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Persistence of announcement effects on the intraday volatility of stock returns: evidence from individual data

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Résumé. Nous proposons une analyse économétrique des effets d'annonce sur la volatilité intra-journalière de quatre actions du CAC40 : Alcatel, Axa, Renault et Société Générale. Les séries horodatées des cours boursiers et les données qualitatives d'événements sont respectivement extraites de SBF-Euronext et de Bloomberg. La composante journalière de la volatilité est estimée par un modèle FIGARCH tandis que la saisonnalité intra-journalière par la Forme Flexible de Fourier. Il ressort que les volatilités individuelles sont affectées par un effet de marché systématique, des effets-jours et des annonces concernant la conjoncture macroéconomique, les opérations financières et stratégiques et les résultats d'exercice, ces deux dernières événements relevant de la firme en question ou de ses concurrents. Les volatilités décrivent des réponses retardées et progressives avec des horizons de persistance allant de une à trois heures, suggérant que les agents n'accèdent que graduellement à l'information complète.

Abstract. We analyze the empirical relationship between announcement effects and return volatilities of four CAC40 companies using intraday financial and event data from SBF-Euronext and Bloomberg, respectively. We estimate the daily component of the intraday volatility using a FIGARCH model and the intraday seasonality by the Fourier Flexible Form. We find that individual return volatilities are affected by a systematic market effect, day effects and announcements related to macroeconomic environment, strategic and financial dealings and commercial outcome, the two latter events being specific to the firm or to its competitors. The volatility responses have delayed and progressive patterns with persistence horizons ranging from one to three hours, suggesting that agents access to complete information gradually.

Mots-clés : volatilité intra-journalière, mémoire longue, persistance des effets d'annonces.

Keywords: Intraday volatility, long memory, persistence of announcement effects.

Classification JEL : G14, C22, C58.

1. Introduction

The expected future volatility of financial market returns is the main element in assessing asset or portfolio risk and plays a key role in derivatives pricing models and portfolio allocation problems. As such, accurate measures and good forecasts of volatility are necessary for the implementation and evaluation of asset and derivative pricing theories as well as trading and hedging strategies. Thus, not surprisingly, much effort has been devoted to modeling return volatility dynamics. The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) has been developed to account for empirical features in the volatility of financial returns. Since the work pioneered by Engle, volatility modeling has been the subject of a voluminous literature and the ARCH model and its extensions (GARCH, EGARCH, etc.) are among the most popular models for forecasting market returns and volatility[1]. A criticism addressed to these models is that they do not allow for a specific source of randomness in the conditional volatility. By introducing a specific error in the volatility dynamics and hence estimating latent variables instead of conditional moments, stochastic volatility models aimed at better describing actual volatility despite increased estimation difficulties. Yet, standard volatility models have not proved to provide good forecasting performance at daily frequencies. However, Andersen and Bollerslev (1998b) have established the ability of these models to provide more accurate volatility forecasts when high frequency (intraday) data are used. This result was an encouraging progress at the dawn of 1990's, where major technological innovations in financial centers, such as continuous listings and electronic transmission of stock market orders, have resulted in the construction of high frequency databases relative to market prices, volumes exchanged, number of transactions, etc. (Admati and Pfleiderer, 1988; Goodhart and O'Hara, 1997).

Modeling high frequency financial data requires considering specific properties. The first specificity, common to all financial assets, is the fact that yields are heteroskedastic[2]. It is also accepted that the series are leptokurtic. This phenomenon is accentuated by the fact that the frequency of data is important (Gouriéroux *et al.*, 1997). Beyond the traditional ARCH effects, studies using intraday data have highlighted two important factors that contribute to explain asset return volatility: intraday factors and announcement effects. Intraday factors comprise intraday activity patterns, which are consistent with the implications of microstructure models (Goodhart and O'Hara, 1997; Andersen and Bollerslev, 1997). Intraday activity involves periodic patterns, such as market openings and closings or other significant phases within a day, which Andersen et *al.* (2000) have shown that they are adequately approximated by a Fourier flexible form (Gallant, 1981). Intraday factors also include all other effects that may impact volatility at the intradaily frequency, such as the usual calendar effects or the market effect when individual asset return volatilities are modeled. As for the announcement effects, they can be responsible of erratic jumps or irregular patterns inherent to asset return volatility. These

[1] For an overview on these models see Bollerslev *et al.* (1992), Degiannakis and Xekalaki (2004) or Engle, Focardi and Fabozzi (2008).
[2] The variance of the errors (innovations) of the process is not stable. Clusters of volatility are observable, that is to say, periods of high volatility followed by periods of low volatility.

announcement effects represent investors' surprise to event shocks which they were not able to predict on the basis of their available information. Such a prediction failure can be attributed to the fact that the cost of information was higher than information yield in terms of a reduction in the forecast error, leading the operator to ignore a subset of (useful) information. An announcement effect is therefore significant when the announced event was too costly to forecast. Symmetrically, an insignificant announcement effect implies that the yield/cost ratio of information was high enough to lead agents to include this information in their forecast. This interpretation is consistent with the *economically rational expectations* theory introduced by Feige and Pearce (1976), where the optimal information collected by the forecaster results from a cost-and-advantage analysis of information.

Andersen and Bollerslev (1998a) provide a robust econometric methodology for capturing the distinct volatility components and isolating macroeconomic announcement effects. They distinguished three components of volatility: calendar effects that represent the intraday and intra-month structure of volatility, the ARCH effect that reflects the inter-day volatility, and the announcement effect that reflects the effect of public information on volatility. The authors analyze the spot German Mark-Dollar exchange rate volatility using intraday data from 1992 to 1993. They show that the calendar effect dominates while the announcement effect is strong but short in duration. Andersen et *al*. (2000) study the Nikkei index intraday return volatility over the 1994 to 1997 period. They also observe a long-memory phenomenon of shocks on volatility. The effects of macroeconomic announcements play a relatively small role in explaining volatility. Moreover, Bollerslev et *al*. (2000) focus on the volatility of futures returns on U.S. Treasury bonds in intraday data frequency from 1994 to 1997. They also highlight a long memory effect of shocks on volatility. However, they show that the announcement effects are an important factor in the intra-day volatility.

Our work retains the methodology developed by Andersen and Bollerslev (1998a), but it also differs on three directions. First, while these studies are mainly carried out on the American and Asian financial centers, we analyze the specific case of the stock market in France[3], which is a first in terms of the issues addressed. Secondly, we have not chosen to study event shocks on global market data (namely, market indices) as in the literature, but on individual data. Given the large quantity of data to be processed, we selected four companies among the CAC40 companies: Axa, Alcatel, Renault and Société Générale. Our individual data framework leads us to consider announcements that are specific to the different companies included, in addition to macroeconomic announcements, and examine which of them have a common effect on all return volatilities and which produce firm-specific impacts. An essential common factor that must be taken into account when individual returns are modeled is the market effect, in the same vein as the Capital Asset Pricing Model (CAPM) approach. We introduce this effect through the volatility of the CAC40 index. We also observe, at the individual level, a long memory effect on each return volatility that we account for using a fractional integrated generalized

[3] For studies concerning the Parisian stock market, see Gouriéroux *et al*. (1998), Szpiro (1998) and Teiletche (1998). Regarding the bond market, a study on the volatility dynamics of the long-run euro rate was conducted by Lespagnol and Teiletche (2005).

autoregressive conditional heteroskedasticity (FIGARCH) model proposed by Baillie *et al.* (1996). Thirdly, our objective is to identify the types of announcements that affect individual return volatilities but also, and more particularly, to analyze the persistence of announcement effects on returns. On this issue, an interesting approach proposed by Andersen and Bollerslev (1998a) is to model the actual and lagged effects of each announcement using an *n*-order polynomial lag structure subject to a predetermined persistence horizon. We apply a more flexible variant of this method and estimate the horizon for each return using a grid search. Thus, an innovative aspect of our approach to the literature is that we endogenize both the form and the horizon of persistence of each announcement effect. We interpret the components of different orders of the polynomial lag structure as different types of reactions of the traders to the announcement released. For each return, all the significant components, simple or mixed according to the event shocks, suggest that reactions increase gradually until they die out at the estimated horizon, ranging between one and three hours. This result can be explained as the gradual availability of the full information after the announcement is released (Ederington and Lee, 1993), or as the time required by mimetic traders to learn the market opinion through the response of the stock price.

From a theoretical point of view, our study is linked to the semi-strong efficiency hypothesis, developed by Fama (1970). According to Fama, the semi-strong informational efficiency on financial markets states that available information on a financial asset is completely integrated in its price immediately as this information becomes public. Accordingly, stock prices adjust immediately to any new information. This imminent adjustment notion implies that investors instantaneously intervene as they access information in real time. Under hypotheses of rational investors, rapid circulation and costless information, no transaction costs, investor atomicity and market liquidity[4], agents cannot benefit from new information and thus perform arbitrage operations. As like the empirical literature, our results invalidate this hypothesis since we show that announcements affect volatilities with persistent horizons.

The article is organized as follows. In the second section, we explain the construction of the quantitative and qualitative database and we outline the statistical properties of the stock returns for the selected four companies. The third section presents the modeling of intraday volatility for our individual returns and discusses the results obtained. The last section concludes.

2. Data and stylized facts

In this section, we describe the data used originating from two types of information: quantitative information on the stock prices of the selected firms and qualitative information about events that have

[4] These are necessary but not sufficient conditions, Fama (1970).

affected these firms. Then, we present the statistical properties of the series of stock returns and the associated U-shaped curves.

