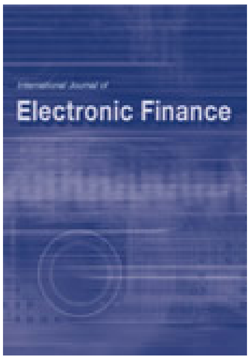

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Company online presence and its effect on stock returns

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Company online presence and its effect on stock returns

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Abstract: This paper investigates the relationship between stock prices and the online presence of companies. Mainly, we study the effect of the online presence of a company on its subsequent stock returns. Moreover, we examine the impact of companies' engagement efforts and the popularity of their search-engine keywords on their stock returns. Based on the companies listed on the Dow Jones industrial average index, results suggest that stock returns are impacted by a change in online presence, as measured by search volumes. Nevertheless, the online engagement efforts show no significant relationship with the stock returns.

Keywords: online presence; engagement efforts; stock returns; VAR model.

JEL codes: G14, G41, C32.

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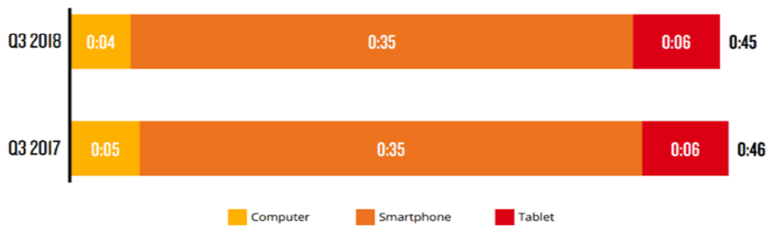
1 Introduction

Social media sparks worldly conversations that have an influence beyond its platforms. It is regarded as the most revolutionary change brought about by the 21st century. The speed and ease of information dissemination brought to fruition a new era of research solely focused on studying people's reactions to that information. Media has overturned financial markets and does not just play a reactionary part, but also a justificatory one. Whether by examining the contents of social media posts or its subsequent reactions, several researchers are leading the way in understanding the effects social media has had and will continue to have on differing issues in various subjects.

To understand the vitality of social media, we must look at its growth in the past years. The first website described as a social media platform was six degrees in 1997, with features such as friend lists and instant messaging. However, it shut down shortly after, as there were not enough internet users to keep it running. Generally, less than 2% of the world population were using the internet before 1999 (Standage, 2014). In 2002, Friendster gained three million users; consequently, other companies became interested in expanding in the social aspect of the internet. Myspace entered with apparent success, gaining most users and being the top choice in online advertising. However, that success was short-lived in 2008, and Facebook surpassed it in terms of global users. In addition, Facebook opened registration to the public and quickly became the top advertiser due to its unique advertising algorithm. The algorithm for advertisers allows for interest-based advertisements, which made the page advertisements lower and the clickthrough numbers higher, thus, satisfying both users and advertisers. In 2007, Twitter was popularised due to its simple interface without a suite of social media features. Twitter also began a new era in understanding user-generated content, with the introduction of the hashtag in 2007. Soon after, the hashtag was turned into a hyperlink in 2008, making it easier for users to group under the same topics and read about them. In 2010, hashtags were turned into trending pages and expanded to other social networking sites such as Facebook, Instagram, LinkedIn, and others. The hashtag is now the most popular way to engage consumers and increase a company's social footprint. It is also considered the fastest way to source news and information about any given topic.

To look at how social media platforms have been performing in recent times, Nielsen (2016) reports that 'nearly 4 in 5 active internet users visit social networks and blogs'. Edison Research (2020) found that the number of Americans using social media sites has more than doubled since 2009 (from 21% to 79% of the population aged 12 and older). The report also noted that the most popular of those social media sites in 2019 are, in order of popularity, Facebook, Instagram, and Twitter. Facebook and Twitter are more popular amongst the older segment (ages 25–45), and Instagram is the only social media site growing in popularity due to its younger reach (ages 12–25). To put numbers to figures, Nielsen (2018) illustrates the number of minute's adult Americans (ages 18+) spend on social networking sites in Figure 1.

Figure 1 Number of minutes spent on social networking (see online version for colours)



Source: Nielson (2018)

On the scholarly side, early research focused on social media as a viable source of consumer/shareholder information, then as a winning brand-building strategy. We now know that social media is a powerful tool in analysing or expanding word of mouth, creating educated/highly aware consumers, leading/understanding consumer sentiment, and as an opportunity for engagement (Nielsen, 2018). Later, research on user-generated content took centre-stage as big data were easier to collect, organise, and analyse using new methods and software. These new methods allowed companies to gain 'unprecedented intelligence on consumer opinion, customer needs, and recognising new business opportunities' [Chen et al., (2012), p.1185]. One of the best examples in business-centred research using big data is the novel paper of Chen et al. (2012) that studies people's interactions in blogs, where the authors created a framework for automated collection and analysis of blog interactions between users. Chen et al. (2012) found multiple patterns in different blog applications. These patterns were used to change business processes relating to delivery and marketing, which eventually increased sales and consumer satisfaction (Chau and Xu, 2012). Some researchers have even toyed with and succeeded in proving the predictive nature of mass user-generated content, such as in cases where increasing Google searches predicted the outbreak of flu (Ginsberg et al., 2009), or positive general sentiments from Twitter users predicted higher stock market prices (Bollen et al., 2011).

As internet searches, applications, and social media are primary sources of news and information. Therefore, we need to understand the effect the internet has on investor behaviour or stock market behaviour. Even though a great deal of research studied the overall online sentiment (Bollen et al., 2011) and company-specific online effect on stock prices and returns (Da et al., 2011), they are still missing the quantifiable factors that indicate peoples' engagement with the company as detailed by digital marketeers. This paper aims to prove the existence of new media's positive impact on investor behaviour by studying the various relationships of social media and Google features with stock returns.

The objective of this research is to investigate the relationships between social media popularity, Google search keyword volumes, and a company's stock returns and trading volumes. To study the financial market, we look at the effect the public-generated online content has on that market. The foundation of this speculated effect relies on online users being a proxy for market perception or investor behaviour. To understand these relationships, we will answer two fundamental questions.

1 Does the level of the online presence of a company affect its subsequent stock returns?

2 Do company engagement efforts and the popularity of its search-engine keywords affect its stock returns?

The remainder of the paper is structured as follows: Section 2 reviews the literature on stock market behaviour, search engines, and social media marketing. Section 3 describes the employed methodology. Section 4 analyses and interprets the results. Section 5 concludes the paper.

2 Literature review

This section contains an overview of prior research on stock market behaviour and attempts made to predict it, as well as a summary of the most prominent digital marketing techniques and the online factors used in predicting stock information. A summary table of the most relevant papers is included at the end of this section.

