ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Bachelor Thesis Economics & Business
Specialization: Financial Economics

Digital Attention and Market Reactions: A Contemporaneous Analysis of Online Search Queries on the Trading Volumes and Prices of indices around Europe

Author:	Bianca Florescu
Student number:	612047
Thesis supervisor:	Sjoerd van den Hauwe
Second reader:	MSc Wei Hou
Finish date:	28th June 2024

ABSTRACT

This research paper examines the impact of the Search Volume Index (SVI) from Google Trends as a direct proxy for investors' attention. Using samples from STOXX Europe 600 and FTSE 100 between January 2013 and December 2023, several models are fitted into time-series regressions to estimate the price returns of indices, considering also the explanatory ability of the moderator, respectively, the volume of trades. I find weak evidence that the Abnormal Search Volume Index of the indices' name has a significant predictive power in explaining individually the fluctuations in the price of FTSE 100. Furthermore, the results provide no evidence of the explanatory power of the Abnormal Search Volume Index of the indices' ticker and the Abnormal Volume for any of the two European indexes. Nevertheless, although investors' attention might have an impact on the performance of indices, I do not find a strong forecasting ability on the price changes of STOXX Europe 600 and FTSE 100 over eleven years.

Keywords: investor attention, Google Trends, STOXX Europe 600, FTSE 100, abnormal returns

TABLE OF CONTENTS

CHAPTER 1 Introduction

In standard trading theories, investors can be categorised based on their knowledge level and involvement in the financial markets. As pointed out by Gârleanu and Pedersen (2022), there are two essential dichotomies about investors: one in which they are “informed” or “uninformed” on the matter, and one in which they can be called “active” or “passive”. With much consideration of this parallel, both divisions, “uninformed” and “passive” investors, have the same aim of “maximising their performance subject to a minimal cost” (Gârleanu & Pedersen, 2022, p. 403). In such situations, many investors choose to invest in diverse indices, as they offer broad exposure and utmost market diversification, keeping in mind the lower cost of acting. Moreover, recent studies analyse the impact of investors’ attention from all classes on the financial market's performance across the globe. The scope of this research paper is to focus on the predictive power of Google Trends’ Search Volume Index (SVI) as a direct proxy for investors’ attention, as proposed by Da et al. (2011), in forecasting the stock market’s price changes, also noticed in the study by Barber and Odean (2007).

In the field of Finance, researchers are looking into the behavioural aspect to understand the buying and selling tendencies of investors and institutions within the market. In the United States, as studied in the paper by Barber and Odean (2007), when purchasing common stocks, individual investors have an “attention-driven buying behaviour” (p. 813). Using the time-series analysis for 1991-1999, the authors use four sources to analyse investors’ trading behaviour. In addition, the study conducted by Da et al. (2011) builds upon this premise and tests the significance and magnitude of a more direct proxy through the Google Trends’ Search Volume Index (SVI). Also, multiple comparable studies have been testing the accuracy of the predictors of the two papers on different outcomes, such as emerging markets stock returns (Swamy et al., 2019) and short-term index performance (Vozlyublennaia, 2014). Undertaking this empirical analysis is essential for European general and particular stock markets. This research brings a new perspective by examining and mirroring the best performances of more developed indices from across the United States. It tests the difference in replicating propositions almost two decades later, after financial crises and global pandemics, and takes a closer look at enlarged and country-specific stock markets, such as the European standard (*STOXX Europe 600*) and one of the most prominent indices from the United Kingdom (*FTSE 100*). On a social level, this paper is of great use to individuals in understanding the importance of the behavioural factor in decision-making and the influence of Google searches on the performance of indices and the country’s economic state.

Considering the papers stated above, most researchers focus on the United States for their analysis. Starting from particular case studies, such as the one on six US asset indices (Vozlyublennaia, 2014), other papers analyse the general aspects of attention to outcomes from Russell 3000 (Da et al., 2011). As investors' buying behaviour is not considered outside the United States, more research on different markets is required to test the hypothesis's consistency with the original findings of Barber and Odean (2007) and Da et al. (2011). So far, the relationship between investor sentiment and returns in European financial markets has not been studied as thoroughly. Thus, STOXX Europe 600 and FTSE 100 are interesting cases to be studied as they represent large, mid, and small-capitalisation companies across the continent, and, for the UK, the index looks explicitly at the top 100 largest companies in specific abundant sectors. Hence, this thesis aims to replicate the analysis from Da et al. (2011) by using new data and answering the following research question: *"How does the effect of attention on STOXX Europe 600 and FTSE 100 affect the buying behaviour of investors, measured through price returns?"*

Following previous studies, measuring the stock market performance is investigated by collecting daily returns (price and volume) of the two indices extracted from the Eikon/Workspace Datastream from January 2013 until December 2023. In Barber and Odean (2007), the sorting methodology is based on combined returns of volume, price and news. However, the authors conclude that abnormal trading volume is the "best indicator of attention" (Barber & Odean, 2007, p. 803), which will be used as the moderator for this research. Further, in order to test the direct attention proxy effect in Europe, as it was conducted in the supporting paper from Da et al. (2011), observations of the Search Volume Index (SVI) are downloaded from Google Trends and time-series regressions (monthly, 2013-2023) are performed with SVI as the independent variable and price returns as the dependent variable, with implications of the moderator, volume returns. Analogous to findings from Barber and Odean (2007) and Da et al. (2011), who studied the effect of attention proxies in the United States, I hypothesise that I will find a similarly significant effect on the European indexes, given that Europe is represented by numerous developed and emerging financial markets, which account for different investment decisions. Nevertheless, I expect the results from the model applied to the United States to be generalisable and significant for out-of-sample research.

The additional structure of the paper is organised as follows. Chapter 2 reviews previous literature in the studied field of behavioural finance. Chapters 3 and 4 describe the data and statistical methods, with the relationship between key variables. Chapter 5 discusses the implications of the results investigated and further assesses the robustness of the analysis. Chapter 6 concludes the research question of this paper and advocates limitations and further research to be developed on this topic.

CHAPTER 2 Theoretical Framework

Understanding the factors that drive market movements and stock price fluctuations is paramount in the dynamic world of financial markets. This knowledge is crucial for both informed and uninformed investors, shaping their decision-making processes and, ultimately, their financial outcomes.

2.1 Investor attention

To begin with, the predictor variable of this thesis is the investors' attention factor. This concept refers to the degree of interest and sentiment that investors collectively focus on the market as a whole or specific financial assets, companies, and sectors within it. Among the first studies on this matter, Merton (1987) noted that "conjoining intrinsic intellectual interest with extrinsic application is a prevailing theme of research in financial economics" (p. 2), paving the way up to later endorsed topics related to the subject of behavioural finance. Since the term encapsulates numerous proxies, it is essential to mention the evolution from indirect to direct measures of investor sentiment.