2.1 The data

The *quantitative data* used in this work is extracted from the SBF-Euronext intraday financial database, which contains high frequency data concerning a large number of stock markets, such as prices (and indices), volumes (transactions, market orders, the number of stocks registered) or dividends for 700 to 800 firms listed on the first, second and new markets[5] depending on the days. These are intra-daily data, in the sense that each observation corresponds to an irregular information recorded at a given day, hour and minute. We selected four companies in the CAC40 index representing different sectors of the French economy, namely Alcatel[6] (electricity, electronics, telecommunications), Axa (insurance), Renault (automotive, OEM[7]) and Société Générale (banking). The dataset covers the period from January 3, 1995 to December 24, 1999[8], which corresponds to 1246 days of quotation and to 2 653 667 transactions for Alcatel, 1 787 262 for Axa, 1 388 771 for Renault and 1 458 325 for Société Générale (note that we also have 1 094 572 observations for the CAC40) [9].

Transaction data arrive in irregular time intervals, so it is necessary to regularize the data. For each of these companies, we adjusted the frequency of the stock price series by calculating the mean of the stock price over each 5-minute interval of a trading day. The choice of the frequency is a compromise between excessively high frequencies, for which a large number of intervals could be characterized by the lack of transactions, and too low frequencies which would prompt a loss of information due to excessive aggregation of stock prices. The Paris stock exchange was open from 10:00 a.m. to 5:00 p.m. until September 17th 1999; then the opening of the session changed to 9:00 a.m. starting from September 20th 1999. The number of 5-minute intervals per trading day is therefore 84 in the first sub-period and 96 in the second sub-period, which, however, must be adjusted. Indeed, given the information released during the night, significant reallocations and high volumes of transactions occur at the opening. Similar increased trading activity operates also before the closing, when traders pass pending orders. Therefore, in order not to bias our results, we chose to remove the data corresponding to the first five and last five minutes of each day. Lastly, in the absence of transaction in one or several consecutive 5-minute intervals, we performed a linear interpolation using the last and the following observed values. In addition, Let $P_{t,n}$ represent the stock price defined in this way, where t and n stand for the day and the 5-minute interval of transaction, respectively. We then define the returns as

[5] Now referred to as the single market.

[6] Alcatel-Alsthon until 1986; Alcatel from 1986 to 2006 and from 2006 on Alcatel-Lucent.

[7] Original Equipment Manufacturer.

[8] The collection and processing of the database have been very time consuming. Moreover, the choice of the time period allows for avoiding the market financial turmoil related to the changeover to the Euro and the NICT stock market crash of 2000. Note, however, that the aim of the paper being to analyze the relation between returns and announcement effects, the oldness of the data does not harm to the generality of our conclusions given the wide spectrum of microeconomic and macroeconomic announcements considered.

[9] Due to the large number of data to be processed, the data handling was carried out with the ACCESS database management system.

logarithmic changes in $P_{t,n}$ between two 5 minute intervals. Indeed, the annual dividends reported at this frequency are negligible. The return can thus be written as:

$$R_{t,n} = 100 \log \frac{P_{t,n}}{P_{t,n-1}} \qquad (1)$$

where t = 1, ..., 1246 and n = 1, ..., N with N = 82 for the 01/03/95 to 09/17/99 period (or 1177 days of market opening at 10:00 a.m.) and N = 94 for the 09/20/99 to 12/24/99 period (or 69 days of market opening at 9:00 a.m.). The sample is composed of 103 000 observations at a 5 minute frequency. Figure 1 presents the log-values of the four individual stock prices and of the CAC40 index at the 5-minute interval frequency. Besides noteworthy specific patterns, each equity exhibits significant co-movement with the CAC40 index. Table 1 confirms these characteristics on the basis of the correlation matrix of returns. We will come back to these own and common components when modeling return volatilities.

< Insert Figure 1 >

< Insert Table 1 >

In Table 2 are reported the descriptive statistics of the returns of the four company stocks and of the CAC40 index. The average returns of Axa and Renault are positive while those of Alcatel and Société Générale are negative, indicating a capital gain for the two former companies and a capital loss for the two latter ones over the whole sample. For the five series, we find that the moment of order 3 is different from zero, indicating an asymmetric distribution due in general to the presence of outliers in the data. For Alcatel, Axa and Société Générale stocks, an asymmetry towards the left (negative asymmetry) is evidenced, which means that volatility is higher after a negative shock than after a positive shock. By contrast, CAC40 and Renault returns are assigned a positive asymmetry. Moreover, we find that the series are highly leptokurtic, the kurtosis exceeding 11 for the five series. There are hence many observations in the distribution tails and around the mean. These characteristics call into question the normality of the distributions of returns. This non-normality is statistically confirmed by the Jarque-Bera test.

< Insert Table 2 >

A *qualitative dataset* completes the quantitative series described above. In a first step, we constructed an intra-daily event dataset for each of our four companies using Bloomberg data sources[10]. This dataset comprises event information broadcasted in real time on operators' screens by Bloomberg and available in archived form. It concerns announcements and rumors related to the selected firms but also those relating to their competitors. Given the sheer amount of information, it was necessary to conduct searches by keywords. Examples of keywords we used are outcomes, mergers and acquisitions,

[10] We would especially like to thank P. Laurent, economist at the Caisse des Dépôts et Consignations, who enabled us to access these qualitative data on Bloomberg.

competitors' performance, cooperation ... We then manually identified the date and time of reception of each event over the considered time period. The large mass of qualitative raw information collected initially were, in a second step, classified according to different categories of events: outcome announcements specific to the company, outcome announcements specific to the industry, macroeconomic announcements, statements relating to mergers and acquisitions, implementation of business strategies. These categories are themselves often broken down into sub-categories when accurate information is available about events (see Appendices A to D).[11] Classification of the information collected raised various difficulties, such as (i) how to classify events that are apparently compatible with several categories, (ii) how to ensure the generality of the categories in the presence of rare but deemed influential events, (iii) how to distinguish between scheduled but undated events and unpredictable events. These difficulties led us to seek, in the history of the concerned company, more information about the events in question in order to avoid arbitrary classification. Note also that many of the announcements are issued outside of the trading periods of Paris stock exchange. We chose to consider only information occurring during the opening period. This information has a very high frequency and arrives with irregular intervals, which must be corrected in order to conform to the quantitative data. This yields to the last step, the one of the codification: once the qualitative information was dated and classified, we transformed the different lists of homogenous events observed at irregular points in time in binary variables with regular intervals, each variable taking the value one when the corresponding event occurs and zero otherwise. Repeating this 3-step procedure for all of our companies, we obtained the individual sets of announcement variables that are our main variables of interest.

In addition to these event dummies representing economic factors, we also constructed dummy variables for the days of the week to study periodic effects on the endogenous variable. For instance, a Monday dummy takes the value one at each 5-minute interval of a Monday and zero elsewhere.

2.2 Stylized facts

For each of the four companies, the volatility of the return, calculated as the average for each 5-minutes interval of the absolute values of stock prices over the whole 5-years sample, exhibit a U-shape (Figure 2). For comparison, we also present the volatility of the CAC40 index. The graphs suggest that the stock price volatility is higher at the beginning and at the end of the day, while it decreases at midday. We also find, more or less clearly depending on the companies, a surge of volatility around 2:30 p.m. that dissipates quickly. In general, these results confirm at the microeconomic level the form obtained on the

[11] Another sub-classification would consist in distinguishing events that should theoretically produce a positive effect on equity prices and those that should affect the latter negatively. These two sub-categories may indeed produce different impacts on return volatilities. We did not, however, use such a partition of the events for two reasons: (i) for many event shocks, the existence of different propagation channels with effects of different signs on equity prices can make the sign of the overall effect inconclusive, and thus the sub-classification of the events according to the sign of their effects questionable; (ii) our sub-classification achieved by breaking down the events is useful for estimation purposes; the sub-classification according to the signs of the event effects, possibly combined with ours, would yield to an increased number of (refined) announcement variables but the very reduced number of occurrences in each event variable would not allow for general conclusions about its effect.

CAC40 by Teiletche (1998) who interprets the 2:30 p.m. pike as the influence of information from U.S. markets. Indeed, this moment corresponds to the announcement of major U.S. macroeconomic statistics. Although this phenomenon is visible for the four titles studied, it is particularly noticeable for the CAC40 index.

< Insert Figure 2 >

Many authors refer to a U or W shaped structure of volatility, when the market closes for lunch. This structure is associated with the opening and closing hours of the stock market. For example, Foster and Viswanathan (1990) and Bollerslev *et al.* (2000) evidence a U-shape for the U.S. market; Andersen *et al.* (2000) a W-shape for the Japanese market; and Teiletche (1998) a U-shape for the French market. This observation on the structure of volatilities is consistent with the literature on market microstructure and emphasizes the role of asymmetric and private information in the formation of financial asset prices. The information transmitted during the night play an important role in the "overactivity" at opening (Chan *et al.,* 2000). The first reason that can be advocated is that a number of public information is released overnight that the price cannot reflect during this period of non-trading. This information is then incorporated into the market opening price. In addition, the daily data model by Foster and Viswanathan (1990) can be adapted to intraday analysis. The authors consider an agent who has private information at the beginning of the week. As time passes, pieces of information are gradually released on the market. The informed agent knows that the value of his information decreases over time and prefers to react relatively quickly before losing his informational advantage. A similar logic applies to intraday frequency: an agent acquires private information during the closing time span; thinking that it will be unveiled during the next session, he reacts at the opening in order not to lose his informational advantage. The importance of the traded volumes at the end of the session is due to significant reallocation of portfolios before the market closes. Admati and Pfleiderer (1988) explain that traders time their trades between the opening and the end of the trading day so as to minimize the expected cost of their transactions. The concentration of volatility at these moments of the day is due to the impossibility to trade after and before and to settlement rules that prevail in many markets (trades are settled by the close several days later irrespective of the time of the day the transactions have occurred).

