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The influence of Google search index on stock markets: an analysis of causality in-mean and variance

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Abstract

Purpose – This empirical work studies the influence of investors' Internet searches on financial markets.

Design/methodology/approach – In this study, an asset pricing model with six factors is used, and autoregression, heteroscedasticity and moving average are taken into account to extract the independent shocks of each variable. Subsequently, a causality in-mean and in-variance analysis is performed to test the influence of Google searches on financial market variables, specifically, to test whether there is an influence on the idiosyncratic returns of financial assets.

Findings – Unlike most of the literature, the results show that Google searches on the name of listed companies have little influence on the trend and volatility of asset returns. On the contrary, these searches are shown to have a significant influence on trading volumes in the following week.

Practical implications – When analyzing specific effects, such as the influence of Internet searches, on financial markets, it is necessary that the model must include financial properties (asset valuation models) and statistical characteristics (stylized facts); otherwise, the empirical results could be inconsistent, since, among other issues, statistical findings may not be robust given autocorrelation and heteroscedasticity, and if an asset valuation model is not considered, the specific effect analyzed could simply be an indirect effect of a risk factor excluded from the model.

Originality/value – The empirical evidence shows that individual investors using Google have a significant influence on volume only so that institutional investors using other sources of information drive market prices. This means that potential investors should only be interested in the Internet searches index if their interest is focused on trading volume

Keywords Internet searching, Financial market, Spillover, Causality

Paper type Research paper

1. Introduction

Recent empirical studies analyze the effect of the Internet search behavior of economic agents on the stock markets. This involves studying only the behavior of retail investors since institutional investors use information that is more qualified and provided by specialized suppliers such as Reuters or Bloomberg, for example, González-Sánchez and Morales (2018).

Empirical research shows that online search queries have great potential to anticipate behavior or decisions, for example, a variety of search words have been used to measure search volumes as index-related search words like Dow Vozlyublennaia (2014), stock tickers Da *et al.* (2011) or negative and positive search words Klemola *et al.* (2016). Among these measures, Google Search Volume Index (GSVI) is widely used in empirical studies, as a specific proxy for firm visibility, for example, observing that it has a positive influence on the relationship between corporate social responsibility and financial performance (Hou (2019)). The predictive capacity of Google trends has been contrasted for different objectives, from macro variable (for example, D'Amuri and Marcucci (2017); Götz and Knetsch (2019); Niesert *et al.* (2019)) to the market's financial data Perlin *et al.* (2017); Audrino *et al.* (2020).

JEL Classification — G12, G14, G41.

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Drake *et al.* (2012) found that abnormal Google search activity increased about two weeks prior to the earnings announcement and continued at high levels for a period afterward. Preis *et al.* (2013) suggest that massive new data sources (big data) resulting from human interaction with the Internet may offer a new perspective on the behavior of market participants.

Bordino *et al.* (2012) found that daily trading volumes of stocks (traded in NASDAQ-100) are correlated to daily volumes of queries related to the same stocks. In many cases, query volumes anticipate trading peaks by one day or more. Chen and Lo (2019) found for Taiwan's top 50 firms that online search activities are significantly correlated to stock turnover, trading volume and stock volatility. Nikkinen and Peltomäki (2020) found that web searches have an immediate effect on stock market returns and the VIX implied volatility, whereas the effect of news articles lasts longer up to 11 weeks.

Conversely, Kim *et al.* (2019) found that Google searches are neither correlated to contemporaneous returns nor able to predict future abnormal returns. However, increased Google searches predict increased volatility and trading volume. This empirical research uses abnormal return, and historical realized variance as a proxy for volatility but does not consider heteroscedastic behavior.

In short, there is no consensus among empirical studies on many issues on this topic: Is the relationship contemporary or not?; should we analyze the variables or their shocks?; what is the ideal econometric methodology to study the effects of the Internet on financial markets?; what happens if we apply an asset pricing model?; or what financial variables are influenced (volume, return, volatility)?

So, this empirical work checks the validity information demand proposal Vlastakis and Markellos (2012), being as we analyze the causality of idiosyncratic searches on the Internet on the negotiated volume of assets, and the investor attention Vozlyublennaia (2014), since we study whether these searches have an effect on the idiosyncratic component of asset returns.

In this context, our aim is to verify if the weekly *GSVI* shocks affect subsequent shocks to returns and the trading volume of market assets, i.e., our objective is to test the predictive power of Google searches in forecasting the idiosyncratic risk of stocks. For that purpose and to overcome some drawbacks in previous studies, first, we define abnormal values or shocks considering both a factorial asset pricing model and the statistical properties of the time series (autocorrelation and heteroscedasticity, among others). Therefore, the findings of empirical research that do not include risk factors should be taken with caution since it could show that the Internet is a transmission belt of investors expectative toward market prices by systematic risk, but not an idiosyncratic risk. Then, we analyze the GSVI shocks causality on European stock market shocks in-mean (trend) and in-variance (variability). So, studies use a larger sample (for both company number and period). In addition, our Google search results are limited exclusively to the company name and not, in general, financial words (systematic risk), so that our objective is to analyze the *GSVI* impact on the idiosyncratic risk of each firm.

The rest of the study is organized as follows: section 2 reviews the literature and establishes the hypothesis to the test. Section 3 describes the methodology used in this study. Section 4 shows the data used. Section 5 discusses the results obtained. The empirical study ends with the main conclusions.

2. Literature review and development hypothesis

Bank *et al.* (2011) found that an increased search volume on Google is associated with a rise in trading activity and stock liquidity from a reduction in asymmetric information costs and also found evidence that an increase in search volume is associated with temporarily higher future returns.

Da *et al.* (2011) provide evidence that *GSVI* captures the attention of retail investors and found that an increase in *GSVI* for the Russell 3000 index predicts higher stock prices in the next two weeks and an eventual price reversal within the year. In this empirical study abnormal GSVI is defined as the first difference between log-GSVI and the average of this indicator during the previous eight weeks. It is the first empirical approach tries to explain the effect of the shocks of the online searches. Similarly, Joseph *et al.* (2011) examine the ability of online ticker searches, as a valid proxy for investor sentiment, to forecast abnormal stock returns and trading volumes. In a weekly sample of S&P 500 firms over 2005–2008, they found that online search intensity reliably predicts abnormal stock returns and trading volume and that the sensitivity of returns to search intensity is positively related to the difficulty with which a stock can be arbitraged.

Preis *et al.* (2013) analyze the performance of a set of 98 search terms in Google Trends and find that strategies based on search volume data for US users are more successful for the US market (Dow Jones Industrial Average) than strategies using global search volume data. Curme *et al.* (2014) found that an increase in search volume for financial topics tends to precede the stock market (Standard & Poor’s 500 index) falls.

Kristoufek (2013) assumes that searches for a stock are correlated to the stockś riskiness, then penalizes the more popular stocks and assigns them lower portfolio weights. This empirical research was found that this strategy dominates both the benchmark index (Dow Jones 30) and the uniformly weighted portfolio, both in-sample and out-of-sample.

Bijl and Sandvik (2016) found that high Google search volumes for the names of companies in the S&P 500 from January 1, 2008, through December 31, 2013, led to negative returns. They regress lags of abnormal GSVI, defined as standardized values, on excess returns of the asset, but they do not use abnormal returns obtained using an asset pricing model. Nguyen *et al.* (2019) found that the volume of Google searches might play an augmented factor in explaining the stock returns. In particular, for five emerging markets (Indonesia, Malaysia, the Philippines, Thailand and Vietnam), they found that the Fama-French model is not always effective since increases in Google search volume appear to have a significant negative impact on stock returns in the case of the Philippines, Thailand and Vietnam.

Perlin *et al.* (2017) studies whether Google’s search queries of finance-related words have an impact on log returns and traded volume of index equity markets (United States, United Kingdom, Australia and Canada). They use a VAR model to test the effect of Google search on historical volatility, asset returns and trading volume, but they do not take into account an asset pricing model for returns, nor the statistical behavior of variables. The latter is noteworthy when they later compare their results with ARMA-GARCH models.

Audrino *et al.* (2020), for 18 companies from the New York Stock Exchange (NYSE) and Nasdaq Stock Market, studies the impact of Googleś search queries of finance related words on realized heteroscedastic volatility. Newly, this empirical research does not include an asset pricing model for asset returns, and realized volatility is estimated from these returns. Finally, Aalborg *et al.* (2019) predict the return, volatility and trading volume of Bitcoin, and found that the trading volume of Bitcoin can be predicted from Google searches for Bitcoin, but none of the considered variables can predict Bitcoin returns.

From the above literature review, we observe several issues with the empirical results’ statistical and financial validity: abnormal value or shock estimates, contemporary or delayed effects and dependent variable selection.

Abnormal value or shocks are extracted as residual values after applying a behavior model to the observed variables, so these residuals represent the values not explained by the model. First, we selected a model for the variables (GSVI, volume, volatility, asset returns, etc.). While asset returns have to be modeled under an asset pricing model (see, among others: Da *et al.* (2011) and Joseph and Wintoki (2011)), the modeling of the other variables has to take into account the statistical characteristics of the time series to obtain independent shocks so that they show information other than the information expected. But this does not always happen. For example, Kristoufek (2013) does not consider optimal portfolio nor does it estimate efficient frontier as defined in financial theory (see Markowitz (1952)). Nguyen *et al.* (2019) include delays of the factors in the original Fama-French asset pricing model and their frequency data analysis is too low (annual) with respect to the immediate effects of Internet searches (daily or weekly).

As the weekly *GSVI* for a keyword search is the number of investors using the *GSVI* searches for that keyword scaled by its time-series average such that it takes a value between 0 and 100 and displays the relative frequency of searches, it seems more reasonable to define the abnormal *GSVI* as a shock on the expected value, and since it is a weekly cumulative indicator, avoid circularity problems as a result of the influence of the previous day's returns on the next day's searches within the same week. The financial literature (see Cont (2001)) shows that financial data usually present, for high frequencies (daily and weekly), autocorrelation, heteroscedasticity and non-normality (stylized facts), among other properties. Nonetheless, most of the empirical researchers show a table of statistics of the asset returns and the web searches, but these do not include the usual tests on autocorrelation and heteroscedasticity.

Since the GSVI frequency is weekly (seven days) and weekly asset returns are for five workdays, GSVI data includes the weekend effect, so it seems more suitable to accumulate the daily returns from Tuesday to Monday to avoid circularity problems, i.e. that the daily returns for one week increase the searching volume of the company within the same week. In that way, any empirical result that shows GSVI's ability to explain the returns of subsequent weeks would really be showing the effects of the previous week's returns. As a consequence, the results of the contemporary influence of GSVI on financial markets should be analyzed with caution, especially if the shocks have not been properly estimated (Bollen *et al.* (2011) and Nikkinen and Peltomäki (2020)). Therefore, the causal analysis seems more appropriate, i.e. testing whether weekly GSVI shocks influence financial market shocks in subsequent weeks. Bank *et al.* (2011) found that the relationship between Google searches and asset return is not contemporaneous, but rather one of causality, i.e., the asset return today is influenced by previous Google searches.