2.1.1 Indirect measures

On the one hand, the paper by Barber and Odean (2007) discusses essential indirect metrics of investor attention by looking at news coverage, extreme one-day returns, and abnormal daily trading volume. The authors test models for purchasing common large and small capitalisation stocks, finding significant evidence of an "attention-driven buying behaviour" (Barber & Odean, 2007, p. 813). Offering targeted awareness of the idea that attention is a scarce resource, it is mentioned that the performance is closely linked to the trade-off between how easily investors can access information and their critical financial option to increase their utility.

In addition to building variables based on news releases, a couple of researchers also looked at the investors' reactions through social media and journal writings. Within this group, analysis of the implications of attention is observed through messages posted on the Yahoo! Finance message board (Kim & Kim, 2014) and the sentiment of Wall Street strategists, newsletter writers, and individual investors (Fisher & Statman, 2000), both which led to no evidence for changes in the structure of stock returns. On a significant side, consecutive studies from Tetlock (2007) and Tetlock et al. (2008) use media pessimism through negative words in the Wall Street Journal and financial media stories to forecast firm earnings and returns on the stock market. A more recent scientific source from Chen et al. (2023) tests the implications of news, online financial websites, stock forums and chat groups, such as WeChat and QQ, which the researchers refer to as the “behaviour paradigm”, and find evidence of irrational attention-buying that negatively affect the performance of the Chinese stock market.

2.1.2 Direct measures

On the other hand, as the indirect metrics have limitations, Barber and Odean (2007) mention the faultiness of the assumptions on the proxies for investors’ attention: “Some stocks appear because of news stories … others appear simply because of routine company press releases” (p. 796). Hence, it is fundamental for the aim of this thesis to apply a more accurate estimation of investors’ focus and interest, which can be quantified through search queries. In this direction, Da et al. (2011) propose a new view on attention, a direct proxy measured through the Search Volume Index (SVI) offered by Google Trends. Moreover, the authors extract the sample from IPOs listed in Russell 3000 stocks, achieving positive and significant results in the short-run, the first two weeks after the offering, and encountering price reversal if the period enlarges to one year, thus, the long-run.

Although a large body of literature has examined the impact of the Google Search Volume Index (SVI) on financial markets, this search engine is universal and can be used to analyse a variety of other fields. One of these distinguishable domains is the healthcare sector, where papers from Dreher et al. (2018) and Espiritu et al. (2022) are recognised for their significant results. In determining the importance of the information-seeking behaviour of users across the internet interested in kidney stone surgery on patient education (Dreher et al., 2018) and in autoimmune diseases on increased awareness across the public and medical community (Espiritu et al., 2022), these researchers found noticeable results that Google Trends search frequencies represent a pre-eminent predictor. Furthermore, other riveting discoveries have been observed in other areas of interest, such as public interest in disastrous natural events on the strategic policy changes on a state level (Knox & Yeo, 2019) and the relationship between university ranking and popularity measured through changes in Search Volume Indexes (SVI) and QS ranking scores of top 500 universities (Rybiński & Wodecki, 2022).

2.2 Stock index returns

Further, this thesis aims to assess the importance of forecasting determinants and models on the financial market and build on the existing literature on this relationship. Guiding the attention in this direction, several papers study the returns of indices worldwide through forecasting the volatility, examples include Hajizadeh et al. (2012), where the authors find empirical reasoning behind how the sample from Standard & Poor’s 500 (S&P 500) can be estimated through two hybrid models (EGARCH and Artificial Neutral

Networks) and Blair et al. (2001), whose analysis focuses on forecasting S&P 100 index's volatility over 20 days by estimating ARCH models. Additionally, with strong negative and significant results, Sarwar (2012) provides insights into how the market volatility index (VIX) is "more of a gauge of investor fear and portfolio insurance price than investor positive sentiment" for the outcome represented by S&P's 100, 500 and 600 price returns. Through testing three subperiods between 1992 and 2011, the authors investigate how the relation is strengthened by having a large VIX and very volatile.

Moving to alternative metrics of index returns, researchers also focus on predicting stock index prices using various qualified models. Sharma and Kennedy (1977) tested random-walk models on stock market indexes over eleven years (1963-1973) on a monthly basis, finding in their study a remarkably similar distribution between the Bombay, New York, and London Stock Exchanges. Apart from that, there was no sign of systematic periodicity when performing the robustness checks between the unfiltered and logarithmic transformed data, thus confirming the random walk. Auxiliary, Kollias et al. (2013) measure the relationship between oil and stock index prices via the implications of war and terrorism for the following American and European indices: S&P 500 (*Standard & Poor's 500*), DAX (*Deutscher Aktien-Index*), CAC 40 (*Cotation Assistée en Continu 40*) and FTSE 100 (*Financial Times Stock Exchange 100 Index*). These mixed associations display a co-movement between CAC 40, DAX, and oil prices but no significance when looking at S&P 500, FTSE 100, and oil returns.

2.3 Empirical Studies on the Investor's attention and Stock index return

In the occurrence of the two variables underlined above, this thesis aims to build on the existing literature and analyse the amplitude of the relationship between investors' attention determined through the Google Search Volume Index (SVI) and the Stock index trade price. Similar empirical studies were established on this predictor and outcome, such as the paper from Vozlyublennaia (2014), which observes a significant short-term change in index performance after an increase in investors' attention. Furthermore, the author concludes that increasing attention diminishes predictability and improves market efficiency. On the same note, a later study by Swamy et al. (2019), composed of the Google Search Volume Index (GSVI) and stock returns, is looking at testing the emerging markets through quantile regression analysis on the basis of two inspirational articles, mainly the studies from Barber and Odean (2007) and Da et al. (2011). As significant results, the researchers highlight that to better forecast the top 500 companies on the Indian Stock Exchange, the presence of the predictor (GSVI) is paramount compared to the absence within the predicting model.

For the purpose of this research, the proxy for attention is observed on the STOXX Europe 600 and FTSE 100 index with the application of the time-series regressions. Since the American financial determinants are common among the topics presented above, it is crucial to investigate if the same results can be extracted from having European indices samples. Regarding the sample proposed by Sharma and Kennedy (1977), this study also uses a more extensive period, specifically from 2013 to 2023, accounting for eleven-year monthly observations. Hence, a first hypothesis will be tested:

Hypothesis 1: *The Google Search Volume Index of the STOXX Europe 600 and FTSE 100 is positively impacting the Stock Indices' Prices in Europe.*

Given the recognition that the direct proxy of investors' attention is receiving in recent studies and the significant outcomes from the analyses, there is good reason to believe that it has predictive power in forecasting the indices' price fluctuations.