3. Modeling and estimation of market volatility

In this section, we model the volatility of the return of each stock: Alcatel, Axa, Renault and Société Générale. Figure 3 shows the correlograms of the absolute values of returns of the four companies and of CAC40[12] over 984 intervals, that is 12 days. It turns out that the autocorrelations exhibit dominant U

[12] The correlograms were calculated for the 01/03/95 to 09/17/99 period containing unchangingly 82 intervals of 5 minutes per day.

shapes every 82 observations, that is to say, for periods of one opening day exactly[13]. One can also observe that they fluctuate with an intra-daily frequency around this daily periodicity. These observations suggest that returns of stocks and of CAC40 are characterized by a daily volatility and an intraday volatility. Each of these volatility components will be analyzed below.

< Insert Figure 3 >

3.1 The model

Following Andersen and Bollerslev (1998a), we decompose the deviations from the mean of stock returns as follows:

$$R_{t,n} - E(R_{t,n}) = \sigma_{t,n}\, s_{t,n}\, Z_{t,n} \tag{2}$$

where $s_{t,n}$ represents the intraday volatility, $Z_{t,n}$ an *iid* innovation with mean zero and unit variance and $\sigma_{t,n}$ the daily volatility expressed at the 5-minutes frequency, namely:

$$\sigma_{t,n} = \sigma_t / \sqrt{N} \tag{3}$$

where σ_t is the daily volatility of returns. Figure 3 shows a slow (or hyperbolic) decrease of daily autocorrelations as delays increase, which characterizes the presence of long memory in the series of return. Baillie *et al.* (1996) showed that a Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) model is appropriate to account for such long memory phenomena, contrary to ARCH or GARCH models that are more suited for describing short memory series where the effect of a shock on the conditional volatility dissipates quickly, at an exponential rate. Hence, we describe the dynamics of σ_t as a FIGARCH-type representation and fit our five returns series of 1246 daily observations using the following MA(1)-FIGARCH (1, d, 1) model:

$$R_t = \mu_0 + \mu_1\varepsilon_{t-1} + \varepsilon_t \tag{4a}$$

$$\varepsilon_t = \sigma_t \xi_t \tag{4b}$$

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + [1 - \beta L - (1-\phi L)(1-L)^d]\varepsilon_t^2 \tag{4c}$$

where R_t represents the daily returns observed at the market closure and d the fractional integration parameter[14]. ξ_t has conditional expectation equal to zero and conditional variance equal to 1 with respect to information available at time *t-1*. To account for the widely established result that the standardized errors are non-normally distributed (leptokurtic) at high frequency data, we assume

[13] This daily regularity is also empirically evidenced by Bollerslev *et al.* (2000) on stock markets and Andersen and Bollerslev (1998) on foreign exchange markets.
[14] See Baillie *et al*. (1996) for the derivation of the conditional variance.

Student distribution for ξ_t[15]. The parameter μ_1 was found to be systematically insignificant. For each stock as for the index CAC40 the mean equation reduces then to a MA(0) with or without a constant term, while the conditional variance is given by a FIGARCH(1,d,1) for Alcatel, Axa and CAC40 and a FIGARCH(1,d,0)[16] for Renault and Société Générale. Table 2 presents the estimated parameters of the MA(0)-FIGARCH(1,d,q) models[17] :

< Insert Table 3 >

The findings reveal that all coefficients have the expected positive sign and are highly significant. The FIGARCH specification is supported by the data for the four equities and the market index, attesting the presence of a long memory in the volatility processes of the returns (see also Bollerslev and Mikkelsen, 1996). Indeed, the fractional integration coefficients $\hat{d}$ are between 0 and 1 and are significantly different from 0 and 1, leading to reject the GARCH and IGARCH specifications. The set of estimates allow for assessing the value of the daily conditional volatility. The difficulty lying in the treatment of the fractional difference operator $(1-L)^d$ can be overcome thanks to Baillie *et al.* (1996) who have shown that this operator can be written in the form of a hypergeometric function:

$$(1-L)^d = 1 - d\sum_{k=1}^{\infty}\Gamma(k-d)\Gamma(1-d)^{-1}\Gamma(k+1)^{-1}L^k$$

$$= 1 - dL - \frac{d(1-d)}{2!}L^2 - \frac{d(1-d)(2-d)}{3!}L^3 - \ldots \qquad (5)$$

where $\Gamma(.)$ represents the Gamma function[18]. In practice, we truncate the infinite sum to the size of the sample, i.e. 1246 daily observations.

From calculated $\hat{\sigma}_t^2$ values, we deduce $\hat{\sigma}_{t,n}^2 = \hat{\sigma}_t^2 / N$ following equation (3). Taking the logarithm of the square of the decomposition (2) and rearranging the equation, we obtain the following econometric model:

$$2\ln\frac{\left|R_{t,n} - \overline{R}\right|}{\hat{\sigma}_{t,n}} = c + 2\ln s_{t,n} + u_{t,n} \qquad (6)$$

with $c = E(\ln Z_{t,n}^2)$ and $u_{t,n} = \ln Z_{t,n}^2 - E(\ln Z_{t,n}^2)$, where $\overline{R}$ stands for the empirical mean of the return and $u_{t,n}$ is stationary. In a second step, we specify the intraday volatility $\ln s_{t,n}^2$ involved in the right-

[15] Empirical studies rely on the assumption of conditionally normal standardized innovations for large sample sizes (see, for example Bollerslev *et al.,* 2000, where 3002 daily returns are considered). Using our daily 1246 observations, we also tested our MA-FIGARCH model assuming normal distribution and found that the estimates are not significantly different from the ones obtained assuming Student distribution.

[16] The daily volatility is represented by a FIGARCH(1,d,0) if its dynamics can be written as $\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + [1-\beta L - (1-L)^d]\varepsilon_t^2$, that is by setting $\phi = 0$ in (4c) (see Baillie *et al.*, 2000).

[17] The computations were performed using the program G@RCH developed under OxMetrics by S. Laurent and J.P. Peters. For more information on this program, see Laurent and Peters (2006).

[18] One can also show that (5) is obtained by the Taylor series expansion of the function $f(z) = (1-z)^d$ around $z = 0$, z being a scalar.

hand side of equation (6). According to the literature, we consider that $\ln s_{t,n}^2$ comprises a seasonal component, event announcements and daily effects. Our model involving individual returns, we add to these terms a market component. We specify below each of these components.

Various methods have been proposed to account for the seasonal volatility. The simplest method is to build binary variables. Baillie and Bollerslev (1990) use a GARCH specification with seasonal dummy variables to model the conditional volatility of the exchange rate with an hourly frequency. Bollerslev and Ghysls (1996) suggested the Periodic GARCH (P-GARCH), which allows the coefficients of the equation for the conditional variance to change periodically. Other authors (Taylor and Xu, 1995; Chang and Taylor, 1998; Andersen and Bollerslev, 1998a) suggest filtering the returns series by normalizing it by the seasonal intraday component of the volatility. To estimate the latter, the procedure proposed by Taylor and Xu (1995) and Chang and Taylor (1998) consists in calculating seasonal multipliers while Andersen and Bollerslev (1997, 1998) suggest using the Flexible Fourier Form (FFF). This function proposed by Gallant (1981, 1982) is particularly suited to approximate the intraday periodicity, and this is why we use the FFF to account for the seasonal effects of our intra-day volatility $\ln s_{t,n}^2$. The FFF can be written in the following form:

$$f(t,n) = \delta_{0,1}\frac{n}{\kappa_1} + \delta_{0,2}\frac{n^2}{\kappa_2} + \sum_{p=1}^{P}\left[\delta_{C,p}.\cos\left(\frac{2\Pi pn}{N}\right) + \delta_{S,p}\sin\left(\frac{2\Pi pn}{N}\right)\right] \tag{7}$$

where $\delta_{0,1}$, $\delta_{0,2}$, $\delta_{C,p}$ and $\delta_{S,p}$ are coefficients to be estimated, $\kappa_1 = (N+1)/2$ and $\kappa_2 = (N+1)(N+2)/6$ are normalization constants of linear and quadratic functions and P determines the number of phases in the daily cycle. After some preliminary estimates, we selected a daily cycle consisting of four phases (P = 4).

Concerning the event shocks, they are represented in the form of multi-response dummy variables for each type of event; their construction is presented in the first section. These binary variables are listed in the appendix for each firm. To reflect both the persistence effects and/or the delayed influences of the announcements, lagged dummy variables are also included. If an event *k* affects the volatility with *h* five-minute lags, then all its lagged effects can be written as:

$$\sum_{i=0}^{h}\lambda_k(i)I_k(t,n-i) \tag{8}$$

where $I_k(t,n-i)$ represents the announcement effect lagged by *i* intervals, $\lambda_k(i)$ its coefficient and *h* the lag-length or persistence horizon of the event shock. However the introduction of a coefficient for each type of event and for each lag up to *h* would lead to increase the number of parameters to estimate by $k(h+1)$, and the model would then become considerably burdened. Rather than freely estimating the coefficients $\lambda_k(i)$, and following Andersen and Bollerslev (1998a), we assume that they follow an *m*-order polynomial lag structure:

$$\lambda_k(i) = \lambda_k \gamma(i) \tag{9a}$$

$$\gamma(i) = \sum_{j=0}^{m-1} \alpha_j \left[1 - \left(\frac{i}{h} \right)^{m-j} \right] i^j, \quad i = 0,1,..,h \tag{9b}$$

Thus, the effect $\lambda_k(i)$ of an announcement *k* evolves with *i* as a weighted sum of *m* structural dynamics before fading completely at the horizon *h* ($\lambda_k(h) = 0$):

- an instantaneous jump of $\lambda_k(0) = \lambda_k \gamma(0) = \lambda_k \alpha_0$ followed by a semi-parabolic decrease (when *j*=0): operators react instantly to the shock, the effect of which wears off gradually to vanish after *h* periods;

- a parabolic dynamics (where *j* = 1): agents react slowly to the announcement whose effect grows at a decreasing rate then decreases to die out after *h* periods;

- *m-2* "half bell - half parabola" shaped dynamics (when $2 \leq j \leq m-1$): operators gradually react to the announcement whose effect grows at an increasing followed by a decreasing rate. It then decreases at an increasing rate until it runs out after *h* periods.

