Behavioral Attention by Google Trends: Evidence from the Car Industry

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Abstract

We investigated the link between stock returns of automobile companies, Fama French factors, and behavioral attention, represented by demand for a selected car brand belonging to an automobile company. Using Google search activity, we focus on the impact of searches about car brands on 17 automobile companies from 2004 to 2020. We concluded that even though general intuition provides positive results, negative historical events can result in a fall in prices in some cases. Dieselgate, an event specific to this industry, engulfed the affected company and resulted in an EU-wide scandal; however, the increase in interest did have not the same effect on automobile companies based in other countries.

Keywords: *automobile industry, behavioural attention, behavioural finance, Dieselgate, financial crisis, Google Trends, sector sentiment*

JEL Classification: G40, G12

DOI: https://doi.org/10.31577/ekoncas.2023.03.02

Article History: *Received*: January 2023 *Accepted*: July 2023

Introduction

The internet has become a significant resource for consumers' reviews on companies or their products, which can influence users in their buying or selling decisions. For consumers, there are no barriers to finding information or becoming part of a group that has the same interests. Furthermore, companies can analyze data for product sales forecasting to reduce losses in production or use it to draw up marketing plans.

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In terms of research, using online information to explain the changes in stock returns has been adopted relatively widely. Our main contribution in this paper is to confirm the price pressure hypothesis in behavioral attention, while we focus on a specific sector. We employed the same attention variable along with similar calculations that are used in the most well-known article (Da et al., 2011), however, we applied these to the automobile industry – 17 car companies (11 listed in the US, 6 listed in EU).

To extend the study, we adopt behavioral attention in conjunction with relevant policy questions. We showed that negative events change a user's sentiment. Dieselgate is a vivid example. Also known as "Emissionsgate" refers to the illegal manipulation of software in Volkswagen certain diesel vehicles that allowed them to emit more harmful pollutants. This event specific to the automotive industry, engulfed the affected company and set off an EU-wide scandal, the increase in interest did not play the same role in terms of its effect on automobile companies in other countries.

The importance of focusing on consumer searches is related to transmission channels. People take actions that evolve from attention, and this makes them search for information, especially for more expensive goods such as cars. In light of the suggestion that consumers are mostly using search engines to help them find information[1] on goods, this action undoubtedly means that they are paying attention. For example, the company publishes car innovations to which consumers react positively. According to the positive news, consumers buy products from the company. In other words, such an increase in searches "predicts" later price increases. Moreover, the purchase of a car results in sales growth, which provides information on company health. Furthermore, according to investment houses, sales performance not only influences the stock market but also the entire economy. Consequently, increased sales performance makes automobile stocks more attractive to investors. Thus, we conclude the positive impact of attention on car brands on stock returns in the automobile industry.

Researchers have started to find new applications for measuring information that is sought out by consumers. In this context, we use the application Google Trends to discover data on the search intensity of specific keywords or groups of keywords typed in Google's search engine. To the best of our knowledge, it appears that, to date, no articles have specifically drawn a link between attention to car brands and stock returns in the automobile industry. To be precise, Da et al. (2011) employed attention to the main product of the company to regression but

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

didn't find its significance to stock returns. However, previous studies have proven the positive impact of investors' attention on stock returns (Da et al., 2011; Drake et al., 2012; Da et al., 2015; Drake et al., 2016; Ben-Rephael et al., 2017; Stejskalová, 2019). More precisely, while economic agents are searching for ticker symbols, they pay attention resulting in investors' decisions.

We chose the automobile industry for several reasons. First, automobile companies are included in one of the world's largest economic sectors by revenue, which makes them high-visibility subjects. Second, we assume that consumers' searches over brand names are associated with car purchases. We applied information on search intensity to measure the searcher's attention related to the demand for information about the car brand. To summarize, this indicator represents a direct measure of searchers' attention. We follow Barber and Odean (2008), who propose attention as the indicator for buying decisions rather than selling because economic agents have more options when searching for information about a product they can potentially buy. The study confirms this presumption by investigating the effect of attention on stock-buying behavior. Therefore, we claim that the same applies to commercial goods. The sellers do not face the problem of data collection because they have already searched for information when buying the product.

The paper is structured as follows: Section 1 contains the literature review related to the importance of investigating behavioral finance and a detailed literature review of studies on the auto industry. Section 2 provides an overview of the methods and data. The basic results of the regressions are presented in Section 3. Section 4 contains a robustness analysis, and the last Section concludes our results.

