Investor Following And Volatility: A GARCH Approach

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ABSTRACT

In this paper, we aim to investigate whether investor following is a determinant of the stock market volatility. To measure investor following, we use “Google Insights for search” freshly introduced to the financial literature. The latter records the online search traffic for any keyword submitted to Google since 2004. Thanks to an extensive database, we focus precisely on the French stock market unlike previous works, which have focused largely on the US stock market. Notably, our findings support strong significant effects of investor following as measured by online search behavior on the conditional volatility estimated from GARCH (1,1) Market model. Our results are robust to additional tests.

Keywords: Investor Following; Online Search; Stock Volatility

1. INTRODUCTION

olatility is a key variable in the financial literature. Yet, up to now, its determinants still partially identified [Wei and Zhang (2006) and Fink et al. (2010)]. At least as early as Shiller (1981), numerous studies show that volatility cannot be exclusively explained by changes in fundamentals. The purpose of this paper is to investigate whether investor following with respect to searching, gathering and processing firm news is a determinant of the stock market volatility. For so long already, Merton (1987) introduces that investors prefer stocks they recognize. Thus, according to the investor recognition theory, stocks followed by investors would be more traded than stocks less familiar. Actually, investors are influenced by the information they hold. Consequently, they tend to invest in what they know. Today, given our digitized world in which information travels very fast, this information-based trading can lead investors to trade too speculatively and may influence asset pricing dynamics.

Assessing investor following presents a major difficulty in that there is no direct measure that can illustrate the investor behavior. In this paper, we introduce a new measure of investor following which relies on the intuition behind works on investor attention such as Da et al. (2011) and Vlastakis and Markellos (2012). We take an original approach and proxy firm's investor following on the basis of investors' online search behavior. The latter is exclusively provided by Google Insights for Search with the methodology described in Section 2 [Mondria et al. (2010) and Da et al.(2011)]. Specifically, we use Google French data by focusing for the first time on the French stock market. By using such data, we add further evidence that Google, the most popular internet search engine, has completely revolutionized the diffusion, supply and demand for information by making it less costly and easily available for retail investors. This is certainly the main reason which explains why people rely mostly on search engines to track information on the web.

Google is popular everywhere. Especially in France, Google continues to dominate the list of most used search engines, by a wide margin. Indeed, according to AT Internet, Google is far and away the search engine of choice, preferred by 91% of the French search users (as of July 2013). Similarly, in December 2012, there are 48 million internet users in France spending on average 26.9 hours/month on the Internet. It seems reasonable to suppose that online search traffic may influence the stock market volatility once it was proven to have an impact on the stock market activity. For instance, an emerging stream of literature suggests that Google search frequency helps

to improve the stock liquidity. Specifically, Bank et al. (2011) find that higher Google search volume decreases stock illiquidity and leads to higher future returns in the short run. Similarly, Ding and Hou (2012) show that online search is positively associated with the shareholder base and liquidity. More interestingly, a growing strand of literature finds consistent evidence that Google search frequency is strongly linked to the stock volatility. Vlastakis and Markellos (2012) show that information demand, proxied by Google search volume, helps to explain approximately 50% of variations in the Market Volatility Index (the VIX). Otherwise, using Google searches as a proxy for retail investors' attention, Dimpfl and Jank (2011) find that online search constitutes an additional source of future market volatility. Further, Kita and Wang (2012) argue that volatility in FX markets is driven by investor attention as proxied by Google search volume. In currencies market, Smith (2012) finds that Google searches for some economic keywords such as "economic crisis", "financial crisis" and "recession" has incremental predictive power for the volatility of seven currencies.

It is important to understand how investor following with respect to information-based trading affects the volatility of stock returns. In particular, any investor would want to know what are the determinants of the risk and value of his portfolio, especially in recent times. The advantage of knowing about risk is that we can change our behavior to avoid it. Moreover, volatility plays an important role in pricing options, risk management (e.g., Value-at-Risk), and asset allocation. For instance, volatility is used to construct optimal hedge ratios to trade against risk and to assess the value of that risk.

Our paper complements and extends prior studies in different ways. First, we add further evidence to the power of online search data over a number of financial settings. We also contribute to the existing literature by introducing a new measure of investor following: investors' online search behavior. Previous work on retail investor behavior use passive measures such as trading volume, price limits or media coverage, which does not automatically guarantee that investor is really devoting attention to a particular firm. Second, we put the first empirical evidence for the French stock market while most prior studies deal exclusively with the US stock market. Notably, we find significant effects of firm's investor following on volatility even after controlling for market's investor following. Most importantly, to the extent that online search is more likely emanating from less sophisticated investors, we suggest that retail investors behave as noise traders in the French stock market [Foucault et al. (2011)]. Last, but not least, we add to the volatility literature since the determinants of the stock market volatility are still under debate.

The remainder of this paper is organized as follows. In Section 2, we describe the data and report basic statistics. We present the empirical results and discuss their implications in Section 3. Further, we check the robustness of our findings to see how sensitive the empirical results are to the inclusion of the online search variables' effect. Section 4 concludes.