Depending on the values of α_j, the market behavior can be represented by a dynamics composed of one of these simple dynamics or any mixture of them. An immediate response with decreasing lagged effects can be considered as being the most standard and intuitive reaction of agents to an unanticipated announcement (case *j*=0). However, progressive and delayed reactions (when *j*>0) may also be justified in different ways. Ederington and Lee (1993) explain the existence of delayed reaction by the fact that when the announcement is released complete information may not be available immediately. Complexity inherent to the information revealed can make that its implications are fully understood only after a certain time of analysis, or can justify the need for additional information. Fleming and Remolona (1999) go even further, by asserting that "the persistence [of volatility] reflects a residual disagreement among investors about what the new information means for prices". This idea of incomplete information can interestingly be linked to the findings of a recent literature that the mimetic behavior is a possible explanation of the excessive volatility in financial markets (Banerjee, 1993; Orléan, 1995). In this vein, following an announcement release, an investor can delay his(her) reaction until (s)he learns about the response of the stock price to the announcement. This information will provide to the investor the market opinion about the equity, which will guides his(her) decision. The evolution of the stock price is here the needed additional information leading to mimetic behavior.

In addition to these possible interpretations, delayed responses to announcements have interesting implications for strategic timing of trade. An investor who is concerned by a single equity and is aware of the existence of such delayed response patterns can take profitable positions in that market. Indeed, suppose that during the time span of h periods, which lasts from one to a few hours, an announcement of a given category is the only factor that affects the volatility of the equity. Since the standard stock valuation model implies a negative relation between price and volatility, the optimal trading strategy of the investor would consist in purchasing the equity when volatility reaches its maximum and selling it when it is zero. Such delayed responses can thus be viewed by the investor as useful indicators for optimally timing the trade orders.

We choose a polynomial of order m=3 to capture the three types of responses described above.

The polynomial (9b) can thus be simplified as:

$$\gamma(i) = \alpha_0 \left[1 - \left(\frac{i}{h}\right)^3\right] + \alpha_1 \left[1 - \left(\frac{i}{h}\right)^2\right] i + \alpha_2 \left[1 - \frac{i}{h}\right] i^2, \quad i = 0,1,..,h \tag{10}$$

and putting together (8), (9a) and (10) yields to the polynomial lag structure we consider. The three dynamic components of (10) are shown in Figure 4.

< Insert Figure 4 >

A choice on the persistence horizon h is also needed. Unlike the empirical literature using intraday data that generally fixes h to one or two hours depending on the announcement, we opted for a more flexible approach by estimating the persistence horizon of each announcement by a grid search. Our aim to test a variety of horizons is motivated by many authors' results that volatility may persist over long horizons. Patell and Wofson (1984) and Jennings and Starks (1985) find that even high volatility may persist for several hours if the transactions are still based on the initial information (see also Fleming and Remolona, 1999).Thus, estimating within the volatility model the polynomial lag structure along with a grid search over h allows us to endogenize both the form and the horizon of persistence of each announcement effect.

Finally, recall that the intra-day volatility $\ln s_{t,n}^2$ refers to an individual stock return; it is then possibly influenced by the "market" effect. To account for this market effect, we introduce into the equation of the intraday volatility of each stock the intraday volatility of CAC40 that we normalize, as before, by its daily volatility $\hat{\sigma}_{t,n}^M$. We calculate $\hat{\sigma}_{t,n}^M$ by solving for equations (3), (4c) and (5) and using estimates provided in Table 3, column 6. The volatility of the CAC40 return, filtered by the daily volatility, can be written as:

$$2\ln(\left|R_{t,n}^M - \overline{R}^M\right| / \hat{\sigma}_{t,n}^M), \tag{11}$$

where the index M refers to market.

By bringing together elements (7) to (11), equation (6) can be written as:

$$2\ln\frac{\left|R_{t,n} - \overline{R}\right|}{\hat{\sigma}_{t,n}} = c + b(2\ln\frac{\left|R_{t,n}^M - \overline{R}^M\right|}{\hat{\sigma}_{t,n}^M}) + f(t,n) + \sum_k \sum_{i=0}^{h} \lambda_k \gamma(i) I_k(t, n-i) + \sum_s \mu_s D_s + \varepsilon_t \tag{12}$$

where $f(t,n)$ is the FFF given by equation (7). The variables D_s represent dummy variables for each day of the week. Their role is to capture the « daily effects » by taking the value 1 at each 5-minute interval belonging to a business-day *s* of the week (*s*=Monday, Tuesday,…, Friday) and 0 otherwise[19]. Note that a consequence of the Capital Asset Pricing Model is that the variance of an individual return is proportional to the variance of the market return (common factor) plus the idiosyncratic variance (own factor). Interestingly, equation (12) accounts also for both of these factors, the market volatility representing the common factor and all other variables (seasonal volatility, announcement shocks and calendar effects) making the own factor. Thus, in line with portfolio choice models, equation (12) implies that there exists an undiversifiable risk and a gain in portfolio diversification.

The coefficients $\lambda_k \alpha_j \; (j = 0,1,2)$ that appear in the lag polynomial (9a)-(10) are estimated as composite coefficients[20]. To ensure their positivity (the initial effect of any announcement on volatility should be positive, whether it is immediate or gradual, because unexploited profit opportunities stimulate trade activity), these coefficients are written as the exponential of some auxiliary coefficients, denoted $(\lambda_k \alpha_j)'$, which are estimated freely. We applied the same constraint to the day-effects parameters μ_S.

3.2. Econometric results

The method of nonlinear least squares has thus been employed to estimate the model. Tables 4 to 7 provide the estimation results of equation (12) for the four companies. The explanatory power of the model proved satisfactory for all stocks except for Société Générale, a company for which the market effect is found to be lower and very few announcements appeared significant. The Durbin-Watson statistics indicate a slight autocorrelation but the model is estimated using heteroskedasticity and autocorrelation (HAC) consistent Non-Linear Least Squares method, so that the estimates are unbiased although possibly inefficient. However the t-statistics are sufficiently high to ascertain the significance of all coefficients at the 5% level, unless otherwise indicated. The term $\hat{u}_{t,n}$ (equation (6)) is stationary in each estimated equation.

< Insert Tables 4 to 7 >

[19] French and Roll (1986) explain that the volatility of returns is much higher in trading periods than in non-trading periods because (i) markets are likely to receive more public information when they are open; (ii) markets receive private information when informed agents trade; and (iii) trading implies some degree of pricing errors which are sources of volatility.

[20] Our approach differs from that of Andersen and Bollerslev (1998) in the sense that they estimated in a first stage the structural coefficients α_j without the parameters λ_k by merging all the events in the volatility model and re-estimating in a second stage the coefficient λ_k for each event *k* as an adjustment coefficient to the common lag structure. Rather, we favor estimating a lag polynomial for each event effect although we cannot identify the parameters λ_k and α_j (see also Boubel et *al.* 2001).

Market volatility has a moderate but highly significant influence on the volatility of all stocks: it is rather low for Société Générale ($\hat{b} = 0{,}11$), more consistent for Alcatel ($\hat{b} = 0{,}20$), while it has an influence in the order of 30% for Axa and Renault stocks.

Concerning announcement effects, several lessons derive from our results. The first relates to the nature of announcements affecting stocks. It appears that the announcements related to internal outcome results (IRR) and to the macroeconomic constraints (MCR) are those with the most universal impact on volatility as they are significant for all four stocks[21]. It seems intuitive that maximizing the own performance given the economic climate appears as a basic core as it reflects the essential barometer of stock volatility. In an environment characterized by the development of financial markets, this basic core extends to announcements on financial and strategic operations. These operations are either conducted intrinsically (ISOR) in the case of Alcatel[22], Axa and Renault, or by the competitors, as shown by the impacts of competitors' strategic operations (CSOR) on Alcatel stock and of competitors' mergers and acquisitions (CMAR) on Axa stock. Due to the growing competitiveness, it also includes releases on competitors' results (CRR), which only affect the volatility of the industrial sector stocks (i.e., Alcatel and Renault stocks): the intense competition prevailing in the automotive and telecommunications sectors and the involvement of these sectors in R&D programs explain the reactivity of financial operators to new information about the positions of Alcatel and Renault in their respective markets. In the analyzed period Alcatel has also experienced turmoil at the executive level and the related announcements, denominated internal problems releases (IPR), appear to be the ones which have the mostly affected the stock returns.

We tested the hypothesis that the effect of each announcement is represented by a flexible lag structure given by a weighted sum of the components of the lag polynomial (10). The estimation of this flexible lag structure allows calculating for each announcement effect a persistence pattern of a specific form. A major result that emerges from our estimates is that no announcement for any stock generates an immediate effect (insignificant $\widehat{\lambda_k \alpha_0}$ coefficients systematically). In contrast, we find that the responses to announcements emerge slowly and gradually (significant $\widehat{\lambda_k \alpha_1}$ or $\widehat{\lambda_k \alpha_2}$ coefficients[23]), reflecting a response time needed by traders when they deal with new information. This result is consistent with Ederington and Lee’s (1993) assumptions that the incompleteness of available information prompts the traders to seek further information and that traders need some time to analyze the implications of the new information (see above).