1. Behavioral Finance Angle

1.1. The Importance of the Behavioral Finance Survey

The first comprehensive approach to capital market analysis is a hypothesis of efficient markets, defining the capital market and individual stock prices as perfectly sensitive to information. The efficient market hypothesis (EMH) posits that stock prices reflect all available information. Fama (1965) was the first person to study the theory from a theoretical approach to empirical analysis and popularized the hypothesis. However, the historical process of capital markets has shown different behavior. Building on a historical review, investors' optimism resulted in excess demand for stock prices, while the prices increased high above the fundamental value and created an economic bubble. The financial crisis appeared after a significant reduction in stock prices caused by panic selling (see the comprehensive review by Chang et al., 2016).

Concerning the inefficiencies of the capital market, studies have started to focus on behavioral finance, which serves to unlock the conditions of EMH and examine investors' behaviors. The important role of studying behavioral finance was highlighted in Curtis' (2004) work. He points out the efficient market approach as a theory to explain the behavior of the entire market, while behavioral finance is credible for describing the reactions of individuals. This finding is important in the context of technological development and, in particular, in the context of communication networks that provide individuals with access to investments.

In such a context, we used the application Google Trends to find out which information users search for. In finance, the researchers used online ticker searches as a valid proxy for investors' attention. Moreover, many studies have supported this conclusion (Andrei and Hasler, 2014; Bijl et al., 2016; Ben-Rephael et al., 2017; and others). They use the application Google Trends to provide data on search intensity. The application measures search query indices on selected keywords or groups of keywords in a selected frequency. This research study is in line with Da et al. (2011) and employs behavioral attention expressed by search intensity, which is measured using the application Google Trends. However, we extended the study to investigate the automobile industry.

As far as we know, few studies are using Google Trends in automobile industry data. The study Fantazzini and Toktamysova (2015) appears to be the closes. They focus on the impact of attention via Google Trends data to forecast monthly car sales. They employed the monthly car sales data of ten car brands in Germany, economic variables,[2] and online search queries as leading indicators for the long-term forecasting of car sales. They showed that the model with Google data outperformed the competing models in the case of long-term forecasts for several brands. We have expanded on the literature to capture attention concerning 17 automobile companies trading around the world.

A growing body of studies related to the car industry highlights the influence of social media (Woolridge, 2011; Abrahams et al., 2012; 2013; 2015; Fan and Gordon, 2014; etc.). Moreover, Stieglitz and Dang-Xuan (2013) point out that companies should pay more attention to the analysis of sentiment related to their brands and products in social media. The focus is appropriate if we consider the results of the studies. Abrahams et al. (2012; 2013; 2015) discover a specific vehicle defect to improve the quality of management via an analysis of social media postings. More interestingly, He et al. (2015) use social media to identify what consumers are saying about competitors' products and services. Zhang et al. (2017) highlight the usefulness of "big data." They take the automobile industry to give suggestions for car sales via large data analysis.

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[2] GDP, unemployment rate, CPI, consumer confidence index, and others.

1.2. Evidence from the Car Industry

Google Trends is presented as a high-potential tool for any social grouping or individual. Choi and Varian (2012) prove that the Google index may help predict automobile and real estate sales and forecast visits to destinations within the tourist industry. In addition, the evidence from Ginsberg et al. (2008) shows that by analyzing the search queries from Google Trends, we can track influenza-like illnesses 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 traditional surveillance systems. There are several studies in this regard in the area of health (Carneiro and Mylonakis, 2009; Ginsberg et al., 2008; Pelat et al., 2009).[3]

On further investigation, economic studies were the first to analyze data on the U.S. stock market using Google Trends (Lui et al., 2011; Vosen and Schmidt, 2011; Choi and Varian, 2012; Preis et al., 2013; and others). This was followed by various geographical categories (Germany, China, United Kingdom, etc.). Nowadays, research using Google Trends has increased dramatically in a wide range of areas. In finance, Da et al. (2011) prove the positive impact of attention on stock prices by employing data from Google Trends. We have expanded on the recent literature to include the use of Google Trends in an investigation of the auto industry.

Hypothesis 1: Behavioral attention has a positive impact on stock returns in the automobile industry.

The impact of news has gained widespread attention among academics (Díaz and Jareno, 2009; Hausman and Wongswan, 2011; Rangel, 2011; Jun et al., 2016). Anderson et al. (2018) examine unexpected (surprise) macroeconomic announcement shocks on sectoral indices. There are significant differences in response to global and regional shocks. The findings reveal that the shocks are not fully incorporated and indicate possible risk diversification. Moreover, the car industry was found to be one of the most sensitive sectors to macroeconomic announcements. Bredin et al. (2007) focus on the impact of UK monetary announcements on sectoral returns. They show that sectors such as oil, gas, or auto parts are influenced by monetary policy shocks.