2. DATA AND PRELIMINARY ANALYSIS

2.1. Online Search Behavior: A Novel Proxy Of Investor Following

As mentioned in the introduction, we proxy investor following on the basis of investors' online search behavior provided by "Google Insights for Search". The online search traffic of a particular term is calculated as the number of searches for this term relative to the overall total number of Internet searches in Google at a particular point in time. To control for the increased use of the Internet over time, this ratio is then, normalized by the highest query share of that term over the time-series. Thus, Google data ranges from 0 to 100 with 100 representing the highest level of search traffic during the sample period. Lastly, the Google data is available on a daily, monthly and weekly frequency beginning in 2004.

To identify a firm's investor following in Google, we employ the firm name rather than the stock ticker. Actually, we use the two alternatives but the latter tend to be unproductive for most of the stocks in our sample. In addition to a proxy of firm's investor following, we construct a proxy for market's investor following on the basis of online search of the term "CAC 40". Finally, note that we filter the data by country so that only queries submitted within France are defined.

2.2 Sample Construction

Our data set ranges from January 2004 to June 2012 to match the Google data. Alternately, we first start by the 40 stocks which constitute the CAC 40 index as of January 2004. Then, for every stock in our sample, we manually download the corresponding online search data. Finally, after some restrictions¹, we have a final sample which consists of 30 out of the 40 initial stocks. Appendix A presents a list of the stocks in our sample along with the corresponding search queries we finally adopted.

Given our sample period, Google data is only available on a weekly frequency. Thus, we use weekly data instead of daily data in the regression analysis. Furthermore, this allows us somehow to reduce any potential biases that may arise, such as non-synchronous trading days.

2.3 Basic Statistics

Before starting the empirical analysis, it is worth assessing the behavior of the data. In the first step, we run statistical tests of the Google data under analysis. The Jarque-Bera (J-B) statistical test calculates the skewness and kurtosis of the series. The null hypothesis is in favor of a normal distribution. As shown in Table 1, the online search variables are not normally distributed displaying positive skewness and excess kurtosis for the majority of stocks at the level 1%. Accordingly, the Google data used hereafter are logarithmically transformed.

¹To guarantee unbiased results, we exclude from our sample stocks such as “Thales” and “TF1” because they have some other meanings in France.

Table 1. Descriptive Statistics Of Google Data

This table reports the descriptive statistics of the original information demand data (GSV). GSV is the firm name search intensity defined as the weekly search volume index of a firm name on Google, scaled from 0 to 100 by Google Insights for search. The sample spans from January 2004 to June 2012. This table reports also the central tendency characteristics (Mean and Median), the kurtosis, the skewness; in addition to the standard deviation (dispersion characteristics) and the coefficient of variation (CV). Lastly, J-B is the Jarque-Bera test for normality based on skewness and excess kurtosis.

Stock	Mean	Median	St.Dev	CV	Skew.	Kurt.	J-B
Accor	43,3589	40	14,9365	0,3444	0,8139	3,1109	40,07***
Axa	73,9548	74	6,8479	0,0925	0,1989	3,1170	143,42***
Air Liquide	36,7652	33	12,4620	0,3389	1,5934	6,2081	3,39
Arcelor	15,1467	14	8,8667	0,5853	3,3686	25,3191	367,19***
Bnp Paribas	38,8532	38	15,6388	0,4025	1,0644	4,4970	77,32***
Bouygues	44,2708	42	9,7337	0,2198	1,0666	5,5091	90,84***
Cap Gemini	22,3115	16	17,8874	0,8017	1,7121	6,2650	153,86***
Carrefour	63,2347	61	11,0266	0,1743	0,6705	3,4319	31,81***
Crédit Agricole	64,3972	67	13,0746	0,2030	-0,57921	2,5968	22,07***
Danone	33,2054	27	19,0002	0,5722	1,1781	1,1781	75,65***
Dexia	15,3860	14	7,0004	0,4549	8,2089	89,0125	670,36***
Eads	37,4763	31	16,3717	0,4368	1,0588	3,5529	64,12***
France Telecom	32,2347	26	24,1480	0,7491	0,6517	2,1488	70,47***
Lafarge	43,2031	40	13,7878	0,3191	0,8103	3,1042	32,09***
Lagardère	13,1286	11	8,7875	0,6693	4,9021	41,9290	485,05***
L'oréal	27,4424	22	18,1123	0,6600	0,9967	3,8601	62,88***
LVMH	35,5349	33	12,8964	0,3629	1,1285	4,5981	84,10***
Michelin	62,0654	60	12,7661	0,2056	0,6662	3,3263	30,43***
Pernod Ricard	23,5553	20	13,1578	0,5585	1,5021	7,6871	150,74***
Peugeot	62,8465	61	9,0052	0,1432	0,8285	3,6971	47,05***
PPR	31,4379	27	13,6110	0,4329	1,60987	6,5334	148,34***
Renault	55,4921	54	9,5813	0,1726	0,7588	3,6742	41,31***
Saint Gobain	41,1535	39	12,9640	0,3150	1,0544	4,5849	77,70***
Sanofi	21,6298	20	8,4790	0,3920	2,7711	21,6114	317,35***
Schneider	46,5237	43	14,8258	0,3186	0,5453	2,8807	20,20***
Société Générale	49,7449	52	14,4687	0,2908	0,1855	3,3176	4,50
STMicroelectronics	21,3476	17	16,0484	0,7517	1,8315	6,9248	170,59***
Total	55,1083	52	11,0926	0,2012	0,7746	3,3281	38,61***
Vinci	6,1986	5	5,5336	0,8927	12,3465	195,6525	840,43***
Vivendi	22,60948	16	15,44113	0,6829	1,988646	7,550328	189,22***
CAC 40	11,03612	9	8,753205	0,7931	6,104132	54,80927	558,49***