2.4 Trade volume

Reflecting the level of activity within markets, the volume of trade is a pivotal metric that acts in this paper as a moderator between the predictor, the Google Trends' Search Volume Index (SVI) and the outcome, the stock index's trade price. This idea arises according to the literature from Da et al. (2011) and Barber and Odean (2007), where the authors also reflect on the impact of abnormal volume in their models, finding significant results that trade quantity is the only variable affecting positively the volatility in price (Barber & Odean, 2007) and that direct proxies for attention, as listed by Da et al. (2011), have an influence on the buy-sell size of shares.

Firstly, looking at the relationship between trading volume and price changes, the publication from Karpoff (1987) critically discusses the significant and positive implications of volume on the magnitude of price change in contrast to previous and current papers on this topic. Further, looking at dynamic causal relationships regarding domestic (US) and foreign country relationships (UK and Japan), Lee and Rui (2002) propose no significant Granger-causal effect of trade volume on the stock market returns. However, cross-country predictive power exists when analysing the fluctuations in volume in the US for financial markets in the UK and Japan. Thus, the past findings suggest that trade volume has predictive power in financial market returns, leading to the second hypothesis:

Hypothesis 2: *The STOXX Europe 600 and FTSE 100 Trade Volumes have predictive power for the Stock Indices' Prices in Europe.*

Secondly, inspecting the predicting power of investors' sentiment proxies on the volatility of trade quantities, Statman et al. (2006) introduce the proposition that "security volume is more responsive to market return shocks than to security return shocks" and displays a positive effect of investor's overconfidence on the trading volume. Based on the number of empirical research on the attention of investors on the volume returns, the third hypothesis will be tested:

Hypothesis 3: *The Google Search Volume Index of the STOXX Europe 600 and FTSE 100 is positively impacting the Stock Indices' Trade Volume in Europe.*

Given this moderator's popularity, there is good reason to believe that it has significant predictive power in forecasting prices and is influenced by attention proxies.

CHAPTER 3 Data

For this research paper, data about trading indices of European markets and retail investors' attention are focused on the most prominent European indices, STOXX Europe 600 and FTSE 100. The samples are drawn from Eikon/Workspace Datastream, a foundational financial database, as well as Google Trends, from which records of trading volume and investors' Search Volume Index (SVI) were extracted from January 2013 until December 2023.

As a general market representation, STOXX Europe 600 is one of the largest stock indices, accounting for 600 large, mid, and small-capitalisation companies in 17 developing and emerging European countries. With a broad economic landscape, this index is recognised as one of the most exhaustive indicators of the European equity market, and it provides a comprehensive view of the diverse sectors across the continent, covering approximately 90% of the free-float market capitalisation. As of the last descriptive statistics observation, the index recorded a total market capitalisation of €13.5 trillion[1], serving as a benchmark for European equity performance. Within this research, the sample consists of 3,984 observations, of which 2,823 are trading days for the previously highlighted period. Focusing on the performance of the STOXX Europe 600 index, the average volume for the period 2013-2023 is approximately 2.37 billion trades, and the average trade price is €382.7 per share, based on the data presented also in Table 3 in Appendix A.

In addition, moving on to a different level of aggregation, one of the second-largest indexes across Europe is the FTSE 100, which accounts for the United Kingdom benchmark based on the performance of the largest 100 publicly traded companies listed on the London Stock Exchange (LSE). As opposed to the previous index, the FTSE 100 focuses more on specific sectors with high market capitalisation, such as oil and gas, financial services, and consumer goods. Being strongly influenced by the economic and political changes, this index follows the accurate performance of economic trends and consumer behaviour changes, recorded at the end of May 2024 by FTSE Russell[2], a net market capitalisation of £2,050,366. This paper's sample consists of 3,984 observations extracted from Eikon/Workspace, with only 2,778 actual trading days recorded between January 2013 and December 2023. When analysing the sample's descriptive statistics, as highlighted in Table 4 in Appendix A, the average volume is approximately 789.4 million trades, with an average trade price of £6,952.2 per share.

Lastly, the final database is represented by Google Trends, from which the aggregated monthly Search Volume Index (SVI) was downloaded for the two indices from January 2013 until December 2023. A more straightforward proxy for investors' attention is introduced based on the new empirical approach adopted

[1] https://stoxx.com/index/sxxp/?factsheet=true
[2] https://www.londonstockexchange.com/indices/ftse-100

in the paper by Da et al. (2011). This proxy measures the search term frequency on a scale from 0 to 100, where the highest point on the chart is the peak popularity worldwide over the selected period, and a score of 0 signifies that there were not enough data entries for the term. For this analysis, the data collection consists of 132 observations from investors worldwide, representing the estimates by Google Trends[3] of the attention exerted each month.

As proposed by Da et al. (2011), this research across European indices uses specific search engines for identification in Google based on the users' search frequencies, which are index name and ticker. On the one hand, the index's name, even though associated with investing aims, based on the selection of stock index and not search term, may appear as other news-related and financial information purposes. However, this may cause little misunderstandings as the indices' name is the only unaffected variable in testing the attention of investors' which does not tend to cancel itself out in case of constant inflows of good and bad responses from shareowners. On the other hand, only for the case of FTSE 100, where the unique assigned ticker is available in certain periods, the purposes being solely related to investing opportunities than other examples of unrelated links, helping in looking at the impact of a direct estimator which cannot be entirely biased.

3.1 Abnormal volume

Focusing on data on abnormal index movements based on the daily trading volume, it is essential to pay attention to the sharp increases or decreases in the sample. Since in previous research from Barber and Odean (2007), the variable *AbnornalVolume*, defined as the abnormally heavy trade volume, was the best indicator of the atypical attention of investors on specific stocks, further in the next section of this paper, a test will be conducted to observe whether investors make rational decisions regarding the flow of trades for ordinary shares within the two indices, or if more significant external factors, such as Google searches, influence the collective decision.

Considering the first variable in the regression, *AbnormalVolume* has to be calculated on the basis of the paper published by Barber and Odean (2007), in which the authors determine the ratio of the stock by dividing each specific sample of a trading day's volume to its average trading yearly volume (i.e., 252 trading days). Hence, the ratio of abnormal trading volume ($AbnormalVolume_{i,t}$) for index i on day t is determined by the following function:

$$AbnormalVolume_{i,t} = \frac{V_{i,t}}{\sum_{d=t-252}^{t-1} \frac{V_{i,d}}{252}}$$

[3] https://trends.google.com/trends/

where $V_{i,t}$ is the volume of index *i* in its specific currency as reported on Eikon/Workspace Datastream as daily return reports.

Based on this attributional division, as mentioned in the inspirational article (Barber & Odean, 2007, p. 794), an increase is expected in trading volume to be translated into an increase in the aggregate motivation of investors in holding or selling shares and thus, an increase in the index's price, which in this research can be identified as the dependent variable *TradePrice*. Moreover, looking at the *AbnormalVolume* as a dependent variable, an increase in the attention of investors is expected to affect the fluctuation in the volume of shares.