Hypothesis 2: Behavioral attention has a different impact on stock returns in times of crisis.

Behavioral finance is being analyzed in various ways. We follow the survey that points out the value of information in transmitted messages according to an amount of uncertainty (Shannon, 1948). In case of negative events, the searches

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[3] The comprehensive usage of application Google Trends is presented in Jun, Yoo and Choi study (2018).

reflect more uncertainty, and stock markets responded negatively (Lyócsa et al., 2020). As a result, it is important to distinguish whether the attention is directed at positive or negative information. On the other hand, the theory behind the value of information is applied in the theory of rational inattention (Sims, 2015). The study introduced the idea that people's abilities to translate external data into actions are constrained by a finite "capacity" to process information. Such models do explain why some freely available information is not used or is imperfectly used. In light of the findings, we focus on the Dieselgate affair, a specific event for the industry, that increases the uncertainty. We believe that people are forced to gather the information, however, the user's data selection could be different for European, American, or Asia car producers.

Hypothesis 3: Behavioral attention has a different impact on stock returns in various countries.

2. Data and Empirical Strategy

The dataset contains weekly data from January 2004 to September 2020 and includes 17 stocks (for further information, see Appendix B.1). Most of the automobile companies are listed on the US market, except for Hyundai, Fiat Chrysler Automobiles, Volkswagen, BMW and Mazda, which are part of the German market, and Renault is listed on the French market (Paris Stock Exchange). In other words, these companies are traded at the following stock exchanges: NYSE, Over the Counter (OTC), XETRA, NASDAQ, the Frankfurt Stock Exchange, and the Paris Stock Exchange. In such a context, we used the Morningstar database to provide historical stock prices. However, data for the European companies were obtained from the official websites of the Paris and Frankfurt Stock Exchanges.

Identifying and understanding investors' attention is challenging. The key issue that must be addressed when using this proxy is how to properly work with SVI data. We chose Google Trends to source data on behavioral attention. The application allows to download a search volume index (SVI) for a specific keyword or groups of keywords. For each car manufacturer, we download SVIs for all the brands that belong to this company. For example, the brands "Hyundai" and "Kia" belong to the same concern 'Hyundai'. Therefore, for the company 'Hyundai', we retrieve from Google Trends the searches that contain either of the terms 'Hyundai' and 'Kia'.

Google Trends provide data as a time series index from 0 to 100. For weekly data, it is possible to download at most 5 years of data at once. We, therefore, downloaded four overlapping time series for each search term. One might ask whether there are structural breakdowns according to the multiple datasets for one keyword, while each dataset includes its own highest search point for a chosen period. To avoid biased results, we downloaded monthly data for each group of car brands, and we recalculated the data as follows:

$$svi_i = \frac{svi_i * svi_m}{100} \tag{1}$$

where svi_i represents search volume during the week *i,* svi_m is obtained from the monthly dataset and is used relative to the date of the calculated svi_i.

The second possible data issue lies in identifying the intended attention, see the introduction section for further information on whose attention we are capturing. By typing the keyword "Jaguar", the index may consist of searches related to the animal or the car manufacturer. To minimize the unintended meaning of a keyword, we restricted the searches to the category "cars and vehicles" (for further information, see Appendix B.1). Finally, we followed Da et al. (2011) and used an abnormal search volume index (ASVI), defined as:

$$ASVI_t = \log\left(SVI_t\right) - log\left[Med\left(SVI_{t-1},\ldots,SVI_{t-n}\right)\right] \tag{2}$$

where $\log\left(SVI_t\right)$ represents the logarithm of *SVI* during week *t*, and $log\left[Med\left(SVI_{t-1},\ldots,SVI_{t-n}\right)\right]$ is the logarithm of the median value of *SVI* during the prior *n* weeks. We consider *n = 1, 2, 3, 8* and we denote the corresponding *ASVI* as *ASVI1*, *ASVI2*, *ASVI3,* and *ASVI8*.

Lastly, the application Google Trends generates weekly data from Monday to Monday, thus we download weekly stock returns for the corresponding period.