*, **, *** denote 10%, 5% and 1% significance levels.

Table 2 reports the unit root tests (Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests) of the Google data. The null hypothesis in both tests is the presence of a unit root. As can be seen in Table 2, for all the stocks in our sample, the time series are stationary around a deterministic trend at the 99% significance level.

Table 2. Unit Root Tests On Google Data

This table reports the results of two unit root tests of Google search volume: the Augmented Dickey-Fuller test (ADF, Dickey and Fuller (1979)) and the Phillips-Perron test (PP, Phillips and Perron (1988)). GSV is the firm name online search frequency, scaled from 0 to 100 by Google Insights for search. In both tests, the null hypothesis is the existence of a unit root (stationarity).

The sample period spans from January 2004 to June 2012.

Stock	ADF	PP
Accor	-8,392***	-8,296***
Air Liquide	-12,454***	-13,210***
Axa	-10,545***	-10,626***
Arcelor Mittal	-8,370***	-8,219***
Bnp Paribas	-4,303 ***	-3,999***
Bouygues	-9,071***	-9,069***
Cap Gemini	-9,273***	-8,948***
Carrefour	-7,227***	-7,262***
Crédit Agricole	-4,258***	-3,381**
Danone	-9,260***	-9,034***
Dexia	-11,558***	-11,632***
EADS	-10,546***	-10,580***
France Télécom	-6,373***	-5,661***
Lafarge	-15,391***	-16,334***
Lagardère	-10,639***	-10,485***
L'oréal	-8,689***	-8,543***
LVMH	-9,560***	-9,457***
Michelin	-3,262***	-4,114***
Pernod Ricard	-10,720***	-10,792***
Peugeot	-7,444***	-7,498***
PPR	-13,178***	-13,597***
Renault	-8,205***	-8,260***
Saint Gobain	-12,324***	-12,493***
Sanofi	-11,811***	-12,031***
Schneider	-8,215***	-7,805***
Société Générale	-4,900***	-4,112***
STMicroelectronics	-8,542***	-7,357***
Total	-9,091***	-9,026***
Vinci	-15,846***	-16,466***
Vivendi	-9,123***	-8,907***
CAC 40	-6,270***	-6,320***

*, **, *** denote 10%, 5% and 1% significance levels.

In the next step, we apply once again the ADF and PP unit root tests to control for the stationarity of the weekly return series. Table 3 shows that; for all the stocks of the chosen firms, returns are stationary at the 99% significance level.

Table 3. Unit Root Tests On The Weekly Return Series

This table reports the results of two unit root tests on the stock returns series: the Augmented Dickey-Fuller test (ADF, Dickey and Fuller (1979)) and the Phillips-Perron test (PP, Phillips and Perron (1988)). The null hypothesis in both tests is the presence of a unit root. The sample period spans from January 2004 to June 2012.

Stock	ADF	PP
Accor	-21,513***	-21,530***
Air liquide	-23,813***	-24,545***
Arcelor Mittal	-21,784***	-21,609***
Axa	-21,244***	-21,260***
Bnp Paribas	-24,832***	-24,729***
Bouygues	-23,866***	-23,777***
Cap Gemini	-21,847***	-21,884***
Carrefour	-22,649***	-22,694***
Crédit Agricole	-21,807***	-21,729***
Danone	-25,670***	-25,686***
Dexia	-18,380***	-18,460***
Eads	-22,659***	-22,710***
France Telecom	-26,434***	-26,515***
Lafarge	-20,627***	-20,638***
Lagardère	-22,988***	-22,972***
L'oréal	-22,294***	-22,294***
LVMH	-22,462***	-22,582***
Michelin	-22,658***	-22,658***
Pernod Ricard	-24,759***	-24,919***
Peugeot	-21,387***	-21,296***
PPR	-21,701***	-21,760***
Renault	-19,427***	-19,595***
Saint Gobain	-21,292***	-21,331***
Sanofi	-26,383***	-26,879***
Schneider	-24,123***	-24,274***
Société Générale	-23,658***	-23,485***
STMicronics	-19,980***	-20,149***
Total	-23,806***	-24,109***
Vinci	-24,011***	-23,828***
Vivendi	-24,317***	-24,352***
CAC 40	-24,194***	-24,192***

*, **, *** denote 10%, 5% and 1% significance levels.