Swamy and Dharani (2019) found that high Google search volumes predict positive and significant returns in the fourth and fifth weeks afterward for the Indian stock market. As the rest of the literature does not analyze shocks in particular but uses a standardized value of Google searches to explain an average realized volatility, and in addition, the asset pricing model only includes the market factor. A question that arises when analyzing this empirical research is related to the behavior of standardized GSVI. Although the reported statistics indicate that the variable is stationary, the model is included in differences and with several delays. For the latter, the panel data model also includes the delayed dependent variable (excess return), and as is known in these cases, the optimal estimation method is GMM (Generalized Moments Method) with instrumental variables (see Arellano and Bover (1995)). However, the study does not make any reference in this regard, nor does it include an autoregression test for residuals nor a test of endogeneity.

Finally, another example is Bollen *et al.* (2011). They found a causality relationship between daily Twitter feeds and the Dow Jones Industrial Average. These results should be studied with caution; however, since the causality tests have not taken into account the statistical properties of the time series (see González-Sánchez (2016)).

The hypothesis of this study is that weekly GSVI shocks influence the trend (mean) and variability (variance) of the shocks of returns (idiosyncratic component) and trading volume. If we find causality on return, then we accept investor attention and/or, if the causality is on trading volume, then we do not reject information demand.

3. Econometric methodology

Based on the literature reviewed, we have seen that the methodologies applied are varied (cross-correlation, linear regression, panel data, vector autoregression and state-space using Kalman filter), but none consider an asset pricing model, as well as the usual statistical behavior of financial time series, and from there, the shocks are extracted to confirm if there is a causal relationship from shocks in Internet searches to shocks of financial market variables.

Then, we define P_t and VOL_t as daily price and trading volume of a financial asset. As expected, the values of these variables cannot be negative; we take them as a logarithm: $p_t = \ln(P_t)$ and $\text{vol}_t = \ln(\text{VOL}_t)$. As these variables are not stationary, we use the first difference: $R_t = p_t - p_{t-1}$ and $V_t = \text{vol}_t - \text{vol}_{t-1}$.

Next, we model asset return (R_t) and trading volume variation (V_t) separately since while volume variation only requires an econometric model to fit its statistical properties, an asset return also needs an asset pricing model.

Expression 1 is the model that adapts excess returns ($r_t = R_t - Rf_t$) on a risk-free rate (Rf_t) for stock market i:

$$\begin{aligned} r_{t,i} &= \beta_{0.i} + \beta_{1.i}\cdot \text{Mkt}_t + \beta_{2.i}\cdot \text{SMB}_t + \beta_{3.i}\cdot \text{HML}_t + \beta_{4.i}\cdot \text{RMW}_t + \beta_{5.i}\cdot \text{CMA}_t \\ &\quad + \beta_{6.i}\cdot \text{MOM}_t + \epsilon_{t,i} \\ \epsilon_{t,i} &\sim \Phi\left(0,\ \sigma^2_{t,i}\right) \\ \sigma^2_{t,i} &= \alpha_{0.i} + \alpha_{1,i}\cdot \epsilon^2_{t-1,i} + \alpha_{2,i}\cdot \sigma^2_{t-1,i} \end{aligned} \tag{1}$$

In expression 1, the asset pricing model includes six risky factors as the Fama-French model: excess returns of market portfolio (Mkt); size factor (SMB), the average return on the small stock portfolios minus the average return on the big stock portfolios; growth factor (HML), the average return on the value portfolios minus the average return on the growth portfolios; robust minus weak factor (RMW), the average return on the value portfolios minus the average return on the growth portfolios; conservative minus aggressive, the average return on the conservative investment portfolios minus the average return on the aggressive investment portfolios; and momentum factor (MOM), the speed at which the price is changing. Additionally, we use a GARCH $(1,\ 1)$model to adapt the heteroscedasticity.

Expression 2 shows the model to adapt for volume changes. This model is defined as $\text{ARMA}(1,\ 1) - \text{GARCH}(1,\ 1)$ to collect the usual statistical properties of volume (autoregression, moving average and heteroscedasticity):

$$\begin{aligned} V_{t,i} &= \gamma_{0.i} + \gamma_{1.i}\cdot V_{t-1,i} + \gamma_{2.i}\cdot \nu_{t-1,i} + \nu_{t,i} \\ \nu_{t,i} &\sim \Phi\left(0,\ \sigma^2_{i,v,t}\right) \\ \sigma^2_{t,i,v} &= \delta_{0.i} + \delta_{1,i}\cdot \nu^2_{t-1,i} + \delta_{2,i}\cdot \sigma^2_{t-1,i,v} \end{aligned} \tag{2}$$

As *GSVI* also has a lower limit in zero value and to avoid unit roots, we define $G_t = \ln(\text{GSVI}_t) - \ln(\text{GSVI}_{t-1})$ and estimate a model similar to trading volume since this index shows search volume:

$$\begin{aligned} G_{t,i} &= \omega_{0.i} + \omega_{1.i}\cdot G_{t-1,i} + \omega_{2.i}\cdot g_{t-1,i} + g_{t,i} \\ g_{t,i} &\sim \Phi\left(0,\ \sigma^2_{i,g,t}\right) \\ \sigma^2_{t,i,g} &= \kappa_{0.i} + \kappa_{1,i}\cdot g^2_{t-1,i} + \kappa_{2,i}\cdot \sigma^2_{t-1,i,g} \end{aligned} \tag{3}$$

We estimate the expressions 1, 2 and 3 by quasi-maximum likelihood (QML).

Then we extract spillover or shocks of asset returns, trading volume and GSVI changes as:

$$rx_{t,i} = \frac{\epsilon_{t,i}}{\sigma t,\ i};\ rx_{t,i} \sim i.i.d.(0,\ 1)$$
$$vx_{t,i} = \frac{\nu_{t,i}}{\sigma t,\ i,\ v}\ rv_{t,i} \sim i.i.d.(0,\ 1) \quad (4)$$
$$gx_{t,i} = \frac{g_{t,i}}{\sigma t,\ i,\ g}\ rg_{t,i} \sim i.i.d.(0,\ 1)$$

Next, we search for causality in-mean for expression 5:

$$rx_{t,i} = \sum_{j=1}^{J} \lambda_{r,i,j} \cdot gx_{t-j,i} + u_{t,i,r}$$
$$vx_{t,i} = \sum_{j=1}^{J} \lambda_{v,i,j} \cdot gx_{t-j,i} + u_{t,i,v} \quad (5)$$

where J is estimated using information criteria (AIC or SIC) and if any $j,\ ,i \neq 0$, then there is causality in-mean from the delay j of GSVI shocks to actual asset return (rx) or volume change (rv) shocks. Note that expression 5 does not include a constant since the mean value of a standardized residual is zero (see expression 4).

Finally, to test the causality in-variance, we define the following variables:

$$rz_{t,i} = \begin{cases} u^2_{t,i,r}, & \text{if any } \lambda_{r,i,j} \neq 0, \\ rx^2_{t,i} & \text{otherwise.} \end{cases} \quad vz_{t,i} = \begin{cases} u^2_{t,i,v}, & \text{if any } \lambda_{v,i,j} \neq 0, \\ vx^2_{t,i} & \text{otherwise.} \end{cases} \quad (6)$$

Note that, in expression 6, testing causality in-variance requires that previously the root of variables show no relationship (see González-Sánchez (2016)). Then we estimate expression 7 to check this causality:

$$rz_{t,i} = \eta_{0,r,i} + \sum_{h=1}^{H} \eta_{r,i,h} \cdot gx^2_{t-h,i} + \xi_{t,i,r}$$
$$vz_{t,i} = \eta_{0,v,i} + \sum_{h=1}^{H} \eta_{v,i,h} \cdot gx^2_{t-h,i} + \xi_{t,i,v} \quad (7)$$

where H is according to information criteria, and there is causality in-variance from the lag h of *GSVI* shocks to actual asset returns or volume changes shocks, if any $\eta_{i,,h} \neq 0$. Also note that equation 7, unlike expression 5, shows constant ($\eta_{0,,i}$) since shocks variance is one. If we find causality in-variance, we expected that $\eta_{0,,i} \neq 1$.

The expressions 5 and 7 are estimated by ordinary least square (OLS).

4. Data

The study sample is composed of the 50 companies on the EURO STOXX-50 stock index for the daily period between September 2014 and July 2019. Daily prices and trading volumes are obtained from Bloomberg. We estimate log-difference first, and then we calculate weekly values as $x_{\text{week}} = \sum_{t=\text{Tuesday}}^{\text{Monday}} x_{\text{daily},\,t}$, since GSVI shows Google searches from Monday to Sunday. Note that we do not calculate Monday-Monday values to avoid overlapping sample problems.

We obtain the six European risk factors data for the asset pricing model from French web data (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.

html). The daily data are compound rate, so we first transform them into continuous form as $x_{cont} = \ln(1 + x_{comp})$and then we calculate weekly values as the sum from Tuesday to Monday.

Finally, we obtained weekly GSVI from https://trends.google.es/trends/. Unlike Joseph and Wintoki (2011), among others, our GSVI shows searches that correspond to the company name, since usually the non-professional investor does not know the company ticker or is not accustomed to searching using that code and she previously has to search for the ticker using the company name. In addition, we avoid possible errors caused by the confusion between the name and the ticker (see Balashov and Nikiforov (2019)).

First, we analyze descriptive statistics of data (Tables 1 and 2), and we observe that while some excess returns show autoregression and heteroscedasticity, all trading volume changes are autoregressive, heteroscedastic and moving average. Note that only the GSVI is always stationary in first log-difference, and these changes show the same statistics characteristics as trading volume. In short, any empirical analysis using these data should consider these statistical properties; otherwise, results are inconsistent (see Table 3)

We extract shocks as standardized residuals of models 1, 2 and 3 Table 4, 5 and 6 show the parameters of models and descriptive statistics for standardized residuals (spillover of sample).

From the results of Tables 4–6, note that descriptive statistics of shocks show non-autoregression, no heteroscedasticity and no moving average.

5. Results and discussion

From the standardized residuals calculated previously, we estimate expression 5 to test the causality in-mean. We include four lags of GSVI from the AIC criteria selection model. Table 7 shows the results.

The results of Table 7 show that Google searches do not influence the excess returns trend, except for some exceptions related mainly to the automobile sector (BMW, DAIMLER and VOLKSWAGEN), which may respond to reputational aspects of the brands. As for the trading volume, the causality in-mean is present in a higher number of cases and mainly from the searches of the two weeks prior to the change in the trading volume.