The stock return *r* is defined as the first differences of log adjusted stock prices of automobile company *i* in time *t*. We used OLS panel regression specified as:

$$\begin{aligned} r_{i,t} &= const + \beta_1 r_{i,t-1} + \beta_2 ASVI1_{i,t} + \beta_3 ASVI2_{i,t} + \beta_3 ASVI3_{i,t} + \\ &+ \beta_4 ASVI8_{i,t} + \beta_5 SMB_t + \beta_6 HML_t + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where the dependent variable r_{t-1} represents stock returns of each company with one week lag. The factor data expressed by the return difference between portfolios of 'small' and 'big' stock (SMB) and the return difference between portfolios of 'high' and 'low' book-to-market stocks (HML) are included in the three-factor Fama-French model. Variable SMB represents size premium, where small cap companies generate higher returns and HML variable represents value premium, where companies with high book-to-market ratios generate higher returns compared to the market. The last set of variables included ASVI for specific automobile companies *i* and time *t.* The differences between the companies were captured by sector-fixed effects μ_i . This approach is in line with Choi and Varian (2012). They applied fixed effects to investigate the link between car sales and Google searches for a car manufacturer. Finally, in the calculation of standard errors, we employed clustering by company. The descriptive statistics, along with a cross-correlation matrix, can be found in Appendix A (see Appendices A.1 and A.2).

To this extent, we applied dummy variables to analyze the differences in various periods. We emphasize the financial crisis and the Dieselgate scandal.

3. Results

This section presents the results of predictive regressions. Table 1 reports the results for the whole sample period. Table 2 reports the results from the same regressions but estimated separately for periods before, during, and after the financial crisis.

Table 1 shows that the relationship between past and current stock returns is very weak, there is small autocorrelation in the stock returns (see the results in Table 1 part ALL). We are in line with Joseph, Wintoki and Zhang (2011) and Fama and French (2017) presenting the positive correlation between the SMB factor and stock returns. In addition, Fama and French (2017) differentiate between sectors in economics and proved the weak impact on dependent variables. The explanatory factor reflects the assumption that small companies produce higher returns than large-cap companies.

On the other hand, the coefficient of the ASVI variable (no matter whether estimated as ASVI1, ASVI2, ASVI3, or ASVI8) is positive and significant which is in line with the first hypothesis. In such context, the study provides evidence that an increase in behavioral attention to car brands is accompanied by an increase in stock returns while the company is placed in the United States which remains the same for the entire dataset (see variables ASVI1, ASVI2, ASVI3, and ASVI8 in Table 1 for the part US and ALL). The evidence confirms general results on the relationship between stock returns and behavioral attention expressed by the search volume index from the application Google Trends. More precisely, Da et al. (2011) were the first to put forward the hypothesis that gathering information influences searchers' decision-making, and this does not differ in the case of the car industry. However, it significantly differs in results when we are comparing it with APSVI.[4] To confirm the price pressure hypothesis in a specific sector, we strictly adhered to Da et al.'s (2011) ASVI calculation (see variable ASVI8).

[4] The log of PSVI (aggregate search frequency based on the main product of the company) during the week minus the log of median PSVI during the previous 8 weeks

T a b l e 1

Behavioral Attention by Google Trends: Basic Analysis

	Dependent variable: r_t											
	US				EU				ALL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
r_{t-1}	–0.106	–0.107	–0.106	–0.107	–0.053	–0.053	–0.052	–0.052	–0.085*	–0.086*	–0.086*	–0.086*
	(0.063)	(0.063)	(0.063)	(0.063)	(0.032)	(0.032)	(0.032)	(0.032)	(0.043)	(0.043)	(0.043)	(0.043)
SMB	0.003***	0.003***	0.003***	0.003***	0.002**	0.002**	0.002**	0.002**	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HML	0.000	0.000	0.000	0.000	0.001*	0.001*	0.001*	0.001*	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)	(0.000)	(0.000)
$ASVI1_t$	0.011**				0.008				0.010***			
	(0.004)				(0.007)				(0.000)			
$ASVI2_t$		0.023**				0.006				0.017**		
		(0.010)				(0.007)				(0.006)		
$ASVI3_t$			0.013**				0.008				0.012***	
			(0.005)				(0.008)				(0.004)	
$ASVI8_t$				0.018***				0.004				0.011**
				(0.005)				(0.005)				(0.005)
R2	0.0143	0.0152	0.0152	0.0154	0.0037	0.0037	0.0039	0.0037	0.0094	0.0097	0.0099	0.0097
Observations	8,345	8,345	8,340	8,310	5,061	5,061	5,055	5,025	13,406	13,406	13,395	13,335
Stocks	11	11	11	11	6	6	6	6	17	17	17	17

Note: This table shows the effect of Google searches, obtained through Google Trends, on stock returns. For each car company, we collect the attention to car brands that the company produces. The stock returns are defined as closing prices for each week as the difference in the logarithm of prices. Each model contains lagged returns, Fama French controls, and fixed effects. Control variables include stock returns with one week lag, Fama French variable size premium (SMB), and value premium (HML) applied by Joseph et al. (2011). We include company fixed effects. The regression coefficients are reported. *, **, and *** denote significance at the 10, 5, and 1 percent level. Clustered standard errors are reported in parentheses.

