Data

The STOXX Europe 600 financial data on closing prices, stock returns and traded volume was sourced from Refinitiv DataStream. The STOXX Europe 600 is a key European stock index consisting of large-, mid-, and small capitalization companies. It covers 17 countries and approximately 90% of the free-float market capitalization of European stock markets. This index represents shares from the UK, France, Switzerland, Germany, among others. From the 600 companies, I selected 53 companies that had complete and relevant data available for the entire study period. Broad coverage and the inclusion of different sectors and countries make the STOXX Europe 600 an effective benchmark for assessing the overall performance and trends of the European stock market.

3.3 Trading Activity

For this study, I take the end-of-week closing stock prices and the number of shares traded per week to calculate the traded activity. This is a clear and robust measure, reflective of general market liquidity and the overall level of investor activity. Furthermore, higher-volume trades generally signal good liquidity and transaction efficiency. Lastly, volume could act as a confirmation of price trends and signal reversals, generally reflecting the sentiment in financial markets.

Following Chen (2011), the traded volume of each stock is calculated as follows:

$$\boldsymbol{T\,Vk,t \;=\; log(Pk,tT\;Sk,t)} \qquad \textbf{(1)}$$

Where TVk,t denotes the traded volume in euros for stock k in week t, Pk,t denotes the end-of-week closing stock price, and TSk,t denotes the number of shares traded during the week.

3.4 Realized volatility

Elaborating on what Andersen, Bollerslev, Diebold, and Labys (1999), introduced for high-frequency data, this paper takes the very same concept and adapts it to weekly data, much like applications at the lower frequency considered by French, Schwert, and Stambaugh (1987). They contributed to field of volatility estimation using models that utilize lower frequency data—monthly, weekly, and daily returns. Their study showed that very useful information about market volatility could be deduced from data at any frequency, not specifically intraday high-frequency observations.

Realized volatility is a non-parametric measure of price variability that has garnered prominence in many recent financial research. I calculate realized volatility on a weekly basis, following the weekly closing prices within my study. The formula for RV on a weekly level is:

$$\textbf{Realized Volatility} = \sqrt{\textstyle\sum_{i=5}^{1} (\textbf{Weekly Returni})\textbf{2}} \qquad \textbf{(2)}$$

Here, WeeklyReturni denotes the log return calculated from weekly closing prices. This method provides an exhaustive and direct measure of price variability for each week and avoids the needs for annualization. Since we apply weekly realized volatility within the panel data regression, we will be in a better position to examine the dynamics of market volatility at a weekly frequency and hence draw lessons from short-term patterns.

CHAPTER 4 Method

4.1 Regression model 1

To answer the sub-question of this research, whether a relationship exists between traded volume and the Google SVI, regression model 1 in equation (3) is used. expresses a multivariate regression model to investigate the relationship between trading volume and Google SVI. According to Vlastakis and Markellos (2012), information demand is significantly positively related to both stock volatility and trading volume. Weekly realized volatility is included as a regressor to capture this relationship. The strong correlation and explaining power that weekly realized volatility holds on search volume, makes it a valuable variable to include in this analysis.

Regression 1:

$$\mathbf{TVk,t = \alpha + \beta 1SVk,t + \beta 2SVM,t + \beta 3RVk,t + \beta 4MRk,t + \beta 5TVk,t-1 + \mathcal{E}k,t} \quad \textbf{(3)}$$

In the equation, TVk,t is the traded volume of stock k in week t, α is the constant term, SVIk,t be the Google search volume for stock k in week t, SVMt be the market-wide Google search volume in week t, RVk,t be the realized volatility of stock k in week t, MRk,t be the market return of stock k in week t, and finally, εk,t be the error term.

Setting weekly traded shares as the first lag aims to pick up autoregressive patterns, thereby capturing persistence and momentum that characterize trading in stocks. The trading volumes are usually continuous from one period to the next, meaning that high trading volumes in a given week are likely to be followed by high volumes from the previous week.

In previous research on lagged variables and trading strategies, Lewellen (2002) highlights momentum in asset returns. This refers to the phenomenon of well-performing stocks outperforming less-performing stocks over intermediate horizons. This indicates persistence in stock performance due to autocorrelation. By incorporating lagged weekly traded shares, the model captures this momentum effect, and thus provides better insight into trading volume predictions.

To check the heteroscedasticity of the regression, a Breusch-Pagan test is used. (Breusch and Pagan (1979)). To check whether a random effects or fixed effects test must be used, a Hausman test is used. To check for multicollinearity, a Variance Inflation Factor (VIF) is used.