2.1 Stock market behaviour

The study of possible predictability of the stock market has been a popular topic since the development of computational tools in the 1960s. Indeed, these tools allow for collecting and analysing hundreds of stocks quickly and with less effort. Early research on stock market behaviour states that predictability is mainly concerned with the random walk theory and the efficient market hypothesis (EMH) (Cootner, 1970). Investors are seeking information beforehand and act on that information to profit from their investments. This rational action leads to the hypothesis that the market price should reflect the real price. It is highly unlikely that stocks are under/overvalued unless a riskier investment were to be made with less available information (Fama and Macbeth, 1973). Since the influential information is mainly unpredictable, stock market prices may also follow in random strides, as Fama and French (1992) argued in the random walk theory, where price movement cannot be predicted with more than 50% accuracy (Qian and Rasheed, 2006).

Further analyses of random walk theory and EMH are conducted in behavioural finance, which note the emotional roles played in investor decision-making, especially in riskier investments (BenSaïda, 2017). One of these factors is the general social mood and its effect on the stock market (Bessembinder et al., 2006; Bollen et al., 2011). The studies in behavioural finance agree that investors act on emotions, and predicting these emotions is the best way to anticipate the eventual stock market behaviour. Many proxies for sentiment can be used in that prediction such as the negative or positive mood of tweets (Bollen et al., 2011).

Whereas the technical advances in big data, analytics, and computing since the 1960s are astonishing, financial analysts and economists understand only a small part of the complex dynamics of stock markets. The financial literature classifies the relevant research variables into three categories:

1. variables relating to company actions, such as revenue increase or announcements
2. variables reflecting alternative investment opportunities, such as real estate index
3. economic/political/social indicators, such as inflation/presidential elections/social strikes.

Our research adopts the first group of variables because it is largely studied by the literature on stock market behaviours. If the nature of company actions or announcements affects the investor's behaviour, then a company could alter its future statements to suit the desired investor's reactions.

2.2 *Presence and engagement online*

Digital marketing concerns the use of online channels to advertise or engage with a specific audience, with the most popular subchannels used by professionals being search engine marketing and social media marketing.

2.2.1 *Search engine marketing*

Charlesworth (2018, p.63) describes search engines as 'the portal – front door – to the internet' because they are the first place a person looks in for insight into a topic, product, or service. For companies, the higher their product or service is ranked in the search engine results page (SERP), the higher the likelihood people will see it and choose it. The rank criteria for each search engine in Table 1 contain some changes in Google's algorithm. The study of implementing the prominent criteria is called search engine optimisation (SEO).

Table 1 Google's rank algorithm changes

Google's rank algorithm changes	
'In The News' Box October 2014	How many times it was mentioned on news websites or trending on social media sites.
AdWords Shake-up February 23, 2016	Paid advertisement to Google to rank the selected link. Higher on searches using specific keywords.
RankBrain October 26, 2015	Rank based on correctly linked keywords, such as Apple Inc. or iPhone instead of just apple for the fruit.

Note: This table reports the changes of Google's algorithm to find the rank criteria.

Companies can do three things in attempting SEO:

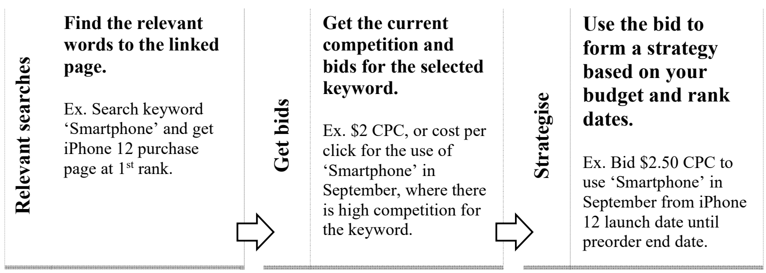
1 pay the search engine provider to increase the rank via advertising (Rutz and Trusov, 2011)

2 use social media to increase interest and mentions of company-relevant keywords, ultimately increasing the rank (Zhang and Cabage, 2016)

3 perform research on the appropriate keywords used by people in searching for the company or its products (Di et al., 2010).

The most popular among SEO means is keyword research because of its low cost and sustained benefits. Keyword finding software tools are available for free online and linked to a specific web address for more detailed responses. A simple example of keyword research and implementation using Google keyword planner is outlined in Figure 2.

Figure 2 Keyword search and implementation using Google



2.2.2 Social media marketing

Social media refers to the internet or mobile-based platforms that allow for user interactions (Chaffey and Smith, 2017). The most important feature of social media is that it enables the creation of user generated content (UGC), which is the most insightful data source for consumer opinions. Companies who use consumer surveys after purchase get only a fraction of the data available online waiting to be analysed (Chau and Xu, 2012; Chen et al., 2012). Social media marketing is the study of using those platforms as additional marketing channels (Geyskens et al., 2002). The Chartered Institute for Public Relations (CIPR) social media panel, available at https://www.cipr.co.uk, describes the process as 'monitoring and facilitating customer to customer interaction, participation, and sharing through digital media to encourage positive engagement with a company and its brands leading to commercial value'. The metrics widely used in academia to study social media effects are classified into four categories:

1 the type and a general sentiment of the content

2 the volume of deliveries, or views

3 response to the content, or user engagement

4 user properties, such as location (McDonald et al., 2014).

In a more practical sense, digital marketeers study more detailed indicators to quantify the effect, both on the brand level and the financial level, as shown in Table 2.

Table 2 Linkages between brand level and financial level

Indicator	*Explanation*
Engagement (1)	Increase in likes and followers, forwarded or retweeted posts, and activity of current followers.
Engagement (2)	Increase in company website activity due to clickthrough from social media.
Share of voice	The company's added engagement value compared to competitors.
Target market	Increase in target brand awareness or change of perception.
Purchase intent	Increase in buyers or potential buyers.
Brand status	An increase in brand recognition, consumer loyalty, or other products offered awareness.
Market share	Increase in brand/product market share or decrease in competitor sales.
Revenue (1)	Sales increase/decrease for the promoted product.
Revenue (2)	Sales specifically generated from the social media clickthrough.
Marketing expenses	Campaign total cost. It can be compared to other channel costs.
Other expenses	Other campaign costs, such as the agency cost for data collection.
Headcount	How many internal/external personnel were involved in the management of the campaign.
Investor's relations	Increase in positive stakeholder's perception, stock price, or investor's perception.

Note: This table explains the indicators usually employed to quantify the effect on the brand level and financial level as reported in the literature.

Source: Cohen (2010), Aspara and Chakravarti (2015) and Charlesworth (2018)

This paper focuses on the highlighted indicators in Table 2 to proxy the investor attention gained from social media and finds the effect a successful social media campaign has on stock returns. Namely, we focus on engagement (1), marketing expenses, and investor relations.

2.3 Stock market prediction

In terms of social media effects on financial drivers, Srinivasan and Hanssens (2009) found that a higher social media presence leads to higher revenue, firm value, stock price, and stock returns. However, the same drivers' effect on investors' behaviour remains ambiguous. In more detail, the effects social media has on financial markets are studied under the guise of investor sentiment theories (Baker and Wurgler, 2006) and the information asymmetry theories (Blankespoor et al., 2012; Peress, 2014). Delving deeper into social media as a data source, numerous research use data from popular media, such as the news (Tetlock, 2007), Twitter (Bollen et al., 2011), Wikipedia, and Google trends (Preis et al., 2013) with varying levels of success.