Therefore, for the sample studied, and after solving the modeling problems, we cannot affirm, unlike the studies reviewed, that there is a generalized causality in-mean (trend) of GSVI on the financial markets. This may be because the economic agents that use Google as a search tool are not institutional investors who move large volumes of assets in the market.

Table 8 shows the results for causality in-variance, estimated according to expressions 6 and 7.

***The results are in the same line as those for causality in-mean. Only seven companies show causality in-variance on the shocks of excess returns, while more than half (28 companies) display causality in-variance on trading volume shocks, essentially an effect caused by the searches of the previous week.

In short, once the econometric and financial modeling problems are solved, weekly Google searches of the company names that make up the EURO STOXX-50 do not show a generalized and significant effect on the trend (causality in-mean) or the volatility (causality in-variance) of stock returns. On the contrary, the effects on the trend and volatility of the trading volume of the stocks are more frequent and caused mainly by the searches of the previous week.

6. Conclusions

The empirical literature prior to this study finds, in general, that Google searches on the returns, and the trading volume of the shares listed has a significant influence.

However, this empirical evidence must be analyzed with caution since, in most cases, the abnormal return and abnormal trading volume are not estimated considering an asset pricing model and the statistical characteristics of the time series. When these financial and

Table 1. Descriptive statistics of excess returns

Companies	ADF	Obs.	Mean	Std. Dev.	Skew.	Exc. Kur.	ARCH(2) LM	LB raw data	LB squared data
ADIDAS	−5.86(**)	253	0.00567	0.03358	0.13832	0.78935	1.15	0.37	2.47
AHOLD	−6.6(**)	253	0.00182	0.03102	−0.77655	3.4836	0.3	1.66	0.62
AIR LIQUIDE	−5.75(**)	253	0.00132	0.02759	−0.48121	1.8944	4.41(*)	1.12	8.59(*)
AIRBUS	−5.81(**)	253	0.00334	0.03934	−0.78853	3.2724	0.09	2.19	0.19
ALLIANZ	−6.32(**)	253	0.00204	0.02901	−0.98816	3.3399	2.88	3.41	5.98
AMADEUS	−6.13(**)	253	0.00351	0.03232	−0.73395	1.9751	0.23	0.49	0.47
ANHEUSER	−5.52(**)	253	0.00011	0.03295	−0.55301	1.5722	0.97	6.72(*)	2
ASML	−6.42(**)	253	0.00317	0.03921	−0.1536	0.90667	0.89	3.92	1.82
AXA	−6.3(**)	253	0.00086	0.03798	−1.4957	8.1321	1.49	0.64	3.16
BASF	−6.29(**)	253	−0.00073	0.03409	−0.6027	0.87745	4.21(*)	8.92(*)	9.15(*)
BAYER	−5.78(**)	253	−0.00278	0.04066	−0.83684	1.8929	0.08	2.45	0.16
BBVA	−6.03(**)	253	−0.00278	0.03961	−0.43866	1.3573	4.95(**)	3.12	11.38(*)
BMW	−6.27(**)	253	−0.00087	0.03698	−0.32939	0.60531	2.31	4.01	4.96
BNP	−5.63(**)	253	−0.00086	0.03999	−0.79533	4.3028	0.41	8.34(*)	0.88
CRH PLC	−5.73(**)	253	0.00153	0.03854	−0.88997	3.0817	4.29	7.68(*)	3.94
DAIMLER	−6.44(**)	253	−0.00078	0.03725	−0.63668	1.2935	3.53	4.22	8.01(*)
DANONE	−6.39(**)	253	0.00159	0.02594	−0.2823	1.6128	0.16	9.01(*)	0.32
DEUTSCHE BOERSE	−6.74(**)	253	0.00309	0.03008	−0.46059	1.3907	2.25	0.03	4.11
DEUTSCHE POST	−6.76(**)	253	0.00065	0.03206	−0.83064	1.4945	0.17	7.18(*)	0.36
DEUTSCHE TELEKOM	−6.21(**)	253	0.00106	0.03093	−0.32064	3.095	5.34(**)	5.61	11.77(*)
ESSILOR	−6.03(**)	253	0.00086	0.02956	−0.57523	2.0362	2.86	10.38(*)	5.16
ENEL	−6.57(**)	253	0.00174	0.03174	−0.5658	2.441	5.1(**)	8.1(*)	9.59(*)
ENGIE	−6.47(**)	253	−0.00059	0.03296	−0.53615	1.9851	1.27	3.83	2.68
ENI	−7.65(**)	253	−0.00072	0.03609	−0.47647	2.3375	10.54(**)	3.45	20.06(*)
FRANCE TELECOM	−5.14(**)	253	0.00086	0.03165	−0.18483	2.4868	4.91(**)	2.47	10.25(*)
FRESENIUS	−7.01(**)	253	0.00001	0.03882	−1.5847	9.2816	0.1	6.3(*)	0.22
IBERDROLA	−5.78(**)	253	0.00214	0.02546	−0.24413	1.8888	2.54	5.22	4.39
INDITEX	−6.23(**)	253	0.00056	0.0334	−0.54769	1.244	1.69	0.75	3.45
ING	−6.25(**)	253	−0.00042	0.03788	−0.71006	3.4369	1.34	2.73	2.83
INTESA	−5.58(**)	253	−0.00085	0.04834	−1.5567	10.607	1.78	7.27(*)	3.67
LINDE	−6.1(**)	253	0.00143	0.02862	−0.42813	0.5627	0.53	2.35	0.98
LOREAL	−5.51(**)	253	0.00255	0.02681	−0.58719	2.5237	5.52(**)	0.56	11.71(*)

(continued)

Table 1.

Companies	ADF	Obs.	Mean	Std. Dev.	Skew.	Exc. Kur.	ARCH(2) LM	LB raw data	LB squared data
LVMH	−6.35(**)	253	0.00422	0.03322	−0.70644	1.5781	6.36(**)	3.6	11.89(*)
MUENCHENER	−6.04(**)	253	0.0018	0.02368	−0.32099	0.56078	5.52(**)	3.34	12.24(*)
NOKIA	−6.22(**)	253	−0.00159	0.04582	−1.0384	3.6637	0.6	0.84	1.3
PHILIPS	−5.57(**)	253	0.00226	0.03266	−0.7714	1.2338	1.93	0.67	4.15
PINAULT	−5.87(**)	253	0.0041	0.03819	−0.54492	1.7631	3.96(*)	10.62(*)	8.44(*)
SAGEM	−5.91(**)	253	0.00348	0.03507	−0.36591	1.763	4.31(*)	10.4(*)	9.2(*)
SANOFI	−5.73(**)	253	−0.00041	0.03175	−0.82063	2.3558	0.25	2.98	0.52
SANTANDER	−5.79(**)	253	−0.00263	0.04199	−0.60756	2.5083	1.44	7.11(*)	3.21
SAP	−7.21(**)	253	0.00235	0.03019	−0.23675	1.794	0.23	3.91	0.49
SCHNEIDER	−6.52(**)	253	0.00084	0.03456	−0.36365	1.4067	2.43	9.44(*)	4.53
SIEMENS	−6.03(**)	253	0.0003	0.03132	−0.34756	0.62855	3.41(*)	2.26	6.37(*)
SOCIETE GENERALE	−6.8(**)	253	−0.00234	0.04688	−0.96211	5.4625	0.97	1.97	2.02
TELEFONICA	−6.11(**)	253	−0.00167	0.03293	−0.30401	2.2328	9.96(**)	2.75	18.88(*)
UNILEVER	−5.2(**)	253	0.00203	0.02807	−0.56852	3.0213	3.28(*)	9.76(*)	6.57(*)
VINCI	−6.42(**)	253	0.0028	0.02879	−0.18818	1.5017	9.84(**)	4.7	19.4(*)
VIVENDI	−5.47(**)	253	0.00144	0.03077	−0.32002	1.8352	0.61	1.29	1.33
VOLKSWAGEN	−6.63(**)	253	−0.0014	0.05174	−1.3551	7.8097	22.56(**)	4.97	42.96(*)
TOTAL	−6.5(**)	253	0.00023	0.0329	−0.6774	2.7766	3.13(*)	2.11	6.53(*)

Note(s): ADF test with AIC criteria for lags, with intercept and no time trend, the asymptotic critical values are at 1% (**) and 5% (*) confidence levels −3.43 and −2.86 respectively. LM ARCH test is a White test on heteroskedasticity ARCH 1–2, which p-value follows a distribution $F(2,248)$. LB is the Ljung–Box or Q test (autoregressive) on raw and squared data