3.2 Investor attention

Through changes in trade prices and volumes, investors' attention to specific indicators is grasped. Thus, since "investors are much more likely to be net buyers of stocks that are in the news" (Barber & Odean, 2007, p. 801), this research is looking at testing whether the increase in attention to certain indices through a high score on Google Trends given all categories (e.g., news, finance) is affecting the variable *TradePrice*.

Moreover, since the sample is looking at eleven years and the data from Google Trends is only available for monthly observations, taking the logarithm of the Search Volume Index (SVI) extracted from Google helps in aggregating within the search frequency, as opposed to the methodology used by Da et al. (2011). It is important to note that none of the proxies used to cover the investors' attention is perfect, however, this method takes a more direct approach to looking at a larger sample of retail and institutional investors. For the regression of this analysis, it is essential to consider the current-month attention proxy as it is a better estimate of investors' reaction to indices tickers:

$$ASVI_{i,m} = \log\left(SVI_{i,m}\right) - \log\left(\frac{\sum_{m=1}^{132} SVI_i}{132}\right)$$

where $ASVI_{i,m}$ is the Abnormal Search Volume Index for index *i* in month *m*, the first term is the logarithm of $SVI_{i,m}$, the aggregated monthly Search Volume Index (SVI) for index *i* in month *m*, and the last term represents the logarithm of the average Search Volume Index (SVI) for index *i* in month *m*.

Nevertheless, since the sample for FTSE 100 also looks at the search frequencies on the index's name (*ASVI_Name*), it is essential to state that the same formula for ASVI has been used to determine investors' attention.

CHAPTER 4 Method

The methodology, as described by Barber and Odean (2007) and Da et al. (2011), is analysing the relationship between the dependent variable (*TradePrice*), the moderator variable (*AbnormalVolume*), and the independent variables (*ASVI* and *ASVI_Name*) based on the collected data over the specified period (January 2013-December 2023). This study employs time-series regression analysed in Stata MP 17, a statistical tool for studying data points collected over time, and the objective is to model and forecast the fluctuations in indexes' price given the impact of abnormal heavy volume and investors' attention historically observed.

As a preliminary step, before performing the regression analysis, the data underwent certain changes before being analysed. Firstly, the daily data for eleven years on trade prices and volumes was converted to be merged with the monthly estimates for the Abnormal Search Volume Index of the index's name and ticker (*ASVI_Name* and *ASVI*), and the missing values for non-trading days, such as weekends, have been dropped. Secondly, in order to assess the normality of the absolute values of the variable *AbnormalVolume*, as mentioned by Barber and Odean (2007) and also used in the paper by Da et al. (2011), the first two months of data on the variable have been skipped, and the returns start from March 2013 until December 2023, to ensure that outliers are not accounted in the research. Also, using the Dickey-Fuller (DF) test, the time series' stationarity is assessed for statistical instruments, such as mean and variance, to remain the same over time, as seen in Appendix B. After considering the analysis of the stationarity in the model's variables, the non-stationary data registered in the dependent variable (*TradePrice*) and two independent variables (*ASVI* and *ASVI_Name*) have been differenced in order to assess the critical assumption, and the last variable (*AbnormalVolume*) has been reported normally.

The following step includes specifying the time-series regression model based on three independent variables mentioned in previous papers: abnormal volume movements (Barber & Odean, 2007) and proxies for investors' attention to indices' names and tickers (Da et al., 2011), compressed into the formula below:

$$TradePrice_{i,t} = \alpha + \beta_1 * AbnormalVolume_{i,t} + \beta_2 * ASVI_{i,t} + \beta_3 * ASVI\_Name_{i,t} + \epsilon$$

where $TradePrice_{i,t}$ is the dependent variable for index *i* at time *t*; the independent variables are the $AbnormalVolume_{i,t}$, $ASVI_{i,t}$ and $ASVI\_Name_{i,t}$ for index *i* at time *t*; α in the constant of the model; β_1, β_2 and β_3 are the coefficients of the regression, and ϵ_t is the error term at time *t*.

Furthermore, it is essential also to mention the time-series regression model where the investors' attention variables (*ASVI* and *ASVI_Name*) are in relation to the dependent variable (*AbnormalVolume*):

$$AbnormalVolume_{i,t} = \alpha + \beta_1 * ASVI_{i,t} + \beta_2 * ASVI\_Name_{i,t} + \epsilon$$

where $AbnormalVolume_{i,t}$ is the dependent variable for index *i* at time *t*; the independent variables are $ASVI_{i,t}$ and $ASVI\_Name_{i,t}$ for index *i* at time *t*; α in the constant of the model; β_1 and β_2 are the coefficients of the regression, and ϵ_t is the error term at time *t*.

In the final steps, the model needs to be estimated and validated, thus, further test checks are performed for heteroskedasticity, autocorrelation and multicollinearity. The White test is performed for heteroskedasticity examination to ensure that the variance of errors is constant. To have a homoscedastic regression for certain models, the dependent variable has been subject to changes by taking the logarithm of *TradePrice* and *AbnormalVolume*. Subsequently, one of the critical assumptions for time-series forecasting is the absence of autocorrelation in residuals, which is solved through Newey-West (1987) autocorrelation correction, as proposed in the previous paper (Da et al., 2011, p. 1483). Ultimately, as multiple exogenous variables are included in the regression model, it is mandatory to conduct the Variance Inflation Factor (VIF) test for multicollinearity, which ensures that the independent variables (*AbnormalVolume*, *ASVI* and *ASVI_Name*) are not highly correlated.

Nonetheless, based on the major analysis path explained above for the data samples presented in Chapter 3, it is vital to evaluate the predictive power to account for forecasting accuracy when validating the model.

CHAPTER 5 Results & Discussion

The model proposed in the above chapter will be estimated through time-series regressions on two dependent variables, as Da et al. (2011) and Barber and Odean (2007) proposed. The first subsection takes into consideration the trade price of the two indices (STOXX Europe 600 and FTSE 100) as dependent on the following independent measures: Abnormal Volume, Abnormal Search Volume Index on the ticker (*d_ASVI*) and Abnormal Search Volume Index on the name of the index (*d_ASVI_Name*). The second subcategory looks at Abnormal Volume as a dependent variable to analyse the impact of the *d_ASVI* and *d_ASVI_Name* on the fluctuations in buy-sell quantities of shares.

When it comes to interpreting the results, the dependent variable *d_TradePrice* is measured differently for the two indices based on the underlying currency, such that STOXX Europe 600 is observed in euros and FTSE 100 is measured in pounds. Thereafter, the variable *AbnormalVolume* is measured through the formula mentioned in the Data section, and its change is calculated in percentages of that specific ratio. Nevertheless, the two variables related to investors' attention are calculated using the logarithmic estimation, and their impact can also be observed in percentage change.