Source: Authors' calculations.

Moreover, we employ additional variables with the same calculation process, which only differs in the number of weeks, to see, whether the results remain the same (see variables ASVI1, ASVI2, and ASVI3). Moving back to the results, for example, ASVI8 for the US dataset increased the stock returns by 0.018% compared to Da et al.'s (2011) negative regression coefficient for APSVI. Finally, behavioral attention is more relevant with a decrease in time trends and low-frequency seasonality (see higher correlation from ASVI1 to ASVI8 in Table 1 for the US data). We should accept the ASVI2, where the impact on stock returns is slightly higher compared to the rest of the behavioral variables.

In terms of automobile companies from Europe, the situation is different. We cannot confirm the significant correlation between explanatory variables and stock returns. However, the situation could change along the time and event that we are focused on (see the results for the Dieselgate affair).

Concerning the above results, we employed time dummies to show changes in behavioral attention before, during, and after the financial crisis (see Table 2). We claim that, even though the general hypothesis provides positive results in terms of the relationship between stock returns and behavioral attention, negative historical events resulted in a fall in car sales along with a decrease in attention to car brands. In such context, we refer to the second hypothesis and conclude that economic recession is associated with a decrease in sales growth, resulting from the consumer behavior expressed by lower searches about car brands.

Do et al. (2018) extended the period of the financial crisis to August/September 2011, when the last breakpoint occurred. Thus, we started the analysis from this point to differentiate between historical incidents. We divided the data into three groups: before the financial crisis (from January 2004 to November 2007), the period of the financial crisis based on Do et al.'s (2018) description, and after the financial crisis, from September 2011 to June 2020.

We incorporated the dummy variables, which limited the investigated periods. First, we looked at the situation before the financial crisis. We employed the data from 1 January 2004 to 30 November 2007. The model confirmed the positive impact of behavioral attention on stock returns. However, the chosen periods represent separated parts of the studied data; thus, the lagged variables could change over the time period. According to the division, the stock returns of automobile companies are characterized by significant and negative correlations with their lagged value before the financial crisis. Concerning the independent variable in the three-factor model, an increase in the HML factor increases the stock returns by 0,4%. The above result follows from stock character representing the dominance of value stocks. Moreover, the companies are undervalued related to high B/M ratios. More interestingly, behavioral attention remains the same in the context of similar studies and is found to be positively linked to stock returns in these times.

T a b l e 2

Behavioral Attention by Google Trends: Financial Crisis

Variable	Before FC	Before FC	Before FC	Before FC	During FC	During FC	During FC	During FC	After FC	After FC	After FC	After FC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
r_{t-1}	–0.069**	–0.070**	–0.068**	–0.069**	–0.144*	–0.144*	–0.144*	–0.144*	–0.041*	–0.042**	–0.042**	–0.042**
	(0.028)	(0.028)	(0.029)	(0.029)	(0.079)	(0.079)	(0.079)	(0.079)	(0.019)	(0.019)	(0.019)	(0.019)
SMB	0.001	0.001	0.001	0.001	0.005***	0.005***	0.005***	0.005***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)				
HML	0.004***	0.004***	0.004***	0.004***	0.001	0.001	0.001	0.001	–0.000	–0.000	–0.000	–0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$ASVI1_t$	0.029**				0.027				0.009***			
	(0.011)				(0.016)				(0.003)			
$ASVI2_t$		0.029**				0.006				0.017**		
		(0.013)				(0.015)				(0.007)		
$ASVI3_t$			0.029**				0.024				0.011**	
			(0.013)				(0.019)				(0.005)	
$ASVI8_t$				0.018**				0.004				0.011*
				(0.007)				(0.013)				(0.006)
R2	0.0109	0.0113	0.0122	0.0119	0.0237	0.0231	0.0239	0.0231	0.0043	0.0050	0.0050	0.0051
Observations	2,625	2,625	2,614	2,554	2,864	2,864	2,864	2,864	7,917	7,917	7,917	7,917
Stocks	14	14	14	14	17	17	17	17	17	17	17	17

Note: This table shows the effect of Google searches, obtained through Google Trends, on stock returns in defined periods – before, during, and after the financial crisis. For each car company, we collect the attention to car brands that the company produces. The stock returns are defined using closing prices for each week as the difference in the logarithm of prices. Each model contains lagged returns, Fama French controls, and fixed effects. Control variables include stock returns with one week lag, Fama French variable size premium (SMB), and value premium (HML) applied by Joseph et al. (2011). We include company fixed effects. The regression coefficients are reported. *, **, and *** denote significance at the 10, 5, and 1 percent level. Clustered standard errors are reported in parentheses.