Table 2. Descriptive statistics of volume changes

Companies	ADF	Obs	Mean	Std. Dev	Skew	Exc. Kur	LM ARCH	LB raw data	LB squared data
ADIDAS	−10.23(**)	253	−0.00426	0.47308	−0.19529	1.2736	5.36(**)	34.63(**)	11.09(**)
AHOLD	−11.74(**)	253	0.00114	0.50357	−0.08305	2.5963	10.78(**)	31.77(**)	24.21(**)
AIR LIQUIDE	−9.78(**)	253	−0.00014	0.50522	−0.03609	3.2327	32.36(**)	46.31(**)	41.64(**)
AIRBUS	−10.61(**)	253	−0.00293	0.50294	0.07533	0.91622	16.18(**)	58.53(**)	29.5(**)
ALLIANZ	−10.93(**)	253	−0.00299	0.44931	0.08196	1.4806	19.07(**)	59.71(**)	29.45(**)
AMADEUS	−9.69(**)	253	−0.00318	0.80121	0.42164	2.8229	2.07	30.01(**)	24.64(**)
ANHEUSER	−9.23(**)	253	0.00304	0.50309	−0.10759	2.2928	14.88(**)	40.29(**)	27.18(**)
ASML	−10.33(**)	253	−0.00148	0.4967	−0.24749	1.9775	13.53(**)	38.13(**)	24.25(**)
AXA	−9.86(**)	253	−0.00347	0.49303	0.28086	2.6057	16.1(**)	41.78(**)	29.91(**)
BASF	−9.62(**)	253	0.00041	0.47801	−0.17119	0.95103	17.08(**)	54.69(**)	29.2(**)
BAYER	−9.51(**)	253	0.00042	0.49886	0.28847	2.7293	6.25(**)	48.59(**)	13.1(**)
BBVA	−8.95(**)	253	−0.00557	0.68399	0.05369	0.44739	26.7(**)	33.62(**)	47.39(**)
BMW	−9.89(**)	253	−0.00351	0.52843	0.09525	0.66915	8.28(**)	55.18(**)	14.1(**)
BNP	−9.47(**)	253	−0.00224	0.46952	−0.2194	1.5096	7.19(**)	37.56(**)	15.69(**)
CRH PLC	−9.76(**)	253	−0.00447	0.77976	0.22551	2.3593	20.2(**)	44.81(**)	32.96(**)
DAIMLER	−8.96(**)	253	0.00057	0.49089	0.14152	1.0237	11.87(**)	51.25(**)	18.45(**)
DANONE	−10.51(**)	253	−0.00062	0.52525	0.16611	1.7225	27.04(**)	58.09(**)	36.35(**)
DEUTSCHE BOERSE	−8.11(**)	253	0.00258	0.52231	0.30318	2.3556	4.2(*)	47.71(**)	8.1(*)
DEUTSCHE POST	−9.42(**)	253	−0.00242	0.4507	−0.16478	2.1474	14.57(**)	40.78(**)	22.36(**)
DEUTSCHE TELEKOM	−9.46(**)	253	0.00186	0.47407	−0.16972	1.5155	10.98(**)	48.68(**)	17.55(**)
ESSILOR	−9.23(**)	253	−0.00075	0.51475	−0.03595	2.6449	24.17(**)	38.46(**)	37.85(**)
ENEL	−10.22(**)	253	−0.00187	0.38882	0.02913	0.72747	9.08(**)	40.56(**)	15.08(**)
ENGIE	−10.05(**)	253	0.00162	0.44316	−0.04384	0.78756	8.43(**)	45.16(**)	14.17(**)
ENI	−9.79(**)	253	−0.00367	0.36182	−0.28131	1.0195	4.15(*)	36.57(**)	8.3(*)
FRANCE TELECOM	−9.46(**)	253	0.00208	0.49368	0.04801	2.1615	12.56(**)	45.26(**)	21.42(**)
FRESENIUS	−9.21(**)	253	0.00315	0.49223	0.05433	1.2161	9.94(**)	48.11(**)	19.43(**)
IBERDROLA	−8.59(**)	253	−0.00471	0.57953	0.08296	0.25556	3.99(*)	43.58(**)	7.18(*)
INDITEX	−9.25(**)	253	−0.00019	0.87403	−0.12632	1.5474	9.01(**)	50.28(**)	20.41(**)
ING	−10.15(**)	253	−0.00566	0.47235	−0.2323	2.6275	10.2(**)	41.76(**)	17.64(**)
INTESA	−9.66(**)	253	−0.00224	0.45748	0.083	0.80733	12.1(**)	45.1(**)	18.78(**)
LINDE	−9.28(**)	253	−0.00339	0.60975	−0.15891	2.6086	34.45(**)	68.98(**)	41.36(**)
LOREAL	−9.76(**)	253	−0.00185	0.43577	−0.10907	0.75098	5.88(**)	36.3(**)	12.53(**)

(*continued*)

Table 2.

Companies	ADF	Obs	Mean	Std. Dev	Skew	Exc. Kur	LM ARCH	LB raw data	LB squared data
LVMH	−10.53(**)	253	−0.00106	0.48316	0.17356	3.0397	26.73(**)	40.34(**)	37.2(**)
MUENCHENER	−10.07(**)	253	−0.00193	0.44965	0.12879	1.0167	16.64(**)	47.78(**)	26.37(**)
NOKIA	−9.3(**)	253	−0.00212	0.54496	0.08117	1.7201	22.38(**)	48.3(**)	52.51(**)
PHILIPS	−9.79(**)	253	−0.00112	0.53974	0.24216	0.90508	4.78(**)	37.57(**)	8.81(*)
PINAULT	−10.12(**)	253	0.00288	0.51193	0.06426	0.74872	3.8(*)	39.4(**)	6.35(*)
SAGEM	−10.2(**)	253	−0.00002	0.52026	0.16165	1.0063	5.03(**)	40.94(**)	9.24(**)
SANOFI	−10.63(**)	253	0.00131	0.47675	0.06417	1.9116	11.72(**)	41.52(**)	20.2(**)
SANTANDER	−9.49(**)	253	−0.00249	0.74244	0.33186	1.1383	10.54(**)	28.13(**)	20.62(**)
SAP	−9.35(**)	253	−0.00202	0.48231	0.02735	1.2608	18.65(**)	51.66(**)	27(**)
SCHNEIDER	−10.07(**)	253	−0.00171	0.53005	−0.03842	1.3649	19.51(**)	43.98(**)	36.98(**)
SIEMENS	−10.1(**)	253	−0.0011	0.45134	0.14638	1.4096	15.94(**)	49.87(**)	22.73(**)
SOCIETE GENERALE	−9.53(**)	253	−0.00152	0.46709	−0.01909	1.663	8.31(**)	36.8(**)	15.03(**)
TELEFONICA	−10.03(**)	253	−0.00227	0.71745	0.07441	1.4634	11.94(**)	53.43(**)	21.16(**)
UNILEVER	−7(**)	253	0.02782	1.0418	0.75956	4.4477	0.18	32.62(**)	36.1(**)
VINCI	−10.13(**)	253	−0.00294	0.46814	0.02405	2.5278	16.67(**)	37.35(**)	25.5(**)
VIVENDI	−9.75(**)	253	0.00006	0.53838	0.13466	3.7332	30.33(**)	49.08(**)	47.15(**)
VOLKSWAGEN	−10.01(**)	253	0.00072	0.54615	0.4	1.8954	3.84(*)	47.65(**)	6.95(*)
TOTAL	−10.29(**)	253	−0.00165	0.43305	−0.20924	2.8323	23.62(**)	39.69(**)	33.95(**)

Table 3. Descriptive statistics of GSVI log-difference

Companies	ADF level	ADF log-diff	Obs	Mean	Std. Dev	Skew	Exc. Kur	LM ARCH	LB raw data	LB squared data
ADIDAS	−2.79	−8.5(**)	253	−0.19845	0.00194	1.4584	9.4476	57.96(**)	4.32	11.4(**)
AHOLD	−2.8	−9.15(**)	253	−0.99425	0.00118	0.60097	8.1981	35.14(**)	18.16(**)	47.72(**)
AIR LIQUIDE	−4.48(**)	−9.46(**)	253	−0.55962	0.00085	0.16573	5.085	73.44(**)	8.65(*)	17.12(**)
AIRBUS	−4.76(**)	−8.48(**)	253	−1.1394	0	2.5485	3.7895	24.76(**)	3.03	36.92(**)
ALLIANZ	−3.35(*)	−10.05(**)	253	−0.36646	−0.00028	−0.17269	7.02	14.94(**)	15.72(**)	31.65(**)
AMADEUS	−2.83	−7.63(**)	253	−0.26136	−0.00105	0.27609	2.923	17.28(**)	18.37(**)	30.36(**)
ANHEUSER	−4.45(**)	−6.99(**)	253	−1.204	0.00182	1.03	1.5441	19.2(**)	5.87	30.92(**)
ASML	−1.59	−9.79(**)	253	−0.59784	0.00238	0.48385	1.2056	75.24(**)	9.09(*)	15.47(**)
AXA	−3.75(**)	−9.02(**)	253	−0.27675	−0.00041	−0.10381	4.1309	17.64(**)	14.55(**)	35.4(**)
BASF	−5.98(**)	−8.89(**)	253	−1.772	0	1.9756	5.7241	43.01(**)	15.5(**)	53.16(**)
BAYER	−3.83(**)	−7.53(**)	253	−0.51083	0.0009	0.59973	3.7648	10.98(**)	16.33(**)	22.22(**)
BBVA	−2.59	−8.34(**)	253	−0.32017	−0.00158	0.27017	−0.05909	11.56(**)	54.67(**)	31.16(**)
BMW	−3.05(*)	−8.47(**)	253	−0.13353	0	0	2.5182	18.81(**)	24.18(**)	36.92(**)
BNP	−1.77	−8.92(**)	253	−0.3285	−0.00269	0.21779	0.76498	97.19(**)	52.42(**)	19.26(**)
CRH PLC	−5.18(**)	−9.36(**)	253	−0.84397	0	0.09172	7.6154	18.86(**)	7.72(*)	32.52(**)
DAIMLER	−3.42(*)	−8.77(**)	253	−0.42744	0.00143	0.3056	2.5665	10.32(**)	8.27(*)	21.03(**)
DANONE	−4.28(**)	−7.36(**)	253	−0.26136	−0.00156	0.25023	2.0703	15.04(**)	23.47(**)	34.31(**)
DEUTSCHE BOERSE	−4.35(**)	−8.48(**)	253	−0.865	−0.00195	0.08705	1.708	31.02(**)	25.2(**)	6.89(*)
DEUTSCHE POST	−4.13(**)	−8.32(**)	253	−0.61576	0.00042	−2.0515	1.2384	30.59(**)	9.51(**)	6.04(*)
DEUTSCHE TELEKOM	−2.84	−7.95(**)	253	−0.47804	−0.00108	0.91276	1.7911	40.29(**)	4.17	49.42(**)
ESSILOR	−4.08(**)	−9.72(**)	253	−1.0788	0.00099	1.0249	3.4979	49.22(**)	8.28(*)	56.47(**)
ENEL	−0.41	−8.75(**)	253	−0.36546	0.00196	−0.36647	1.8789	68.39(**)	19.53(**)	15.49(**)
ENGIE	−1.33	−7.64(**)	253	−0.34831	0.00301	0.23297	1.9733	11.12(**)	12.7(**)	26.19(**)
ENI	−3.66(**)	−8.97(**)	253	−0.44629	0.00011	−0.45573	5.2038	14.56(**)	11.07(**)	29.73(**)
FRANCE TELECOM	−1.47	−8.48(**)	253	−0.15719	−0.00385	0.41564	1.2588	80.01(**)	16.58(**)	17.24(**)
FRESENIUS	−2.33	−9.73(**)	253	−0.60392	0.00078	0.37367	3.4614	15.79(**)	11.84(**)	27.58(**)
IBERDROLA	−2.11	−9.48(**)	253	−0.43178	0.00012	−0.13342	0.57481	50.85(**)	14.18(**)	96.21(**)
INDITEX	−4.23(**)	−8.26(**)	253	−0.43286	−0.00163	0.39026	1.6125	0.39	17.75(**)	0.81
ING	−1.67	−7.83(**)	253	−0.28061	−0.00266	0.57255	2.0843	42.51(**)	68.73(**)	7.68(*)
INTESA	−2.84	−8.65(**)	253	−0.43078	−0.00045	−0.51326	1.5562	66.74(**)	20.99(**)	15.52(**)
LINDE	−6.39(**)	−9.3(**)	253	−0.59205	−0.00039	−0.51932	7.2144	65.68(**)	9.82(**)	14.21(**)
LOREAL	−2.05	−5.66(**)	253	−0.08923	0.00143	1.7041	1.0661	0.56	6.02(*)	1.15

(*continued*)

Table 3.

