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Stock Prices, Attention, and Google Searches

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Abstract

With the increasing availability of data and the expanded use of digital trading platforms, the behaviour of individual investors actively involved in trading has a greater impact on stock returns on capital markets. Traditional models assume that investors are perfectly rational economic agents, but, as prior research has shown, this constraint is not fully honoured in the actual world most of the time. Our paper investigates the dynamics of the relationship of investors' attention and its impact on the stock market for an institutional investor-dominated stock exchange. The research was centred on the FTSE 100 Index of London Stock Exchange (LSE), and we constructed an investor's attention indicator based on the Google Search Index, which measures in real-time the information with whom individuals come into contact daily. We introduced the indicator in the Fama and French 3-factor model. To explore the association between investors' cognitive limitations and stock prices, we used weekly data for five years, from the beginning of 2015 to the end of 2019. We then used multiple and panel regression to categorise quintile portfolios according to market capitalization levels. Despite the minimal presence of private investors on the LSE, our findings show that there is a positive correlation between the volume of Google searches and stock prices. Furthermore, there is a positive effect of attention on the portfolio of companies with the smallest market capitalization. Our findings have implications for investment approaches and, specifically, for active portfolio management strategies.

Keywords: Google Searches, Investor's attention, Panel regression, Stock returns, FTSE 100.

JEL Classification: G12, G41.

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1. Introduction

Especially in an environment where the use of digital trading platforms has become a widely employed method of trading, and the European average of the population with Internet access is 90 percent (Eurostat, 2020), individual investors enjoy searching online for information about the companies they are interested in investing. As a result, the frequency with which a specific asset is searched may be a direct reflection of the amount of attention that investors pay to that asset, in general. Given the availability of Google Trends (GT), a free public online service provided by Google that offers data on the number of searches for a specific topic, it is possible to use it to gauge investor interest in a particular topic.

Da et al. (2011) were the first to propose using the volume of Google searches as a proxy for investor attention. Following this, Joseph et al. (2011), Bank et al. (2011), Vlastakis, Markellos (2012), Takeda, Wakao (2014), and Ekinci, Bulut (2021) demonstrated that search volume is positively correlated with returns.

Our paper addresses the Barber and Oden's theory of attention, but for companies in the FTSE 100 index for which no research has been conducted thus far using Google searches volume as a direct measurement of investor's attention. The choice of this index was motivated by the fact that its constituents account for 80% of the capitalization of the London Stock Exchange. Furthermore, according to Barton (2021), 33 percent of the English population owns shares, and more than 21 percent want to invest in the future, making the FTSE 100 the recommended subjects for this research. Our research conducted on 125 companies during a period of five years shows that the volume of Google searches is significant and can be associated with a positive change in returns, which confirms the hypothesis on which it was built and confirms the results of the other works mentioned above. Three variables based on data downloaded from Google Trends were used to measure investor attention and introduced in both multivariate regression as well as in panel data regression.

Regarding the structure of the paper, it consists of four sections and a conclusion. Firstly, we reviewed the most significant research in the field, we propose our research questions considering the literature gap identified. In addition, we stated the premise on which we have constructed our study. The fourth part introduces the methodology used, and the next chapter presents our result and discussions.

2. Problem Statement

Merton (1987) develops an equilibrium model for a market with inattentive investors and introduces the theory of asset recognition. He notes that familiarity with the issuing company is a pre-requisite for acquiring or collecting additional information about a particular asset. As a result, the theory of asset recognition or visibility is developed. An entire branch of literature has developed around Merton's (1987) model and theories of constrained rationality. Thus, we can distinguish, according to the variable used to measure investor attention, two categories: (i) indirect / proxy which can be expressed by extreme values of returns / trading volume (Gervais et al., 2001; Hou et al., 2008), media coverage (Huberman, Regev, 2001; Fehle et al., 2005; Barber, Odean, 2008; Fang, Peress, 2009; Kim, Meschke, 2011), advertising spending (Grullon et al., 2004; Lou, 2014), upper price limit events (Seasholes, Wu, 2007), other types of online searches (Antweriler, Frank, 2004; Moat et al., 2013) and (ii) directly through the volume of Internet searches (Da et al., 2011; Bank et al., 2011; Vlastakis, Markellos, 2012; Takeda, Wakao, 2014; Tang, Zhu, 2017; Ying et al., 2015; Bijl et al., 2016; Tang, Zhu, 2017; Weng et al., 2018; Hu et al., 2018; Nguyen, Schinckus, Nguyen, 2019; Salisu et al., 2019; Ekinci, Bulut, 2021). We noticed that most of the revised papers were studies conducted for the American or Asian capital markets, where the presence of individual investors is higher. As a result, we found a gap in the literature regarding the UK capital market, which is addressed in this paper. This research examines the importance of the attention factor in asset valuation in developed markets with a high presence of investors, confirming the theory of attention of Braber and Odean's (2008).