Source: Authors' calculations.

The most significant and interesting results are presented in the period during the financial crisis. Searching for information about car brands is not accompanied by a change in stock returns. In such a context, consumers don't gather information about car brands because they don't make buying decisions during the economic recession, thus the attention to car brands is not a significant variable in case of stock returns in these times (see Table 2, ASVI variables in models 'During FC'). Our intuition is confirmed in the period after the financial crisis, while the economy is recovering from recession along with the increase of expenditures. To conclude, people extend their spending for durable goods which forces them to search for information to make their buying decisions. These findings are in line with the second hypothesis that behavioral attention has a different impact on stock returns in times of crisis. The rest of the explanatory variables retain their impact as in Table 1 (see variables SMB, HML, and past stock returns).

4. Robustness Analysis

In late 2015, the US Environmental Protection Agency (EPA) announced that Volkswagen had installed illegal devices to meet exhaust pollution standards. The scandal engulfed the company and was the beginning of a worldwide problem. First, Volkswagen is the biggest car manufacturer; thus, the issue applied to 11 million cars across the world, and finally, as a result of the scandal, it was discovered that diesel engines by other competitors were also more polluting than during the initial tests. We claim that this incident had an impact on the relationship between studied behavioral attention and stock returns.

The incident represents a unique event that affected all parts of the automobile sector, similar to the financial crisis. The event was linked to Volkswagen; thus, we conclude that the negative attention was revealed to be significant in the case of the affected company.

At the same time, the increasing interest did not have a significant effect on all automobile companies. To summarize, our main contribution is to point out a strongly negative case that led to changes in attention, and Dieselgate is an example of an incident that is specific to the industry.

Finally, we employed simple OLS regression with robust standard errors for each company, compared to the rest of the analyses where we applied OLS panel regression. We follow the previous analyses and employed stock returns with a one-week lag and behavioral attention with the same calculation as was presented in previous analyses. Last, we limited the period from September 2015 to January 2019 when the affair occurred.

T a b l e 3

Behavioral Attention by Google Trends: Dieselgate Scandal (Europe)

Variable	VOW	VOW	VOW	VOW	BMW	BMW	BMW	BMW	Fiat	Fiat	Fiat	Fiat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
r_{t-1}	0.073	0.042	–0.002	–0.008	–0.107	–0.107	–0.106	–0.108	–0.049	–0.060	–0.060	–0.059
	(0.158)	(0.142)	(0.131)	(0.126)	(0.085)	(0.085)	(0.085)	(0.085)	(0.087)	(0.088)	(0.088)	(0.088)
SMB	0.002	0.002	0.002	0.001	0.002	0.002	0.002	0.002	0.005	0.004	0.004	0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
HML	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.006**	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$ASVI1_t$	–0.301				–0.001				–0.217*			
	(0.237)				(0.004)				(0.122)			
$ASVI2_t$		–0.353*				–0.004				–0.150		
		(0.207)				(0.006)				(0.116)		
$ASVI3_t$			–0.303*				–0.005				–0.073	
			(0.182)				(0.004)				(0.102)	
$ASVI8_t$				–0.221*				–0.004				–0.010
				(0.131)				(0.003)				(0.073)
R2	0.0678	0.1132	0.1016	0.0857	0.0137	0.0142	0.0147	0.0149	0.0478	0.0359	0.0266	0.0227
Observations	178	178	178	178	178	178	178	178	178	178	178	178

Note: This table shows the effect of Google searches, obtained through Google Trends, on stock returns in defined periods – before, during, and after the financial crisis. For each car company, we collect the attention to car brands that the company produces. The stock returns are defined using closing prices for each week as the difference in the logarithm of prices. Each model contains lagged returns, Fama French controls, and fixed effects. Control variables include stock returns with one week lag, Fama French variable size premium (SMB), and value premium (HML) applied by Joseph et al. (2011). We include company fixed effects. The regression coefficients are reported. *, **, and *** denote significance at the 10, 5, and 1 percent level. Clustered standard errors are reported in parentheses.

Source: Authors' calculations.

Table 3 shows the commonly used dependent variable – lagged returns determinant and its relationship to the stock returns of selected automobile companies (see variable r_{t-1}). The above results confirm an insignificant influence during the Dieselgate incident that was revealed to be similar compared to Table 1. We chose the companies according to where they were founded to highlight the various impact of attention and divided the tables for Europe and for the United States and Japan.