Companies	ADF level	ADF log-diff	Obs	Mean	Std. Dev	Skew	Exc. Kur	LM ARCH	LB raw data	LB squared data
LVMH	−1.31	−6.73(**)	253	−0.22314	0.00176	−0.75188	4.0514	15.1(**)	0.96	25.52(**)
MUENCHENER	−4.33(**)	−8.77(**)	253	−0.76214	0.0012	−0.2414	2.3053	10.01(**)	15.76(**)	21.65(**)
NOKIA	−3.52(**)	−6.52(**)	253	−0.65493	−0.00577	0.66935	3.2517	67.91(**)	2.39	83.37(**)
PHILIPS	−4.86(**)	−5.24(**)	253	−0.2043	−0.00064	0.98867	7.6743	10.88(**)	0.52	18.55(**)
PINAULT	−5.74(**)	−10.44(**)	253	−2.5257	0	1.8962	1.7299	92.38(**)	8.24(*)	16.59(**)
SAGEM	−1.39	−8.26(**)	253	−0.30538	−0.00532	0.04564	1.5674	19.17(**)	24.52(**)	39.92(**)
SANOFI	−2.14	−9.49(**)	253	−0.65059	−0.00304	−0.04601	1.3055	13.2(**)	12.59(**)	30.8(**)
SANTANDER	−0.22	−8.34(**)	253	−0.26136	−0.00125	0.21719	−0.35791	10.77(**)	63.55(**)	22.34(**)
SAP	−5.54(**)	−9.29(**)	253	−0.5193	−0.00073	−0.04897	12.07	18.69(**)	13.94(**)	37.34(**)
SCHNEIDER	−5.09(**)	−9.13(**)	253	−0.3996	−0.00031	0.02311	9.9689	22.4(**)	4.01	43.87(**)
SIEMENS	−1.3	−8.73(**)	253	−0.2464	−0.00085	0.13977	31.877	15.08(**)	9.31(**)	28.72(**)
SOCIETE GENERALE	−1.54	−8.58(**)	253	−0.22314	−0.00298	1.0045	−0.46116	21.91(**)	69.31(**)	8.71(*)
TELEFONICA	−2.23	−10.04(**)	253	−0.57982	−0.00295	0.47741	12.449	20.29(**)	14.51(**)	33.11(**)
UNILEVER	−5.03(**)	−7.25(**)	253	−0.54473	−0.00116	0.62406	73.651	11.93(**)	4.28	24.87(**)
VINCI	−3.3(*)	−9.53(**)	253	−0.63488	0.00019	0.38217	96.367	25.84(**)	7.22(*)	40.92(**)
VIVENDI	−4.22(**)	−8.97(**)	253	−0.87807	0.00066	7.0127	25.217	78.97(**)	14.6(**)	17.95(**)
VOLKSWAGEN	−4.43(**)	−8.39(**)	253	−0.34249	0.00019	0.85543	96.302	39.45(**)	6.81(*)	8.2(*)
TOTAL	−2.49	−9.11(**)	253	−0.96758	0.00126	0.07098	40.832	55.85(**)	7.46(*)	60.29(**)

Table 4. Results of model for excess returns and descriptive statistics of standardized residuals

Companies	Cte	Mkt	SMB	HML	RMW	CMA	MOM	ARCH(1)	GARCH(1)	LM ARCH	LB raw	LB squr.
Adidas	0.005(**)	0.579(**)	−0.697(**)	−0.019	0.178	−0.9	0.432(*)			1.11	0.01	0.4
Ahold	0.002	0.389(**)	−1.242(**)	−0.301	0.058	−0.113	0.093			0.02	0.85	0.44
Air Liquide	0.001	0.678(**)	−1.381(**)	−0.446	−0.016	0.193	0.054	0.085(*)	0.862(**)	0.14	3.49	0.29
Airbus	0.004	0.855(**)	−1.403(**)	−1.225(**)	−0.627	0.234	−0.059			0.1	0.38	3.02
Allianz	0.003(*)	0.745(**)	−1.159(**)	−0.064	−0.828(**)	−0.639(*)	0.015			0.51	0.86	3.15
Amadeus	0.002	0.937(**)	−0.522(**)	−0.663(*)	0.064	−0.9(*)	0.457(**)			0.01	2.17	0.75
Anheuser	0.001	0.705(**)	−1.348(**)	−1.366(**)	0.025	0.237	−0.103			3.39	0.38	1.12
ASML	0.002	1.03(**)	−0.736(**)	−1.095(**)	−0.009	−0.059	0.114			0.66	1.87	0.81
AXA	0.002	1.025(**)	−1.189(**)	−0.533	−2.115(**)	−0.502	0.038			0.67	0.46	4.11
BASF	0.001	0.883(**)	−0.97(**)	0.71(*)	0.917(*)	−0.088	−0.177	0.084(*)	0.569(*)	1.92	4.22	3.97
BAYER	−0.003	0.922(**)	−1.041(**)	−1.105(*)	−0.12	0.584	−0.192			0.12	0.12	0.98
BBVA	−0.001	0.962(**)	−1.108(**)	−0.398	−1.689(**)	−0.048	−0.59(**)	0.099(*)	0.763(**)	0.78	1.39	1.55
BMW	0.001	0.761(**)	−1.361(**)	0.417	0.004	−1.05(*)	−0.363(*)			1.56	0.29	1.36
BNP	0.002	1.055(**)	−0.938(**)	−0.282	−2.618(**)	−0.765	−0.246			2.84	0.28	1.12
CRH PLC	0.002	1.167(**)	−0.545(*)	−0.276	−0.456	−0.747	0.057			0.13	2.05	4.03
Daimler	−0.001	0.806(**)	−1.151(**)	0.464	0.622	−0.587	−0.444(**)	0.038(*)	0.931(**)	1.46	2.51	3.27
Danone	0.001	0.551(**)	−1.37(**)	−0.789(**)	0.398	0.557	0.015			0.47	4.01	0.39
Deuts. Boerse	0.003	0.608(**)	−0.932(**)	−1.031(**)	−0.657	−0.134	0.057			0.66	1.31	2.17
Deuts. Post	0.001	0.802(**)	−0.82(**)	0.004	0.435	−0.524	−0.173			0.36	2.56	0.94
Deuts. Telekom	0.001	0.615(**)	−1.504(**)	0.156	0.719(*)	−0.206	0.206	0.048(*)	0.928(**)	0.81	4.03	1.63
Essilor	0.001	0.59(**)	−1.216(**)	−1.213(**)	−0.46	0.076	0.054			1.13	0.43	1.03
ENEL	0.002	0.792(**)	−1.444(**)	0.304	0.432	−0.178	0.411(**)	0.15(*)	0.798(*)	0.05	4.11	0.1
Engie	−0.001	0.826(**)	−1.332(**)	0.162	0.674	0.154	0.174			0.01	2.45	1.68
ENI	−0.001	0.945(**)	−1.05(**)	1.278(**)	1.415(**)	0.722	−0.01	0.064(*)	0.837(**)	0.11	0.02	0.21
France Telecom	0.001	0.56(**)	−1.452(**)	0.203	0.739(*)	0.151	0.19	0.066(*)	0.912(**)	0.27	1.53	0.54
Fresenius	0.001	0.804(**)	−1.035(**)	−1.25(**)	−0.669	0.161	0.236			0.01	1.69	1.87
Ibedrola	0.001	0.652(**)	−1.082(**)	−0.1	0.532	0.344	0.323(**)			1.02	1.01	3.36
Inditex	0.001	0.774(**)	−1.117(**)	−0.773(*)	0.33	0.094	−0.229			0.6	0.82	0.84
ING	0.002	0.997(**)	−0.843(**)	−0.94(**)	−2.635(**)	−0.223	−0.327(*)			0.29	0.15	2.07

(*continued*)

Table 4.

Companies	Cte	Mkt	SMB	HML	RMW	CMA	MOM	ARCH(1)	GARCH(1)	LM ARCH	LB raw	LB squr.
Intesa	0.002	1.18(**)	−1.035(**)	−0.831	−3.24(**)	−0.602	−0.229			0.49	0.28	4.02
Linde	0.002	0.397(**)	−0.829(**)	−0.341	0.058	0.695	−0.107			0.01	4.13	1.53
Loreal	0.002	0.506(**)	−1.564(**)	−0.951(**)	0.267	0.317	0.065	0.121(*)	0.566(*)	0.26	0.54	0.53
LVMH	0.004(**)	0.877(**)	−1.026(**)	−0.203	0.368	−0.26	0.029	0.034(*)	0.906(**)	0.89	0.27	1.74
Muenchener	0.001	0.456(**)	−1.178(**)	−0.166	−0.769(*)	−0.771(*)	0.179	0.011(*)	0.949(**)	1.26	0.83	2.38
Nokia	−0.001	0.718(**)	−1.343(**)	−1.531(**)	−1.328(*)	−0.116	0.115			1.64	0.59	0.62
Philips	0.002	0.801(**)	−1.087(**)	−0.327	−0.442	−0.539	0.205			0.11	0.08	1.01
Pinault	0.003	0.964(**)	−0.706(**)	−0.376	0.71	0.243	0.107	0.096(*)	0.528(**)	0.1	1.96	0.16
Sagem	0.002	0.83(**)	−1.116(**)	−1.572(**)	−0.883(*)	0.5	0.043	0.269(*)	0.624(*)	0.55	4.09	1.13
Sanofi	0.001	0.586(**)	−1.384(**)	−1.956(**)	−1.858(**)	0.647	0.026			0.01	0.64	4.03
Santander	0.001	1.008(**)	−1.096(**)	0.359	−1.86(**)	−0.616	−0.509(**)			1.77	0.78	0.79
SAP	0.002	0.707(**)	−1.166(**)	−0.808(**)	−0.307	−0.637	0.145			0.02	1.52	1.98
Schneider	0.001	0.971(**)	−0.872(**)	−0.206	0.32	0.324	−0.244			1.49	1.53	1.86
Siemens	0.001	0.795(**)	−1.138(**)	−0.278	0.026	0.191	−0.063	0.048(*)	0.944(**)	1.33	0.97	2.57
Soc. Generale	0.001	1.184(**)	−0.81(**)	−0.754	−3.357(**)	−0.504	−0.445(**)			0.01	0.38	1.3
Telefonica	−0.001	0.842(**)	−1.131(**)	−0.128	0.193	0.258	−0.34(**)	0.092(*)	0.883(**)	1.06	1.11	2.01
Unilever	0.001	0.425(**)	−1.696(**)	−1.063(**)	0.192	0.519	0.093	0.241(*)	0.486(*)	1.18	1.09	2.41
Vinci	0.002	0.862(**)	−0.775(**)	−0.526	0.361	0.07	0.121	0.045(*)	0.921(**)	0.12	3.49	0.25
Vivendi	0.002	0.756(**)	−0.928(**)	−0.887(**)	−0.557	0.499	−0.061			2.18	2.47	3.07
Volkswagen	0.001	0.969(**)	−0.628(*)	1.685	1.15	−1.627	−0.241	0.13(*)	0.684(**)	2.42	3.42	4.09
Total	0.001	0.832(**)	−1.011(**)	1.227(**)	1.29(**)	0.252	0.055	0.024(*)	0.957(**)	0.24	2.28	0.5