3. Research Questions / Aims of the Research

In conjunction with previous research, the purpose of this study is to examine and reconfirm the existence of a relationship between investor attention and capital market asset returns. The primary factor investigated is the effect of individual investors' attention on price movements. This element derives from the following research questions: is there any relationship to be confirmed between attention and returns even in a capital market with multiple institutional investors, are there any differences in the relationship between attention and returns when companies are sorted by market capitalization, and what is the correlation a low or high volume of searches and returns? Our research aim is obtained by quantifying investor's attention using three variables derived from data downloaded from Google Trends.

4. Research Methods

4.1 Data Selection

We constructed the attention index using Google Search Volume data from the Google Trends site. This open source is a Google Inc.-operated website that was launched in 2006 and provides access to the Google Search Volume (GSV/SVI) for a particular term. This data is available across multiple regions / countries, categories, and the type of search / category of object you are looking for (images, news, YouTube), and its frequency varies depending on the time period selected (weekly data for long periods, hourly data for short periods). The critical aspect of this data is that the values are not provided in their absolute form, but rather in a relative, normalized form. Each keyword produces a time series containing an entry for a particular frequency. The data used in our research are at the national level (i.e., Great Britain), as Da et al. (2011) argue that country-level data are more significant than global data. We have considered in our GSV data retrieval process the following premise: In 2016, Google Trends has made improvements to its database, as well as the way in which keyword information is made available. Consequently, when you enter a term in the search field, its feature appears, which may be one of the following: "search term" - which includes all searches for that topic, "topic" – which includes searches related to that topic, and "company" – which includes searches for the keyword as a company.

For the market data, the sample included the closing prices and trading volume of the companies that comprise the FTSE 100 Index for a five-year period, from 2015 to 2020, as obtained from the Bloomberg platform. This sample encompasses all 125 companies that have been included in the FTSE 100 Index during the review period. We chose this method to avoid survivorship bias and the potential impact of adding or removing companies, given the index's composition is adjusted quarterly (as opposed to the S&P 500, Dow Jones, or Nikkei 250).

4.2 Variables

We define the independent variable, Google search volume, in three ways, following Takeda and Wakao's methodology (2014) (Table 1). We use the methodology proposed by Da et al. (2011), Tang and Zhu (2017) to construct the index of abnormal investor attention, as the relationship between the value of SVI and returns may not accurately reflect the true effect of investor attention on market returns, as the level of SVI is relative. In this sense, an abnormal search index, called ASVI has been developed.

Table 1. Google Searches Index Variables

Name of variable	Equation
Simple Search Volume Index	$SVI_{t-j} = \ln SVI_{t-j}$
Delta Search Volume Index	$\Delta SVI_{t-j} = \ln SVI_{t-j} - \ln SVI_{t-j-1}$
Abnormal Search Volume Index	$ASVI_{i,t-j} = \ln SVI_{i,t-1} - \ln[Med(SVIi,t\text{-}1, \ldots, SVI_{i,t-7})]$

Source: Authors' work.

We sorted the portfolios into quantiles based on their market capitalization level. Thus, portfolio 1 (P1) will contain the companies with the smallest market capitalization, while portfolio 4 (P4) will contain the largest. Portfolios are composed of equally weighted. Then, we integrated our variables in the Fama and French (Fama, French, 1993) three-factor model (Equation 1).

$$R_{Pk,t} - R_{f,t} = \alpha_k + \beta_{1k}X_t + \beta_{2k}(R_{M,t} - R_{f,t}) + \beta_{3k}SMBt + \beta_{3k}HML_t + \varepsilon_{k,t} \quad (1)$$

The second part of the analysis rebuilds four portfolios in which the assets are sorted into four quantiles according to the search volume defined in Table 1, with portfolio k = 1 having the fewest searches and portfolio k = 4 having the most. Each portfolio's assets are equally weighted. If β_{1k} is significant for portfolios with a higher search volume (i.e., the Fama and French 3 factors do not fully explain the change in returns), this leads to the conclusion that returns and search volume are correlated. Further, we regressed a simple FF3 model upon the above-mentioned portfolios, in which α_k will be the abnormal search volume return as proposed by Joseph et al. (2011), Bank et al. (2011), Takeda, Wakao (2014), and Ekinci, Bulut (2021).