In addition to its form, the persistence of an announcement effect on volatility has a second specificity: its horizon. We considered three possible horizons, h = 13, h = 25 and h = 37: we thereby assume that

[21] In the case of Société Générale, a subset of the variable MCR, macroeconomic conditions affecting the customers (MCRC, see Appendix D), appeared to be significant.

[22] Note that in the case of Alcatel, the ISOR variable has been replaced by its two main components, IMAR and ICDR (see Appendix A), which were both found to be significant.

[23] Note that only one of these two coefficients is significant, precluding a mixture of the two gradual responses.

the effect of each announcement persist for one hour (12 intervals of 5 minutes), two hours (24 intervals of 5 minutes) or three hours (36 intervals of 5 minutes) before vanishing at interval *h*. These horizons seem reasonable to represent the effect duration of an announcement, since a longer duration would imply implausible long-lasting profit opportunities. We estimated equation (12) for each stock by combining in turn all possible horizons with each announcement variable, and chose the combination for which the AIC was minimal[24]. It appears that announcements related to internal outcomes (IRR) have the most lasting effects on absolute returns since their persistence length is 3 hours regardless of the stock in question. Within this response window, the absolute returns reach a peak of $100[\exp(\lambda_{IRR}\hat{\gamma}(i^*)/2)-1]$ = 14.2 percent, 50.6 percent, 73.8 percent and 9 percent[25] at the i^* = 26th, 22d, 26th and 26th 5-minutes interval in the case of Alcatel, Axa, Renault and Société Générale, respectively. Interestingly, traders learn about this news after its release and increase trade during unchangingly 130 minutes for all stocks, except Axa for which volatility increases during 110 minutes. The macroeconomic announcements (MCR) have a persistence length ranging from 1 to 3 hours depending on the stock. A persistence length of 2 to 3 hours (Alcatel, Axa and Renault) is recorded for strategic orientations releases (ISOR and CSOR), while announcements on competitors' results (CRR) have a 2 hours persistence (Alcatel and Renault). Finally, the response of Alcatel stock volatility to internal problems announcements (IPR) and the one of Axa stock volatility to competitors' mergers and acquisitions releases (CMAR) appear to be particularly short since they die off after an hour. Generally speaking, our findings on individual returns depart from the literature dealing with market indices in terms of shapes and horizons of persistence. Indeed, the related studies evidence in most cases instantaneous responses with one or two horizons of 1 to 2 hours that are in all cases previously fixed (Andersen and Bollerslev, 1998; Andersen *et al.*, 2000). In our framework with endogenous persistence horizons, it turns out that despite a variety of responses of the volatility to announcements some common features emerge: all responses occur gradually and cover mostly 2 or 3 hours horizons (Figure 5). These horizons seem to point to the complex nature of information to be processed by investors.

< Insert Figure 5 >

To assess the total effect of an event shock over its lifetime, we cumulated the responses of the absolute returns over the response horizon (Table 8). A salient feature is the high volatility of Renault's absolute

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[24] However these combinations were subjected to a natural constraint : for a given announcement, the three components of the lag polynomial (10) have the same horizon.

[25] Generally speaking, following an announcement *k* released at the interval n of day t, the absolute value of the filtered return increases at the *i*'th lag by the multiplicative factor $\exp(\lambda_k \gamma(i)/2)$ where *i* = 0,1, .., *h* ($\exp(\lambda_k \gamma(0)/2)$ measures thus the instantaneous jump). This volatility response may equivalently be expressed as $100[\exp(\lambda_k \gamma(i)/2)-1]$ percent while the cumulative response of the absolute return over the whole period of influence of the announcement is $100\sum_{i=0}^{h}\left[\exp(\lambda_k \gamma(i)/2)-1\right]$ percent.

returns in response to all news announcements, with long persistence horizons of 2 or 3 hours (see Table 6). This typically reflects active searching behavior after the initial information is perceived. In particular, a 3405.2 percent increase in volatility is reached 3 hours after a macroeconomic information (MCR) is recorded. Conversely, other stocks seem to be less sensitive to macroeconomic announcements, whether in volatility magnitude or in impact duration. Note, however, that they were able to impulse within one hour an increase in volatility of about 400 percent on Société Générale returns, while releases on commercial outcome (IRR) have relatively little but significant effect despite a period of influence of 3 hours.

< Insert Table 8 >

Last but not least, it can be seen from Tables 4 to 7 that volatility of each stock is also influenced by day effects, corresponding to Tuesday, Wednesday, Thursday and Friday in the cases of Alcatel, Axa and Renault and Monday, Thursday and Friday in the case of Société Générale. In all cases, these effects grow throughout the week, whether monotonically (Alcatel, Renault and Société Générale) or in tendency (Axa). In the case of Alcatel for example, the absolute returns increase by $100[\exp(\mu_S / 2) - 1] =$ 11.1 percent, 12.2 percent, 13.9 percent and 16.8 percent throughout the influent days, whereas Axa's volatility evolves as 12 percent, 10.5 percent, 22.1 percent and 17.9 percent. The increasing structure of day effects can be explained by announcement releases becoming more numerous throughout the week (Ederington and Lee, 1993) and by increasing trade as the non-trading weekend approaches.

4.Conclusion

The purpose of this article was to investigate the persistence of the effects of event shocks on the intraday volatility of returns of four CAC40 firms, namely Alcatel, Axa, Renault and Société Générale. With this aim, we extracted the individual series of stock prices from SBF-Euronext intraday financial database and developed a qualitative database on event information using Bloomberg archived data. We showed that intra-day average absolute returns exhibit, as expected, U-shape curves and we modeled the intraday return volatility of each stock. In the presence of long memory, we filtered the absolute return by its daily component that we estimated using a FIGARCH model. Intraday seasonality has been approximated by the Fourier Flexible Form and day effects by daily dummies. The market effect was represented by the filtered intraday volatility of the CAC40 index. Announcement effects were introduced using a polynomial lag structure reflecting different types of reactions of traders to the perceived information. An innovative aspect of our approach with respect to the literature is that we endogenized both the form and the horizon of persistence of each announcement effect.

Several lessons in terms of volatility response to announcements can be derived from our results. Regarding the nature of the announcements affecting the equities, two announcements were shown to produce universal effects on the four return volatilities: the internal commercial outcome releases and the macroeconomic announcements. Alcatel, Axa and Renault absolute returns also show a high sensitivity to announcements related to internal financial and strategic operations while Alcatel and Axa returns are also impacted by the financial and strategic operations announced by the competitors.

Another important result concerns the persistence forms and horizons of event shocks on volatility. For none of returns we found that an announcement has an immediate effect. Responses to announcements emerge slowly and gradually, suggesting that complete information is not available immediately and that some time is indeed to analyze the information or to learn the market opinion through the response of the stock price. Concerning the persistence horizons, they change between one and three hours depending on the announcements and the companies, corroborating the complex nature of information to be processed by investors. Under certain conditions, our results provide profitable purchasing and selling strategies for an investor in an equity market.

Our findings contradict the hypothesis of market efficiency, which fell into disgrace after the financial crisis; they indeed imply that prices do not immediately reflect all publicly available information at the time an announcement is released, since its effects on volatility are spread over time. Our findings can be extended in two directions. An immediate extension is to expand the sample to other CAC40 firms belonging to sectors considered in this work but also to other sectors (food, chemicals, energy ...). Another study would examine the effects of macroeconomic, financial and political announcements on national stock indices of the European Union and enable a comparison of the volatility responses of these various indices.

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Appendix

Appendix A: Announcement releases related to Alcatel stock

Announcements	Number of releases	Name of the binary variable
Macroeconomic Conditions	18	MCR
Internal Outcome	35	IRR
Competitors' Outcome	19	CRR
Internal Issues (Indictment of an Executive)	4	IPR
Strategy and Orientation of Alcatel	58	ISOR
- Internal Restructuring	6	
- Shareholding, Mergers and Acquisitions	31	IMAR
- Cooperation and Development	21	ICDR
Strategy et Orientation of Competitors	19	CSOR
- Mergers and Acquisitions	3	
- Trade Policy	3	
- Cooperation	7	
- Innovation	6	

153 releases listed with ISOR (6 binary variables) and 147 with IMAR and ICDR (7 binary variables).

Appendix B: Announcement releases related to Axa stock

Announcements	Number of releases	Name of the binary variable
Macroeconomic Conditions	12	MCR
Internal Outcome	55	IRR
Competitors' Outcome	22	CRR
Strategy and Orientation of AXA	49	ISOR
- Group Restructuring	3	
- Shareholding, Mergers and Acquisitions	37	IMAR
- Cooperation and Development	6	
- Strategy	3	
Competitors' Mergers and Acquisitions	20	CMAR

158 releases listed with ISOR (5 binary variables) and 146 with IMAR (5 binary variables).

Appendix C: Announcement releases related to Renault stock

Announcements	Number of releases	Name of the binary variable
Macroeconomic Conditions	5	MCR
Internal Outcome	24	IRR
Competitors’ Outcome	21	CRR
Strategy et Orientation of Renault	18	ISOR
- Executive Announcements	8	
- Shareholding, Mergers and Acquisitions	6	
- Cooperation and Development	4	
Branch Strategy and Orientation	5	BSOR

73 releases listed (5 binary variables).

Appendix D: Announcement releases related to Société Générale stock

Announcements	Number of releases	Name of the binary variable
Macroeconomic Conditions	16	MCR
- affecting Financial Markets	10	MCRM
- affecting the Customers	6	MCRC
Internal Outcome	21	IRR
Competitors' Outcome	10	CRR
Strategy and Orientation of Société Générale	44	ISOR
- Group Restructuring	2	
- Shareholding, Merger, Acquisition	38	IMAR
- Cooperation et Development	4	
Merger, Competitor Acquisition	26	CMAR

117 releases listed with MCR and ISOR (5 binary variables) or with MCRM, MCRC and ISOR (6 binary variables), 111 releases listed with MCR and IMAR (5 binary variables) or with MCRM, MCRC and IMAR (6 binary variables).