5.1 Trade price

To begin with, breaking down the models from Table 1, the dependent variable in each one of them is the Trade Price of the STOXX Europe 600 and FTSE 100. For model (1), the independent variable is the *d_ASVI_Name*, and in model (2), another control variable is added to the previous version, the *AbnormalVolume*. Moving to the largest index from the UK, models (3) and (4) separately look at the impact of the independent variables *d_ASVI* and *d_ASVI_Name*, respectively, while model (5) analyses the impact of both determinants of attention on the differenced Trade Price. Lastly, model (6) considers all three independent variables mentioned and their importance in testing the price of trade fluctuations.

The six models proposed in Table 1 can be assessed for their statistical fit by mentioning and interpreting the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as seen in Appendix C. Given both their low AIC and BIC, models (2), (3), (5) and (6) have a variance in the overall performance rating of individuals that can be explained by the variables included in the models. Hence, a model that includes all the relevant variables or just the variable representing the Abnormal Search Volume Index of the ticker yields a higher explaining ability than the independent variables individually observed.

As opposed to the statistical fit of the models from Table 7 in Appendix C, by looking at the majority of the results from Table 1, most of the accounted independent determinants have corresponding P-values larger than the last benchmark of 10% level, indicating that the effect of *d_ASVI_Name*, *d_ASVI*, *AbnormalVolume* and combinations of them are not significant. Opportunely, the results of model (4), which looks at the specific index of FTSE 100 and the relationship between *TradePrice* and *d_ASVI_Name* individually, have a corresponding P-value that is smaller than a 10% significance level. Even though not statistically significant at all conventional levels, the results can be interpreted as follows: a 1% increase in the attention of investors through the Abnormal Search Volume Index of the index's name on average leads to an increase in the FTSE 100 trade price of £226.945, assuming other variables remain unchanged.

Table 1

Regressions of Investors' Attention determinants and Abnormal Volume on the Trade Price of the two largest indices in Europe

	STOXX Europe 600		FTSE 100			
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
d_ASVI_Name	17.563	1.749		226.945*	386.196	330.706
	(16.718)	(1.129)		(124.412)	(493.015)	(556.458)
AbnormalVolume		0.432				147.814
		(0.322)				(201.361)
d_ASVI			345.023		278.858	319.149
			(214.386)		(237.7475)	(220.784)
Constant	1.339	1.426***	30.410	8.290	33.703	-105.449
	(1.0905)	(0.357)	(29.197)	(11.333)	(29.728)	(184.040)
Observations	129	78	19	129	19	19
F-statistics	1.10	2.15	2.59	3.33	1.79	1.70

Note. This table presents the regressions of different determinants, such as *AbnormalVolume*, Abnormal Search Volume Index of the ticker (*d_ASVI*) and Abnormal Search Volume Index of the name (*d_ASVI_Name*), considered as independent variables. The dependent variable is the *d_TradePrice* of STOXX Europe 600 and FTSE 100. Independent variables are presented in Column 1 of the table. The sample period is from January 2013 to December 2023. Only valid indicators are retained in the sample by dropping the missing values of the variables. The Newey-West standard errors are presented in parentheses. *p<0.1, **p<0.05, ***p<0.01 representing the significance at 10%, 5% and 1% levels.

5.2 Abnormal volume

Additionally, discussing the models from Table 2, the dependent variable is the Abnormal Volume of the STOXX Europe 600 and FTSE 100. For models (1) and (2), the independent variable is the *d_ASVI_Name*, while for model (3), as the sample included the impact of the independent variable *d_ASVI*, the analysis requires looking at the impact of investors' attention on the trade price, based on the index's ticker.

The three models proposed in Table 8[4] can be assessed for their statistical fit by mentioning and interpreting the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Although all models present very low AIC and BIC, compared to the models previously mentioned in the above subsection, one of the relationships has a variance in the overall performance rating of individuals that can be explained by the variables included in the models, represented by the model (3). Hence, including the singular relevant variable of *d_ASVI* in the volume fluctuations of FTSE 100 yields a higher explanatory power in contrast to the independent variables accounted for STOXX Europe 600.

Although the models result in high statistical fit based on Table 8 in Appendix C, by looking at the results from Table 2, the findings fall short of statistical significance at the 90% confidence interval threshold, lacking the strength to meet the conventional criteria. Thus, the corresponding P-values are larger in each case than the 10% significance level, indicating that the observed effects of *d_ASVI_Name* and *d_ASVI* on *AbnormalVolume* do not suggest a definitive pattern but rather leave room for interpretation of the relationship between variables. At the same time, while there are observable patterns in the sample data, the insignificance of the independent variables proposes further investigation into a larger spectrum of determinants, which might have a more substantial explanatory power associated with investors' attention measures.

[4] See Appendix C.

Table 2

Regressions of Investors' Attention determinants on the Abnormal Volume of the two largest indices in Europe

	STOXX Europe 600	FTSE 100	
Variable	**(1)**	**(2)**	**(3)**
d_ASVI_Name	0.134 (0.387)	-0.026 (0.176)	
d_ASVI			-0.208 (0.235)
Constant	1.018*** (0.038)	1.0595*** (0.0396)	0.938*** (0.041)
Observations	129	129	19
F-statistics	0.12	0.02	0.79

Note. This table presents the regressions of different determinants, such as the Abnormal Search Volume Index of the ticker (*d_ASVI*) and the Abnormal Search Volume Index of the name (*d_ASVI_Name*), considered as independent variables. The dependent variable is the *AbnormalVolume* of STOXX Europe 600 and FTSE 100. Independent variables are presented in Column 1 of the table. The sample period is from January 2013 to December 2023. Only valid indicators are retained in the sample by dropping the missing values of the variables. The Newey-West standard errors are presented in parentheses. *p<0.1, **p<0.05, ***p<0.01 representing the significance at 10%, 5% and 1% levels.

Fundamentally, with regard to the hypotheses of this research paper, given the dissipated results, I find only partial support for the statement that investors' attention drives the trade price of specific indices across Europe. Seeing that only in Table 1, the relationship between *d_ASVI_Name* and *d_TradePrice* for the index FTSE 100 displays statistical significance on the last 10% conventional level, the null hypothesis cannot be disregarded entirely for Hypothesis 1, highlighted in Chapter 2. However, based on the findings of subsections 5.1 and 5.2, due to the insignificance of the models with *AbnormalVolume* as a moderator, in assessing the statements of Hypotheses 2 and 3, it is insoluble to analyse the impact and magnitude of the variable. In particular, the findings look to be sensitive to the incorporation of more critical variables.