4.2 Regression model 2

To answer the main research question of this paper, whether weekly returns have a relationship with the Google SVI, a second regression model outlined in equation (4) is used. Weekly returns is the dependent variable to capture the influence of Google SVI on stock performance. According to Costa, Vieira, & Madalen (2024), no significant impact of Google search activity on the Euronext stock return was found and even pointed out a negative relation between investor sentiment and returns. This regression will examine if data from the Euro Stoxx 600 Index indicates a relationship.

$$\mathbf{WRk,t = \alpha + \beta1TVk,t + \beta2SVk,t + \beta3SVM,t + \beta4RVk,t + \beta5MRk,t + \beta5WRk,t - 1 + \mathcal{E}k,t} \quad \textbf{(4)}$$

In this regression, WRk,t is the weekly returns of stock k in week t, TVk_t is the traded volume of stock k in week t, SVk,t is the Google SVI for stock k in week t, SVMt is the market-wide Google search volume in week t, RVk,t is the realized volatility of stock k in week t, MRk,t is the market return of stock k in week t, WRk,t−1 is the lagged weekly return of stock k, α is the constant term, and ϵ,t is the error term.

Once again, including weekly returns and their lags in the regression model serves to help detect any autoregressive patterns of stock performance. The model includes lagged weekly returns so that persistence and momentum, which are intrinsic characteristics of stock returns, can be considered. This consideration ensures that weekly returns are likely to be a linear function of the previous weekly returns, thus making the model more capable of reflecting time dependencies and hence further enhancing its potential for predictive accuracy.

For this second regression, the same statistical tests are employed as with the first regression. A Breusch-Pagan test is used to check heteroscedasticity. (Breusch and Pagan (1979)). A Hausman test to check if the regression should use random effects or fixed effects test. To check for multicollinearity, a Variance Inflation Factor (VIF) is used.

CHAPTER 5 Results & Discussion

5.1 Results regression model 1

This regression analysis looks at the relationship between trading volume, Google search activity, market-wide Google searches, realized volatility, and market return in the STOXX Europe 600 index.

Table 1: The Effect of Google SVI on Weekly Traded Shares

	Weekly_Traded_Shares_
Google_Trend_Score_	4.984***
	1.361
SP500_Google_Searches	-0.016***
	0.003
Realized_Volatility	-0.116
	1.055
SP500_Returns	1.850***
	0.389
L_Weekly_Traded_Shares	0.988***
	0.005
_cons	0.509**
	0.148
N	10865.000
R-squared	0.967

Notes: The period of estimation is from June 2016 to June 2020, using data from the STOXX Europe 600 Index and the Google Search Volume Index. All standard errors are robust and clustered at the firm level. The dependent variable is weekly traded shares. The independent variables are Google Trend Score (Google SVI), the amount of Google searches for the S&P500, realized volatility of the stock, returns of the S&P500 and lagged weekly traded shares. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The standout finding from this regression is the robust positive relationship between the Google SVI score and weekly traded shares. The significant coefficient of 4.984 illustrates that an increase in investor attention considerably boosts trading volumes. This would align with the hypothesis of investor attention, as measured by Google search behaviour, being a driver of market activity.

A different trend is observed in the relationship that S&P500 Google searches share with weekly traded shares. The significant coefficient is −0.016 and indicates an inverse relation. It reveals that when investors' focus shifts to broad-market searches, trading volumes for individual stocks tend to dip. This might imply that in times with high levels of market-wide interest, attention shifts away from specific stocks to more general market trends, leading to less trading activity compared to STOXX Europe 600-specific stocks.

The relationship that S&P500 Google searches shares with the weekly traded shares indicates a different trend. The significant coefficient is −0.016, indicating some form of inverse relationship. It shows that when investor focus shifts to broader market searches, individual stock trading volumes tend to dip. It could mean that during times of heightened market-wide interest, attention might focus away from individual stocks and turn to the wider market trends, leading to a decrease in trading activity in comparison with STOXX Europe 600 specific stocks.

Contrary to previous research that emphasized the role of volatility as a significant influence on trading activity, the coefficient for realized volatility (-0.116) does not turn out to have a significant effect on weekly traded shares. The volatility element seems less influential, indicating other, more significant factors that have an effect on trading behaviour within this European index. Market returns, however, do tell a very distinct story. The coefficient for S&P500 returns is 1.850 and significant, indicating that high market returns are linked to a rise in trading volumes. This positive relationship underlies the influence of general performance on the market in trading activities; rising returns likely boost investor confidence and trading engagement. Additionally, the coefficient for lagged weekly traded shares is 0.988, which suggests that there is persistence in trading volumes. A high volume traded in one week is bound to carry over into another week, with approximately 0.988. These observations suggest a strong momentum effect. Thus, it supports the argument of momentum in trading, since there is continuity and further interest in the actively traded stocks.

