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Behavioural Attention to Financial Indicators: Evidence from Google Trends Data*

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Abstract

We investigate the link between stock returns, market risks, financial indicators and behavioural attention, which represents supply and demand for the selected assets. We assume that behavioural attention represents actions emphasising the importance of information followed by information-selection behaviour. Using a rich dataset of 100 US stocks we show the impact of financial ratios along with indicators related to dividends on stock returns. Moreover, we find evidence that stock returns are influenced by behavioural attention based on the level of search intensity. The results show that behavioural attention to stock (share) prices is positively associated with stock returns, attention varies across the sectors and during the financial crisis, attention began to be significant.

1. Introduction

People gather information when making decisions. Most importantly, they are increasingly using the internet for this, and as a search engine it is currently the centre of interest of researchers in many fields. They are measuring economic agents' behaviour through attention.

In finance, the importance of focusing on investor attention is based on the transmission channel. People are taking actions evolving from the attention that makes them search for the information. In the light of this suggestion investors are mostly using search engines to help them find information1 about stocks, moreover this act undoubtedly means that they pay attention. According to the data gathered, they are buying preferred stocks. It is worth noting that investors are looking for information about stocks that they do not hold, because they have already paid attention to the companies included in their portfolios. Thus they are net buyers, which temporarily causes positive price pressure.

There is no simple way to find a measure or proxy for investor sentiment. As far as we know there are number of unobserved topics. We have improved the data from Google Trends, presented as direct measure of attention, while we provide evidence that there is a link between the investors' interest (attention) in companies'

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[1] Fallows (2005) points out that almost 90 % of U.S. adults use a search engine to help them find information, and moreover this is one of the most popular internet activities (only sending and receiving e-mail ranking higher).

financial indicators and changes in stock returns, thereby improving on the previous literature searching generally for attention to companies tickers or names (Preis et al., 2010; Da et al., 2011; Drake, Roulstone, Thornock, 2012; Kristoufek, 2013; Preis et al., 2013; Drake, Roulstone and Thornock, 2016; and others). In other words we specify (make precise) the investors' searches by incorporating additional information. Here, the keyword is represented by ticker symbol and financial indicator. Moreover, we hypothesise that attention has a differing influence on capital market behaviour depending on the level of search intensity. We identify nonlinearity via a threshold model. One other point worth mentioning is that recent studies have mostly used textual analysis (see the summarised literature in Loughran and McDonald, 2016). Moreover, we follow the Theory of Rational Inattention (Sims, 2003; 2010). He claims that people are only able to process a limited amount of information.

In addition we require further improvements, especially in the analytical part, where estimates include sectoral data. In such contexts, we extend the literature to provide evidence of whether behavioural attention has influenced each sector. We are not aware of any comprehensive studies dealing with this topic. Correlations were found for example in the automotive sector (Choi, Varian, 2012). Moreover, the model with Google data outperformed competing models in the case of long-term forecasts for several car brands (Fantazzini, Toktamysova, 2015).

Furthermore, we follow Preis et al. (2010) and investigate how important a role was played by search volume data in the financial crisis, while we confirm the suggestion of Preis et al. (2010) that Google data can contribute to understanding the financial crises. This focus is appropriate while we consider the fact that in such periods investors may search for more information to decide whether to sell or buy.

Attention is the ultimate scarce cognitive resource and it has become valuable due to the increasing amount of available information. For example, the publication of an article in the New York Times about a new cancer-curing drug attracted great public attention and increased the daily return on its stocks by more than 300 %. This was despite the same story already having been published several times earlier in other newspapers. Thus, the obvious example is internet search engines since they allow users to find the most valuable information linked to the context of the keywords. In the light of the findings, we believe that internet search queries can be proxies for attention allocation.

The paper is structured as follows - Section 2 contains a literature review related to behavioural finance applications, and moreover we further specify studies focusing on firm-level data in the field of investigation. Section 3 provides a detailed overview of the methods and data. Basic results of regressions are presented in Section 4. In Section 5 we extend the results with a robustness check, while we divide the data into sectors and finally, we provide the evidence about the significance of behavioural attention due to the financial crisis comparing the results with the period before and after the financial crisis and Section 6 has conclusions based on our results.

2. Behavioural Finance

2.1 Behavioural Finance Applications

Behavioural finance can credibly describe the existence of inefficiencies in capital markets by dropping the idea of complete investor rationality due to the limited amount of time available and the effort required to process information. The early literature based on the Efficient Market Hypothesis (EMH) investigating stock market predictions posits that stock prices fully reflect all the available information. In previous studies indirect proxies were used to measure information (see Otoo, 1999; Charoenrook, 2005; Barber and Odean 2008 or Yuan, 2008). The financial environment has changed since then. The rising activity of technologies provides access to a huge amount of data, which leads to investigation of the field of limited attention and information overload (Mackowiak and Wiederholt, 2015).

Shannon (1948) points out the value of information; or more precisely he devised the Information Theory. The key measure is “entropy” related to the amount of uncertainty before reception. In other words, when the economic agent sends the message “yes”, the amount of information contained in that message depends on what other response might have been sent instead. If the recipient is sure that the message is going to be “yes” then there is no transmitted information. But if the recipient knows that the response would be either “yes” or “no”, and moreover he’s only sure that the message will an English word, the transmitted information is much more valuable due to the amount of uncertainty. The theory behind the value of information is applied in the Theory of Rational Inattention (Sims, 2003, 2010).

The Theory of Rational Inattention introduced the idea that people’s ability to translate external data into action are constrained by a finite “capacity” to process information. Such models explain why some freely available information is not used, or imperfectly used. The author presents the idea through analysing the available data from newspapers. The vast majority of newspaper readers do not look at the regular report on the Federal Funds Rate, consisting of three significant figures, every day. On the other hand, if there is a front-page headline about the raising of rates unexpectedly to 1.5 %, many readers of the newspaper would be likely to act on the news. To sum up, investors gather the information to make their decisions. Building on Sims’ theory, an increasing number of studies focuses on new insights into the information-gathering process that precedes investment decisions.

Mondria et al. (2010) put it succinctly: “However, the exponential growth in the number of documents available, one of the main reasons for its increasing popularity, also creates the problem referred to as information overload”. There are vivid examples proving the impact of information overload on capital markets. Hirshleifer et al. (2004) show that investors sometimes ignore useful information in firms’ financial statements. Della Vigna and Pollett (2003) show that stock prices do not fully incorporate demographic information that is publicly available. Furthermore, Corwin and Coughenour (2005) provide evidence that the limited attention of NYSE specialists affects execution quality (price improvement and transaction cost) in securities that they are responsible for. To sum up, these findings shed light on the role of inattention and its effects on decision-making. In addition, the studies have shown the difference in the value of information according to the level of uncertainty or its quantity.