In Table 3, the variables ASVI (see ASVI, ASVI2, ASVI2, and ASVI8) for companies based in Germany (Volkswagen Group and BMW) and even Italy (Fiat Chrysler Automobiles).

In recent years, there is a push of the EU on car emissions. The EU Commission fears the pollutants from diesel vehicles and regulates the industry to achieve zero emissions. These goals are resulting in European car producers cheating on the emission parameters and standards. The main actor Volkswagen experienced a decrease in stock price by 0.221% because of negative attention during Dieselgate (see the variable ASVI8 in the fourth column VOW). More interestingly, the negative sentiment was not confirmed in the case of BMW (see the variable ASVI8 in the last column BMW).

However, Italy was affected by the negative event (see the variable ASVI1 in the ninth column Fiat). The findings are in line with the third hypothesis that refers to different impacts in various countries (also see the results for American and Asia producers in Table 4).

The explanation could be linked to geographical position, while the other car producers were automatically hit by this affair by tougher regulations that drive up the costs of making diesel cars, and not the least the consumers look at the EU producers equally.

Table 4 employs the same analyses for companies placed in the United States and Japan. From the results, attention is associated with an insignificant or weak positive correlation to stock returns. The results explain how the American and Asia producers react to the event.

From different product perspectives, we can compare the Volkswagen diesel cars and Tesla electric cars producing zero emissions. In light of the results and the intuition, the event doesn't have an impact on companies' stocks (see the variables ASVI1, ASVI2, ASVI3, and ASVI 8 in columns 1 – 4 in Table 4).

More interestingly, Asia producers could profit from this event. According to Statista data, Mitsubishi car sales increased by almost 43% in 2015 compared to the year before. The results show a positive impact on stock price by 0.110% (see the variable ASVI2 in column 10 in Table 4).

T a b l e 4

Behavioral Attention by Google Trends: Dieselgate Scandal (USA, Japan)

Variable	Tesla	Tesla	Tesla	Tesla	Toyota	Toyota	Toyota	Toyota	Mitsubishi	Mitsubishi	Mitsubishi	Mitsubishi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
r_{t-1}	–0.056	–0.055	–0.055	–0.057	–0.011	–0.011	–0.011	–0.010	–0.056	–0.068	–0.071	–0.063
	(0.075)	(0.074)	(0.075)	(0.075)	(0.078)	(0.078)	(0.078)	(0.078)	(0.073)	(0.074)	(0.074)	(0.074)
SMB	–0.002	–0.002	–0.003	–0.002	0.004**	0.004**	0.004**	0.004**	0.004	0.004	0.004	0.004*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
HML	–0.003	–0.003	–0.003	–0.003	–0.000	–0.000	–0.000	–0.000	–0.001	–0.001	–0.001	–0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$ASVI1_t$	0.001				0.001				0.125			
	(0.008)				(0.047)				(0.077)			
$ASVI2_t$		0.002				–0.006				0.110*		
		(0.011)				(0.050)				(0.062)		
$ASVI3_t$			–0.009				–0.001				0.081*	
			(0.009)				(0.047)				(0.046)	
$ASVI8_t$				0.001				–0.019				0.025
				(0.009)				(0.034)				(0.026)
R2	0.0083	0.0083	0.0138	0.0082	0.0319	0.0320	0.0319	0.0335	0.0440	0.0445	0.0391	0.0225
Observations	178	178	178	178	178	178	178	178	178	178	178	178

Note: This table shows the effect of Google searches, obtained through Google Trends, on stock returns in defined time period – Dieselgate affair. For each car company we collect the attention to car brands that the company produces. The stock returns are defined using closing prices for each week as the difference in logarithm of prices. Each model contains lagged returns, Fama French controls, and fixed effects. Control variables include stock returns with one week lag, Fama French variable size premium (SMB), and value premium (HML) applied by Joseph et al. (2011). The regression coefficients are reported. *, **, and *** denote significance at the 10, 5, and 1 per cent level. Robust standard errors are reported in parentheses.

Source: Authors' calculations.

To sum up, these findings are in line with other studies (Da et al., 2011; 2015; Klemola et al., 2016) that argue that behavioral attention represents a relevant sentiment variable. In such a context, the negative economic situation changes people's decision-making while they gather information using Google's search engine. To summarize, we claim that the specific event is one of the illustrative examples of increasing interest in each company that can lead to the predictive power of attention. This issue is outlined in Preis et al. (2010; 2013).

Conclusions

While previous studies focus on the effect of investor attention on single stocks, we extend the previous studies by analyzing the impact on specific industries. Online users are seeking information related to car brands. Such action is in line with the price pressure hypothesis. Behavioral attention is associated with a positive influence on stock returns that could reflect positive fundamental information.