Due to the multidimensionality of the data (companies, years), we proposed to use a multifactorial panel data regression integrating only theabnornal volume of searches, which is similar to the methodology used by Bank et al. (2011), Takeda and Wakao (2014), Vlastakis, Markellos (2012), Ekinci, Bulut (2013), among others (2021) (Equation 2).

$$R_{Qk,t} - R_{f,t} = \alpha_k + \beta_{1k}ASVI_t + \beta_{2k}(R_{M,t} - R_{f,t}) + \beta_{3k}SMBt + \beta_{4k}HML_t + \varepsilon_{k,t} \quad (2)$$

5. Findings

5.1 Portfolios by Market Capitalization

The results for portfolios based on market capitalization show a positive and significant relationship between the volume of Google searches a week in advance (i.e., with lag j equal to 1) for portfolios that include small market capitalization companies (P1, P2) (Da et al., 2011; Takeda, Wakao, 2014; Ekinci, Bulut, 2021). The link between search volume and portfolio 3 returns is weak. This may be related to the search results. In particular, negative news can cause investors to sell their shares. Thus, the volume of searches has a significant effect on companies with low market capitalization, confirming Barber and Odean's price pressure hypothesis (2008). When the weekly search volume is compared to the weekly returns, it is observed that the relationship is positive for portfolios with low market capitalization (P1, P2) as well as portfolios with the highest capitalization. On the other hand, the relationship between Google searches and portfolio 3 (P3) returns is insignificant in this case as well, which may be due to the low level of recognition of its member companies. Additionally, for time t+1, three of the four portfolios' dynamics of the relationship between search volume and returns is positive. Thus, it is demonstrated that there is a positive correlation between the increase in yields and the subsequent week's searches.

The results varied depending on the form of the independent variable used. The results for the logarithmic search volume (SVI) and the abnormal search volume index (ASVI) are similar. Contrarily, the search volume delta shows no correlation with the excess returns on portfolios sorted by market cap at time t-j. Overall, the results for each type of search volume show a positive correlation with returns for portfolios with small market capitalization companies.

5.2 Portfolios by Search Volume

When portfolios were grouped according to search volume, the results confirmed that an increase in search volume is associated with an increase in the returns on those investments (Table 2). Increased volume would result in lower returns for all time periods (t-j, t, and t + j) for the first portfolio (P1), which contains the companies with the lowest level of searches; however, the p-value indicates that the variable SVI is not statistically significant for this portfolio. The second portfolio (P2) exhibits an increase in coefficients as the temporal characteristic of the previous portfolio's search volume increases (P1).

Table 2. Abnormal Returns

SVI				
		t-j	t	t+j
P1	αk	-0.0001	-0.0011	0.0023
	p-value	0.0865***	0.1461	0.9821
P2	αk	0.0006	-0.0005	0.0008
	p-value	0.0571***	0.5075	0.4571
P3	αk	0.0041	-0.000	0.0084
	p-value	0.0967***	0.0266**	0.0933***
P4	αk	0.0008	0.0001	0.0010
	p-value	0.0436**	0.0870***	0.0348**
ΔSVI				
		t-j	t	t+j
P1	αk	0.0003	-0.0005	0.0005
	p-value	0.7284	0.533	0.5385
P2	αk	-0.0003	-0.0011	0.0087
	p-value	0.7245	0.2012	0.9372
P3	αk	0.0001	0.0009	0.0002
	p-value	0.0305**	0.0248**	0.0407**
P4	αk	0.0012	0.0032	0.0011
	p-value	0.0216**	0.0296**	0.0240**
ASVI				
		t-j	t	t+j
P1	αk	-0.0001	-0.0011	0.0023
	p-value	0.0865***	0.1461	0.9821
P2	αk	0.0006	-0.0005	0.0008
	p-value	0.0571***	0.5075	0.4571
P3	αk	0.0041	-0.000	0.0084
	p-value	0.0967***	0.0266**	0.0933***
P4	αk	0.0008	0.0001	0.0010
	p-value	0.0436**	0.0870***	0.0348**

Note: * The null hypothesis is rejected at 1%; ** The null hypothesis is rejected at 5%.