Table 3 Studies on stock market returns

Title	*Authors/year*	*Journal*	*Studied variables*	*Main results*
Stock market prediction with multiple classifiers	Qian and Rasheed (2006)	Applied Intelligence	*Dow Jones index	Increased the theoretical predictability of stock market behaviour from 50% up to 65%.
Predictable behaviour, profits, and attention.	Seasholes and Wu (2007)	Journal of Empirical Finance	*Price limit events *Returns *Trading volume *News	Upper price limit events cause a short-term price increase followed by reversion.
Giving content to investor sentiment: the role of media in the stock market.	Tetlock (2007)	The Journal of Finance	*News *Sentiment *Trading volume	Media pessimism predicts downward pressure on market prices followed by a reversion.
Advertising, attention, and stock returns.	Chemmanur and Yan (2019)	Quarterly Journal of Finance	*Advertising expense *Trading volume	Greater advertising increases stock returns in the advertising year, followed by a reversion in the next year.
The determinants of international investment and attention allocation: using internet search query data.	Mondria et al. (2010)	Journal of International Economics	*Search engine volume *Clickthrough rate	Global news bias to a region highly affects investor attention of that region's stocks.
Twitter mood predicts the stock market.	Bollen et al. (2011)	Journal of Computational Science	*Tweet content *Tweet volume *Dow Jones index	Increased prediction accuracy to 86.7%, and lowered error by 6% in the Dow Jones index.
In search of attention	Da et al. (2011)	The Journal of Finance	*Search engine volume *Twitter volume *News volume	Increased stock prices in the following two weeks, and reversion within the year.
Market-wide attention, trading, and stock returns	Yuan (2015)	Journal of Financial Economics	*News	Market-wide attention events lead to aggressive selling, lower stock prices, and lower returns by 19 basis points following the event.
Selective publicity and stock prices	Solomon (2012)	The Journal of Finance	*News	Investor relations firms' news increase investor attention but lower stock returns.
Attracting investor attention through advertising	Lou (2014)	Review of Financial Studies	*Advertising expense	Short-term increased stock returns, followed by reversion.
The media and the diffusion of information in financial markets: evidence from newspaper strikes.	Peress (2014)	The Journal of Finance	*News *Trading volume *Stock returns	News strikes cause lower trading volume and less volatility in stock returns.
Investors' reactions to company advertisements: the persuasive effect of product-featuring ads.	Aspara and Chakravarti (2015)	European Journal of Marketing	*Volume of product ads	The increase in a product featuring ads increases investor attention and perception of stock returns.

Note: This table exhibits the relevant studies on the prediction of stock market returns.

Several studies conclude that the company online advertising increases its stock returns for a short period of time, followed by a reversion. For instance, Seaholes and Wu (2007), Tetlock (2007), Da et al. (2011), Lou (2014), and Chemmanur and Yan (2019) agree that advertising, investor attention, and media increase stock returns in the short term with an eventual price reversal within the year. Moreover, Da et al. (2011) show that search frequency in Google captures investor attention in a more timely fashion. Alternatively, Bollen et al. (2011) find that Twitter mood accurately predicts the daily changes in DJIA by 86.7%.

In recent papers, Chai et al. (2021), Cziraki et al. (2021), and Rakowski et al. (2021) investigate the effect of Internet search intensity and social media activity on trading activity and stock returns. The main results show that attention influences stock trading activity and drives higher returns during a short period and a reversal over a long period.

Table 3 summarises some relevant studies, where online-based company data and stock returns are studied and found a short-term significant positive impact.

2.4 Research gap

Only a few studies relate company-led online advertising with the stock market behaviour. Indeed, most researchers cited in Table 3 focus on numerical measures, such as the number of mentions/hashtags of the company or its main products by users. Our paper pushes the analysis further and investigates the interactive values, such as campaign-led retweets and likes.

Furthermore, there is insufficient empirical research on the success of digital marketing techniques, such as SEO and rank, especially when inspiring a positive stock market reaction. SEO is studied in digital marketing for securing a product or company keywords in a top-ranking spot in Google searches or Amazon. Rank can also be purchased or increased with higher clickthrough from social media and integrating online with traditional marketing initiatives.

Marketeers and financial analysts need quantifiable research to determine which variables in online presence affect stock returns and to what degree. Some studies are conducted on using online company data as a measure of investor increased interest. Nevertheless, to the best of our knowledge, there is no research detailing the core values that make for abnormal online engagement (like retweets) and their relationships with changes in stock returns.

3 Methodology

This section develops the theoretical framework for the study and the detailed explanation and reasoning for the used variables.

3.1 Framework

Table 4 presents the conceptual framework segmented into parts that describe the collected variables, the adjusted control variables (CV), and their applications to find the effects on stock returns.

In the abovementioned framework in Table 4, the first column has the IV included in this study, segmented into search engine and social media related variables. The second column contains the CV based on their significance in the previous relevant research. The third column is the dependent variable (DV), which refers to the abnormal stock returns. Our collected sample includes the 30 companies listed on the Dow Jones industrial average (DJIA) for the year 2020, in alignment with Qian and Rasheed (2006), Tetlock (2007), Bollen et al. (2011), Peress (2014), Yuan (2015), and Cziraki et al. (2021).

Table 4 Presentation of the variables

IV	*Search engine: Google*	*CV*	*Control variables*	*DV*	*Stock returns*
	Company search volume		Market capitalisation		Abnormal returns from the portfolio
	Keyword search volume		Abnormal trading turnover		
	Clickthrough volume		Advertising expense		
	Repeat search volume		News		
	Social media				
	Twitter engagement				
	Twitter reach				
	Facebook engagement				
	Facebook reach				

Note: This table presents the independent variables (IV), the control variables (CV), and the dependent variables (DV).

3.2 Research variables

Detailed variables are explained in this section, along with the rationale behind their usage in our model.

1 The selected search engine is Google because it is the top choice for US users (Edison Research, 2020). The data are collected from Google trends and Google analytics.

- Company name/ticker search volume (*SV*) is the number of searches made using company name or ticker. We adjust this variable to remove words of double meaning, such as 'apple', meaning the fruit or company (Da et al., 2011).
- Keyword search volume (*KSV*) is similar to the above variable SV, but only searches were made using relevant keywords, such as iPhone for Apple Inc. (Da et al., 2011).
- Total search volume (*TSV*) is the total searches made in relation to the company.
- Clicks per search (*CPS*) is the average number of clickthroughs from all relevant searches multiplied by the dollar value per click to analyse the engagement of people searching, calculated with SV or KSV.
- Returns per search (*RPS*) is the average number of repeated searches used to analyse the interest of searchers, calculated with SV or KSV.

2 The selected social media are Facebook and Twitter, as they are preferred by adults and often follow recent or trending events (Edison Research, 2020). The data are collected from Social Blade (SocialBlade.com – YouTube, Twitch, Twitter, and Instagram, 2022).