Even though the general relationship between attention and stock returns was found to be positive, negative events can change a user's sentiment. However, it depends on the character of the situation. Attention in times of financial crisis doesn't have the predictive power in stock returns changes because it affected consumer spending.

On the other hand, Dieselgate is a negative event that is specific to the industry, where negative attention was found to be significant in the case of an affected company and Italy car producer. A possible explanation is the geographical location, while the company is traded in the European Union.

In light of the findings, it is worth looking at the regulatory push of the EU on car emissions. We see the potential in studying the company-specific effects using the model with interactions. The EU government should consider the fact that the issue related to the unrealistic increase in the regulations could create an advantage for non-European car producers.

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Appendix A

Table A.1
Descriptive Statistics for United States Dataset

Variables	Obs	Mean	Std. Dev.	Min	0.25	0.75	Max
Ret	8,356	0.0011	0.0576	–0.7106	–0.0237	0.0268	0.6931
SMB	9,614	0.0035	1.1891	–5.7900	–0.7200	0.7000	6.1200
HML	9,614	–0.0534	1.5815	–8.9400	–0.7400	0.5900	10.0800
ASVI1	9,602	0.0111	0.5683	–4.6052	–0.0270	0.0324	4.5539
ASVI2	9,592	0.0010	0.1568	–2.1308	–0.0343	0.0294	2.5903
ASVI3	9,582	0.0121	0.5774	–6.3969	–0.0368	0.0382	4.5480
ASVI8	9,526	0.0057	0.1989	–1.7614	–0.0626	0.0524	4.3498

Source: Authors' calculations.

Table A.2
Cross-Correlation Matrix for United States Dataset

	Ret	r_{t-1}	SMB	HML	ASVI1	ASVI2	ASVI3	ASVI8
Ret	1.000							
r_{t-1}	–0.0894	1.000						
SMB	0.0524	0.1668	1.000					
HML	–0.0196	0.2393	0.0019	1.000				
ASVI1	0.0465	0.0550	0.0010	–0.0099	1.000			
ASVI2	0.0403	0.0603	–0.0010	0.0257	0.0110	1.000		
ASVI3	0.0535	0.0586	0.0015	–0.0082	0.9673	0.0259	1.000	
ASVI8	0.0447	0.0678	0.0169	0.0287	0.0761	0.6759	0.1214	1.000

Source: Authors' calculations.

A p p e n d i x B

T a b l e B.1

Automobile Companies

Ticker	Market	Company	Keywords	Category
TM	NYSE	Toyota Motor Corporation	Daihatsu, Hino, Lexus, Scion, Toyota	All categories
GM	NYSE	General Motors Corporation	Buick, Cadillac, Chevrolet, Daewoo, GMC, Holden, Opel, Vauxhall, Baojun, Wuling, Jiefang	All categories
VOW.DE	OTC	Volkswagen Group	Audi, Bentley, Bugatti, Lamborghini, Scania, SEAT, Škoda, Volkswagen, Volkswagen CV, Porsche	All categories
HYU.F	Frankf. Exchange	Hyundai	Hyundai, Kia	All categories
F	NYSE	Ford Motor Company	Ford, Lincoln, Troller	Car and vehicles
NSANY	OTC	Nissan	Nissan, Infiniti	Cars and vehicles
2FI.F	Frankf. Exchange	Fiat Chrysler Automobiles	Abarth, Alfa Romeo, Ferrari, Fiat, Fiat Professional, Irisbus, Iveco, Lancia, Maserati, Chrysler, Dodge, Jeep	All categories
HMC	NYSE	Honda	Acura, Honda	All categories
PUGOY	OTC	PSA Peugeot Citroen	Citroen, Peugeot	All categories
RNO.PA	Paris Exch.	Renault	Dacia, Renault	All categories
BMW.DE	XETRA	BMW	BMW, Mini, Rolls-Royce	Cars and vehicles
DDAIF	OTC	Daimler AG	Freightliner, Master, Maybach, Mercedes-Benz, Mitsubishi Fuso, BharatBenz, Setra, Smart, Thomas Built Buses, Western Star	Cars and vehicles
MZA.F	Frankf. Exchange	Mazda	Mazda	All categories
MSBHY	OTC	Mitsubishi	Mitsubishi	All categories
TTM	NYSE	Tata Motors	Jaguar, Range Rover, Land Rover, Tata, Daewoo	Cars and vehicles
GELYF	OTC	Geely	Geely, Volvo	All categories
TSLA	NASDAQ	Tesla	Tesla	Cars and vehicles

Source: Google Trends.