Then, before undertaking an estimation of the conditional volatility, we analyze the behavior of the return series. First, we assess whether the stock returns have an autoregressive conditional heteroskedastic structure (ARCH *effect*). Thus, we use the Lagrange multiplier (LM) test, whose null hypothesis is the existence of homoskedastic variances. We also check the presence of autocorrelation of the stock returns by applying the Ljung-Box test which the null hypothesis is no autocorrelation.

Table 4. Statistical Tests On The Weekly Return Series

This table reports the descriptive statistics of the logarithmic stock returns. The sample spans from January 2004 to June 2012. This table reports not only the central tendency characteristics (Mean and Median), the kurtosis and the skewness; but also the standard deviation (dispersion characteristics) of returns. J-B is the Jarque–Bera (J–B) normality test statistic estimated on the basis of the skewness and excess kurtosis. LM(6) refers to the Lagrange multiplier test for autoregressive conditional heteroskedasticity and more precisely the ARCH effects of order 6. Q(6) are the Portmanteau tests for white noise of order 6 for the returns.

Stock	Mean	Median	St.Dev	Skew,	Kurt,	LM(6)	Q(6)	J-B
Accor	0,0001	0,0038	0,0468	-0,3809	4,8058	62,484***	7,2279	70,9066***
Axa	-0,0011	0,0016	0,0612	-0,5405	8,2865	61,872***	6,9682	537,4461***
Air Liquide	0,0016	0,0023	0,0301	-0,4994	5,3775	98,786***	18,544***	122,7611***
Arcelor	0,0014	0,0050	0,0717	-0,3688	7,0288	52,819***	9,8926	309,6516***
Bnp Paribas	-0,0010	0,0009	0,0610	-0,3390	11,0515	157,216***	22,8136***	1205,100***
Bouygues	-0,0003	0,0014	0,0468	0,1211	7,8222	64,983***	14,8725**	430,3084***
Cap Gemini	-0,0006	-0,0010	0,0517	-0,5811	6,7921	1,715	3,6918	290,3745***
Carrefour	-0,0020	-0,0002	0,0418	-0,8776	8,9238	26,984***	6,7363	704,6170***
Crédit Agricole	-0,0036	-0,0008	0,0635	-0,3082	6,8227	84,293***	9,0385	276,7534***
Danone	0,0010	0,0008	0,0318	-0,3346	5,1565	16,142***	30,3888***	94,11286***
Dexia	-0,0034	0,0000	0,0464	-2,5037	24,3462	145,683***	22,5754***	8873,633***
Eads	0,0009	0,0017	0,0522	-0,4071	6,8567	17,360***	7,1832	286,7945***
France Telecom	-0,0017	0,0000	0,0339	-0,0784	7,3763	57,450***	24,0056***	353,9770***
Lafarge	-0,0011	0,0008	0,0512	-0,5769	7,7565	79,93612	15,428**	442,2045***
Lagardère	-0,0016	0,0008	0,0443	-0,6942	7,5582	62,301***	10,7316*	419,1038***
L'oréal	0,0008	0,0017	0,0304	-0,3334	4,9502	29,240***	4,8640	78,41971***
LVMH	0,0015	0,0017	0,0380	-0,2498	5,7158	85,857***	8,8792	140,7580***
Michelin	0,0008	0,0051	0,0509	-0,3695	4,4287	33,674***	7,4867	47,76518***
Pernod Ricard	0,0021	0,0033	0,0399	-0,7820	13,8522	158,623***	17,4691***	2219,043***
Peugeot	-0,0034	-0,0035	0,0562	-0,3781	5,0756	89,082***	10,8649*	90,08503***
PPR	0,0007	0,0033	0,0503	-0,2407	9,2399	149,894***	8,4517	722,9974***
Renault	-0,0012	0,0002	0,0615	-0,8223	8,1107	80,183***	12,4444**	532,0599***
Saint Gobain	-0,0004	0,0007	0,0526	-0,5373	8,3626	50,407***	5,0421	552,1382***
Sanofi	9,2E-05	0,0021	0,0362	-1,4330	13,5594	94,015***	38,6758***	2209,759***
Schneider	0,0012	0,0021	0,0464	-0,3368	6,3417	65,928***	9,9681	214,5111***
Société Générale	-0,0028	-0,0006	0,0689	-0,4540	6,6876	83,699***	10,6282	266,2356***
STMicroelectronics	-0,0037	-0,0041	0,04973	-0,0816	4,1773	35,048***	14,7491**	26,07950***
Total	4,6E-05	0,0019	0,0346	-0,7057	10,7258	80,068***	16,7653***	1138,514***
Vinci	0,0018	0,0023	0,0423	-0,2784	7,2684	31,964***	13,3334**	342,0336***
Vivendi	-0,0006	0,0024	0,0355	-0,8434	7,5717	14,902**	11,5241*	438,3193***
CAC 40	0,0002	0,0023	0,0315	-0,9164	9,6706	45,278***	15,7711**	883,3629***

*, **, *** denote 10%, 5% and 1% significance levels.