- Twitter reach (*TR*) is the number of followers the company has on Twitter (Prokofieva, 2015).
- Twitter engagement (*TE*) is the number of retweets and likes the company account made by mentioning other Twitter accounts (Blankespoor et al., 2012).
- Facebook reach (*FBR*) is the number of likes a company's page has on Facebook.
- Facebook engagement (*FBE*) is the average number of users interacting in the page community, and it is sourced from the company's Facebook page under 'people talking about this'.

3 The CV is used to mimic prior successes in the literature. The data are extracted from Yahoo Finance (https://finance.yahoo.com/).

- Abnormal volume turnover (*AbnVol*) is the adjusted volume turnover for each company, i.e., daily trading volume scaled by daily market capitalisation (Gervais et al., 2001; Barber and Odean, 2007; Chordia et al., 2007).
- News and headlines (*News*) is a dummy variable quantifying the existence of articles mentioned in the Zacks Investment Research News Archive (2022) archive (Barber and Odean, 2007; Yuan, 2015).
- Market capitalisation (*MktCap*) is a measure of size and an investor attention control variable specifically.
- Average stock price (*AvgPrice*) is a measure of a general market tendency.
- Advertising expense/sales ratio (*ADExp*) (Grullon et al., 2004; Lou, 2014; Chemmanur and Yan, 2019).
- Cost per click (*CPC*) is a control variable for search volume variations and selected keyword relevancy.

4 Abnormal stock returns (*AbnRet*) is the independent variable, which represents the desired prediction by shareholders (Srinivasan and Hanssens, 2009). The data are extracted from Yahoo Finance (https://finance.yahoo.com/).

3.3 The model

Our study investigates the following two hypotheses.

H1 Higher online presence in a company increases its stock market returns.

H2 Company engagement efforts and search engine keyword choices are directly related to stock market returns.

The Hypothesis H1 is formally investigated through equation (1), where we employ a vector autoregressive (VAR) model (regression H1, henceforth). The model contains five dependent variables (DV) in alignment with Da et al. (2011). First, we run an unrestricted VAR model using the variables specified in Table 4 to find the appropriate lag-order that minimises the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Next, we perform a heteroskedasticity test to determine the presence of serial autocorrelation. Then, we conduct a Granger causality test to reduce the lag-order if the causality of one of the elements was insignificant. Finally, we estimate the VAR model with the optimal lag-order p (Wooldridge, 2019).

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + Bx_t + e_t \tag{1}$$

where y_t is a five-dimensional random vector of DV, such that:

$$y_t = \begin{pmatrix} AbnRet_t \\ \ln AbnVol_t \\ TSV_t \\ News_t \\ ADExp_t \end{pmatrix}$$

and x_t is a three-dimensional random vector of exogenous variables, such that:

$$x_t = \begin{pmatrix} AvgPrice_t \\ \ln MktCap_t \\ CPC_t \end{pmatrix}$$

And e_t is a vector of residuals.

The coefficients to be estimated are the (5 × 1) vector of intercepts c, the (5 × 5) autoregressive matrices A_i for $i = 1, \cdots, p$, and the (5 × 3) matrix B for exogenous variables.

The Hypothesis H2 is investigated through equation (2), where we employ a multiple regression analysis (regression H2, henceforth). The model is an equation of the endogenous variable AbnRet and considering several exogenous variables. First, we perform a correlation test to determine the relationships between variables and their significances. Next, we run a regression with the weighted least squares (WLS) method to reduce the standard errors in the residuals caused by autocorrelation. Finally, we conduct a Granger causality test to determine the causal relationship between variables (Wooldridge, 2019).

$$\begin{aligned} AbnRwet_t = c + c_1 \times AbnVol_t + c_2 \times CPS_{KSV_t} + c_3 \times CPS_{SV_t} + c_4 \times FBE_t + c_5 \\ \times FBR_t + c_6 \times RPS_{KSV_t} + c_7 \times RPS_{SV_t} + c_8 \times TE_t + c_9 \times TR_t + \varepsilon_t \end{aligned} \tag{2}$$

4 Results and discussion

This section analyses and interprets the results from both regressions of equations (1) and (2).

4.1 Data and descriptive statistics

The collected data corresponds to the weekly average for 30 companies, constituents of the Dow Jones index, from March 24, 2017, to March 24, 2020. Table 5 illustrates the descriptive statistics of the variables listed in the regression H1 from equation (1). Starting from March 2020, the COVID-19 health pandemic caused the variable measures to divert slowly. An example of that impact is the *MktCap* with negative skewness, implying that the distribution has a fat left-tail.

Table 5 Descriptive statistics of the variables under regression H1

	AbnRet	*AbnVol*	*ADExp*	*MktCap*	*CPC*	*TSV*
	Abnormal returns	*Abnormal volume*	*Ad expense ratio*	*Market capitalisation*	*Cost per click*	*Search volume*
Mean	0.34%	0.17%	14.85%	2.29E+11	0.0031	6.66E+6
Median	0.26%	0.11%	15.86%	2.02E+11	0.0569	7.02E+5
Maximum	11.86%	19.85%	37.75%	1.42E+12	0.0948	7.91E+7
Minimum	0.13%	0.05%	7.93%	1.01E+11	2.84E-2	0
Std. dev.	0. 3%	0.2%	1.1%	2.82E+10	0.306	1.24E+6
Skewness	2.178	3.398	0.275	–0.087	13.240	1.336
Kurtosis	12.476	19.323	2.953	3.158	43.128	7.585
Jarque-Bera	180,425*	360,659*	3,798*	11,413*	1,233*	71,491*

Note: This table reports the descriptive statistics of the variables used in the regression H1 from equation (1).
*The Jarque-Bera statistic rejects normality at the 5% confidence level.

Table 6 reports the descriptive statistics of the remaining variables of the regression H2 from equation (2).

4.2 Regression H1

Lag-order selection of the unrestricted VAR model in equation (1) is based on the minimum of AIC and BIC. We set a maximum lag-length of $p = 12$ and we perform the VAR regressions.[1] The optimal lag-order is 1.

The results of the autocorrelation of the residuals are presented in Table 7. We deduce that the residuals from the VAR estimation are autocorrelated. Consequently, we employ an appropriate WLS method for the final VAR estimation.

In the next step, we conduct a Granger causality test to determine if the lag-length or some other values need to be excluded from the model in equation (1). Table 8 reports the results, where the DV can be caused by all the IV combined.

Table 9 depicts the estimation results of the VAR model in equation (1) with optimal lag-order $p = 1$. The findings show that the abnormal returns *AbnRet* and the abnormal volume *AbnVol* are impacted by all the variables at 20% significance level, except for ADExp and CPC. While the average price *AvgPrice* and News have an inverse relationship with *AbnRet*, the abnormal volume *AbnVol* has an inverse relationship with *AbnRet*, *News*, and *MktCap*. The search volume TSV is impacted by all other variables except the ad expense ratio *ADExp*, and has an inverse relationship with *MktCap*. Moreover, *News* has a negative relationship with all variables except for *AbnRet* and *MktCap*. Additionally, *ADExp* has no significant relationships even at the 20% level. Finally, the R^2 values are all above 75% except for the *AbnVol* equation, which indicates good fitting results.