Actual studies use the application Google Trends to measure how much information investors decide to process. Google Trends is presented as a high potential tool for any social grouping or individual. Choi and Varian (2012) proved that the Google index may help in predicting automobile and real estate sales and forecasting visits to destinations within the tourist industry. In addition the evidence from Ginsberg et al (2008) shows that the analysing the search queries from Google Trends can track influenza-like illness in a population. Moreover, it can accurately estimate the current level of weekly influenza activity with a reporting lag of about one day, which is more efficient than the traditional surveillance systems. In the area of health there have been a number of studies (Carneiro and Mylonakis, 2009; Ginsberg et al., 2008; Pelat et al., 2009). Moreover, economic activity shows the importance of real-time data in predictions. The disadvantage of the available data lies in time lags, where a clear example is macroeconomic data which are typically revised several months later. According to the evidence, the alternative tools appeared to be important. The Czech National Bank published a working paper showing the significant impact of search queries from applications on forecasting mortgage lending. Their usefulness should lie in providing real-time data as compared to lagged traditional statistical information (Saxa, 2014). The connection between search queries and the prediction of mortgage lending is simple; borrowers search for the information before they make decision and the main source of data is the internet. Such behaviour has been found in a macroeconomic variable – gross domestic product (Preis et al., 2012).

Finally, a number of studies argue that is the relevant variable for forecasting sentiment. Festré and Garrouste (2015) have described attention as a scarce good that is depletable by overload of information. More precisely, attention economics is about the interplay of attention and information, where the emphasis is on the relevance of data. Klemola, Nikkinen and Peltomaki (2016) worked with the negative search term volumes of "market crash" and "bear market" and changes in the positive search term volume "market rally". They claim, that these market-related search terms as measures of investors' market attention gauge stock market sentiment. Moreover, they contribute to studies on investor's attention such as Solt and Statman (1988), Otoo (1999).

2.2 Behavioural Finance – Evidence from the Firm-Level

In accounting and finance the internet is producing a growing body of corporate reports, news articles and press releases related to each firm. Finally, information could be provided by investor message boards. Past studies had the problem that information was difficult to observe (expensive surveys or laboratory experiments). With regard to information technology development, recent research has applied processes to provide data on textual sentiment. The financial literature defines sentiment as "a belief about future cash flows and investment risks that is not justified by the facts at hand." (Baker and Wurgler, 2007). Moreover, Kaplanski and Levy (2010) characterised the variable as the sum of all "irrational" factors possibly leading to incorrect stock price valuation and biases that are not related to fundamental values.

According to the literature review, the first group of articles focused on analysing the frequency of words associated with a particular sentiment. Empirically, the method counts the words (negative and positive). Using the lists of words, the authors (Tetlock, 2007; Engelberg, 2008; Li, 2008) measure the sentiment of financial documents or earnings conference calls. The results confirmed the impact of negative word classification on other financial variables. These findings were followed by many articles (Henry, 2008; Loughran and McDonald, 2011; Price et al., 2012). Recent works have used internet posting as a source of textual sentiment. Internet–expressed sentiment consists of messages posted on Yahoo!Finance, Facebook or Twitter and other online sources of commentaries. For example the impact of Twitter activities on the stock market is described by Bollen, Mao, and Zeng (2011); Castillo et al. (2012) and for the current studies of social media views by Creamer and Houlihan (2017); Thomas (2017); Fang et al. (2017).

In the field of accounting and finance researchers have shown the association between qualitative information and stock returns, earnings and basically the influence on equity valuations (see the summarised literature in Kearney and Liu, 2014). In spite of the increased attention to textual analysis provided by a number of dictionaries, the lists of words were not created with financial text in mind. The authors mostly used these four dictionaries: Henry (2008), Harvard's GI, Diction, and Loughran and McDonald (2011). The limitation of this approach lies in the use of the non-finance-specific lists (Harvard's GI and Diction) that might be proxies for industry or other unintended effects. Loughran and McDonald (2011) developed the L&M list assessed from 10-Ks2.

The second group of articles investigated the readability of accounting narratives. Li (2008) published the first paper investigating the link between the annual report, expressed by the number of words contained, and company performance. In addition, the author used the Fog Index followed by other investigators (Biddle, Hilary, and Verdi, 2009; Lundholm, Rogo, and Zhang, 2014; Guay, Samuels, and Taylor, 2016) confirming the impact of searched for variables.

The third group of studies focused on sentiment by analysing data from the application Google Trends. We addressed this issue and followed studies3 which used the companies' name or ticker as the search criteria. Da et al. (2011) presented significant evidence that high SVI predict higher stock prices in the short term. To sum up, there is group of investors – retail investors - who use more non-professional information channels for decision making. These investors search for all the relevant news on the internet. They are more likely to be influenced by noise information in the media (Veronesi, 1999; Barber, Odean, 2011). Further studies have shown that retail investors tend to overreact to shocks in economics (Barberis, Shleifer, and Vishny, 1998; Lo, MacKinlay, 1990). To conclude, Da et al. (2011) examine retail investors as those whose attention Google Trends is capturing. Here, we claim that retail investors become a significant players in capital markets. We follow the interesting suggestion by Mondaria, Wu and Zhang (2010) that the attention of retail investors not only affects their investment decisions, but also those of institutional investors, which is improved by Chan et al. (2005) arguing that fund managers are directly influenced by the preferences of their clients, who are individual (retail) investors. In such contexts we propose Google Trends data as a direct measure of retail investors' attention.

3. Data and Empirical Strategy

We use monthly data in the period from 2004M01 to 2017M12 (168 observations) that includes 101 stocks listed on the Nasdaq 100. Moreover, the stock

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[2] The form consists of a corporation´s annual report filed with the U.S. Securities and Exchange Commission (SEC)

[3] For a consistent explanation of usage, the Google data for behavioural attention, the studies are presented in Introduction.

index represents 100 of the largest non-financial companies listed on the NASDAQ based on market capitalisation. We use the Morningstar database to provide company-specific data (see Table 1).

To analyse the relationship between investors' attention and stock returns, we include data about the largest companies as high visibility subjects. We assume that investors are regularly searching for information, thus we expect a wealth of searches in chosen period resulting in a consistent dataset. Google Trends provides the search intensity for a keyword or group of keywords. Here, it measures how investors search for the financial information about each company using the Google search engine. The application generates a time series index (known as a SVI index) from 0 to 100 in a selected frequency. The measured value is obtained from the order of 100 million searches per day. We follow Da et al. (2011) by inserting the ticker symbol with a financial indicator4. We use the process to capture strictly investors' attention5. To avoid an unintended meaning of a keyword we inserted the full names of Costco Wholesale Corp (COST), Fastenal Co. (FAST) and Hasbro Inc. (HAS). This resulted from the study by Markellos and Vlastakis (2012). All the data were transformed by logs.

To avoid biased behavioural data, the study focused on ticker symbols that undoubtedly mean gathering the information for investment reasons. In addition, we add the financial indicator's keyword to specify the investor's attention. We type various keywords representing searches for financial information; however, we had to deal with a lack of data. Inconsistent data was found for the keywords: debt, cash flow, PE ratio, PB ratio, dividend yield, payout, and others. We focus on the attention for ratios that are employed in regression (see Table 1) and regressors which contribute to prediction of stock returns according to the literature.