According to the results reported in Table 4, the LM test at 6 lags confirms the presence of an ARCH effect in the return series with the exception of Cap Gemini and Lafarge. This evinces that the variance of the errors of the returns is not constant, but rather varies over time. This finding can be essentially attributed to the high volatility of financial markets and mainly over the last decades. Otherwise, the Portmanteau (Q) test at 6 lags rejects the hypothesis that there is no autocorrelation in the time series for 13 out of 40 stocks in our sample. Finally, the J-B test for normality rejects also the null hypothesis of normality of the returns for all the stocks in our sample.

Taken together, our results suggest that volatility can be estimated through a model of the ARCH family, firstly introduced by Engle (1982). Indeed, given the heteroskedasticity of the stock returns, these models are appropriate for financial series displaying non constant conditional variance over time. In our setting, we make use of the Generalized Autoregressive Conditional Heteroskedasticity model [GARCH (p,q)] to estimate the conditional volatility of the return series [Bollerslev (1986)]. Actually, GARCH (p,q) models are easy to estimate and, even in its simplest form, it has proven surprisingly successful in estimating conditional variances. Further, the GARCH model has the appeal of considering the evolving conditional volatility as well as the volatility clustering [Nikolaos et al. (2009)].

3. EMPIRICAL ANALYSIS

As previously introduced, we investigate whether investor following proxied by online search behavior is a determinant of the stock market volatility. Before undertaking the main empirical analysis, a natural starting point is to test the correlation between online search and volatility on the French stock market. Volatility is measured by the standard deviations of returns.

Table 5. Correlation Between Stock Volatility And Investors' Online Search

This table presents the Pearson correlation coefficients between stock unconditional volatility and online search variables. Unconditional volatility is proxied by the standard deviations of stock returns. While, stock-specific and market-related online information search are measured by Google search volume of the firm name and Google search volume of the term "CAC40", respectively.

Stock	Stock-specific	Market-related
Accor	-0,3606***	0,6492***
Air liquide	-0,1254***	0,5751***
Arcelor Mittal	0,1049**	0,5958***
Axa	0,3792***	0,6821***
Bnp Paribas	0,2434***	0,6017***
Bouygues	0,1005**	0,7122***
Cap Gemini	-0,0588	0,4949***
Carrefour	0,1938***	0,6257***
Crédit Agricole	-0,1210**	0,6345***
Danone	-0,1397***	0,5971***
Dexia	0,3780***	0,6068***
Eads	-0,0942**	0,4267***
France Telecom	-0,0793*	0,5045***
Lafarge	-0,2930***	0,6453***
Lagardère	-0,0277	0,6478***
L'oréal	-0,1715***	0,5957***
LVMH	-0,2419***	0,6459***
Michelin	0,0677	0,3804***
Pernod Ricard	0,0547	0,7349***
Peugeot	-0,3926***	0,5443***
PPR	-0,2120***	0,6424***
Renault	-0,3246***	0,6762***
Saint Gobain	-0,1491***	0,6941***
Sanofi	0,0452	0,5461***
Schneider	-0,1747***	0,7203***
Société Générale	-0,1282***	0,6356***
STMicroelectronics	-0,1671***	0,5204***
Total	-0,1653***	0,7324***
Vinci	-0,0777	0,7353***
Vivendi	-0,0959**	0,6148***

*, **, *** denote significance at the 10%, 5% and 1% level, respectively.

The results reported in Table 5 show that firm's investor following and the stock volatility are negatively and significantly correlated in most cases (17 out of 30 cases) at the 95% significance level; while correlation is significant and positive in 7 cases at the 5% level. This evidence is even stronger for the market's investor following with all the correlation coefficients being significantly positive at the 99% significance level.

3.1 Regression models

As mentioned above, to model the conditional variance of the returns, we use the autoregressive model with generalized conditional heteroskedasticity (GARCH). Since our primary interest lies on how investor following affects the conditional volatility of the French stocks, we augment the GARCH (1,1) Market model with measures of investor following by allowing it to enter the specification of the conditional variance.

The model used in this study is illustrated in Equation (1). Note that the presence of heteroskedasticity in the series, as reported in Section 2.3, suggests that the GARCH specification is suitable for the analysis:

$$r_{i,t} = \mu + \lambda R_{CAC40} + \varepsilon_t \quad / \quad \varepsilon_t \sim N(0, \sigma_t^2) \quad (1)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta \ln(\text{Online_Search}_{i,t}) + \theta \ln(\text{Online_Search}_{M,t})$$

Where, $r_{i,t}$ is the weekly stock return of the firm i in week t ; R_{CAC40} is the market return² at time t ; and ε_t is the stochastic error term of the regression, with the conditional variance σ_t^2 following a GARCH (p,q) model. p represents the number of lags of the conditional variance (ARCH effect); while q defines the number of lags of the squared innovations (GARCH effect). μ and w are constants.

Online search is a proxy of investor following. For each stock in our sample, firm's investor following $[\ln(\text{Online_Search}_{i,t})]$ is derived from the online search traffic of the firm name. Similarly, we proxy market's investor following $[\ln(\text{Online_Search}_{M,t})]$ on the basis of online search traffic for the term "CAC 40". As can be seen, interestingly, Google allows us to cleanly separate the effect of investor following at the firm and market level, respectively.