A Hausman test was conducted to determine the suitability of either the fixed or random effects model in the analysis. The Chi-Square value of 73.68 and associated p-value of 0.0000 indicate that the fixed effects model is more appropriate; it provides more consistent estimates in terms of coefficients due to controlling for the correlation between regressors and the error term. A Breusch-Pagan test was performed for heteroscedasticity, yielding a p-value of 0.0000, confirming the presence of heteroscedasticity. Thus, it is necessary using robust standard errors to obtain unbiased regression results. Multicollinearity was checked with the use of the Variance Inflation Factor (VIF), which fell below 10, ensuring that no significant multicollinearity problem existed. Details of these tests are presented in the appendix.

5.2 Results regression model 2

This second regression analysis examines the relationship between weekly stock returns, Google search activity, trading volume, realized volatility, and market return in the STOXX Europe 600 index.

Table 2: The Effect of Google SVI on Weekly Returns

	Weekly_Returns_
Weekly_Traded_Shares_	0.003**
	0.001
Google_Trend_Score_	-1.403***
	0.182
SP500_Google_Searches	0.000
	0.000
Realized_Volatilityy	1.831***
	0.076
SP500_Returns	-0.076
	0.040
L_Weekly_Returns_	0.672***
	0.018
_cons	1.604***
	0.085
N	10865.000
R-squared	0.607

Notes: The period of estimation is from June 2016 to June 2020, using data from the STOXX Europe 600 Index and the Google Search Volume Index. All standard errors are robust and clustered at the firm level. The dependent variable is weekly returns. The independent variables are Google Trend Score (Google SVI), the amount of Google searches for the S&P500, realized volatility of the stock, returns of the S&P500 and lagged weekly returns. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The key result of this regression is a strong positive relation between realized volatility and weekly returns. This coefficient is significant and, at 1.831, it clearly goes on to show that higher returns are related to STOXX Europe 600. This is in line with the theory of a risk-return trade-off, where investors expect a higher compensation due to higher risk. Interestingly, this result is somewhat unexpected since in the first regression, realized volatility was insignificant and negative. While trading volume might not be driven by volatility, it certainly plays a role in explaining weekly returns.

The Google trend score, however, tells a very different story. Its coefficient of -1.403 clearly indicates a significant negative relationship between investor attention and weekly returns. This finding suggests that high investor attention might be driven by negative news or some speculative behaviour and thus diminishes stock performance. This shows a scenario where, due to investor concerns, higher search volumes may trigger sell-offs and thus yields lower returns.

The role of weekly traded shares is less influential, as evidenced by the small but significant coefficient (0.003). The intuition does however seem to hold true: an increase in trading activity leads to higher weekly returns, highlighting how liquidity and active trading can boost stock performance. The coefficient for the amount of S&P 500 Google searches is -0.000, not statistically significant, and therefore cannot be interpreted. This may suggest that there is no direct spillover from investor attention to the broader market onto changes in performance for individual stocks.

Surprisingly, the coefficient of the S&P 500 returns variable is significant and negative (-0.077). This is surprising, since one would typically expect positive spillover effects from a significant market like the S&P 500 to Europe. Such a negative relation could however imply that high market returns in the US would be associated with lower returns in the European market, perhaps due to portfolio reallocation or differences in the market environment.

The lagged weekly returns have a very strong momentum effect, with a coefficient of 0.672. Such a high coefficient suggests that there is great persistence in stock performance, so stocks that did well last week are likely to have done well this week. This confirms the momentum effect persisting in financial markets, that due to past performance, future performance is influenced.

A Hausman test was conducted to decide which of the fixed or random effects models is appropriate for the second regression. The Chi-Square value, 1868.58, is statistically significant with a p-value of 0.0000. This indicates that the fixed effects model should be used, since it provides more reliable coefficient estimates by controlling for correlations among regressors and the error term (see Table 6 in the appendix). A Breusch-Pagan test for heteroscedasticity indicates an approximate Chi-Square of 3.79 with a p-value of 0.0516. Therefore, the null hypothesis of homoscedasticity cannot be rejected at the 5% significance level. The use of robust standard errors makes the regression estimate more accurate. From the VIF analysis it can be observed that high multicollinearity occurred only in the case of L_Weekly_Returns (47.75), and for the constant term (43.08). To test whether this leads to multicollinearity problems, I include and exclude the lagged variable L_Weekly_Returns_. This resulted in no changes in the coefficients, standard errors, or significance levels of the other predictors. Hence, it is appropriate to keep the lagged variable in the model and to capture any autoregressive patterns whilst retaining stable estimates. Other variables had moderate to low multicollinearity (VIF values 1.00 to 3.61), indicating that multicollinearity is not a significant issue for the remaining variables. Details of these tests are presented in the appendix.