Table 5. Results of model for volume changes and descriptive statistics of standardized residuals

Companies	CTE	AR(1)	MA(1)	CTE	ARCH(1)	GARCH(1)	LM ARCH	LB raw data	LB squared data
ADIDAS	−0.0037	0.2525(**)	−0.944(**)	0.0794(**)	0.0966(*)	0.3617(*)	0.06	0.42	0.13
AHOLD	0.0019	0.257(**)	−0.9156(**)	0.1007(*)	0.0455(*)	0.3796(*)	0.08	2.95	0.15
AIR LIQUIDE	−0.0104	0.1634(**)	−0.9564(**)	0.0177	0.0065(*)	0.8975(**)	0.04	0.24	0.11
AIRBUS	−0.0035(**)	0.056(*)	−0.9794(**)	0.0107	0.0554(*)	0.9835(**)	0.31	3.03	0.68
ALLIANZ	−0.0034	−0.0525(*)	−0.7948(**)	0.0399(*)	0.0886(*)	0.5832(**)	0.5	0.5	1.07
AMADEUS	−0.0057(*)	0.4137(**)	−0.9642(**)	0.1464(**)	0.3607(*)	0.3931(**)	0.31	2.38	0.65
ANHEUSER	−0.001	0.2438(**)	−0.9266(**)	0.1285(**)	0.0344(*)	0.2109(*)	0.57	0.53	0.36
ASML	−0.0004	0.2523(**)	−0.9521(**)	0.1454(*)	0.0412(*)	0.0596(*)	0.01	1.13	0.03
AXA	−0.0023	0.2708(**)	−0.9658(**)	0.0873(**)	0.0663(*)	0.3866(**)	0.1	0.18	0.21
BASF	−0.0009	0.2161(**)	−0.9401(**)	0.0529	0.0852(*)	0.5455(**)	0.31	1.69	0.63
BAYER	0.0029	0.1175(*)	−0.9039(**)	0.107(**)	0.193(*)	0.1485(*)	0.07	0.41	0.14
BBVA	−0.0031	0.406(**)	−0.9751(**)	0.1582(**)	0.2165(*)	0.3376(*)	1.13	1.64	2.32
BMW	0.0003	0.0658(*)	−0.9461(**)	0.1207	−0.0136(*)	0.2706(*)	0.17	0.29	0.33
BNP	−0.0006	0.3345(**)	−0.9565(**)	0.1104(**)	0.137(*)	0.1521(*)	0.24	0.46	0.49
CRH PLC	0.0523	0.1438(*)	−0.9709(**)	0.0063	0.0202(*)	0.9605(**)	0.15	1.95	0.31
DAIMLER	0.0006	0.1361(*)	−0.9484(**)	0.0446(*)	0.0075(*)	0.683(**)	0.03	0.48	0.07
DANONE	0.0068	0.5843(**)	−0.8709(**)	0.1471(**)	0.2742(*)	0.0114(*)	0.17	4.21	0.34
DEUTSCHE BOERSE	0.0017	0.0491(*)	−0.7467(**)	0.0186	0.1455(*)	0.7608(**)	0.44	1.51	0.78
DEUTSCHE POST	−0.0008	0.2543(**)	−0.9038(**)	0.1466(**)	0.0917(*)	0.164(*)	0.05	0.06	0.11
DEUTSCHE TELEKOM	−0.0012	0.095(*)	−0.8817(**)	0.0094(*)	0.0402(*)	0.9274(**)	0.39	0.41	0.75
ESSILOR	0.0001	0.2575(*)	−0.9633(**)	0.0946	0.0041(*)	0.4467(**)	0.25	0.08	0.52
ENEL	−0.0021	0.3462(*)	−0.9585(**)	0.0704(*)	0.0841(*)	0.238(*)	0.06	0.59	0.14
ENGIE	0.0047	0.2168(**)	−0.9585(**)	0.0092(*)	0.054(*)	0.9794(**)	0.37	0.01	0.76
ENI	0.0011	0.3033(**)	−0.9427(**)	0.041	0.0295(*)	0.5111(*)	0.13	0.18	0.27
FRANCE TELECOM	−0.0012	0.2111(**)	−0.9444(**)	0.0467	0.0383(*)	0.6624(*)	0.26	0.19	0.53
FRESENIUS	0.0011	0.1568(*)	−0.9037(**)	0.0216	0.0231(*)	0.3689(*)	0.03	0.11	0.06
IBERDROLA	−0.0012	0.2427(**)	−0.9215(**)	0.0283	0.0461(*)	0.8338(**)	0.19	2.73	0.36
INDITEX	−0.0006	0.2548(**)	−0.9986(**)	0.2287(**)	0.1815(*)	0.3825(**)	1.55	1.74	3.21
ING	−0.0007	0.1216(*)	−0.9282(**)	0.0008	0.009(*)	0.9731(**)	1.18	2.29	2.24
INTESA	−0.0032	0.2477(**)	−0.9048(**)	0.0059	0.049(**)	0.9401(**)	0.01	1.32	0.02
LINDE	−0.0025	0.0998(*)	−0.8608(**)	0.0221(*)	0.0197(*)	0.8789(**)	0.09	0.45	0.19
LOREAL	−0.0143	0.2665(**)	−0.9513(**)	0.102(**)	0.0289(*)	0.1659(*)	0.01	0.59	0.02

(continued)

Table 5.

Companies	CTE	AR(1)	MA(1)	CTE	ARCH(1)	GARCH(1)	LM ARCH	LB raw data	LB squared data
LVMH	−0.0554	0.2827(*)	−0.9681(**)	0.1397	0.2642(*)	0.6125(*)	0.17	0.41	0.35
MUENCHENER	−0.0013	0.1572(*)	−0.9349(**)	0.0099	0.0145(*)	0.9366(**)	0.39	0.13	0.81
NOKIA	−0.0002	0.1473(*)	−0.9631(**)	0.047(**)	0.184(*)	0.563(**)	0.24	2.41	0.72
PHILIPS	0.0015	0.2138(**)	−0.9627(**)	0.2363(**)	0.0884(*)	0.3523(*)	0.53	0.33	1.07
PINAULT	−0.0012	0.1717(*)	−0.9327(**)	0.0191(**)	0.0516(**)	0.949(**)	2.19	0.14	3.87
SAGEM	0.0002	0.1861(**)	−0.92(**)	0.0059	0.0113(*)	0.9555(**)	0.28	0.16	0.54
SANOFI	−0.0011	0.2106(**)	−0.9573(**)	0.0947	0.0243(*)	0.316(*)	0.13	0.01	0.27
SANTANDER	−0.0002	0.151(*)	−0.566(*)	0.2097(*)	0.0394(*)	0.5103(**)	0.14	3.66	0.29
SAP	−0.0016	0.0697(*)	−0.9079(**)	0.0162(*)	0.025(*)	0.908(**)	1.06	0.48	2.18
SCHNEIDER	−0.0019	0.1948(**)	−0.9584(**)	0.0518	0.0353(*)	0.6719(**)	0.39	0.12	0.83
SIEMENS	−0.0018	0.1161	−0.9348(**)	0.01(**)	0.0471(**)	0.9442(**)	1.54	0.07	2.32
SOCIETE GENERALE	−0.0007	0.35(**)	−0.9663(**)	0.1462(**)	0.1459(*)	0.7192(*)	0.03	0.35	0.05
TELEFONICA	−0.0027	0.2305(**)	−0.9444(**)	0.2016(**)	0.16(*)	0.252(*)	0.89	2.88	1.87
UNILEVER	0.0014	0.1758(*)	−0.8863(**)	0.1926	0.1171(**)	0.6703(**)	0.32	1.37	0.69
VINCI	0.0021	0.2506(**)	−0.9528(**)	0.0157	0.0293(*)	0.8958(*)	0.73	0.27	1.45
VIVENDI	0.0046	0.2555(**)	−0.9516(**)	0.0178	0.0891(*)	0.8221(**)	0.21	1.2	0.44
VOLKSWAGEN	−0.0006	0.1848	−0.9427(**)	0.0283(**)	0.0554(*)	0.7963(**)	0.18	0.41	0.37
TOTAL	−0.0002	0.2229(**)	−0.8978(**)	0.0165	0.0575(*)	0.8787(**)	0.02	0.21	0.04

Table 6. Results of model for GSVI and descriptive statistics of standardized residuals