The ARCH parameters illustrate the reaction of the volatility, while the parameters associated with the GARCH component represent the persistence of the volatility, and in less technical words; the risk in the return series. In the GARCH model, volatility persistence is assessed by the sum of these two parameters. Thus, the sum of the ARCH and GARCH parameters defines whether the risk in the stock return series persists over time.

We are staying with a GARCH (1,1) model. For instance, Hansen and Lunde (2005) find no other more sophisticated model can describe the conditional variance better than GARCH (1,1). In our setting, the choice of the best model is taken not only on the basis of the statistical significance of the estimated coefficient, but the Akaike information criterion (AIC) and Bayesian information criterion (BIC) as well, always adopting models with low order. Note that the estimation of the models' coefficients is done by the conditional maximum likelihood method.

3.2 GARCH estimation results

Regression results are summarized in Table 6. At first, our results suggest that the GARCH (1,1) market model is appropriate for each stock in our sample. Indeed, we believe that the choice of this specification is judicious, since the coefficient λ and the ARCH and GARCH coefficients are significant, as well as the fact that the influence of investor following was well captured by the models.

²In this study, we use the CAC40 index as the benchmark for the overall French stock market.

Table 6. Investor Following And Conditional Volatility

This table assesses the role of investor following as a determinant of the stock market volatility. Volatility is estimated via Maximum Likelihood with normally distributed errors of the extended GARCH Market Model after controlling for online search variables. For each stock in our sample, the estimated set of equations is:

$$r_t = \mu + \lambda v_t + \varepsilon_t / \varepsilon_t \sim N(0, \sigma_t^2) ; \text{ For the conditional mean}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta OIS_{i,t} + \theta OIS_{M,t} ; \text{ For the conditional variance}$$

μ is the constant; r_t is the stock log return; δ and θ are the estimated coefficients for firm-specific online information search and market-related online information search, respectively and; λ is the coefficient for market return. While, α and β denote the ARCH and GARCH term coefficients, respectively. The sample spans from January 2004 to June 2012. LM(6) is the Lagrange multiplier test for conditional heteroskedasticity of order 6. Q(6) and Q²(6) are the Portmanteau (Q) tests for white noise of order 6 for the standardized residuals and for the squared standardized residuals, respectively. J-B is the Jarque-Bera test for normality. The AdjR² values assess if the independent variables that are added to the regression enhance the overall explanatory power of the regression. Robust standard errors are presented in parentheses under the coefficient estimates.

Stock	ω	α	β	δ	θ	μ	λ	LM(6)	Q(6)	Q ² (6)	J-B	Adj. R ²
Accor	-0,0007** (0,0003)		0,8210*** (0,062362)		0,0003*** (0,0001)		1,0723*** (0,0505)	1,1840	3,3347	1,1910	20,7695***	0,5493
Air liquide		0,0892*** (0,0319)	0,8477*** (0,0427)			0,0013* (0,0007)	0,7857*** (0,0275)	10,5689	6,9883	11,396**	12,7064***	0,6223
Arcelor Mittal	-0,0014** (0,0007)	0,2910*** (0,0506)	0,4278*** (0,1154)	0,0006*** (0,0002)			1,4880*** (0,0663)	2,8033	5,3317	2,9482	25,3553***	0,4626
Axa	0,0001*** (1,81E-05)	0,0656** (0,0305)	0,7788*** (0,0372)	-0,0001*** (6,75E-06)	0,0002*** (3,08E-05)		1,5762*** (0,0423)	2,4195	6,6595	2,7918	109,3163***	0,7283
Bnp Paribas	-0,0002** (4,91E-05)	0,1174*** (0,0351)	0,8392*** (0,0391)		5,36E-05** (3,02E-05)		1,2723*** (0,0413)	5,6925	4,9433	5,6909	181,6979***	0,5559
Bouygues		0,0954** (0,0420)	0,6293*** (0,0908)	-0,0002*** (7,55E-05)	0,0003*** (7,92E-05)		1,1160*** (0,0408)	4,4946	8,1276	4,5158	18,7856***	0,5394
Cap Gemini			0,8904*** (0,0671)				1,1040*** (0,0486)	3,7527	6,2550	3,6315	12,5039***	0,4552
Carrefour			0,6741*** (0,1723)		0,0002** (0,0001)		0,8866*** (0,0480)	7,6590	12,376**	8,4511	159,9640***	0,4775
Crédit Agricole	0,0003*** (0,0001)	0,0590*** (0,0198)	0,8952*** (0,0298)		9,08E-05*** (3,03E-05)	-0,0030** (0,0014)	1,4365*** (0,0674)	1,0613	5,2610	1,0130	21,0186***	0,5686
Danone	0,0002* (0,0001)	0,0893*** (0,0272)	0,8076*** (0,0582)	-5,30E-05*** (1,89E-05)			0,6406*** (0,0445)	3,1341	7,7354	2,8124	165,9029***	0,3836
Dexia	0,0005*** (4,23E-05)	0,1661*** (0,0169)	0,6000*** (0,0197)	-0,0001*** (1,95E-05)	-6,15E-05*** (1,88E-05)		0,5829*** (0,0313)	1,1100	8,9806	1,1370	237,0385***	0,1436
Eads	-0,0056*** (0,0008)		-0,3250* (0,1873)	0,0012*** (0,0001)	0,0015*** (0,0001)		1,0542*** (0,0661)	2,7960	4,5612	2,8960	159,2776***	0,3992