5.3 Robustness checks

Additionally, this study's sensitivity analysis is observed by performing regression tests on the raw and unfiltered data, which can be seen in Tables 9 and 10[5]. Comparing the primary findings with the outcomes in Appendix D, the aim is to discuss the consistency and reliability of the results under certain conditions mentioned in the Methodology section.

At first glance, the coefficients in the robustness checks are meaningfully higher than in the main study, with most models showing significant P-values smaller than the 99% confidence intervals, suggesting that the filtering process impacted the results in the primary analysis. With ten models for Table 9 and four models for Table 10, the robustness checks include more regressions due to the absence of any assumption tests performed on the main results, such as the heteroskedasticity, which remains unresolved in the upcoming mentioned relationships. Regressions that appear only on the unfiltered data are models (2) and (5), which assess the singular impact of *AbnormalVolume* on the trade prices of STOXX Europe 600 and FTSE 100 and models (7) and (8), where *AbnormalVolume* is in relation to the attention proxies separately. Lastly, model (4) observes the impact on the *AbnormalVolume* as a dependent variable of both independent variables for the Abnormal Search Volume Index for indices' name and ticker (*ASVI* and *ASVI_Name*). Noticing Table 9, the coefficients are inflated due to the bias they hold, also having a large marginal negative effect, significant for variable *AbnormalVolume* and insignificant for variable *ASVI*. When it comes to *ASVI_Name*, the independent variable has a marginal positive effect for the majority of the models, but it can also propose large significant negative coefficients when adding all the controls in the regression, for instance, model (10), where a 1% increase in the attention of investors through the Abnormal Search Volume Index of the index's name on average leads to a decrease in the FTSE 100 trade price of £1,908.5, assuming other variables remain unchanged. Nonetheless, Table 10 generates an opposite outcome, with adverse significant marginal effects for all coefficients of *ASVI_Name* and insignificant coefficients for the variable *ASVI* on the fluctuations of the dependent variable, *AbnormalVolume*.

Thinking about the potential reasons for these disparate outcomes, the unaltered data likely contains outliers and noise that obscure the relationships in each model, as well as not considering dropping the missing or extreme values, which ultimately might cause biases or distortions. Thus, the primary data results are the best estimate for reduced noise, leading to a clear and more accurate picture and accounting for the sensitivity to the distortions by the filtering process.

[5] See Appendix D.

5.4 Discussion

This thesis has delved into three hypotheses concerning the impact of investors' attention, gauged through Google search queries, on the performance of two of the most prominent indices in Europe, particularly STOXX Europe 600 and FTSE 100, while also factoring in the influence of the abnormal volume of trade, considered a moderator within the analysis. The results, as highlighted in previous sections of this Chapter, have unveiled differences from the findings of earlier literature on this subject, such as the works of Barber and Odean (2007), Da et al. (2011) and Vozlyublennaia (2014).

Firstly, when assessing the importance of the variable *AbnormalVolume* in time-series regression models for STOXX Europe 600 and FTSE 100, as opposed to the results from Barber and Odean (2007), it was shown that the moderator is not significantly influenced by the independent variables consistent of Abnormal Search Volume Index of the indices' ticker and name (*ASVI* and *ASVI_Name*). Moreover, even if the previous research methods have significantly improved people's views on the behavioural finance theories of that time, I believe replicating the analysis will not yield the same significant results. One justification can represent the different levels of aggregation of the dependent determinant of the regression, as this study diverted in the dataset extracted, looking at an index level for the European continent, as opposed to the brokerage level from the US (Barber & Odean, 2007). It is, therefore, possible that investor attention and trade prices are related to the abnormal volume only in specific cases of pellicular data but do not influence the market composite outcomes.

Secondly, taking into account the direct approach to attention-buying behaviour proposed by Da et al. (2011), this thesis proceeds to two case studies. On the one hand, the variable derived from the Google Trends' Seach Volume Index (SVI) has predictive power for FTSE 100 on some conventional statistically significant levels, expressing that the findings of this paper align with the previously mentioned study, although the timeframe is extended from 2013 to 2023 compared to 2004-2008 (Da et al., 2011). On the other hand, when looking at the STOXX Europe 600 index, the independent variable (*ASVI_Name*) has no predictive power in forecasting the fluctuations in trade price, even with the introduction of the control variable *AbnormalVolume*. Hence, it can be deduced that the Search Volume Index (SVI) is a good attention proxy for certain market indices. Lastly, relating the outcomes of these tests to the findings from Vozlyublennaia (2014) and Da et al. (2011), it is possible that investors' attention is related to indices that display companies with high market capitalisation (FTSE 100), as those appear to be mentioned more in daily lives of investors from all classes (i.e., informed, uninformed, active and passive), as compared to indices that include large, mid and small market capitalisation companies (STOXX Europe 600).

CHAPTER 6 Conclusion

This thesis investigates the explanatory power of the Google Trends' Search Volume Index (SVI) as a direct proxy for investors' attention in forecasting the price changes of STOXX Europe 600 and FTSE 100, also accounting for the volume of trade as a moderator. The volatility in volumes and prices of trades reflect the implications of investment decision-making regarding financial market factors. Previous research on this relationship has shown the significant effects of different indirect and direct measures of investors' attention on the financial market determinants. Although grasping the US market in numerous papers, the implications have not been examined in many studies on the European indices, despite the diversification of the markets compounding it. Thus, the research question studied within this paper was: *"How does the effect of attention on STOXX Europe 600 and FTSE 100 affect the buying behaviour of investors, measured through price returns?"*

In answering this research question, three different samples were extracted for eleven years between January 2013 and December 2023. For volume and price changes, samples were extracted from Eikon/Workspace Datastream, looking at daily outputs, whereas, for the attention proxy, data was downloaded for the monthly Search Volume Index (SVI) from Google Trends. Considering the analysis performed on STOXX Europe 600 and FTSE 100, results have shown that in the case of indices, abnormal volume is not a significant moderator as it is not influenced by attention-buying behaviour and it does not affect the volatility in prices, even when considered a control variable. Moreover, given also previous studies from Barber and Odean (2007), Da et al. (2011) and Vozlyublennaia (2014), only for indices containing high market capitalisation listings, the results showed a slight significance of the relationship between the Abnormal Search Volume Index from Google Trends on the index's name (*ASVI_Name*) and no implications of the variable describing the attention exerted on the index's ticker (*ASVI*).

All in all, this research study concludes that although the literature review finds significant implications of abnormal volume and attention-buying behaviour on price changes, when taking a different measure of financial markets, respectively indices, the fluctuations in volume lose their importance, and direct proxies for attention are significant only for specific cases. Nevertheless, indices that include only high market capitalisation companies, for instance, FTSE 100, are more likely to be affected by the direct proxy, as opposed to indices that include listings of all sizes, such as STOXX Europe 600.