Companies	CTE	AR(1)	MA(1)	CTE	ARCH(1)	GARCH(1)	LM ARCH	LB raw data	LB squared data
ADIDAS	0.0024		−0.1907(*)	0.0012	0.0335(*)	0.5911(*)	0.07	0.42	0.14
AHOLD	0.0006	0.2699(**)	−0.7961(**)	0.0029	0.2101(*)	0.7196(**)	0.15	2.65	0.32
AIR LIQUIDE	0.0008	0.4713(**)	−0.9515(**)	0.013(**)	0.1492(*)	0.5257(*)	0.01	0.82	0.01
AIRBUS	0.001		−0.653(**)	0.005(*)	0.012(*)	0.791(**)	0.02	2.6	0.03
ALLIANZ	−0.0003	0.4811(**)	−0.9315(**)	19.2914(**)	0.0723(*)	0.4767(**)	1.07	3.88	2.19
AMADEUS	0.0001	0.0928(*)	−0.6109(**)	18.4311(**)	0.1745(*)	0.3674(**)	0.46	2.1	0.95
ANHEUSER	0.003		−0.256(*)	0.005	0.17(*)	0.703(**)	0.06	4.16	0.13
ASML	0.0014	0.3641(**)	−0.9095(**)	0.0609(**)	0.0651(**)	0.8964(**)	0.13	4.19	0.24
AXA	−0.0004	0.4807(**)	−0.9398(**)	0.0017	0.0577(*)	0.4012(**)	1.26	4.54	2.58
BASF	0.0014(*)	0.2086(**)	−0.9753(**)	0.0046(**)	0.1098(*)	0.6815(**)	0.07	0.78	0.15
BAYER	0.0012	0.6299(*)	−0.9437(**)	0.0111	0.1342(*)	0.6904(*)	0.03	3.99	0.07
BBVA	−0.0005	0.4848(**)	0.8908(*)	0.0071(**)	0.0939(*)	0.7452(*)	0.02	2.7	0.04
BMW	0.0002	0.1389(*)	−0.6904(**)	9.8449(**)	0.1813(**)	0.2558(*)	0.03	0.15	0.06
BNP	0.0002	0.0899(*)	−0.6483(**)	0.0002	0.0453(**)	0.9012(**)	0.36	2.65	0.74
CRH PLC	0.0009	0.4595(**)	−0.9602(**)	0.0071(*)	0.0551(*)	0.6698(**)	0.03	0.14	0.06
DAIMLER	0.0025	0.5936(**)	−0.9596(**)	0.0069(**)	0.1056(**)	0.4079(**)	1.92	0.96	3.95
DANONE	−0.0008	0.7346(**)	−0.9652(**)	0.0013(**)	0.4795(**)	0.3275(**)	0.25	2.27	2.08
DEUTSCHE BOERSE	−0.002	0.4359(**)	−0.9581(**)	−0.0042	0.055(*)	0.8656(**)	0.22	0.89	0.46
DEUTSCHE POST	0.0028	0.2424(*)	−0.2846(**)	0.0013(**)	0.6315(**)	0.264(*)	0.46	0.63	0.94
DEUTSCHE TELEKOM	−0.0012		−0.2846(**)	0.006(**)	0.0289(*)	0.6121(*)	0.02	0.64	0.05
ESSILOR	−0.0016	0.5965(**)	−0.8757(**)	0.0051(**)	0.1769(*)	0.7552(*)	0.01	2.44	0.02
ENEL	0.002	0.4824(**)	−0.8915(**)	0.0055(**)	0.0354(*)	0.5012(*)	0.46	4.24	0.95
ENGIE	0.0031	0.6017(*)	−0.88(*)	0.0043(*)	0.165(*)	0.2378(*)	1.5	1.42	3.09
ENI	−0.0005	0.6875(**)	−0.9305(**)	0.003(**)	0.0251(*)	0.9784(*)	0.29	2.45	0.56
FRANCE TELECOM	−0.0042(**)	0.3507(*)	−0.7334(**)	0.0014(**)	0.2399(*)	0.6348(*)	0.04	0.02	0.08
FRESENIUS	0.0005	0.2917(**)	−0.9194(**)	0.0081	0.1948(*)	0.6793(*)	0.36	1.37	0.75
IBERDROLA	−0.0003	0.6317(**)	−0.9038(**)	0.0123	0.1232(*)	0.5915(*)	0.14	0.93	0.28
INDITEX	−0.001	0.611(**)	−0.958(**)				0.42	0.33	0.83
ING	−0.0015	0.4856(**)	−0.2138(*)	0.0039(**)	0.2686(*)	0.5096(*)	1.51	2.01	2.66
INTESA	0.0013	0.322(**)	−0.8576(**)	0.0039(**)	0.4854(*)	0.2412(**)	0.26	0.04	0.54
LINDE	0.0046	0.3691(**)	−0.9923(**)	0.0054(**)	0.1925(*)	0.6303(*)	0.27	1.41	0.53
LOREAL	0	0.12(*)	−0.555(**)	0.001	0.193(*)	0.633(*)	0.13	1.09	0.27

(*continued*)

Table 6.

Companies	CTE	AR(1)	MA(1)	CTE	ARCH(1)	GARCH(1)	LM ARCH	LB raw data	LB squared data
LVMH	0.0001	0.156(*)	−0.3884(*)	0.0043(*)	0.182(*)	0.3456(*)	0.63	1.78	1.28
MUENCHENER	0.0007	0.3681(**)	−0.9767(**)	0.0264(**)	0.1152(*)	0.6102(*)	0.01	1.89	0.02
NOKIA	−0.0054(*)			0.0104(*)	0.2702(**)	0.7629(**)	0.06	0.57	0.13
PHILIPS	−0.0067(*)			0.0044(*)	0.3532(*)	0.4649(**)	0.3	0.7	0.63
PINAULT	0.0276	0.2462(**)	−0.7086(*)	0.0261	0.1855(*)	0.7682(**)	0.11	4.11	0.22
SAGEM	−0.005(**)	0.1343(*)	−0.7262(**)	0.0021	0.1018(*)	0.6041(**)	0.72	0.24	1.49
SANOFI	−0.0033(*)	0.346(**)	−0.9356(**)	0.0063(*)	0.1713(*)	0.6041(**)	0.05	1.46	0.11
SANTANDER	−0.0003	0.0683(*)	−0.6498(**)	0.0012	0.066(*)	0.7079(**)	0.34	0.45	0.69
SAP	0.0065	0.2341(**)	0.9889(**)	0.0025(**)	0.1565(*)	0.5872(*)	1.01	3.69	2.14
SCHNEIDER	0.0022	0.5784(**)	−0.9655(**)	0.0036(**)	0.3819(*)	0.6083(*)	0.19	3.7	0.69
SIEMENS	−0.001	0.124(*)	−0.596(**)	0.001	0.196(*)	0.416(*)	2.72	3.21	4.51
SOCIETE GENERALE	−0.001(**)	0.789(**)	−0.987(**)	0.001	0.145(*)	0.573(**)	0.64	2.98	1.3
TELEFONICA	−0.0028(**)	0.3758(**)	−0.9348(**)	0.0116(*)	0.0184(*)	0.7181(*)	0.01	3.14	0.02
UNILEVER	−0.0007(*)	0.5792(**)	−0.9866(**)	0.0094(*)	0.2233(*)	0.6014(*)	0.02	2.55	0.01
VINCI	0.0008	0.4118(**)	−0.9276(**)	0.0117(**)	0.0376(*)	0.8309(*)	0.01	0.16	0.01
VIVENDI	−0.0002	0.5334(**)	−0.9486(**)	0.0018	0.0378(*)	0.9229(**)	0.22	0.12	0.47
VOLKSWAGEN	−0.004	0.2448(**)	−0.753(**)	5.4312(**)	0.065(*)	0.5362(*)	0.09	4.13	0.18
TOTAL	0.0022	0.2163(*)	−0.7115(**)	0.0011	0.5058(**)	0.3989(**)	0.02	0.49	0.05

Companies	Shocks of excess returns GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)	Shocks of volume changes GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)
ADIDAS	−0.004	−0.001	0.032	−0.112	0.035	−0.056	−0.054	−0.042
AHOLD	0.034	−0.086	−0.015	−0.024	0.319(**)	0.287(**)	−0.136(*)	0.056
AIR LIQUIDE	0.001	−0.106	−0.01	0.069	0.316(**)	0.136(*)	−0.014	0.044
AIRBUS	−0.075	0.136	−0.028	0.031	0.088	0.041	−0.063	0.014
ALLIANZ	0.022	0.165(**)	−0.102	0.027	−0.017	0.214(**)	−0.037	0.04
AMADEUS	0.016	−0.047	0.014	0.014	−0.02	0.076	0.092	0.015
ANHEUSER	0.014	0.104	−0.054	−0.001	0.17(**)	0.098	−0.01	0.047
ASML	−0.016	0.209(**)	0.013	0.02	0.216(**)	0.237(**)	0.067	−0.072
AXA	−0.029	0.099	−0.05	−0.034	0.28(**)	0.103	0.005	0.029
BASF	0.034	−0.048	0.018	0.024	0.062	0.166(**)	−0.013	0.003
BAYER	−0.147(*)	−0.144(*)	−0.01	0.084	0.159(**)	0.222(**)	−0.055	0.131(*)
BBVA	0.124(*)	−0.112	0.008	0.068	0.067	−0.052	0.005	0.038
BMW	−0.005	−0.154(**)	−0.029	0.006	−0.021	0.001	−0.076	0.009
BNP	0.176(**)	−0.058	−0.025	−0.043	0.229(**)	−0.052	0.033	−0.083
CRH PLC	0.009	0.117	0.007	−0.031	0.325(**)	0.184(**)	0.036	0.022
DAIMLER	−0.038	−0.05	−0.168	0.017	0.248(**)	0.212(**)	−0.008	0.057
DANONE	0.043	0.066	−0.04	0.016	0.136(*)	0.104	0.102	−0.131(*)
DEUTSCHE BOERSE	−0.088	0.014	0.037	−0.039	0.118	0.221(**)	−0.013	−0.12(*)
DEUTSCHE POST	−0.031	−0.023	−0.033	0.116	0.002	0.117	−0.02	−0.011
DEUTSCHE TELEKOM	0.072	−0.014	0.012	0.012	−0.022	0.133(*)	0.119	0.094
ESSILOR	0.133(*)	−0.115	−0.065	−0.012	0.317(**)	0.165(**)	0.021	0.018
ENEL	−0.048	−0.006	0.12	0.008	0.007	0.024	0.01	0.047
ENGIE	−0.012	0.004	−0.049	0.013	0.157(**)	0.116	0.036	0.052
ENI	−0.015	0.122	−0.016	0.026	0.241(**)	0.147(**)	−0.016	0.153(**)
FRANCE TELECOM	0.041	−0.138	0.032	0.008	0.175(**)	0.012	0.073	0.048
FRESENIUS	−0.025	−0.135	−0.02	−0.035	0.261(**)	0.206(**)	−0.075	0.124(*)
IBERDROLA	−0.003	−0.096	0	0.055	−0.066	0.04	0.067	0.026
INDITEX	0.006	−0.07	−0.004	0.147(*)	0.003	0.13(*)	0.029	−0.005
ING	0.071	−0.019	−0.011	0.021	0.087	0.045	0.008	0.019
INTESA	−0.001	0.054	0.063	−0.063	0.133(*)	−0.003	0.029	0.092
LINDE	−0.055	0.037	−0.114	0.022	0.031	0.153(**)	−0.031	0.008

(*continued*)

Table 7.
Results of causality in-mean

Table 7.