Moreover, the application Google Trends allows us to gain global data or the data for different countries. We follow Preis et al. (2013) and put a constraint on Google data to gain U.S. users' search volume data. We are in line with that study and claim that the U.S. population posits a higher part of the traders on the U.S. markets than the remaining part of worldwide users (Wysocki, 2000 and Ryu, Han, 2010).

We use the generally known CAPM model with additional regressors related to investors' attention:

$$return_{it} = const + \sum_{m=1}^{M} \beta_m market_{it} + \sum_{b}^{B} \beta_b cvalues_{it} + \sum_{a}^{A} \beta_a attention_{it} + u_{it} + \varepsilon_{it}. \quad (1)$$

The *return* is expressed by stock return *i* in time *t*, the excess return of the SP500 market decreased by the risk free return *m* is represented by the variable *market*, the

[4] For example, Apple behavioural data were provided by inserting firstly: AAPL earnings and secondly: AAPL stock price+AAPL share price. The specification downloads the results including searches containing both AAPL and another word in any order. For a futher explanation of search tips see Google Trends Support.

[5] For example, typing the keyword "Apple" into a search engine does not mean that the economic subject is searching for the company as an investment. The searched for word possibly represents food or a company's products.

variable *cvalues* represents particular financial indicators and the last variable contains the search intensity of particular financial indicators from the application Google Trends and we applied the OLS robust estimator to estimate robust standard within-entity errors ε_{it}. Finally, we use random effects to include between-entity errors u_{it}.

Our panel regression model is extended to various levels of attention[6]:

$$return_{it} = const + \delta_1 xrattention_{it} + \sum_{m=1}^{M} \beta_m market_{it} + \sum_{b}^{B} \beta_b cvalues_{it} + u_{it} + \varepsilon_{it} \text{ if } xrattention_{it} < \theta, \tag{2a}$$

$$return_{it} = const + \delta_2 xrattention_{it} + \sum_{m=1}^{M} \beta_m market_{it} + \sum_{b}^{B} \beta_b cvalues_{it} + u_{it} + \varepsilon_{it} \text{ if } xrattention_{it} \geq \theta, \tag{2b}$$

where θ represents investors' attention. We define *return* via logarithmic differences. We use several thresholds starting from a search intensity of less than 1 SVI index and continue to the thresholds 5, 10, 25, 50, 75 and 90 related to a search intensity of less than 90 SVI index.

4. Results

First, we show the impact of financial indicators on the model. Moreover, we extend the variables to behavioural attention. We assume that the effect of behavioural attention is nonlinear. Regarding this assumption we identify the specific level of behavioural attention.

Table 1 contains companies' financial ratios data available in the database Morningstar. We provide evidence that PE ratio and PB ratio represent the most popular financial ratios for investors. Regarding the financial literature, the PE ratio shows the amount that an investor will pay to obtain the company's earnings, while the PB ratio is based on historical valuations and calculate payments for a company's assets. There is a large amount of literature that proves the predictive power of financial indicators (especially price-to-earnings ratio, price-to-book ratio or dividend yield)[7]. A similar paper by Bauer et al. (2004) considers using a panel regression and focus on the impact of financial indicators on U.S. stock returns. Moreover, they apply dummy variables for industries.

We follow the generally known CAPM model and thus we choose the risk-free rate of the 10-year yield of US treasury bonds and excess market return (see the variables *Price_10ybond* and *Mkt_rf*). According to economic theory, a positive

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[6] See the threshold model in Hansen (2000).

[7] A comprehensive literature review is presented by Li, 2010 that provides a survey of the literature, while Bauer et al. (2004) propose specific studies related to the link between stock returns and various firm characteristics.

relationship has been proven between stock returns and explanatory variables. The model points to a negative relationship between *Dividend yield* and stock returns. The reverse causality results from the negative impact of paid dividends, which decrease a firm's earnings. In addition, the *Payout* reflects the share of the profit reported for dividends. An increase in *Payout* is accompanied by a decrease in stock returns above 0.094 % (see Model 4).

Finally, we show that an increase in *CF per share* is accompanied by an increase in stock returns above 0.036 % (see Table 2, Model 5). The results are in line with a business strategy preferring a positive growth in companies' financial situation as characterised by cash flow per share. To sum up, investors translate external data into action when the financial ratio has been changed - where the most common variables are the *PE ratio* and *PB ratio*. The robust results are represented by stable significance at the 1 per cent level across the models. Finally, we show that investors perceive stocks as heterogeneous.

Table 1 The Impact of Financial Indicators

Variables	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
PE ratio	0.089***	0.073***	0.066***	0.102***	0.076***	0.094***
	(0.013)	(0.011)	(0.010)	(0.015)	(0.012)	(0.015)
PB ratio	0.331***	0.279***	0.263***	0.272***	0.279***	0.258***
	(0.042)	(0.039)	(0.038)	(0.038)	(0.039)	(0.037)
Price_10ybond		0.902***	0.829***	0.884***	0.881***	0.800***
		(0.080)	(0.076)	(0.078)	(0.078)	(0.073)
Mkt_rf		0.808***	0.733***	0.792***	0.802***	0.720***
		(0.060)	(0.058)	(0.060)	(0.060)	(0.059)
Dividend yield			-0.215***			-0.200***
			(0.017)			(0.017)
Payout ratio				-0.094***		-0.078***
				(0.015)		(0.015)
CF per share					0.036***	0.034***
					(0.008)	(0.008)
Constant	1.112***	0.400**	0.510***	0.469***	0.405**	0.563***
	(0.076)	(0.175)	(0.170)	(0.172)	(0.172)	(0.167)
Observations	15,661	15,560	15,560	15,560	15,560	15,560
Stocks	101	101	101	101	101	101
Sigma_u	0.173	0.194	0.089	0.223	0.000	0.000
Sigma_e	8.126	7.525	7.367	7.461	7.508	7.307
rho	0.001	0.001	0.001	0.001	0.000	0.000

Notes: *, **, and *** denote significance at the 10, 5 and 1 per cent levels. Standard errors are reported in parentheses.

A closer look at the chosen variables supports the significant influence of market development, financial factors and Google Trends searches made in keywords related to financial indicators. According to the results, investors realising their investment decisions followed the above factors.

Moving further into the models we confirmed the influence of behavioural attention to financial indicators on stocks returns. We employ the data about investors' search intensities for "*earnings*" and "*share or stock price*". In other words, we capture investors' attention to the keywords "*earnings*" and "*share or stock price*" for each company that they type into the Google search engine to gain further information. The results confirmed the significant positive impact of investors' attention on companies' earnings (see Table 2, Model 1). However, the stock returns are negatively influenced by investors' searches for "*stock price*" or "*share price*" at a 10 per cent significance level (see Table 2, Model 3).