Table 6 Descriptive statistics of the variables under regression H2

	CPS_{KSV}	CPS_{SV}	*FBE*	*FBR*
	Keywords clicks	*Name clicks*	*Facebook engagement*	*Facebook reach*
Mean	1,167,931	580,002.2	49,252.38	15,249,848
Median	647,424	219,681	7,309	4,473,888
Maximum	11,015,277	3,547,951	539,134	1.07E+8
Minimum	10,008	4,064	171	18,105
Std. Dev.	2,128,606	836,044.9	117,972.1	25,885,684
Skewness	3.710	2.178	3.246	2.252
Kurtosis	17.22	7.449	12.75	7.533
Jarque-Bera	310.96*	46.850*	165.82*	49.336*
	TE	*TR*	RR_{KSV}	RR_{SV}
	Keyword return search	*Name return search*	*Twitter engagement*	*Twitter reach*
Mean	9,582.41	1,775,209	879,265	1,106,673
Median	70	579,601	202,193.6	150,113.4
Maximum	271,833	8,878,316	4,092,510	11,043,699
Minimum	0	19,597	26,775.39	3,534.475
Std. Dev.	50,440.4	2,494,494	1,264,406	2,450,360
Skewness	5.102	1.719	1.562	3.123
Kurtosis	27.031	4.778	3.950	12.064
Jarque-Bera	823.57*	18.099*	12.882*	146.42*

Notes: This table reports the descriptive statistics of the variables used in the regression H2 from equation (2).
*The Jarque-Bera statistic rejects normality at the 5% confidence level.

All IV show a relationship with stock returns, except for advertising expense (*ADExp*) and the *CPC* ratios. The exception of *ADExp* and CPC is most probably due to their relationship with the control variable market capitalisation (*MktCap*), since advertising and click costs are repetitive measures of how much a company spends on promoting its brand/s, and generally, the bigger the company's *MktCap*, the higher the ratios (Srinivasan and Hanssens, 2009). Moreover, the News variable has a negative coefficient, which implies a negative impact on abnormal returns. This is most probably due to the reactive nature of the news source selected (Zacks Investment Research News Archive, 2022), unlike the news source used in Da et al. (2011).

The *TSV* is negatively impacted by *MktCap*, which could be explained by the lack of SEO efforts in the larger portion of the 30 companies. These results show progress in proving the hypothesis that *TSV* increases stock market returns, yet those responses are not detailed.

Table 7 Autocorrelation of the residuals

DV	*R2*	*F(240, 22378)*	*p-value*	$\chi^2(240)$	*p-value*
res1*res1	0.58	130.3	0	13,185	0
res2*res2	0.61	143.2	0	13,701	0
res3*res3	0.27	33.95	0	6,037.6	0
res4*res4	0.18	20.50	0	4,077.2	0
res5*res5	0.17	19.36	0	3,889.4	0
res2*res1	0.58	130.8	0	13,206	0
res3*res1	0.57	122.6	0	12,848	0
res3*res2	0.57	122.0	0	12,822	0
res4*res1	0.27	34.53	0	6,112.1	0
res4*res2	0.39	58.65	0	8,734.2	0
res4*res3	0.25	31.84	0	5,757.3	0
res5*res1	0.09	8.668	0	1,924.0	0
res5*res2	0.08	8.108	0	1,809.6	0
res5*res3	0.08	8.030	0	1,793.5	0
res5*res4	0.07	7.067	0	1,593.5	0

Note: This table reports the autocorrelation results of the VAR model residuals.

Table 8 Relationship between dependent and IV

Dependent		*Chi-square*	*dof*	*p-value*
AbnRet	Abnormal returns	7,375.3	104	0
AbnVol	Abnormal volume	13,753	104	0
TSV	Search volume	6,313.7	104	0
News	News	2,979.3	104	0
ADExp	Ad expense ratio	4,850.7	104	0

Notes: This table reports the Granger causality test between the variables under regression H1. The term *dof* stands for degrees-of-freedom.

To understand the effect of the *TSV*, we illustrate the impulse response function of the abnormal returns to the volatility of *TSV*. Figure 3 illustrates the responses per company as noted by their tickers. The overwhelming shared line between all companies is outlined in green, which clearly shows that the response of stock returns to search volume is positive in the first few periods, then drops in the following periods, due to its reversion to its usual returns, and becomes eventually stable.

Finally, the responses of abnormal returns to search volume answer question 1 and prove the Hypothesis H1 that 'higher online presence in a company increases its stock market returns' for a short period of time, in alignment with Da et al. (2011), Chai et al. (2021), Cziraki et al. (2021), and Rakowski et al. (2021), among others.

4.3 Regression H2

We estimate the regression H2 in equation (2) with the WLS method, where the abnormal returns *AbnRet* is the dependent variable. Table 10 presents the correlation matrix between variables. The results show significant correlations between CPS_{KSV}/CPS_{SV}, CPS_{KSV}/RR_{SV}, CPS_{KSV}/TR, CPS_{SV}/RR_{SV}, FBE/RR_{SV}, FBE/TE, FBE/TR, FBR/TR, RRK_{SV}/TR, and TE/TR.

Table 9 Estimation results under H1

Equation		*AbnRet*	*ln(AbnVol)*	*TSV*	*News*	*ADExp*
c	Intercept	0.0132*	–0.0011	–0.0009	0.0563***	0.0037
		(0.0812)	(0.1678)	(0.1588)	(0.0000)	(0.2182)
AbnRet	Abnormal returns	0.0287*	–0.0021	–0.0005	0.0001	–0.0001
		(0.0760)	(0.1492)	(0.1320)	(0.1659)	(0.1890)
ln(AbnVol)	Abnormal volume	0.0191	–0.0715*	0.0010	–0.0012	0.0004
		(0.1491)	(0.0682)	(0.1396)	(0.1777)	(0.2823)
TSV	Search volume	0.0028	0.0003	0.0363	–0.0002	0.0000
		(0.1138)	(0.1547)	(0.2032)	(0.1497)	(0.2637)
News	News	–0.0011	–0.0020	–0.0010	–0.0032	–0.0001
		(0.1457)	(0.1531)	(0.1686)	(0.1304)	(0.2064)
ADExp	Ad expense ratio	0.0009	0.0006	0.0005	0.0005	–0.0011
		(0.2109)	(0.2103)	(0.2027)	(0.2141)	(0.4250)
AvgPrice	Average price	–0.8777*	0.1226*	0.4632	–0.0970	–0.1010
		(0.0668)	(0.0690)	(0.1138)	(0.1098)	(0.2552)
ln(*MktCap*)	Market capitalisation	0.8614*	–0.1321*	–0.4558**	0.0966	0.0994
		(0.0760)	(0.0776)	(0.0335)	(0.1210)	(0.2170)
CPC	Cost per click	0.0038	0.0087	0.0205	–0.0001	–0.0002
		(0.4733)	(0.5876)	(0.1262)	(0.6691)	(0.9017)
R^2		*80.02%*	*26.22%*	*95.42%*	*75.54%*	*97.91%*

Notes: This table reports the VAR model estimation results under H1 in equation (1) with optimal lag-order *p* = 1. Numbers in parentheses are the p-values of the estimated coefficients.
*, **, and ***denote significance at the 10%, 5%, and 1% confidence levels, respectively.