6.1 Recommendations

These findings have several important implications for investors and financial advisors. On the one hand, investors of all categories need to understand behavioural theories when engaging in investment activities that require observing the factors that strongly impact decision-making. Additionally, if investors are "uninformed" or "passive" and are looking to maximise their utility through limited time and costs of searching, looking at recent literature on buying behaviour can help them grasp the markets better. On the other hand, given the indirect and direct proxies of attention studied in previous papers, financial advisors can better choose factors to analyse to grasp the implications of the variability of returns and shape their recommendations based on the client's requirements and the market's winner's strategies.

6.2 Limitations

Lastly, reflecting on the avenues of this research, a potential obstacle is the introduction of control variables only related to returns, as proposed in previous literature. Hence, by doing that, other categories of control variables have been undiscovered, such as macroeconomic factors and socioeconomic matters. It is essential for future research to include them for specific periods in the large sample as crucial events, such as the global pandemic, have entirely shaped the investors' buying tendencies concerning restrictions and increased risk related to the uncertainty of times.

Furthermore, as mentioned before, no perfect indicator of attention has proven to be the only estimate for investors. The idea is also highlighted in numerous papers that test the accuracy of indirect and direct proxies in better imitating people's tendencies when acquiring shares. Other possibilities for future references can be analysing the implications for institutional investors separately through Bloomberg estimates to capture the buying behaviour of "active" and "informed" individuals.

REFERENCES

Barber, B. M., & Odean, T. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *The Review of Financial Studies*, *21*(2), 785-818. doi: https://doi.org/10.1093/rfs/hhm079

BENCHMARK INDICES STOXX EUROPE 600. (n.d.). Retrieved from: https://stoxx.com/index/sxxp/?factsheet=true

Blair, B. J., Poon, S., & Taylor, S. J. (2001). Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns. *Journal of Econometrics*, *105*(1), 5–26. doi: https://doi.org/10.1016/s0304-4076(01)00068-9

Chen, C., Lu, X., & Zhang, Y. (2023). Is attention-based stock buying profitable? Empirical evidence from Chinese individual investors. *Pacific-basin Finance Journal*, *82*, 102120. doi: https://doi.org/10.1016/j.pacfin.2023.102120

Da, Z., Engelberg, J., & Gao, P. (2011). In Search of Attention. *The Journal of Finance*, *66*(5), 1461-1499. doi: https://doi.org/10.1111/j.1540-6261.2011.01679.x

Dreher, P. C., Tong, C., Ghiraldi, E., & Friedlander, J. I. (2018). Use of Google Trends to track online behavior and interest in kidney stone surgery. *Urology*, *121*, 74–78. doi: https://doi.org/10.1016/j.urology.2018.05.040

Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal*, *56*(2), 16–23. doi: https://doi.org/10.2469/faj.v56.n2.2340

FTSE overview. (n.d.). Retrieved from: https://www.londonstockexchange.com/indices/ftse-100

Gârleanu, N., & Pedersen, L. H. (2022). Active and passive investing: Understanding Samuelson's dictum. *The Review of Asset Pricing Studies*. doi: https://doi.org/10.1093/rapstu/raab020

Google Trends. (n.d.). Trends. Retrieved from: https://trends.google.com/trends/

Hajizadeh, E., Seifi, A., Zarandi, M. F., & Turksen, I. (2012). A hybrid modeling approach for forecasting the volatility of S&P 500 index return. *Expert Systems With Applications*, *39*(1), 431–436. doi: https://doi.org/10.1016/j.eswa.2011.07.033

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis*, *22*(1), 109. doi: https://doi.org/10.2307/2330874

Kim, S., & Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. *Journal of Economic Behavior & Organization*, *107*, 708–729. doi: https://doi.org/10.1016/j.jebo.2014.04.015

Kollias, C., Kyrtsou, C., & Papadamou, S. (2013). The effects of terrorism and war on the oil price–stock index relationship. *Energy Economics*, *40*, 743–752. doi: https://doi.org/10.1016/j.eneco.2013.09.006

Lee, B., & Rui, O. M. (2002). The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. *Journal of Banking & Finance*, *26*(1), 51–78. doi: https://doi.org/10.1016/s0378-4266(00)00173-4

Merton, R. C. (1987). A SIMPLE MODEL OF CAPITAL MARKET EQUILIBRIUM WITH INCOMPLETE INFORMATION. In *Working Paper* (No. 1869–87). Retrieved from: https://dspace.mit.edu/bitstream/handle/1721.1/2166/SWP-1869-18148074.pdf

Roberto, K. T., Jamora, R. D. G., Moalong, K. M. C., & Espiritu, A. I. (2022). Infodemiology of autoimmune encephalitis, autoimmune seizures, and autoimmune epilepsy: An analysis of online search behavior using Google Trends. *Epilepsy & Behavior*, *132*, 108730. doi: https://doi.org/10.1016/j.yebeh.2022.108730

Rybiński, K., & Wodecki, A. (2022). Are university ranking and popularity related? An analysis of 500 universities in Google Trends and the QS ranking in 2012-2020. *Journal of Marketing for Higher Education*, 1–18. doi: https://doi.org/10.1080/08841241.2022.2049952

Sarwar, G. (2012). Intertemporal relations between the market volatility index and stock index returns. *Applied Financial Economics*, *22*(11), 899–909. doi: https://doi.org/10.1080/09603107.2011.629980

Sharma, J. L., & Kennedy, R. E. (1977). A comparative analysis of stock price behavior on the Bombay, London, and New York stock exchanges. *Journal of Financial and Quantitative Analysis*, *12*(3), 391. doi: https://doi.org/10.2307/2330542

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor Overconfidence and Trading Volume. *The Review of Financial Studies*, *19*(4), 1531-1565. doi: https://doi.org/10.1093/rfs/hhj032

Swamy, V., Dharani, M., & Takeda, F. (2019). Investor attention and Google Search Volume Index: Evidence from an emerging market using quantile regression analysis. *Research in International Business and Finance*, *50*, 1–17. doi: https://doi.org/10.1016/j.ribaf.2019.04.010

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, *62*(3), 1139-1168. doi: https://doi.org/10.1111/j.1540-6261.2007.01232.x

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More Than Words: Quantifying Language to Measure Firms' Fundamentals. *The Journal of Finance*, *63*(3), 1437-1467. doi: https://doi.org/10.1111/j.1540-6261.2008.01362.x

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance*, *41*, 17–35. doi: https://doi.org/10.1016/j.jbankfin.2013.12.010

Yeo, J., & Knox, C. C. (2019). Public Attention to a Local Disaster Versus Competing Focusing Events: Google Trends Analysis Following the 2016 Louisiana Flood. *Social Science Quarterly, 100*(7), 2542-2554. doi: https://doi.org/10.1111/ssqu.12666

APPENDIX A Descriptive statistics

Table 3

Compact descriptive statistics of STOXX Europe 600

Variable	Number of observations	Mean	Median	Standard Deviation	Min	Max	Skewness	Kurtosis
TradePrice	2832	382.70	380.58	49.60	275.66	494.35	0.19	2.28
AbnormalVolume	2781	1.05	0.94	0.54	0	7.60	4.46	32.30
ASVI_Name	130	-0.25	-0.31	0.20	-0.54	0.15	0.35	1.66

Note. The table displays the descriptive statistics of the independent variable (*ASVI_Name*), dependent variable (*TradePrice*) and the moderator (*AbnormalVolume*).