Table 2 The Impact of Financial Indicators and Behavioural Attention

Variables	***(1)***	***(2)***	***(3)***
Price_10ybond	0.838***	0.785***	0.794***
	(0.078)	(0.081)	(0.082)
Mkt_rf	0.719***	0.721***	0.720***
	(0.059)	(0.059)	(0.059)
PE ratio	0.094***	0.094***	0.094***
	(0.015)	(0.015)	(0.015)
PB ratio	0.258***	0.258***	0.258***
	(0.037)	(0.037)	(0.037)
Dividend yield	-0.200***	-0.200***	-0.200***
	(0.017)	(0.017)	(0.017)
Payout	-0.078***	-0.078***	-0.078***
	(0.015)	(0.015)	(0.015)
CF per share	0.034***	0.034***	0.034***
	(0.008)	(0.008)	(0.008)
Google Trends	0.098**		0.125**
("earnings")	(0.049)		(0.053)
Google Trends		-0.020	-0.070*
("price")		(0.038)	(0.040)
Constant	0.347	0.639***	0.559**
	(0.216)	(0.243)	(0.252)
Observations	15,560	15,560	15,560
Stocks	101	101	101
Sigma_u	0.000	0.000	0.000
Sigma_e	7.307	7.308	7.307
rho	0.000	0.000	0.000

Notes: *, **, *** denote significance at the 10, 5 and 1 per cent levels. Standard errors are reported in parentheses.

With panel dataset and multiple explanatory variables, it is appropriate to apply levels of diversification. Moreover, we expect the firm specifics in dataset, and thus we put constraints on dataset and look at the various groups. First, we put the levels of attention (thresholds). With respect to the literature that the information is processed in stock prices while the investors pay attention (see the Introduction), we expect that the attention results in a predictive variable with a higher amount of search intensity.

The threshold model starts at 1% of search intensity, and thus level 1 includes investors' attention from index[8] 1 and less, while level 5 consists of investors' attention from index 0 to 5, etc., and level 90 provides the data about investors' attention from index 0 to 90. To sum up an increasing index value represents an increasing level of attention.

Taking a closer look at the behavioural variables, investors' attention to earnings is not associated with stock returns. Building on these findings we focus our attention on the robustness check. We show that attention to earnings is important only

[8] Google Trends generate a time series index from 0 to 100 in a selected frequency.

for specific sectors. Moving further into models, investors' attention to companies' prices provides significant results from level 10 to the highest level. In addition, an increase in searching for companies' stock prices (or share prices) is accompanied by increasing stock returns. To sum up, we demonstrated the nonlinear effect of behavioural attention. However, the results shed light on the significance of searches for stock or share prices of companies compared to Table 2.

Table 3 Level of Investors' Attention

Variables	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***
	1	***5***	***10***	***25***	***50***	***75***	***90***
Price_10ybond	0.939***	0.893***	1.008***	0.989***	0.976***	0.967***	0.967***
	(0.133)	(0.114)	(0.110)	(0.095)	(0.089)	(0.086)	(0.085)
Mkt_rf	0.697***	0.688***	0.700***	0.722***	0.724***	0.720***	0.717***
	(0.074)	(0.072)	(0.067)	(0.058)	(0.061)	(0.058)	(0.058)
PE ratio	0.099***	0.099***	0.107***	0.090***	0.093***	0.091***	0.092***
	(0.019)	(0.018)	(0.018)	(0.016)	(0.015)	(0.015)	(0.015)
PB ratio	0.289***	0.299***	0.287***	0.279***	0.262***	0.258***	0.257***
	(0.041)	(0.042)	(0.042)	(0.038)	(0.041)	(0.038)	(0.037)
Dividend yield	-0.198***	-0.189***	-0.171***	-0.177***	-0.191***	-0.196***	-0.199***
	(0.022)	(0.021)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
Payout	-0.063***	-0.062***	-0.072***	-0.080***	-0.078***	-0.076***	-0.077***
	(0.019)	(0.018)	(0.016)	(0.014)	(0.015)	(0.015)	(0.015)
CF per share	0.043***	0.050***	0.048***	0.038***	0.038***	0.033***	0.034***
	(0.012)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)
Google Trends	-	0.309	0.188	-0.015	0.040	0.052	0.061
("earnings")		(0.472)	(0.173)	(0.070)	(0.058)	(0.054)	(0.052)
Google Trends	0.449	0.383	0.651***	0.480***	0.428***	0.395***	0.384***
("price[9]")	(0.315)	(0.242)	(0.244)	(0.151)	(0.113)	(0.107)	(0.103)
Constant	-1.489	-1.130	-2.364**	-1.687***	-1.500***	-1.383***	-1.359***
	(1.249)	(0.923)	(0.944)	(0.610)	(0.499)	(0.476)	(0.462)
Observations	6,544	7,134	8,263	11,427	13,989	15,000	15,298
Stocks	94	95	95	101	101	101	101
Sigma_u	0.118	0.000	0.704	0.000	0.000	0.000	0.000
Sigma_e	7.912	7.870	7.695	7.462	7.387	7.332	7.306
Rho	0.000	0.000	0.008	0.000	0.000	0.000	0.000

Notes: *, **, *** denote a significance at the 10, 5 or 1 per cent levels. Standard errors are reported in parentheses.

5. Robustness Check

In the results section we provide the evidence that stock returns are influenced, among other things, by behavioural attention to companies' prices. However, we have not demonstrated the significance of attention to companies' earnings. Thus, we move further into data diversification followed by studies that focus on the effects of industries in panel datasets (Haugen, Baker, 1996; Cavaglia, Moroz, 2002; or Bauer et al., 2004).

First, we present the results related to each sector. As we move further into investigation, we focus on the financial crisis and show the role of behavioural attention in three time periods: before, during and after the financial crisis. We claim

[9] Search intensity consists of the keywords "stock price" and "share price".

that the crisis is one of the illustrative examples of increasing interest in financial markets or more precisely in each company, which can lead to the predictive power of attention. The issue is covered in Preis et al. (2010) and Preis et al. (2013). They posit that significant drops in the financial markets are preceded by periods of investor concern. The arguments are in line with the evidence that important news or information is not reflected in prices until investors pay attention to it (Hirshleifer et al., 2004; Della Vigna and Pollett, 2003; Corwin and Coughenour, 2005).

We put constraints on and investigate various impacts of attention across the sectors. Technology (see Table 4), Healthcare and Communication Services (see Table B1 in the Appendix) confirmed the positive effect of attention to prices on stock returns. The results are in line with previous findings, while the analyses on the investors' attention to companies' earnings provide a weak significance level or employ less robust data. Moving on further with the investigation, we provide evidence that searching for companies' prices has been negatively associated with stock returns in the Consumer Defensive sector (see Table 4). The stocks are characterised by stable earnings regardless of the business cycle and they provide constant dividends. It represents well-established companies such as Procter & Gamble, Coca-Cola or Phillip and Morris, providing protection to the investors' portfolio in most cases. Investors do not tend to regularly search for information; thus, we presume that while they are paying attention to companies' prices some negative shock occurred.

Compared to the Consumer Defensive sector, we show no evidence for the significant link between attention and stock returns in industry. Moreover, stock returns are not influenced by the PE ratio or cash flow (see *PE ratio, CF per share* in Table 5). Investors tend to pay attention to the industry trends and the progression of the growth cycle; thus, the investigation is more macroeconomic compared to other sectors.