The estimation output of equation (2) is presented in Table 11. All coefficients are insignificant, except for CPS_{SV}, which negatively affects the abnormal returns *AbnRet*.

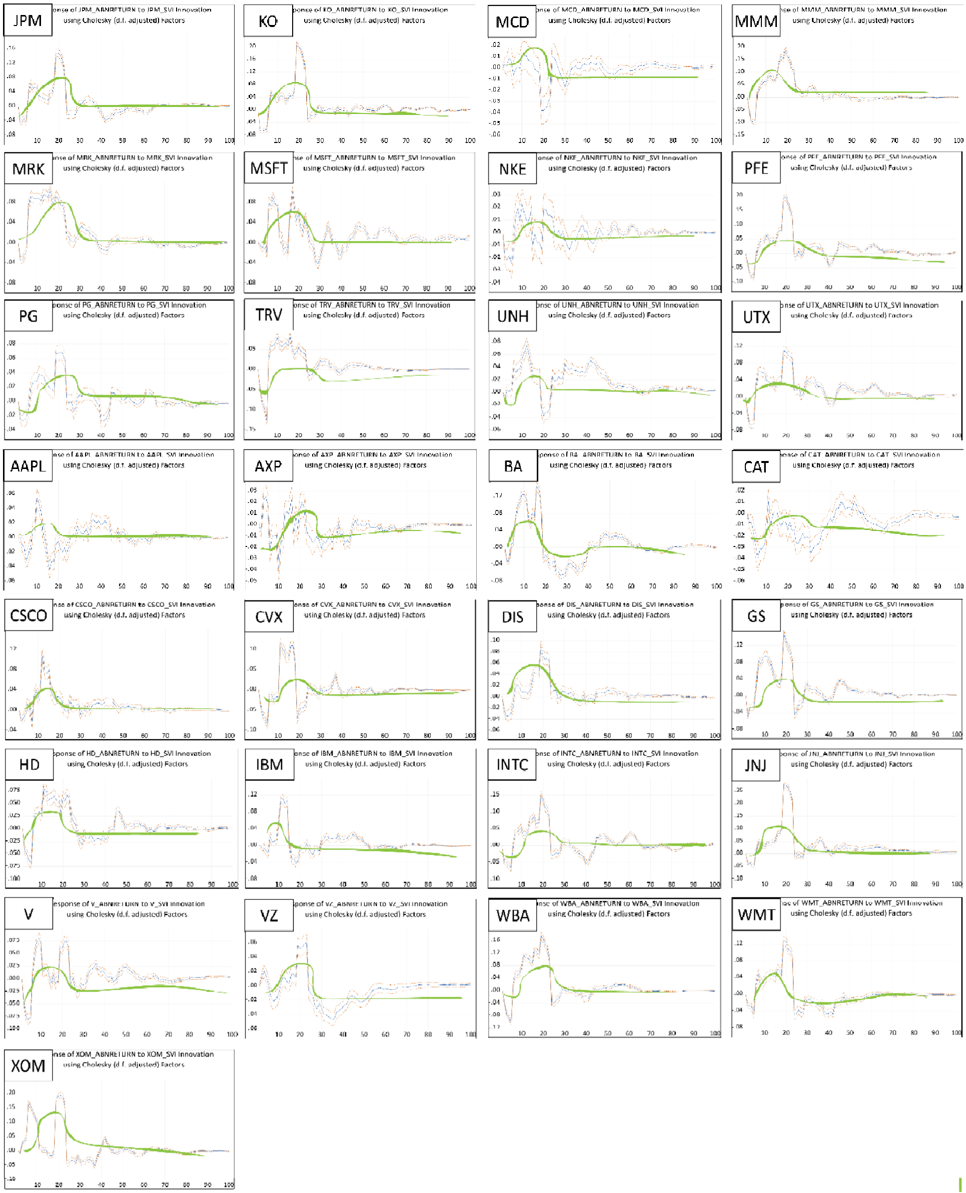
Table 10 Correlation analysis under H2

Correlation	*AbnRet*	*AbnVol*	CPS_{KSV}	CPS_{SV}	*FBE*	*FBR*	RR_{KSV}	RR_{SV}	*TE*	*TR*
	Abnormal returns	*Abnormal volume*	*Keywords clicks*	*Name clicks*	*Facebook engagement*	*Facebook reach*	*Keyword return search*	*Name return search*	*Twitter engagement*	*Twitter reach*
AbnRet	1.0000									

AbnVol	0.2278	1.0000								
	(0.2346)	--------								
CPSKSV	–0.2488	–0.1842	1.0000							
	(0.1931)	(0.3388)	--------							
CPSSV	–0.0035	–0.0973	0.4311**	1.0000						
	(0.9855)	(0.6156)	(0.0196)	--------						
FBE	0.1877	–0.0433	–0.0760	–0.0193	1.0000					
	(0.3296)	(0.8234)	(0.6950)	(0.9210)	--------					
FBR	–0.0988	–0.1275	–0.0125	–0.0225	0.2838	1.0000				
	(0.6102)	(0.5099)	(0.9487)	(0.9078)	(0.1357)	--------				
RRKSV	–0.0092	–0.1733	0.6177***	0.3103	0.1340	0.1542	1.0000			
	(0.9621)	(0.3686)	(0.0004)	(0.1014)	(0.4884)	(0.4245)	--------			
RRSV	0.0270	0.0013	0.0607	0.3283*	0.4409**	0.1380	0.2266	1.0000		
	(0.8893)	(0.9948)	(0.7546)	(0.0820)	(0.0167)	(0.4752)	(0.2372)	--------		
TE	0.1334	–0.1117	–0.0944	–0.1129	0.8006***	0.1418	–0.0952	0.0001	1.0000	
	(0.4903)	(0.5641)	(0.6262)	(0.5599)	(0.0000)	(0.4630)	(0.6233)	(0.9998)	--------	
TR	0.0016	–0.212	0.518***	0.1428	0.487***	0.515***	0.547***	0.0385	0.496***	1.0000
	(0.9936)	(0.2700)	(0.0040)	(0.4599)	(0.0074)	(0.0043)	(0.0021)	(0.8428)	(0.0062)	--------

Notes: This table reports the correlation matrix between variables under regression H2 in equation (2). Numbers in parentheses are the *p*-values of the correlation coefficients. *, ** and *** denote significance at the 10%, 5% and 1% confidence levels, respectively.

Figure 3 Overwhelming shared line between all studied companies (see online version for colours)



From Table 11, the relationships between abnormal return and the other variables are insignificant at the 90% confidence level. Nevertheless, if an 80% confidence level were selected, the *AbnRet* would have a negative relationship with the keyword return search (RR_{KSV}). This implies that for the main keywords relevant to the company, the generated number of clicks or engagement from searchers are inversely correlated with stock returns, likely due to market competitors for those keywords.