Source: Authors' work.

The results indicate that increasing the number of searches a week in advance has a significant effect on the returns for that week, as predicted. Therefore, an increase in returns is positively correlated with an increase in search volume. Similar situations are identified and analysed for portfolios with the highest search volume. For time t, the results indicate that the assets in portfolio two will experience the highest abnormal returns associated with searches. The value of the coefficient increases from portfolio two to three, but this increase is not sustained, as the portfolio with the highest search volume has the lowest level of abnormal returns. Additionally, a decreasing trend in abnormal returns associated with search volume can be observed for time t + j. It is critical to note that the results indicate that the portfolio comprised of companies with the highest search volume has the lowest returns, which contradicts Takeda and Wakao's findings (2014). According to Ekinci and Bulut (2021), because the relationship between returns and search volume is contemporaneous, we cannot conclusively determine whether the abnormal results reflect a high level of public interest visible in Google searches or whether the high returns attract attention, causing people to search.

The final section of the analysis, which involved applying a regression to panel data, confirmed the previous findings in large part (Appendix 1). Specifically, the regression coefficient of the search volume is positive and significant for time t, indicating that a change in Google searches during the current week is associated with an increase in returns during the same period. For time t-j, the search volume is also a significant predictor of returns, with a positive relationship between them (similar results were obtained by Takeda and Wakao, 2014). On the other hand, it is observed that the search volume is associated with a decrease in returns at time t + j, but this relationship is not statistically significant. It is worth noting that in regression on panel data at time t + 1, the search volume coefficient is negative and statistically insignificant, whereas the remaining variables are positive and significant. This result is comparable to that of Bijl et al. (2016). This finding may imply that an increase in returns is associated with a decline in search volume in the coming week.

6. Conclusions

The results confirm that the impact of individual investors' attention on capital market prices must not be neglected, even if more than 50% of the market is occupied by institutional investors. First, despite the low presence of individual investors in the English stock market, the results show a significant positive relationship between investor attention and returns. According to the findings in the literature, small-cap companies will benefit from investor attention more than large-cap companies. Second, the finding of a positive relationship between prices and searches in the absence of individual investors calls into question the theory of attention's applicability. Barber and Odean (2008) hypothesize that institutional investors are rational agents who select assets differently than individual investors. Specifically, retail investors will buy assets that catch their eye, whereas institutional investors will buy assets based on fundamental value. Individual investors' anomalies, reflected in my research by abnormal returns, should be offset by institutional investors' actions. The FTSE 100's assets' visibility may be an answer to this situation. It is possible that many of the included companies are well-known, resulting in large returns. This can be considered for future studies that analyse all companies listed on the London Stock Exchange to confirm or deny the results. If this is not the case, the subject opens the door for further research into the asset's ownership structure. However, the frequency of the data depends on the time period selected. For periods longer than five years, only monthly data are available. This limited the length of the data used and its frequency. Thus, the present study's limitations allow for future research, improvement of data processing methods, and revision of model variables. However, data availability constraints are unavoidable.

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Appendix

Appendix 1. Panel data regression results

At time t-j				
Variable	**Coef.**	**Std. Error**	**t-Statistic**	**p-value**
ASVI	0.0295	0.0159	1.8542	0.0237**
MKT_RF	0.0055	0.0003	15.6322	0*
SMB	0.0022	0.0002	8.2312	0*
HML	0.0009	0.0002	3.8064	0.0001*
C	0.0001	0.0003	0.4097	0.682
At time t-j				
ASVI	0.0769	0.0151	5.0772	0*
MKT_RF	0.0014	0.0003	3.9337	0.0001*
SMB	0.0025	0.0006	4.0194	0.0001*
HML	0.0008	0.0005	1.5096	0.1312
C	0.0007	0.0007	1.0180	0.3087
At time t-j				
ASVI	-0.0120	0.0159	-0.7544	0.4506
MKT_RF	0.0055	0.0003	15.7199	0*
SMB	0.0022	0.0002	8.2222	0*
HML	0.0000	0.0002	3.6556	0.0003*
C	1.28E-05	0.0003	0.0407	0.9675

Source: Authors' work.