Finally, a different trend is represented by Communication Services. Investors are seeking for earnings information (see the significance levels for *Google Trends "earnings"*, Table 5). The sector consists of three sub-sectors: telecoms equipment, telecoms services and wireless communications. This piece of the market has fast-growing potential. Regarding information, investors are increasingly searching for earnings compared to other sectors.

To sum up, we confirmed the positive and significant link between behavioural attention to stock (or share) prices and stock returns in most sectors. In addition, we extended the investigation to demonstrate the significance of behavioural attention to earnings in the rapidly growing Communication Services sector. Finally, market risk and financial indicators are robust across the models and sectors. Moreover, the nature of the relationship between the presented variables and stock returns remained the same.

Finally, we focus on time periods related to the financial crisis. According to the National Bureau of Economic Research (NBER), the US recession began in December 2007 and ended in June 2009.

Table 4 The Impact of Financial Indicators and Behavioural Attention the the Technology and Consumer Defensive Sectors

Variables	*Tech. 1*	*Tech. 5*	*Tech. 10*	*Tech. 25*	*Tech. 50*	*Tech. 75*	*Tech. 90*	*Cons. Def. 1*	*Cons. Def. 5*	*Cons. Def. 10*	*Cons. Def. 25*	*Cons. Def. 50*	*Cons. Def. 75*	*Cons. Def. 90*
Price_10ybond	0.797***	0.780***	0.866***	0.881***	0.898***	0.870***	0.870***	0.252	0.248	0.187	0.186	0.122	0.089	0.038
	(0.129)	(0.115)	(0.105)	(0.100)	(0.107)	(0.104)	(0.103)	(0.380)	(0.375)	(0.333)	(0.423)	(0.381)	(0.312)	(0.345)
Mkt_rf	0.609***	0.585***	0.601***	0.592***	0.581***	0.573***	0.576***	0.072***	0.071***	0.077**	0.091***	0.151***	0.212***	0.215***
	(0.108)	(0.098)	(0.096)	(0.084)	(0.076)	(0.072)	(0.071)	(0.027)	(0.027)	(0.030)	(0.017)	(0.046)	(0.026)	(0.026)
PE ratio	0.136***	0.120***	0.120***	0.081***	0.080***	0.077***	0.077***	0.098	0.098	0.109	0.398**	0.401***	0.578***	0.562***
	(0.027)	(0.029)	(0.028)	(0.026)	(0.024)	(0.023)	(0.024)	(0.180)	(0.180)	(0.177)	(0.180)	(0.063)	(0.064)	(0.073)
PB ratio	0.313***	0.348***	0.369***	0.407***	0.409***	0.412***	0.407***	0.706***	0.706***	0.696***	0.372**	0.356***	0.100	0.102
	(0.075)	(0.084)	(0.083)	(0.079)	(0.067)	(0.065)	(0.063)	(0.200)	(0.200)	(0.194)	(0.166)	(0.079)	(0.070)	(0.073)
Dividend yield	-0.193***	-0.188***	-0.155***	-0.163***	-0.167***	-0.176***	-0.177***	-0.141***	-0.140***	-0.138***	-0.117***	-0.039	-0.010	-0.018
	(0.037)	(0.037)	(0.027)	(0.027)	(0.024)	(0.024)	(0.023)	(0.041)	(0.039)	(0.040)	(0.029)	(0.065)	(0.086)	(0.089)
Payout	-0.110***	-0.095***	-0.100***	-0.067***	-0.042	-0.041	-0.042	-0.086	-0.085	-0.098	-0.403**	-0.403***	-0.564***	-0.552***
	(0.025)	(0.025)	(0.024)	(0.021)	(0.029)	(0.028)	(0.028)	(0.168)	(0.168)	(0.162)	(0.182)	(0.061)	(0.058)	(0.066)
CF per share	0.065***	0.071***	0.067***	0.053***	0.054***	0.055***	0.054***	0.076***	0.076***	0.083***	0.096***	0.096***	0.081***	0.083***
	(0.019)	(0.021)	(0.018)	(0.017)	(0.016)	(0.015)	(0.015)	(0.023)	(0.022)	(0.026)	(0.017)	(0.032)	(0.024)	(0.026)
Google Trends	-	-0.130	0.418*	0.091	0.164*	0.152*	0.150**	-	-	-	0.169	0.128	0.082	0.052
(“earnings”)		(0.425)	(0.247)	(0.097)	(0.087)	(0.081)	(0.076)				(0.212)	(0.157)	(0.209)	(0.228)
Google Trends	0.416**	0.359**	0.486***	0.424***	0.429***	0.444***	0.421***	-0.987***	-0.986***	-0.966***	-1.019***	-0.982***	-1.130***	-1.072**
(“stock, share price”)	(0.206)	(0.180)	(0.170)	(0.126)	(0.113)	(0.111)	(0.111)	(0.278)	(0.276)	(0.253)	(0.254)	(0.289)	(0.393)	(0.428)
Constant	-1.228	-1.049	-1.790***	-1.718***	-1.872***	-1.857***	-1.780***	3.403***	3.414***	3.642***	3.974***	4.226***	5.124***	5.166***
	(0.882)	(0.695)	(0.589)	(0.470)	(0.440)	(0.435)	(0.430)	(0.614)	(0.615)	(0.447)	(0.920)	(0.491)	(0.612)	(0.702)
Observations	2,456	2,807	3,386	4,766	5,679	6,022	6,150	405	408	427	493	613	674	683
Stocks	37	38	38	41	41	41	41	4	4	4	5	5	5	5
Sigma_u	0.497	0.405	0.322	0.000	0.000	0.000	0.114	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sigma_e	5.990	5.971	5.885	5.621	5.614	5.592	5.614	3.561	3.548	3.494	3.943	4.169	4.713	4.778
rho	0.007	0.005	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: *, **, and *** denote significance at the 10, 5 and 1 per cent levels. Standard errors are reported in parentheses.

Table 5 The Impact of Financial Indicators and Behavioural Attention to Consumer Services and Industry