Companies	Shocks of excess returns GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)	Shocks of volume changes GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)
LOREAL	−0.125(*)	0.077	−0.054	0.03	0.07	0.164(**)	−0.034	0.06
LVMH	−0.041	−0.046	−0.075	0	−0.024	−0.007	0.081	−0.07
MUENCHENER	0.043	−0.118	−0.026	−0.036	0.178(**)	0.088	0.007	−0.012
NOKIA	0.02	0.079	0.055	0.011	0.093	−0.085	−0.099	−0.014
PHILIPS	−0.07	0.006	−0.068	0.01	−0.005	−0.057	0.146(*)	−0.053
PINAULT	0.099	0.021	0.046	0.08	−0.055	0.13(*)	−0.029	−0.001
SAGEM	0.021	−0.074	−0.023	0.036	0.025	0.114	0.006	0.076
SANOFI	0.073	−0.141	−0.081	0.129	0.153(**)	0.044	0.012	−0.025
SANTANDER	0.186(**)	0.032	−0.127	0.089	0.065	0.011	−0.067	−0.103
SAP	−0.045	−0.036	−0.042	0.009	−0.06	0.234(**)	−0.066	−0.027
SCHNEIDER	0.087	−0.037	−0.005	0.004	0.22(**)	0.125(*)	0.026	0.05
SIEMENS	0.073	−0.091	−0.016	−0.048	0.069	0.168(**)	0.028	0.031
SOCIETE GENERALE	0.084	−0.057	0.019	−0.017	0.124	−0.061	−0.022	−0.014
TELEFONICA	0.081	−0.014	−0.104	0.085	0.028	0.171(**)	0.023	−0.002
UNILEVER	0.066	0.009	−0.067	0.051	−0.083	0.101	0.02	0.026
VINCI	0.042	−0.004	−0.076	0.094	0.236(**)	0.076	0.017	0.084
VIVENDI	0.062	0.092	−0.055	0.039	0.17(**)	0.121	−0.056	−0.082
VOLKSWAGEN	−0.194(**)	−0.222(**)	−0.057	−0.05	0.089	0.18(**)	0.125(*)	0.005
TOTAL	0.01	−0.009	0.033	−0.05	0.089	0	0.048	0.011

Table 8. Results of causality in-variance

Companies	Shocks of excess returns					Shocks of volume changes				
	CTE	GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)	CTE	GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)
ADIDAS	1.0546(**)	−0.0218	0.0032	−0.0186	−0.0103	1.0252(**)	−0.0206	−0.0101	−0.0145	0.0207
AHOLD	0.6999(**)	0.1268	0.2653(**)	−0.0569	−0.0311	0.5136(**)	0.0857(*)	0.0906(*)	0.1464(**)	−0.043
AIR LIQUIDE	0.8167(**)	0.0282	0.0932(**)	0.0156	0.052	0.8729(**)	0.0264	0.0015	0.0069	−0.0213
AIRBUS	0.9588(**)	0.0237	−0.0042	−0.0102	−0.012	1.0283(**)	−0.0057	−0.0076	0.0114	−0.012
ALLIANZ	1.022(**)	−0.02	−0.0115	−0.0221	−0.0371	0.8645(**)	0.081(**)	−0.0135	0.0238	−0.0092
AMADEUS	1.0366(**)	−0.0435	0.0003	−0.0559	0.0413	0.9398(**)	−0.0681	−0.0082	0.1205	0.0077
ANHEUSER	1.0181(**)	−0.0033	0.0099	−0.0156	0.0052	0.9885(**)	0.0101	−0.0107	−0.004	−0.0078
ASML	0.8236(**)	−0.0367	0.1785(**)	0.0185	−0.0262	0.8232(**)	0.0288	−0.0671	−0.0017	0.0854
AXA	1.0676(**)	0.0298	−0.0255	−0.0337	−0.0318	0.9051(**)	0.04	0.0103	−0.0082	−0.029
BASF	1.0236(**)	−0.001	−0.0076	−0.0037	−0.0089	0.9515(**)	0.0034	0.033(*)	−0.0103	−0.0029
BAYER	0.8776(**)	0.0924	0.0409	−0.0226	−0.0226	0.7412(**)	0.1488(**)	−0.009	0.0114	0.019
BBVA	1.0405(**)	−0.1232	−0.0159	0.1132	−0.0351	0.7864(**)	0.1758(**)	−0.0401	0.0299	0.0591
BMW	0.8924(**)	−0.0119	0.0285	0.0863	−0.0147	1.0053(**)	0.0055	0.0217	0.0058	−0.045
BNP	0.9942(**)	−0.0339	0.022	−0.0026	−0.0093	0.6431(**)	0.1849(**)	0.0529	0.0945	−0.0508
CRH PLC	1.0157(**)	0.0117	−0.008	−0.0163	−0.0055	0.8094(**)	0.0801(**)	0.0156	−0.0117	−0.0224
DAIMLER	0.9915(**)	−0.0881	−0.0074	0.0434	0.0258	0.7351(**)	0.1821(**)	−0.0173	0.0113	−0.0252
DANONE	1.0686(**)	−0.0825	0.0692	−0.0198	−0.024	0.9465(**)	−0.0237	0.1218	−0.0494	−0.0441
DEUTSCHE BOERSE	0.9597(**)	0.0336	0.0316	0.011	−0.0286	0.7397(**)	0.108(**)	0.0412	0.023	0.0076
DEUTSCHE POST	1.0372(**)	0.0188	−0.0737	0.0175	0.0042	0.9443(**)	0.0387	0.0455	−0.0343	−0.0099
DEUTSCHE TELEKOM	0.9857(**)	−0.009	−0.012	0.0341	−0.0093	0.981(**)	−0.0071	−0.0023	−0.0052	−0.0093
ESSILOR	0.8347(**)	0.1692(**)	0.0071	−0.0239	−0.0177	0.8015(**)	0.0884(**)	0.0097	−0.0051	−0.0098
ENEL	1.0291(**)	−0.0259	−0.0269	0.0249	−0.0026	0.8389(**)	0.0146	0.0584	0.1247(**)	−0.0297
ENGIE	1.051(**)	−0.0431	−0.0476	0.0405	0.0086	0.8527(**)	0.0661	0.0274	0.0401	−0.0356
ENI	0.87(**)	0.093(*)	−0.0347	0.0289	0.0101	0.6142(**)	0.2124(**)	−0.0271	0.077(*)	0.0255
FRANCE TELECOM	0.9248(**)	−0.0682	0.0222	−0.0006	0.1019	0.5676(**)	0.1871(**)	0.2259(**)	−0.0021	−0.012
FRESENIUS	0.631(**)	−0.0169	0.3484(**)	−0.0255	0.0445	0.6595(**)	0.1174(**)	0.0408	0.0086	0.0534
IBERDROLA	0.9815(**)	−0.0194	−0.0404	0.1061	−0.0169	0.9011(**)	0.0284	−0.0744	0.155(**)	−0.0118
INDITEX	1.0479(**)	−0.0791	0.1169	−0.0499	−0.0587	0.9458(**)	−0.011	0.2235(**)	−0.0942	−0.0671
ING	1.0473(**)	0.0016	−0.0562	0.0742	−0.0573	0.4182	0.2043(*)	0.1073	0.2179(**)	0.0628
INTESA	0.9274(**)	0.0354	−0.024	0.0737	0.0001	0.6713(**)	0.1255(**)	0.0277	0.1076(*)	0.0507
LINDE	1.0053(**)	0.0031	−0.0193	0.0093	−0.0122	0.8602(**)	0.1442(**)	0.0204	−0.013	−0.0295

(*continued*)

Table 8.

Companies	Shocks of excess returns CTE	GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)	Shocks of volume changes CTE	GSVI(-1)	GSVI(-2)	GSVI(-3)	GSVI(-4)
LOREAL	1.0914(**)	−0.0177	−0.0355	−0.0249	−0.0329	1.058(**)	0.0046	−0.018	−0.0351	−0.0327
LVMH	1.2047(**)	−0.1056	0.0724	−0.101	−0.0534	0.8955(**)	−0.0232	−0.0022	0.0321	0.1119
MUENCHENER	0.9393(**)	0.0087	0.0794	−0.0412	0.016	0.8234(**)	0.1886(**)	0.0006	−0.0335	−0.0299
NOKIA	1.1445(**)	−0.0454	−0.0437	−0.0257	−0.0215	0.9575(**)	0.0183	−0.0225	−0.0062	0.0306
PHILIPS	0.9844(**)	0.002	−0.0342	0.0159	−0.0343	1.0596(**)	−0.0269	−0.0156	0.0034	−0.0389
PINAULT	1.0155(**)	−0.0061	0.0312	−0.0128	−0.0221	0.992(**)	−0.0061	0.0189	−0.0051	−0.0153
SAGEM	0.9707(**)	−0.0583	0.0152	0.1113	−0.0468	0.9347(**)	0.1074	−0.0142	−0.0628	0.0396
SANOFI	1.0549(**)	−0.0371	−0.0521	0.034	−0.0448	0.8536(**)	0.1327(*)	0.0715	−0.0254	−0.0496
SANTANDER	0.8657(**)	−0.0664	−0.0203	0.1036	0.0688	0.9318(**)	−0.0229	−0.0546	−0.0626	0.1883(**)
SAP	0.9929(**)	−0.0319	−0.0453	−0.0015	0.064	0.7839(**)	0.0864(**)	0.0104	0.0026	0.0161
SCHNEIDER	1.0853(**)	−0.0201	−0.0146	−0.0224	−0.0166	0.9251(**)	0.0322	0.0065	0.0005	−0.0243
SIEMENS	1.1199(**)	−0.0002	0.0608	−0.0706	−0.1153	0.7163(**)	0.1756(**)	−0.0433	0.026	0.0465
SOCIETE GENERALE	0.9251(**)	0.0241	0.0082	−0.0229	0.0659	0.5566(*)	0.2592(**)	0.0929	0.0968	0.0041
TELEFONICA	0.9442(**)	−0.0064	0.0413	0.0118	0.007	0.9921(**)	−0.0152	0.0072	−0.0168	0.016
UNILEVER	0.8876(**)	0.0015	0.1429(**)	−0.0102	−0.016	1.0007(**)	0.0006	0.0805	−0.024	−0.0424
VINCI	0.9988(**)	0	−0.0197	−0.0107	0.0312	0.8646(**)	0.0875(**)	0.0215	−0.0192	−0.0157
VIVENDI	1.075(**)	−0.0573	0.0104	0.0261	−0.0438	0.9525(**)	0.0307	0.0103	−0.0432	0.0102
VOLKSWAGEN	0.658(**)	0.2484(**)	0.0289	−0.0056	−0.0117	0.7338(**)	0.2604(**)	−0.0114	−0.0095	−0.0159
TOTAL	1.0356(**)	−0.0287	0.0086	−0.0299	−0.0132	0.8938(**)	0.0996(*)	0.0298	−0.0204	−0.0077

econometric requirements are included in the estimates, the results differ substantially from the rest of the literature.

Therefore, of a weekly sample of EURO STOXX-50 stocks from September 2014 to July 2019, we found that the Google Search Volume Index shows itself to have a minimum influence on asset returns, both in trend and in volatility. Conversely, the main influence of *GSVI* is on the trend and volatility of stock trading volume changes. So, the causality in-mean and in-variance on the trading volume indicates that individual and non-professional investors that use Google for their searches only affect the financial markets through the trading volume the next week, which seems consistent with the fact of that institutional investors and market makers have the highest influence on returns. Therefore, our empirical results reject the investor attention hypothesis since they show no influence on asset returns. On the contrary, there is a causal relationship on the trading volume, so we accept the information demand hypothesis. These results are consistent with the findings of Aalborg *et al.* (2019).

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