Table 6 continued

Stock	ω	α	β	δ	θ	μ	Γ	LM(6)	Q(6)	Q ² (6)	J-B	Adj. R ²
France Télécom	-0,0002*** (7,64E-05)	0,0259** (0,0129)	0,9074*** (0,0389)	3,34E-05*** (1,15E-05)	7,67E-05*** (2,73E-05)	-0,0021* (0,0012)	0,6663*** (0,0461)	3,275859	8,6310	3,2852	210,6759***	0,3285
Lafarge		0,0465** (0,0220)	0,8590*** (0,0691)	-7,26E-05*** (4,22E-05)			1,2177*** (0,0468)	3,919534	7,1420	4,1151	367,0556***	0,6514
Lagardère	-0,0002*** (5,77E-05)		0,8742*** (0,0386)		0,0001*** (4,32E-05)		0,9932*** (0,0514)	1,025491	8,0384	1,0729	326,4199***	0,5046
L'oréal			0,4711* (0,2660)		0,0002*** (0,0001)		0,6614*** (0,0407)	1,883101	12,438**	2,1092	60,3657***	0,4141
LVMH	-0,0007*** (0,0002)		0,4437*** (0,1005)	0,0001* (6,11E-05)	0,0002*** (4,59E-05)		1,0049*** (0,0325)	3,103606	7,6921	3,1669	42,1161***	0,6241
Michelin	-0,0033*** (0,0012)			0,0007** (0,0003)	0,0007*** (0,0001)		1,1554*** (0,0515)	10,63297	15,822**	10,961*	96,0143***	0,4797
Pernod Ricard		0,1046*** (0,0277)	0,8018*** (0,0493)			0,0023* (0,0012)	0,6510*** (0,0408)	9,313102	6,4231	8,2174	84,7974***	0,4047
Peugeot			0,9621*** (0,0159)		0,0001** (3,38E-05)	-0,0026** (0,0015)	1,2224*** (0,0622)	5,769627	8,7527	4,9286	4,1718***	0,5049
PPR		0,1595*** (0,0466)	0,7004*** (0,0980)		0,0002** (7,30E-05)		0,9059*** (0,0524)	1,273321	4,5408	1,3632	18,3853***	0,4914
Renault		0,0580*** (0,0221)	0,8740*** (0,0413)				1,4587*** (0,0609)	4,504048	3,6629	4,7116	14,7316***	0,6455
Saint Gobain	-0,0004*** (1,76E-05)	0,0676*** (0,0224)	0,8453*** (0,0348)	5,99E-05*** (2,12E-06)	0,0001*** (1,73E-05)		1,2965*** (0,0374)	1,743099	4,1046	1,6835	30,6541***	0,7086
Sanofi		0,0678*** (0,0166)	0,8975*** (0,0185)				0,6558*** (0,0371)	2,569288	3,0004	2,3343	133,9879***	0,4105
Schneider			0,9082*** (0,0722)				1,1821*** (0,0485)	2,540438	16,402***	2,6625	5,4083*	0,6649
Société Générale		0,1039*** (0,0238)	0,8321*** (0,0299)		0,0001*** (2,95E-05)		1,5202*** (0,0587)	4,413363	13,287**	4,3422	54,4514***	0,6115
STMicroelectronics	-0,0005* (0,0002)		0,5046* (0,3016)		0,0005** (0,0002)	-0,0050*** (0,0017)	1,1044*** (0,0543)	1,094751	6,6197	1,0922	6,8837**	0,4101
Total		0,0800*** (0,0282)	0,8501*** (0,0562)				0,8763*** (0,0323)	15,61069**	6,7270	14,241**	27,9319***	0,6631
Vinci		0,0298*** (0,0113)	0,9575*** (0,0143)	1,72E-05* (1,01E-05)			1,0871*** (0,0341)	8,171485	7,3192	9,1411	90,8086***	0,6466
Vivendi	-0,0008*** (0,0003)	0,1463** (0,0657)		0,0002*** (8,43E-05)	0,0003*** (5,11E-05)		0,8295*** (0,0367)	2,432822	1,8229	2,4099	241,3342***	0,5250

*, **, *** denote significance at the 10%, 5% and 1% level, respectively.

Specifically, for all the stocks in our sample, the GARCH models were able to neutralize the effect of the conditional variance. The LM test (to control for conditional heteroskedasticity) did not reject the null hypothesis of absence of heteroskedasticity of the residuals and the Ljung-Box test (Q test) reports there is no autocorrelation of the standardized residuals as well as the squared residuals.