Variables	*Com. Serv.* **1**	*Com. Serv.* **5**	*Com. Serv.* **10**	*Com. Serv.* **25**	*Com. Serv.* **50**	*Com. Serv.* **75**	*Com. Serv.* **90**	*Industry* **1**	*Industry* **5**	*Industry* **10**	*Industry* **25**	*Industry* **50**	*Industry* **75**	*Industry* **90**
Price_10ybond	1.195***	1.199***	1.157***	1.165***	1.248***	1.204***	1.221***	1.058***	0.900***	0.957***	1.031***	0.956***	0.943***	0.948***
	(0.361)	(0.359)	(0.370)	(0.267)	(0.241)	(0.247)	(0.247)	(0.261)	(0.216)	(0.245)	(0.258)	(0.280)	(0.294)	(0.301)
Mkt_rf	0.912***	0.912***	0.926***	0.935***	0.933***	0.917***	0.915***	0.763**	0.816**	0.798**	0.717***	0.625***	0.596***	0.604***
	(0.224)	(0.224)	(0.206)	(0.182)	(0.169)	(0.174)	(0.174)	(0.319)	(0.361)	(0.351)	(0.275)	(0.235)	(0.220)	(0.225)
PE ratio	0.155**	0.155**	0.159**	0.042**	0.044***	0.046***	0.047***	0.040	0.064	0.071	0.098	0.114	0.139	0.142
	(0.068)	(0.068)	(0.070)	(0.018)	(0.012)	(0.013)	(0.014)	(0.089)	(0.078)	(0.080)	(0.094)	(0.100)	(0.093)	(0.092)
PB ratio	0.165***	0.165***	0.157***	0.182***	0.137***	0.141***	0.142***	0.256***	0.248***	0.255***	0.199*	0.209**	0.201**	0.184**
	(0.037)	(0.037)	(0.031)	(0.054)	(0.033)	(0.032)	(0.033)	(0.075)	(0.072)	(0.073)	(0.102)	(0.103)	(0.090)	(0.072)
Dividend yield	-0.190***	-0.190***	-0.184***	-0.117**	-0.170***	-0.185***	-0.187***	-0.211***	-0.201***	-0.180***	-0.215***	-0.234***	-0.233***	-0.241***
	(0.030)	(0.030)	(0.033)	(0.056)	(0.058)	(0.063)	(0.061)	(0.052)	(0.052)	(0.047)	(0.057)	(0.055)	(0.048)	(0.044)
Payout	-0.128	-0.128	-0.130*	-0.049***	-0.048***	-0.051***	-0.051***	-0.034	-0.047	-0.047	-0.075	-0.082	-0.092	-0.100*
	(0.081)	(0.081)	(0.078)	(0.015)	(0.009)	(0.010)	(0.010)	(0.048)	(0.046)	(0.047)	(0.061)	(0.060)	(0.061)	(0.056)
CF per share	0.037	0.037	0.037	-0.009	-0.013	-0.011	-0.011	0.011	0.041*	0.048	0.049	0.045	0.026*	0.019
	(0.055)	(0.055)	(0.055)	(0.029)	(0.034)	(0.038)	(0.038)	(0.012)	(0.024)	(0.029)	(0.032)	(0.028)	(0.014)	(0.012)
Google Trends	-	-	1.793***	-0.109	0.386***	0.369***	0.325**	-	-	0.275	0.054	-0.119	-0.048	0.019
(“earnings”)			(0.283)	(0.152)	(0.126)	(0.140)	(0.155)			(1.574)	(0.117)	(0.129)	(0.108)	(0.118)
Google Trends	0.387	0.392	0.445	0.499*	0.599**	0.449*	0.492**	2.491*	1.893	1.593	1.350	1.119	1.080	1.033
(“stock, share price”)	(0.363)	(0.358)	(0.285)	(0.261)	(0.264)	(0.253)	(0.235)	(1.496)	(1.169)	(1.066)	(0.875)	(0.778)	(0.760)	(0.730)
Constant	-2.003	-2.035	-1.955	-2.128*	-2.840***	-2.298**	-2.480**	-8.955**	-6.101**	-5.354*	-5.103*	-4.304	-4.234	-4.068
	(1.495)	(1.461)	(1.416)	(1.144)	(1.082)	(1.051)	(0.999)	(4.436)	(2.858)	(3.059)	(2.932)	(2.921)	(2.977)	(2.870)
Observations	568	570	632	794	949	995	1,013	717	740	806	1,107	1,446	1,543	1,569
Stocks	7	7	7	7	7	7	7	10	10	10	10	10	10	10
Sigma_u	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sigma_e	7.262	7.250	7.064	7.067	7.009	6.959	6.924	11.78	12.08	11.65	10.12	8.950	8.795	8.754
Rho	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: *, **, and *** denote significance at the 10, 5 and 1 per cent levels. Standard errors are reported in parentheses.

Table 6 The Impact of Financial Indicators and Behavioural Attention – Financial Crisis

Vaariables	*During FC 1*	*During FC 5*	*During FC 10*	*During FC 25*	*During FC 50*	*During FC 75*	*During FC 90*	*After FC 1*	*After FC 5*	*After FC 10*	*After FC 25*	*After FC 50*	*After FC 75*	*After FC 90*
Price_10ybond	-0.077	-0.108	0.038	-0.033	-0.093	-0.064	-0.055	1.377***	1.261***	1.263***	1.118***	1.121***	1.115***	1.105***
	(0.468)	(0.456)	(0.407)	(0.468)	(0.647)	(0.634)	(0.632)	(0.202)	(0.168)	(0.147)	(0.129)	(0.127)	(0.126)	(0.125)
Mkt_rf	0.558***	0.532***	0.518***	0.518***	0.582***	0.575***	0.572***	0.733***	0.732***	0.718***	0.748***	0.716***	0.714***	0.711***
	(0.091)	(0.090)	(0.085)	(0.076)	(0.097)	(0.095)	(0.094)	(0.082)	(0.081)	(0.070)	(0.060)	(0.052)	(0.048)	(0.048)
PE ratio	0.173**	0.174***	0.163***	0.176***	0.205***	0.199***	0.199***	0.054*	0.058*	0.068**	0.059***	0.068***	0.068***	0.070***
	(0.068)	(0.067)	(0.060)	(0.055)	(0.056)	(0.053)	(0.053)	(0.031)	(0.030)	(0.029)	(0.018)	(0.017)	(0.016)	(0.016)
PB ratio	0.305***	0.319***	0.340***	0.354***	0.287***	0.292***	0.292***	0.256***	0.284***	0.300***	0.255***	0.238***	0.230***	0.229***
	(0.076)	(0.077)	(0.079)	(0.074)	(0.087)	(0.087)	(0.087)	(0.066)	(0.067)	(0.061)	(0.057)	(0.044)	(0.040)	(0.039)
Dividend yield	-0.218***	-0.215***	-0.214***	-0.186***	-0.206***	-0.212***	-0.212***	-0.217***	-0.188***	-0.159***	-0.177***	-0.207***	-0.213***	-0.217***
	(0.050)	(0.048)	(0.045)	(0.048)	(0.048)	(0.047)	(0.047)	(0.040)	(0.036)	(0.026)	(0.026)	(0.025)	(0.024)	(0.024)
Payout	-0.165***	-0.170***	-0.152***	-0.166***	-0.197***	-0.191***	-0.192***	-0.051**	-0.045*	-0.056**	-0.062***	-0.061***	-0.062***	-0.063***
	(0.062)	(0.061)	(0.054)	(0.051)	(0.054)	(0.052)	(0.052)	(0.024)	(0.023)	(0.023)	(0.016)	(0.018)	(0.017)	(0.017)
CF per share	0.103***	0.107***	0.103***	0.094***	0.095***	0.093***	0.093***	0.029**	0.044***	0.036***	0.023**	0.026**	0.019**	0.020**
	(0.035)	(0.034)	(0.033)	(0.030)	(0.026)	(0.026)	(0.026)	(0.013)	(0.016)	(0.014)	(0.011)	(0.010)	(0.008)	(0.008)
Google Trends	-	-1.485	-0.175	0.011	0.103	0.132	0.142	-	0.786	0.315*	0.030	0.088	0.099*	0.105*
("earnings")		(1.357)	(0.669)	(0.194)	(0.167)	(0.153)	(0.152)		(0.548)	(0.171)	(0.078)	(0.061)	(0.058)	(0.055)
Google Trends	1.444***	1.409***	1.932***	2.048***	1.414***	1.376***	1.377***	0.991*	0.630**	0.556***	0.461***	0.432***	0.401***	0.381***
("stock,share price")	(0.541)	(0.451)	(0.545)	(0.624)	(0.332)	(0.331)	(0.332)	(0.577)	(0.306)	(0.208)	(0.127)	(0.113)	(0.111)	(0.107)
Constant	-1.087	-0.988	-3.280*	-3.320**	-0.884	-0.903	-0.947	-4.597**	-3.020***	-2.780***	-1.974***	-1.956***	-1.849***	-1.770***
	(2.101)	(1.982)	(1.966)	(1.682)	(2.119)	(2.044)	(2.034)	(2.251)	(1.130)	(0.794)	(0.578)	(0.526)	(0.520)	(0.511)
Observations	1,120	1,214	1,326	1,587	1,772	1,810	1,814	2,317	2,725	3,644	6,342	8,483	9,378	9,642
Stocks	82	88	89	91	91	91	91	82	87	94	101	101	101	101
Sigma_u	0.000	0.000	0.332	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sigma_e	8.842	8.761	8.738	8.803	9.478	9.426	9.418	8.000	7.919	7.316	6.890	6.720	6.686	6.663
rho	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