CHAPTER 6 Conclusion

This paper investigates the relationship between investor attention, proxied by Google Search Volume Index (SVI), and the performance of stocks within the STOXX Europe 600 Index. Two main regressions were conducted to explore the impact of investor attention on weekly traded volumes and weekly stock returns. The first regression presents a solid positive relationship between the Google SVI score and weekly traded volumes. One unit of change in the attention of investors, as captured by Google searches, increases the traded volumes by 4.984. The S&P500 Google search data are negatively linked to weekly traded shares, indicating that such broad-market attention can divert people's eyes away from individual stocks to more general market trends.

The second regression indicates a good and strong positive relation between realized volatility and weekly returns, with a coefficient of 1.831, this supports the argument of the risk-return tradeoff. Higher volatility, usually indicating higher risk, thus leads to higher returns. Surprisingly, the Google SVI score has a negative coefficient, meaning that an increase in investor attention results in reduced stock returns.

Such results are evidence of the fact that investor attention seems to perform a significant role in driving trading activity and stock performance. Therefore, it is entirely plausible for these two main findings to co-exist. An increase in investor attention leads to higher traded shares, which in turn does not necessarily translate to more weekly returns. Increased trading activity on account of investor attention may often represent reactions to bad news or speculative trading, which depress stock performance irrespective of the increased trading volumes.

A prominent limitation of this study is that it takes Google SVI as a proxy for the measure of investor attention. Although useful, other factors, such as activity on social media, news coverage, company-specific factors or macroeconomic developments may also considerably have an impact on market behavior. Moreover, the focus on stocks within the STOXX Europe 600 index might restrict generalizability in comparison to other markets or sectors. Future research could expand this study by including more measures to estimate investor attention and more search terms per company.

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APPENDIX

Table 3: Hausman Test Results of Regression 1.

Variable	Test Summary	Chi-Square Statistic	p-Value
Weekly_Traded_Shares	Fixed-Effects Test	73.68	0.0000

Table 4: Breusch-Pagan Test for Heteroskedasticity of Regression 1.

Variable	Test Summary	Chi-Square Statistic	p-Value
Weekly_Traded_Shares	Breusch-Pagan/Cook-Weisberg test for heteroskedasticity	46293.08	0.0000

Table 5: Variance Inflation Factor of Regression 1.

Variable	VIF	1/VIF
_cons	2.82	0.354729
SP500_Google_Searches	2.7	0.369978
Realized_Volatility	2.34	0.428034
L_Weekly_Traded_Shares	1.51	0.660291
SP500_Returns	1	0.996539

Note: Minimum possible value = 1.0; values >10.0 may indicate a collinearity problem.

Table 6: Hausman Test Results of Regression 2.

Variable	Test Summary	Chi-Square Statistic	p-Value
Weekly_Returns	Fixed-Effects Test	1868.58	0.0000

Table 7: Breusch-Pagan Test for Heteroskedasticity of Regression 2.

Variable	Test Summary	Chi-Square Statistic	p-Value
Weekly_Returns	Breusch-Pagan/Cook-Weisberg test for heteroskedasticity	3.79	0.0516

Table 8: Variance Inflation Factor of Regression 2.

Variable	VIF	1/VIF
L_Weekly_Returns	47.75	0.020941
cons	43.08	0.023214
SP500_Google_Searches	3.61	0.276971
Realized_Volatility	2.71	0.368842
Google_Trend_Score	2.50	0.399788
L_Weekly_Traded_Shares	1.92	0.521636
SP500_Returns	1.00	0.996190

Table 9: Names Used in Google Trends for Search Volume Index Analysis:

1. A2A
2. ANA
3. ACS
4. AENA
5. Amadeus
6. Amplifon
7. Assicurazioni Generali
8. Azimut Holding
9. Banco BPM
10. Banca Popolare di Sondrio
11. Banco Bilbao Vizcaya Argentaria

12. Banco Sabadell
13. Banco Santander SA
14. Banca Popolare dell'Emilia Romagna
15. Brunello Cucinelli
16. Caixabank
17. Davide Campari-Milano
18. DiaSorin
19. Enagás
20. Endesa
21. Enel
22. Eni
23. Ferrari
24. Ferrovial SE
25. Fineco
26. Grifols
27. Hera Group
28. Iberdrola
29. Inditex
30. Interpump Group
31. Intesa Sanpaolo
32. INWIT
33. Leonardo
34. Mediobanca
35. Merlin Properties
36. Moncler
37. Naturgy
38. Poste Italiane
39. Prysmian Group
40. Recordati
41. Red Eléctrica de España
42. Reply
43. Repsol
44. Snam
45. Stellantis
46. STMicroelectronics

47. Telecom Italia
48. Telefónica
49. Tenaris
50. Terna
51. UniCredit
52. Unipol
53. Viscofan