Figure 1: Log-values of the individual stock prices and of the CAC40 index

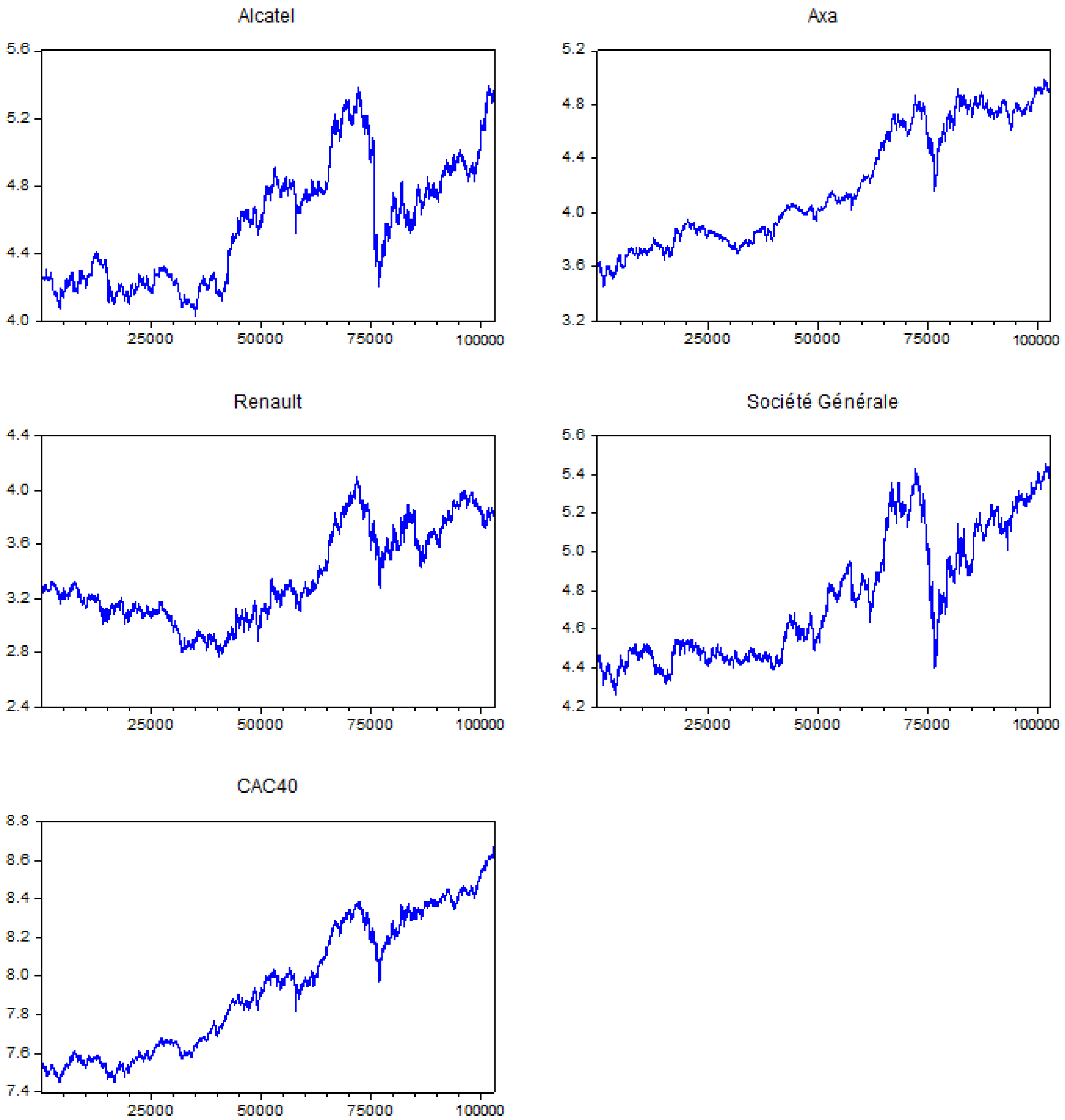
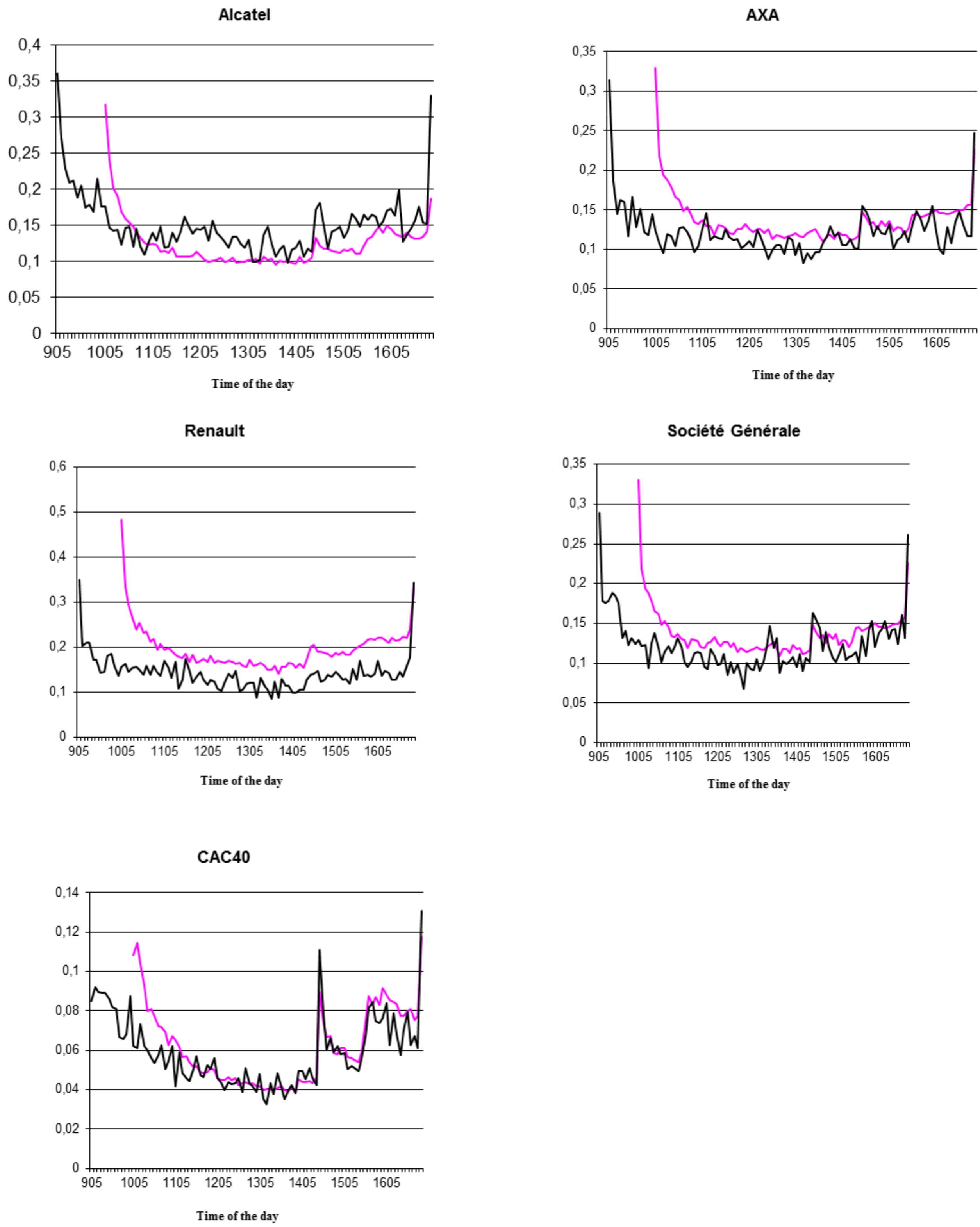


Figure 2: Sample-average volatility by 5 minute interval



Note. Black lines represent a market opening at 9:00 a.m. (01/03/95 to 09/17/99) and gray lines represent a market opening at 10:00 a.m. (20/09/99 to 12/24/99)