We divide the data into three groups: before the financial crisis (from January 2004 to November 2007), the period of the financial crisis from the NBER description, and after the financial crisis from July 2009 to December 2017.

We show that a significant effect of attention to searches for companies' prices is provided by the period of the financial crisis (see the models *During FC* in Table 6), moreover the highest coefficients occur there. Building on the results we prove that investors' attention influences stock returns in shocks in economics. However, searching for companies' names lead to negative returns (Bijl et al., 2016). Moreover, Preis et al. (2013) claim that the increasing attention reflects concerns that precede trends to sell stock at lower prices. Kristoufek (2013) focuses on search queries to contribute to risk diversification, while he provides evidence that the more frequently searched for the terms related to the stock, the higher the risk of the specific stock. On the other hand, there are number of studies presenting a positive relationship between searches for companies' names and stock returns (Da et al., 2011; Drake, Roulstone, and Thornock, 2012; Vlastakis, Markellos, 2012). The authors refer to the second group of studies.

We add additional information; thus, we analyse different search terms on different stock markets (most of the studies used companies listed on the Dow Jones Industrial Average or SP 500 companies). According to the results, we are in line with studies that explained the higher search intensity by investors as net buyers of attention-grabbing stock. The conclusion is clear, while we show the positive effect of attention along with the highest coefficients in the period of the financial crisis.

After the financial crisis investors' attention remain its trend, moreover it is differing compared to period before the financial crisis that is characterised by insignificant coefficients (see Table B2 in the Appendix). However, the evidence shows that investors are not paying attention to companies' earnings across the model.

6. Conclusions

We investigate the data of the largest non-financial companies as high visibility subjects, where investors are regularly seeking for companies' information. We show that investors are mostly selecting PE ratio and PB ratio, acting on changes in these. Moreover, we find evidence that stock returns are positively influenced by behavioural attention to companies' stock prices.

However, analysis of investors' attention has its limitations. Firstly, we are in line with Da et al. (2011) in that we presume that strictly investors' attention from the application Google Trends is captured by typing the ticker symbol for companies. According to this approach, each company represents unique data for search intensity along with manually collecting. Secondly, investors can obtain external data from various sources (investment websites, social media, etc.) or by typing in a general specification of the searched for keyword (annual report, etc.).

We show that attention to prices or earnings varies across the sectors. The Consumer Defensive sector has different relationships between attention and stock returns compared to the others. Moreover, investors' attention began to be significant during the financial crisis where we identify the highest impact. We suggest gaining and analysing the behavioural data for Dow Jones Industrial Average, which is used in a high number of studies on this topic (Da et al., 2011; Preis et al., 2013; Kristoufek, 2013; Bilj et al., 2016; and others) and has shown a strong link between the online searches and stock returns in various cases.

Finally, our contribution is to move on further with the investigation and prove that not only searches for companies' names or their ticker symbols but also searches for financial indicators related to companies are associated with changes in stock returns. In the light of the findings, we see the implications in short-term predictions of stock price changes with a potential emphasis on sector investment strategies. Most importantly, we consider the research to be promising in new data analysis based on a mix of fundamentals and search data.

APPENDIX

Table A1 Descriptive Statistics

Variables	**Obs**	**Mean**	**Std. Dev.**	**Quantiles** **Min**	**Max**
Return	15661	1.11	9.96	-210.24	78.28
Price_10ybond	15661	3.04	1.05	1.45	5.15
Mkt_rf	15661	-2.5	4.11	-22.53	8.11
PE ratio	13436	45.89	161.4	0.88	8146
PB ratio	15062	11.58	220.5	0.34	16963.1
Debt to capital	12205	33.43	36.92	0	1391.27
Dividend yield	6633	1.75	1.26	0.02	12.14
Payout	15356	0.19	1.15	0	84
CF per share	15661	3.48	4.75	-15.76	54.28
Google Trends (“earnings”)	15661	8.14	16.18	0	100
G. Trends (“stock, share price”)	15661	13.34	20.55	0	100

Table A2 Cross-Correlation Matrix

	Return	*Price_ 10ybond*	*Mkt_rf*	*PE ratio*	*PB ratio*	*Debt to capital*	*Dividend yield*	*Payout*	*CF per share*	*"earnings"*	*"stock, share price"*
Price_10ybond	-0.0273	1.000									
Mkt_rf	0.4426	-0.3195	1.000								
PE ratio	0.0228	0.0127	0.0137	1.000							
PB ratio	0.0152	-0.0037	0.0010	0.0051	1.000						
Debt to capital	-0.0555	-0.0717	-0.0017	0.0158	0.0740	1.000					
Dividend yield	-0.0990	-0.2508	0.0247	-0.0482	0.0042	0.0270	1.000				
Payout	0.0003	-0.0421	0.0270	0.6075	0.0024	-0.0145	0.1362	1.000			
CF per share	-0.0003	-0.2795	0.1001	-0.0215	0.0372	0.0421	0.0836	-0.0014	1.000		
"earnings"	0.0280	-0.1771	0.0878	0.0058	0.0081	0.0018	-0.0669	0.0063	0.1468	1.000	
"stock, share price"	0.0148	-0.3935	0.1621	-0.0029	0.0043	0.0937	0.0772	0.0316	0.2745	0.3554	1.000

Table B1 The Impact of Financial Indicators and Behavioural Attention on the Healthcare and Consumer Cyclical Sectors