The causal relationships between variables are analysed with the Granger test in Table 12. The results show that only the abnormal volume *AbnVol* Granger causes the dependent variable *AbnRet*.

Table 11 Estimation results under H2

		Coefficient	*p-value*
c	Intercept	0.4350	(0.2866)
AbnVol	Abnormal volume	3E-16	(1.0000)
CPSKSV	Keyword clicks	0.1841	(0.2957)
CPSSV	Name clicks	–0.5760*	(0.0512)
FBE	Facebook engagement	0.1787	(0.3717)
FBR	Facebook reach	0.3293	(0.4877)
RRKSV	Keyword return search	–0.3497	(0.1618)
RRSV	Name return search	0.0964	(0.7253)
TE	Twitter engagement	–0.1324	(0.6244)
TR	Twitter reach	–0.3007	(0.5160)
R^2		*23.71%*	

Notes: This table reports the estimation results of regression H2 in equation (2). Numbers in parentheses are the *p*-values of the estimated coefficients.
*Denotes significance at the 10% confidence level.

Finally, Hypothesis H2, according to which 'company engagement efforts and search engine keyword choices are directly related to stock market returns', could not be determined with any certainty by the tests performed in this paper.

5 Conclusions

This paper studies the relationship between stock returns and the online presence of companies. Mainly, we investigate whether the level of the online presence of a company affects its subsequent stock returns and whether the company engagement efforts and the popularity of its search-engine keywords affects its stock returns.

Based on companies listed on the DJIA index, results suggest that stock returns are impacted by a change in online presence, proxied by the search volumes. Nevertheless, the stock returns are not significantly affected by online engagement efforts, such as search engine clicks and repeat searches, as well as social media reach and engagement from official accounts on both Twitter and Facebook.

Further research on the impact of search volumes is recommended, with a bigger sample size of companies, and/or focusing on other online presence presentations, for instance, company tweets per week.

Table 12 Granger causality test

Granger causality	*AbnRet* *Abnormal returns*	*AbnVol* *Abnormal volume*	CPS_{KSV} *Keywords clicks*	CPS_{SV} *Name clicks*	*FBE* *Facebook engagement*	*FBR* *Facebook reach*	RR_{KSV} *Keyword return search*	RR_{SV} *Name return search*	*TE* *Twitter engagement*	*TR* *Twitter reach*
AbnRet	-	0.0218**	0.6245	0.1964	0.8814	0.5685	0.3242	0.4732	0.9716	0.3556
AbnVol	0.8469	-	0.4366	0.0154**	0.7711	0.7669	0.7727	0.6487	0.5632	0.7527
CPSKSV	0.7369	0.4006	-	0.4397	0.5350	0.4639	0.9711	0.5991	0.7246	0.5304
CPSSV	0.1642	0.4006	0.8374	-	0.4664	0.9052	0.2145	0.7135	0.5449	0.8432
FBE	0.5593	0.3941	0.0001***	0.7482	-	0.9118	0.0008***	0.8286	0.6432	0.0033
FBR	0.1044	0.5973	0.7119	0.3714	0.1941	-	0.8151	0.2917	0.4802	0.5751
RRKSV	0.8301	0.3487	0.2984	0.9439	0.5344	0.6847	-	0.8057	0.8692	0.2602
RRSV	0.6796	0.6783	0.9055	0.5238	0.6771	0.8303	0.0985*	-	0.6901	0.7057
TE	0.2178	0.5961	0.0001***	0.2424	0.7596	0.9617	0.0101**	0.9303	-	0.0002
TR	0.0849*	0.2506	0.0657*	0.7064	0.1042	0.6780	0.5366	0.4701	0.2478	-

Notes: This table reports the Granger causality test results between the variables under the regression H2. *, **, and ***denote significance at the 10%, 5%, and 1% confidence levels, respectively.

References

Aspara, J. and Chakravarti, A. (2015) 'Investors' reactions to company advertisements: the persuasive effect of product-featuring ads', *European Journal of Marketing*, Vol. 49, Nos. 5/6, pp.943–967, DOI: 10.1108/ejm-11-2013-0661.

Baker, M. and Wurgler, J. (2006) 'Investor sentiment and the cross-section of stock returns', *The Journal of Finance*, Vol. 61, No. 4, pp.1645–1680, DOI: 10.1111/j.1540-6261.2006.00885.x.

Barber, B.M. and Odean, T. (2007) 'All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors', *Review of Financial Studies*, Vol. 21, No. 2, pp.785–818, DOI: 10.1093/rfs/hhm079.

BenSaïda, A. (2017) 'Herding effect on idiosyncratic volatility in U.S. industries', *Finance Research Letters*, Vol. 23, pp.121–132, DOI: 10.1016/j.frl.2017.03.001.

Bessembinder, H., Maxwell, W. and Venkataraman, K. (2006) 'Market transparency, liquidity externalities and institutional trading costs in corporate bonds', *Journal of Financial Economics*, Vol. 82, No. 2, pp.251–288, DOI: 10.1016/j.jfineco.2005.10.002.

Blankespoor, E., Miller, G.S. and White, H.D. (2012) 'Dissemination, direct-access information technology and information asymmetry', *SSRN Electronic Journal*, DOI: 10.2139/ssrn.1657169.

Bollen, J., Mao, H. and Zeng, X. (2011) 'Twitter mood predicts the stock market', *Journal of Computational Science*, Vol. 2, No. 1, pp.1–8, DOI: 10.1016/j.jocs.2010.12.007.

Chaffey, D. and Smith, P.R. (2017) *Digital Marketing Excellence Planning, Optimizing and Integration Online Marketing*, 5th ed., Routledge, London.

Chai, D., Dai, M., Gharghori, P. and Hong, B. (2021) 'Internet search intensity and its relation with trading activity and stock returns', *International Review of Finance*, Vol. 21, No. 1, pp.282–311, DOI: 10.1111/irfi.12268.

Charlesworth, A. (2018) *Digital Marketing: A Practical Approach*, 3rd ed., Routledge, Taylor and Francis Group, London.

Chau, M. and Xu, J. (2012) 'Business intelligence in blogs: understanding consumer interactions and communities', *MIS Quarterly*, Vol. 36, No. 4, pp.1189–1216, DOI: 10.2307/41703504.

Chemmanur, T.J. and Yan, A. (2019) 'Advertising, attention and stock returns', *Quarterly Journal of Finance*, Vol. 9, No. 3, p.1950009, DOI: 10.1142/S2010139219500095.

Chen, H., Chiang, R. and Storey, V. (2012) 'Business intelligence and analytics: from big data to big impact', *MIS Quarterly*, Vol. 36, No. 4, pp.1165–1188, DOI: 10.2307/41703503.

Chordia, T., Huh, S.W. and Subrahmanyam, A. (2007) 'The cross-section of expected trading activity', *Review of Financial Studies*, Vol. 20, No. 3, pp.709–740, DOI: 10.1093/rfs/hhl014.