Table 4

Compact descriptive statistics of FTSE 100

Variable	Number of observations	Mean	Median	Standard Deviation	Min	Max	Skewness	Kurtosis
TradePrice	2778	6952.19	7024.82	534.91	4993.89	8014.31	-0.47	2.52
AbnormalVolume	2736	1.09	0.97	0.60	0.15	9.47	5.33	49.02
ASVI_Name	130	-0.18	-0.16	0.25	-0.66	0.42	-0.07	1.88
ASVI	34	0.21	0.23	0.16	-0.16	0.46	-0.53	2.66

Note. The table displays the descriptive statistics of the independent variables (*ASVI_Name* and *ASVI*), dependent variable (*TradePrice*) and the moderator (*AbnormalVolume*).

APPENDIX B Stationarity

Table 5

Dickey-Fuller test for STOXX Europe 600

Variable	Test statistic	P-value
d_TradePrice	-10.649	0.000
d_ASVI_Name	-12.364	0.000

Note. The table shows the test statistics and the corresponding P-values of the Dickey-Fuller (DF) test. The null hypothesis states that the variable is non-stationary. The variables of the regression are the independent variable (*ASVI_Name*), the dependent variable (*TradePrice*) and the moderator (*AbnormalVolume*). The first difference is denoted as d_TradePrice and d_ASVI_Name, respectively. *p<0.1, **p<0.05**,** ***p<0.01 representing the significance at 10%, 5% and 1% levels.

Table 6

Dickey-Fuller test for FTSE 100

Variable	Test statistic	P-value
d_TradePrice	-11.017	0.000
d_ASVI_Name	-13.274	0.000
d_ASVI	-4.982	0.000

Note. The table shows the test statistics and the corresponding P-values of the Dickey-Fuller (DF) test. The null hypothesis states that the variable is non-stationary. The variables of the regression are the independent variables (*ASVI_Name* and *ASVI*), the dependent variable (*TradePrice*) and the moderator (*AbnormalVolume*). The first difference is denoted as d_TradePrice, d_ASVI_Name and d_ASVI, respectively. *p<0.1, **p<0.05**,** ***p<0.01 representing the significance at 10%, 5% and 1% levels.

APPENDIX C Model Performance

Table 7

Overall models' performance given the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) with Trade Price as a dependent variable

	STOXX Europe 600		FTSE 100			
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
AIC	1052.935	236.134	239.946	1768.397	241.259	242.401
BIC	1058.655	243.204	241.835	1774.116	244.093	246.179

Note. AIC measures the relative quality of each statistical model observed between 2013 and 2023, where a lower value signifies a better-fitting model. Similarly, a lower BIC value indicates a better model, which introduces a penalty term for the number of parameters in each model observed between 2013 and 2023.

Table 8

Overall models' performance given the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) with Abnormal Volume as a dependent variable

	STOXX Europe 600	FTSE 100	
Variable	**(1)**	**(2)**	**(3)**
AIC	86.022	97.796	-9.538
BIC	91.741	103.516	-7.6495

Note. AIC measures the relative quality of each statistical model observed between 2013 and 2023, where a lower value signifies a better-fitting model. Similarly, a lower BIC value indicates a better model, which introduces a penalty term for the number of parameters in each model observed between 2013 and 2023.

APPENDIX D Robustness checks

Table 9

Regressions of Investors' Attention determinants and Abnormal Volume on the Trade Price of the indices, using unfiltered data

	STOXX Europe 600			FTSE 100						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ASVI_Name	163.191***		151.316***	573.552***			475.103***		-703.945	-1908.501**
	(15.913)		(14.989)	(177.2375)			(178.922)		(781.387)	(755.995)
Abnormal Volume		-40.127***	-29.279***		-256.180***		-203.744**	-835.1767**		-1256.175***
		(8.304)	(6.3015)		(85.143)		(85.511)	(348.7605)		(362.5975)
ASVI						-372.955		-474.82	-275.1495	-261.002
						(655.653)		(613.420)	(666.493)	(572.602)
Constant	424.292***	426.156***	452.045***	7067.917***	7244.767***	7024.087***	7273.005***	7882.329***	7033.077***	8339.327***
	(5.0255)	(9.537)	(7.5785)	(54.483)	(103.149)	(170.1735)	(101.354)	(392.010)	(170.968)	(404.65)
Observations	130	130	130	130	130	34	130	34	34	34
R^2	0.451	0.154	0.531	0.076	0.066	0.010	0.115	0.165	0.035	0.311

Note. This table presents the regressions of different determinants, such as *AbnormalVolume,* Abnormal Search Volume Index of the ticker (*ASVI*) and Abnormal Search Volume Index of the name (*ASVI_Name*), considered as independent variables. The dependent variable is the *TradePrice* of STOXX Europe 600 and FTSE 100. Independent variables are presented in Column 1 of the table. The sample period is from January 2013 to December 2023. The standard errors are presented in parentheses. *p<0.1, **p<0.05, ***p<0.01 representing the significance at 10%, 5% and 1% levels.

Table 10

Regressions of Investors' Attention determinants on the Abnormal Volume of the indices, using unfiltered data

	STOXX Europe 600	FTSE 100		
Variable	**(1)**	**(2)**	**(3)**	**(4)**
ASVI_Name	-0.4056*	-0.483***		-0.959***
	(0.207)	(0.1799)		(0.3325)
ASVI			-0.122	0.011
			(0.310)	(0.284)
Constant	0.948***	1.007***	1.028***	1.0399***
	(0.065)	(0.055)	(0.0805)	(0.073)
Observations	130	130	34	34
R^2	0.029	0.053	0.005	0.215

Note. This table presents the regressions of different determinants, such as the Abnormal Search Volume Index of the ticker (*ASVI*) and the Abnormal Search Volume Index of the name (*ASVI_Name*), considered as independent variables. The dependent variable is the *AbnormalVolume* of STOXX Europe 600 and FTSE 100. Independent variables are presented in Column 1 of the table. The sample period is from January 2013 to December 2023. The standard errors are presented squared in parentheses. *p<0.1, **p<0.05**,** ***p<0.01 representing the significance at 10%, 5% and 1% levels.