Variables	*Healthcare 1*	*Healthcare 5*	*Healthcare 10*	*Healthcare 25*	*Healthcare 50*	*Healthcare 75*	*Healthcare 90*	*Cons. Cycl. 1*	*Cons. Cycl. 5*	*Cons. Cycl. 10*	*Cons. Cycl. 25*	*Cons. Cycl. 50*	*Cons. Cycl. 75*
Price_10ybond	1.200***	1.155***	1.140***	1.057***	1.112***	1.112***	1.124***	0.767*	0.809**	1.593***	1.212***	0.942***	0.952***
	(0.281)	(0.290)	(0.288)	(0.249)	(0.250)	(0.237)	(0.231)	(0.444)	(0.393)	(0.447)	(0.278)	(0.225)	(0.228)
Mkt_rf	0.831***	0.824***	0.774***	0.765***	0.761***	0.757***	0.754***	0.400***	0.481***	0.703***	0.871***	0.892***	0.882***
	(0.139)	(0.138)	(0.131)	(0.118)	(0.114)	(0.113)	(0.113)	(0.101)	(0.102)	(0.180)	(0.134)	(0.167)	(0.163)
PE ratio	0.047***	0.049***	0.053***	0.060***	0.069***	0.075***	0.076***	0.042	0.086**	0.134***	0.138***	0.141***	0.111***
	(0.017)	(0.017)	(0.019)	(0.021)	(0.022)	(0.023)	(0.022)	(0.041)	(0.044)	(0.026)	(0.015)	(0.020)	(0.031)
PB ratio	0.233***	0.235***	0.241***	0.240***	0.249***	0.249***	0.251***	0.630***	0.520***	0.286**	0.220***	0.179**	0.190**
	(0.063)	(0.063)	(0.063)	(0.057)	(0.055)	(0.056)	(0.057)	(0.100)	(0.111)	(0.138)	(0.076)	(0.083)	(0.082)
Dividend yield	-0.155***	-0.152***	-0.158***	-0.167***	-0.168***	-0.160***	-0.165***	-0.129***	-0.129***	-0.173***	-0.143***	-0.181***	-0.206***
	(0.040)	(0.039)	(0.034)	(0.036)	(0.036)	(0.032)	(0.029)	(0.042)	(0.040)	(0.053)	(0.039)	(0.042)	(0.042)
Payout	0.026	0.024	0.016	-0.012	-0.023	-0.031	-0.029	0.005	-0.018	-0.052**	-0.133***	-0.139***	-0.110***
	(0.047)	(0.047)	(0.042)	(0.026)	(0.024)	(0.023)	(0.022)	(0.037)	(0.028)	(0.023)	(0.018)	(0.023)	(0.031)
CF per share	0.018	0.019	0.020	0.022	0.035**	0.030*	0.030*	0.011	0.021	0.033	0.021	0.018	0.015
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.015)	(0.016)	(0.019)	(0.022)	(0.021)	(0.021)	(0.013)	(0.014)
Google Trends	-	1.866***	-0.127	-0.199	-0.110	-0.253	-0.235	-	-0.245	-0.111	-0.195	-0.206*	-0.117
("earnings")		(0.242)	(0.513)	(0.233)	(0.164)	(0.158)	(0.155)		(1.650)	(0.644)	(0.180)	(0.119)	(0.101)
Google Trends	0.864**	0.856**	0.813***	0.674**	0.666***	0.676***	0.652***	0.515	0.342	1.105*	0.561***	0.365***	0.323***
("stock, share price")	(0.369)	(0.349)	(0.307)	(0.267)	(0.227)	(0.219)	(0.215)	(0.540)	(0.377)	(0.623)	(0.195)	(0.101)	(0.092)
Constant	-3.113**	-2.978*	-2.978**	-2.243*	-2.431**	-2.456**	-2.428**	-1.720	-1.025	-5.627*	-1.718*	-0.155	-0.173
	(1.586)	(1.578)	(1.449)	(1.228)	(1.185)	(1.114)	(1.091)	(2.504)	(1.668)	(3.198)	(0.967)	(0.792)	(0.811)
Observations	1,750	1,805	2,024	2,519	2,873	3,052	3,104	641	793	974	1,702	2,300	2,535
Stocks	19	19	19	19	19	19	19	16	16	16	17	17	17
Sigma_u	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	2.317	0.000	0.000	0.000
Sigma_e	8.823	8.729	8.435	8.273	8.222	8.148	8.118	5.889	6.804	8.026	8.550	8.712	8.590
rho	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.077	0.000	0.000	0.000

Notes: *, **, and *** denote significance at the 10, 5 and 1 per cent levels. Standard errors are reported in parentheses.

Table B2 The Impact Of Financial Indicators and Behavioural Attention – Before the Financial Crisis

Variables	**Before FC 1**	**Before FC 5**	**Before FC 10**	**Before FC 25**	**Before FC 50**	**Before FC 75**	**Before FC 90**
Price_10ybond	-0.281	-0.222	-0.358	-0.404	-0.303	-0.349	-0.372
	(0.347)	(0.342)	(0.350)	(0.345)	(0.334)	(0.340)	(0.341)
Mkt_rf	0.965***	0.971***	1.027***	1.015***	0.991***	0.979***	0.979***
	(0.102)	(0.101)	(0.107)	(0.104)	(0.102)	(0.101)	(0.101)
PE ratio	0.106***	0.107***	0.120***	0.119***	0.114***	0.115***	0.116***
	(0.023)	(0.022)	(0.024)	(0.023)	(0.022)	(0.022)	(0.022)
PB ratio	0.289***	0.289***	0.248***	0.256***	0.268***	0.273***	0.274***
	(0.065)	(0.063)	(0.059)	(0.061)	(0.062)	(0.063)	(0.063)
Dividend yield	-0.175***	-0.175***	-0.168***	-0.171***	-0.158***	-0.163***	-0.163***
	(0.030)	(0.029)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
Payout	-0.045*	-0.046*	-0.051*	-0.046*	-0.051**	-0.051**	-0.051**
	(0.026)	(0.026)	(0.027)	(0.027)	(0.023)	(0.023)	(0.023)
CF per share	0.031***	0.033***	0.036***	0.040***	0.041***	0.042***	0.043***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Google Trends	-	-0.152	1.615***	0.013	-0.096	-0.103	-0.086
("earnings")		(0.461)	(0.549)	(0.253)	(0.157)	(0.121)	(0.114)
Google Trends	0.420	0.231	0.233	0.295	0.446	0.406	0.408
("stock, share price")	(0.395)	(0.383)	(0.373)	(0.359)	(0.363)	(0.356)	(0.354)
Constant	5.128***	5.454***	6.285***	6.320***	5.275***	5.555***	5.650***
	(1.740)	(1.720)	(1.818)	(1.776)	(1.615)	(1.623)	(1.628)
Observations	3,107	3,195	3,293	3,498	3,734	3,812	3,842
Stocks	89	89	89	90	90	90	90
Sigma_u	0.925	0.565	0.548	0.580	0.648	0.618	0.591
Sigma_e	7.217	7.191	7.345	7.293	7.291	7.272	7.262
rho	0.016	0.006	0.006	0.006	0.008	0.007	0.007

Notes: *, **, and *** denote significance at the 10, 5 and 1 per cent levels. Standard errors are reported in parentheses.

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