However, the GARCH models are still unable to correct the excess kurtosis of the distributions, despite the huge reduction of values of the J-B test relative to the preliminary analysis of the return series. According to the J-B test for normality of the standardized residuals, the null hypothesis of normality of the residuals is rejected, keeping the leptokurtic distribution feature of the residuals.

The estimates of the ARCH and GARCH parameters are positive and their sum is less than 1, suggesting stationarity of the covariance. Most of the stocks have low ARCH effects (below 0.2) and high GARCH effects (greater than 0.6). Thus, in our setting, the conditional volatility does not vary suddenly, but rather tends to persist for long periods of time.

Lastly, the coefficient of determination of the regression (Adj.R^2) ranges between 14, 36 % and 72, 83% suggesting good fit of the models.

As expected from correlation analysis presented in Table 5, the GARCH estimation results confirm that investor following has a significant effect on the volatility for stocks listed in the CAC 40. Intuitively, if investor online search result in retail trading, this would incorporate noise on stock prices which may in turn result in variations in the volatility of stock returns.

As can be seen in Table 6, we find that in most cases either firm-specific or market-related online information search is significant at the 95% significance level. Firm's investor following is a significant regressor in 13 cases, whereas market's investor following is significant for 19 out of the 30 stocks in our sample. The magnitude of estimated coefficients suggests that the effect of the two variables is comparable. Whereas, while all coefficients related to market's investor following are positive, the signs of firm's investor following remain mixed.

Taken together, our results suggest that investor following of market-related information has a significant positive association with conditional volatility. While, investor following of firm-specific information is also significant, but still has a lesser effect. Accordingly, the stock conditional volatility is more sensitive to investor following of market-related information. This confirms that investors are more likely to process more market news than firm-specific news [Peng and Xiong(2006)].

As a primary inference, we attribute these findings to a higher market-wide uncertainty leading to excessive transactions. Further, the online search effect on the stock volatility can partially be explained by shifts in investor overconfidence [(Kita et Wang (2012))].

In financial markets, searching activity (information-based trading) is a two edged sword in the sense that more search equals better information and closer matches between firm's information supply and investor interest on the one hand, while increasing investor confusion on the other hand. Thus, we cannot identify clearly even searching activity for firm-specific information is actually resolving information asymmetry or increasing uncertainty; which may partially explain our mixed results.

3.3 Robustness Check

In Table 5 and Table 6, we find strong evidence that investor following, proxied by online search behavior, is linked to the stock conditional volatility. In this section, we turn our attention from conditional to unconditional volatility and make use of the standard deviations of returns as an alternative measure of the stock volatility. More precisely, we regress, for each stock in our sample, the standard deviations of returns by online search variables, as

previously defined, while controlling for other known determinants of volatility³ (trading volume and stock return). Robustness check results are provided upon request from authors.

In sum, our findings confirm our central hypothesis that investor following is a priced source of volatility in most cases. Accordingly, our results do not depend on the way we measure volatility.

4. CONCLUSION

In this paper, we investigate whether changes in firm's investor following can influence volatility in the French stock market. By defining a novel proxy of investor following, we contribute to the emerging literature of the impact of information technology on financial markets.

Theoretically, we draw on both the extensive literature on volatility and the more recent literature on Google search volume to examine another channel through which investors affect stock volatility. Empirically, results reveal that investor following, proxied by online search traffic, seems to co-move with the conditional volatility as estimated from GARCH (1,1). Building on this evidence, we argue that this effect is consistent with the fact that some retail investors behave as noise traders in securities markets. In support of this claim, we further control for the investor following's effect on volatility by using the standard deviations of returns as an alternative measure of volatility and find the same results.

Natural extensions of this paper include testing for the predictive power of Google search volume data over other settings in the French stock market. While our results would not necessarily generalize to other stock markets, which generally do not face the same interactions, they do suggest that when trying to understand the stock market dynamics (especially in crises times); it is worth to identify less conventional determinants of the stock market activity.

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³Details of the model specifications are not reported here to save space but available upon request.

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APPENDIX A. LIST OF STOCKS IN THE SAMPLE AND GOOGLE SEARCH QUERIES

Stock	Google searchquery
Accor	"accor"
Air Liquide	"air Liquide"
Axa	"axa"
Arcelor Mittal	"arcelormittal"
Bnp Paribas	"bnpparibas"
Bouygues	"bouygues"
Cap Gemini	"cap Gemini"
Carrefour	"carrefour"
Crédit Agricole	"credit Agricole"
Danone	"danone"
Dexia	"dexia"
EADS	"eads"
France Télécom	"france télécom"
Lafarge	"lafarge"
Lagardère	"lagardère"
L'oréal	"l'oréal"
LVMH	"lvmh"
Michelin	"michelin"
Pernod Ricard	"pernod ricard"
Peugeot	"peugeot"
PPR	"ppr"
Renault	"renault"
Saint Gobain	"saint gobain"
Sanofi	"sanofi "
Schneider	"schneider"
Société Générale	"société générale"
STMicroelectronics	"stmicroelectronics"
Total	"total"
Vinci	"vinci"
Vivendi	"vivendi"
CAC 40	"cac 40"

NOTES