Cohen, H. (2010) *Content Marketing Metrics for Newbies: 28 Content-Related Measures to Track* [online] https://contentmarketinginstitute.com/2010/10/content-marketing-metrics (accessed 17 January 2022).

Cootner, P.H. (1970) *The Random Character of Stock Market Prices*, MIT Press, Cambridge, MA.

Cziraki, P., Mondria, J. and Wu, T. (2021) 'Asymmetric attention and stock returns', *Management Science*, Vol. 67, No. 1, pp.48–71, DOI: 10.1287/mnsc.2019.3460.

Da, Z., Engelberg, J. and Gao, P. (2011) 'In search of attention', *The Journal of Finance*, Vol. 66, No. 5, pp.1461–1499, DOI: 10.1111/j.1540-6261.2011.01679.x.

Di, W., Tian, L., Yan, B., Liyuan, W. and Yanhui, L. (2010) 'Study on SEO monitoring system based on keywords and links', *2010 3rd International Conference on Computer Science and Information Technology*, DOI: 10.1109/iccsit.2010.5563940.

Edison Research (2020) *The Infinite Dial* [online] https://www.edisonresearch.com/the-infinite-dial-2020 (accessed 2 April 2022).

Fama, E.F. and French, K.R. (1992) 'The cross-section of expected stock returns', *The Journal of Finance*, Vol. 47, No. 2, pp.427–465, DOI: 10.1111/j.1540-6261.1992.tb04398.x.

Fama, E.F. and Macbeth, J.D. (1973) 'Risk, return and equilibrium: empirical tests', *Journal of Political Economy*, Vol. 81, No. 3, pp.607–636, DOI: 10.1086/260061.

Gervais, S., Kaniel, R. and Mingelgrin, D.H. (2001) 'The high-volume return premium', *The Journal of Finance*, Vol. 56, No. 3, pp.877–919, DOI: 10.1111/0022-1082.00349.

Geyskens, I., Gielens, K. and Dekimpe, M.G. (2002) 'The market valuation of internet channel additions', *Journal of Marketing*, Vol. 66, No. 2, pp.102–119, DOI: 10.1509/jmkg.66.2.102.18478.

Ginsberg, J., Mohebbi, M.H., Patel, R.S., Brammer, L., Smolinski, M.S. and Brilliant, L. (2009) 'Detecting influenza epidemics using search engine query data', *Nature*, Vol. 457, No. 7232, pp.1012–1014, DOI: 10.1038/nature07634.

Grullon, G., Kanatas, G. and Weston, J.P. (2004) 'Advertising, breadth of ownership and liquidity', *Review of Financial Studies*, Vol. 17, No. 2, pp.439–461, DOI: 10.1093/rfs/hhg039.

Lou, D. (2014) 'Attracting investor attention through advertising', *Review of Financial Studies*, Vol. 27, No. 6, pp.1797–1829, DOI: 10.1093/rfs/hhu019.

McDonald, M., Mouncey, P. and Maklan, S. (2014) *Marketing Value Metrics: A New Metrics Model to Measure Marketing Effectiveness*, 2nd ed., Kogan Page, London.

Mondria, J., Wu, T. and Zhang, Y. (2010) 'The determinants of international investment and attention allocation: using internet search query data', *Journal of International Economics*, Vol. 82, No. 1, pp.85–95, DOI: 10.1016/j.jinteco.2010.04.007.

Nielsen (2016) The Social Media Report [online] https://www.nielsen.com/us/en/insights/report/2017/2016-nielsen-social-media-report/ (accessed 6 June 2022).

Nielsen (2018) *Total Audience Report* [online] https://www.nielsen.com/wp-content/uploads/sites/3/2019/04/q3-2018-total-audience-report.pdf (accessed 31 August 2022).

Peress, J. (2014) 'The media and the diffusion of information in financial markets: evidence from newspaper strikes', *The Journal of Finance*, Vol. 69, No. 5, pp.2007–2043, DOI: 10.1111/jofi.12179.

Preis, T., Moat, H.S. and Stanley, H.E. (2013) 'Quantifying trading behavior in financial markets using Google trends', *Scientific Reports*, Vol. 3, No. 1, p.1648, DOI: 10.1038/srep01684.

Prokofieva, M. (2015) 'Twitter-based dissemination of corporate disclosure and the intervening effects of firms visibility: evidence from Australian-listed companies', *Journal of Information Systems*, Vol. 29, No. 2, pp.107–136, DOI: 10.2308/isys-50994.

Qian, B. and Rasheed, K. (2006) 'Stock market prediction with multiple classifiers', *Applied Intelligence*, Vol. 26, No. 1, pp.25–33, DOI: 10.1007/s10489-006-0001-7.

Rakowski, D., Shirley, S. and Stark, J. (2021) 'Twitter activity, investor attention and the diffusion of information', *Financial Management*, Vol. 50, No. 1, pp.3–46, DOI: 10.1111/fima.12307.

Rutz, O.J. and Trusov, M. (2011) 'Zooming in on paid search ads – a consumer-level model calibrated on aggregated data', *Marketing Science*, Vol. 30, No. 5, pp.789–800, DOI: 10.1287/mksc.1110.0647.

Seasholes, M.S. and Wu, G. (2007) 'Predictable behavior, profits and attention', *Journal of Empirical Finance*, Vol. 14, No. 5, pp.590–610, DOI: 10.1016/j.jempfin.2007.03.002.

SocialBlade.com – YouTube, Twitch, Twitter, and Instagram (2022) [online] https://socialblade.com/ (accessed 17 December 2022).

Solomon, D.H. (2012) 'Selective publicity and stock prices', *The Journal of Finance*, Vol. 67, No. 2, pp.599–638, DOI: 10.1111/j.1540-6261.2012.01726.x.

Srinivasan, S. and Hanssens, D. (2009) 'Marketing and firm value: metrics, methods, findings and future directions', *Journal of Marketing Research*, Vol. 46, No. 3, pp.293–312, DOI: 10.1509/jmkr.46.3.293.

Standage, T. (2014) *Writing on the Wall: Social Media, The First 2,000 Years*, Bloomsbury, New York.

Tetlock, P.C. (2007) 'Giving content to investor sentiment: the role of media in the stock market', *The Journal of Finance*, Vol. 62, No. 3, pp.1139–1168, DOI: 10.1111/j.1540-6261.2007.01232.x.

Wooldridge, J.M. (2019) *Introductory Econometrics: A Modern Approach*, 7th ed., Cengage Learning, Boston.

Yuan, Y. (2015) 'Market-wide attention, trading and stock returns', *Journal of Financial Economics*, Vol. 116, No. 3, pp.548–564, DOI: 10.1016/j.jfineco.2015.03.006.

Zacks Investment Research News Archive (2022) [online] https://www.zacks.com/stock/research//all-news (accessed 9 May 2022).

Zhang, S. and Cabage, N. (2016) 'Search engine optimization: comparison of link building and social sharing', *Journal of Computer Information Systems*, Vol. 57, No. 2, pp.148–159, DOI: 10.1080/08874417.2016.1183447.

Notes

1 All estimations are conducted using EViews software from http://www.eviews.com/.