Figure 3: Absolute Value of Returns Correlograms

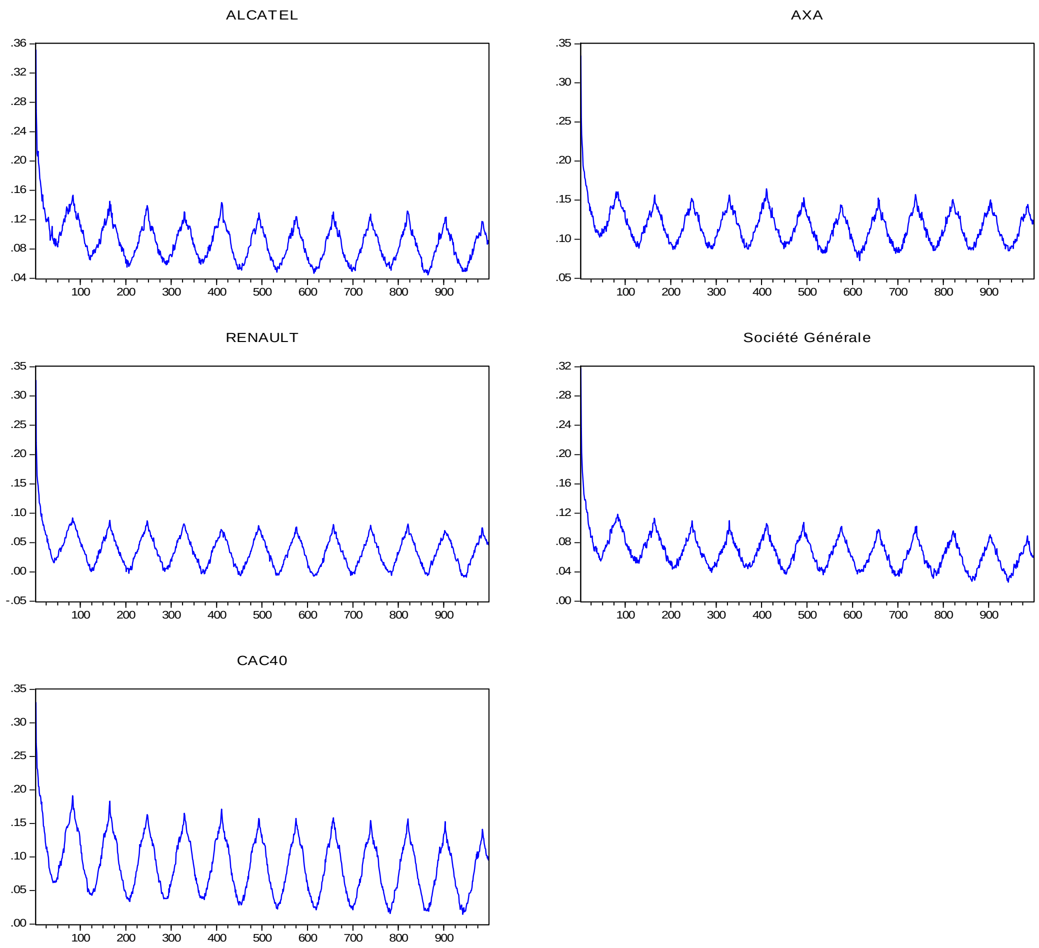


Figure 4: Dynamic components of persistence effects of event shocks using a polynomial lag structure of order 3 and lag-length h

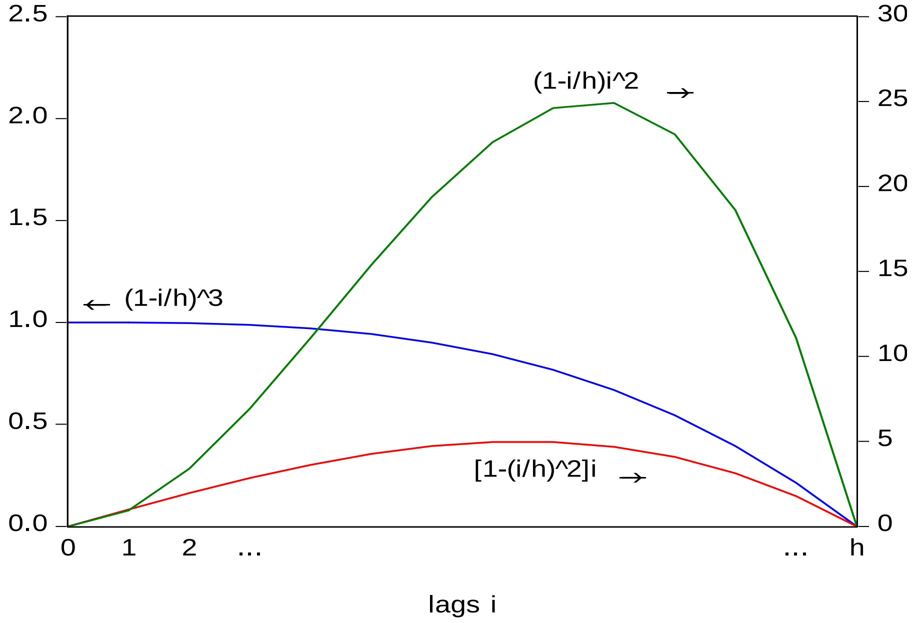


Figure 5: Persistence of the Effects of Event Shocks on Return Volatility

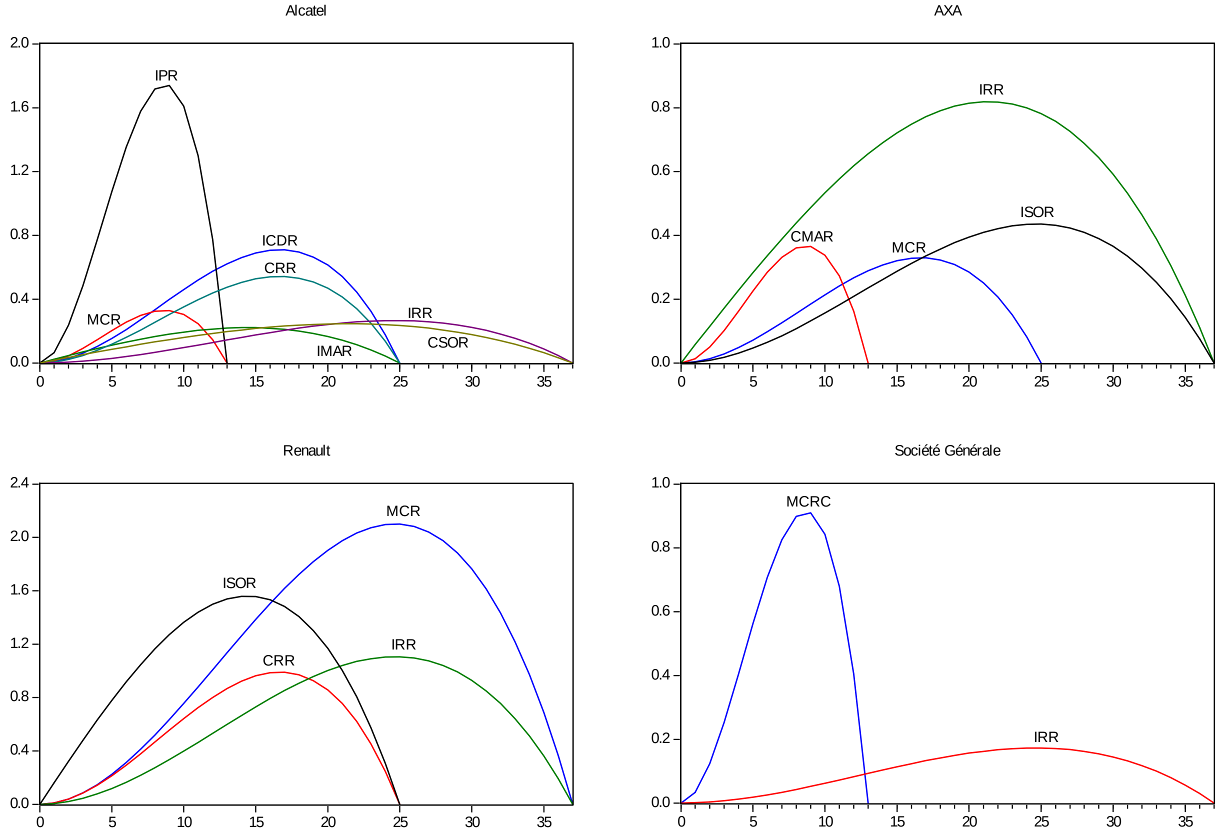


Table 1: Correlation matrix for stock returns

	Alcatel	Axa	Renault	Société Générale	CAC40
Alcatel	1.000000	0.353608	0.271537	0.339994	0.588826
Axa	0.353608	1.000000	0.285104	0.364780	0.597848
Renault	0.271537	0.285104	1.000000	0.289646	0.476973
Société Générale	0.339994	0.364780	0.289646	1.000000	0.553895
CAC40	0.588826	0.597848	0.476973	0.553895	1.000000

Table 2: Descriptive statistics of stock returns (in %)

	Alcatel	Axa	Renault	Société Générale	CAC40
Mean	-0.000549	0.000421	0.001325	-0.000506	0.000675
Median	0.000000	0.000000	0.000000	0.000000	0.00077
Maximum	4.872458	2.246203	4.441624	2.702216	1.74989
Minimum	-4.073110	-3.676272	-3.356935	-4.673213	-1.16252
Standard deviation	0.184308	0.159501	0.279936	0.190413	0.092901
Skewness	-0.030284	-0.092971	0.102094	-0.162296	0.111734
Kurtosis	24.87487	13.46094	11.1746	15.47007	14.12033
Jarque-Bera	2047280	462062	286263	664646	530929.2
JB probability	0.000000	0.000000	0.000000	0.000000	0.000000

Note. Descriptive statistics are calculated on the basis of 103 000 observations.

Table 3: Estimation Results of MA(0)-FIGARCH(1,d,q) models

	Alcatel	Axa	Renault	Société Générale	CAC40
Model	MA(0)-FIGARCH(1,d,1)	MA(0)-FIGARCH(1,d,1)	MA(0)-FIGARCH(1,d,0)	MA(0)-FIGARCH(1,d,0)	MA(0)-FIGARCH(1,d,1)
μ_0	NS	NS	0.042 (0.01) [0.00]	NS	0.029 (0.004) [0.00]
ω	0.046 (0.014) [0.001]	0.072 (0.037) [0.049]	0.194 (0.045) [0.00]	0.096 (0.02) [0.00]	0.026 (0.005) [0.00]
d	0.369 (0.069) [0.00]	0.595 (0.134) [0.00]	0.22 (0.05) [0.00]	0.244 (0.039) [0.00]	0.264 (0.07) [0.00]
ϕ	0.334 (0.131) [0.011]	0.15 (0.065) [0.021]	-	-	0.415 (0.115) [0.00]
β	0.617 (0.154) [0.00]	0.778 (0.079) [0.00]	0.162 (0.067) [0.016]	0.256 (0.04) [0.0]	0.613 (0.104) [0.00]
Log L	45.67	200.95	-649.85	-184.59	639.39

Notes. The values in parentheses (brackets) are the standard deviations of estimates (p-values). The mean equations $R_t = \mu_0 + \varepsilon_t$ and the conditional variances $\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + [1 - \beta L - (1-\phi L)(1-L)^d]\varepsilon_t^2$, with $\phi \geq 0$, are estimated using Chung's (1999) method on our 1246 daily observations. Student distribution is assumed for the standardized innovations ε_t / σ_t. The conditional volatility has been initialized to the empirical mean of the squared residuals or, in our case, to the squared returns. NS means that μ_0 was not significant. The other parameters being estimated without this intercept in the mean equation.

Table 4: Estimation of the Volatility of Alcatel Stock

Coefficient	**Variable**	**Persistence horizon**	**NLLS estimates (t-stats)**
c			-1.39 (-17.65)
$\delta_{0,1}$	FFF		2.37 10^{-5} (9.21)
$\delta_{0,2}$	FFF		-4.09 10^{-11} (-1.75)*
$\delta_{C,1}$	FFF		0.78 (28.82)
$\delta_{C,2}$	FFF		-0.21 (-10.61)
$\delta_{C,3}$	FFF		0.18 (10.34)
$\delta_{C,4}$	FFF		-0.04 (-2.30)
$\delta_{S,1}$	FFF		-0.10 (-4.84)
$\delta_{S,2}$	FFF		0.10 (4.98)
$\delta_{S,3}$	FFF		-0.03 (-1.66)*
$\delta_{S,4}$	FFF		0.08 (5.62)
b	Volatility of CAC40 return (market effect)		0.20 (24.72)
$(\lambda_{MCR}\,\alpha_2)'$	*Macroeconomic Conditions releases*	13	-4.33 (-4.05)
$(\lambda_{IRR}\,\alpha_2)'$	*Internal Outcomes releases*	37	-6.64 (-2.73)
$(\lambda_{IPR}\,\alpha_2)'$	*Internal Problems releases*	13	-2.66 (-12.89)
$(\lambda_{IMAR}\,\alpha_1)'$	*Internal Ownership, Merger & Acquisitions releases*	25	-3.77 (-3.08)
$(\lambda_{ICDR}\,\alpha_2)'$	*Internal Cooperation and Development releases*	25	-4.87(-11.68)
$(\lambda_{CRR}\,\alpha_2)'$	*Competitors' Outcome releases*	25	-5.14 (-6.53)
$(\lambda_{CSOR}\,\alpha_1)'$	*Competitors' Strategy and Orientation releases*	37	-4.06 (-4.87)
$\mu_{TUESDAY}'$	Tuesday effect		-1.55 (-5.65)
$\mu_{WEDNESDAY}'$	Wednesday effect		-1.46 (-5.60)
$\mu_{THURSDAY}'$	Thursday effect		-1.35 (-5.64)
μ_{FRIDAY}'	Friday effect		-1.17 (-6.19)
$\overline{R}^2$	0.11		
SE	3.09		
DW	1.47		
ADF	-61.01		

Notes. The numbers in parentheses are the Student t-statistics. Estimates with a * indicate 10% level of significance. 5 or 1% level otherwise. The estimated model is given by equation (12) and the estimation period runs from 01/03/95 to 12/24/99, with a total of 103 000 observations of 5 minute intervals. The persistence horizons of announcements and the number of daily cycles (p = 4) of the FFF are estimated by grid search. To ensure the positivity of the coefficients associated with the lag-polynomial and with the day effects. These coefficients were expressed as the exponentials of those marked with a prime which were estimated along with the other parameters using the heteroskedasticity and autocorrelation (HAC) consistent Non-Linear Least Squares (NLLS) method. The results presented are those obtained after elimination of insignificant variables and re-estimation.

Table 5: Estimation of the Volatility of Axa Stock

Coefficient	**Variable**	**Persistence horizon**	**NLLS Estimates (t-stats)**
c			-4.64 (-43.61)
$\delta_{0,1}$	FFF		$8.07\ 10^{-5}$ (23.04)
$\delta_{0,2}$	FFF		$-3.23\ 10^{-10}$ (-10.81)
$\delta_{C,1}$	FFF		0.99 (29.75)
$\delta_{C,2}$	FFF		-0.24 (-8.91)
$\delta_{C,3}$	FFF		0.19 (8.37)
$\delta_{S,1}$	FFF		-0.11 (-3.84)
$\delta_{S,2}$	FFF		0.09 (3.30)
$\delta_{S,3}$	FFF		-0.07 (-2.83)
b	Volatility of CAC40 return (market effect)		0.29 (34.32)
$(\lambda_{MCR}\,\alpha_2)'$	*Macroeconomic Conditions releases*	25	-5.64 (-5.03)
$(\lambda_{IRR}\,\alpha_1)'$	*Internal Outcomes releases*	37	-2.86 (-9.33)
$(\lambda_{ISOR}\,\alpha_2)'$	*Internal Strategy and Orientation releases*	37	-6.14 (-6.90)
$(\lambda_{CMAR}\,\alpha_2)'$	*Competitors' Ownership. Merger & Acquisitions releases*	13	-4.22 (-3.03)
$\mu_{TUESDAY}'$	Tuesday effect		-1.49(-4.68)
$\mu_{WEDNESDAY}'$	Wednesday effect		-1.62 (-4.31)
$\mu_{THURSDAY}'$	Thursday effect		-0.91 (-5.16)
μ_{FRIDAY}'	Friday effect		-1.10 (-5.08)
$\bar{R}^2$	0.194		
SE	3.86		
DW	1.29		
ADF	-50.80		

Note. See Table 4.

Table 6: Estimated of the Volatility of Renault Stock

Coefficient	**Variable**	**Persistance Horizon**	**NLLS Estimates (t-stats)**
c			-4.56 (-38.44)
$\delta_{0,1}$	FFF		$7.86\ 10^{-5}$ (18.93)
$\delta_{0,2}$	FFF		$-3.91\ 10^{-10}$ (-10.13)
$\delta_{C,1}$	FFF		1.59 (37.50)
$\delta_{C,2}$	FFF		-0.53 (-16.13)
$\delta_{C,3}$	FFF		0.32 (11.65)
$\delta_{S,1}$	FFF		-0.22 (-5.86)
$\delta_{S,2}$	FFF		0.38 (11.35)
$\delta_{S,3}$	FFF		-0.22 (-7.61)
$\delta_{S,4}$	FFF		0.10 (3.87)
b	Volatility of CAC40 Return (market effect)		0.30 (29.63)
$(\lambda_{MCR}\,\alpha_2)'$	*Macroeconomic Conditions releases*	37	-4.57 (-10.78)
$(\lambda_{IRR}\,\alpha_2)'$	*Internal Outcome releases*	37	-5.21 (-7.91)
$(\lambda_{ISOR}\,\alpha_1)'$	*Internal Strategy and Orientation releases*	25	-1.82 (-2.65)
$(\lambda_{CRR}\,\alpha_2)'$	*Competitors' Outcome releases*	25	-4.54 (-8.45)
$\mu_{TUESDAY}'$	Tuesday effects		-0.36 (-2.63)
$\mu_{WEDNESDAY}'$	Wednesday effects		-0.36 (-2.52)
$\mu_{THURSDAY}'$	Thursday effects		-0.27 (-2.11)
μ_{FRIDAY}'	Friday effects		-0.26 (-1.97)
$\overline{R}^2$	0.16		
SE	4.79		
DW	1.27		
ADF	-60.50		

Note. See Table 4.

Table 7: Estimation of the Volatility of Société Générale Stock

Coefficient	**Variable**	**Persistence Horizon**	**NLLS Estimates (t-stats)**
c			-1.89 (-18.60)
$\delta_{0,1}$	FFF		4.44 10^{-5} (11.51)
$\delta_{0,2}$	FFF		-2.38 10^{-10} (-6.82)
$\delta_{C,1}$	FFF		-0.65 (-16.72)
$\delta_{C,2}$	FFF		-0.13 (-4.89)
$\delta_{C,3}$	FFF		0.06 (2.81)
$\delta_{C,4}$	FFF		0.08 (3.89)
$\delta_{S,1}$	FFF		0.34 (10.52)
$\delta_{S,2}$	FFF		0.41 (14.17)
$\delta_{S,3}$	FFF		0.19 (8.62)
b	Volatility of CAC40 Return (market effect)		0.11 (14.05)
$(\lambda_{MCRC}\,\alpha_2)'$	*Macroeconomic Conditions (Customers oriented) releases*	13	-3.31 (-5.09)
$(\lambda_{IRR}\,\alpha_2)'$	*Internal Outcome releases*	37	-7.07 (-2.94)
μ_{MONDAY}'	Monday effect		-2.36 (-2.90)
$\mu_{THURSDAY}'$	Thursday effect		-1.55 (-4.53)
μ_{FRIDAY}'	Friday effect		-1.33 (-5.00)
$\overline{R}^2$		0.05	
SE		3.90	
DW		1.29	
ADF		-60.32	

Note. See Table 4.

Table 8: Cumulative responses of the return volatilities to the announcement effects

Announcements	Alcatel	Axa	Renault	Société Générale
MCR(C)	273.48	246.73	3405.16	399.43
IRR	290.72	1163.47	1439.14	185.53
IPR	915.18			
ISOR		492.92	1760.93	
of which IMAR	187.51			
of which ICDR	573.86			
CRR	423.59		849.24	
CSOR	309.31			
CMAR		246.73		

Notes. A cumulative response is calculated as the sum of the absolute returns over the persistence period of the announcement effect (see footnote 23). The related persistence horizons are given in Tables 4 to 7.