Research Journal of Finance and Accounting www.iiste.org
ISSN 2222-1697 (Paper) ISSN 2222-2847 (Online)
Vol.6, No.9, 2015

Analyzes and Volatility Measures at the Financial Markets: Case of the French Market

Shiraz AYADI
Departement of finance University, of Economic and Management, SFAX-Tunisia

Abstract
The financial markets are often volatile, and this, for multiple reasons, like; crises, slower growth, higher inflation, and several other uncertainties which affect our economic and social life. The main tendency of these markets is their ability to respond to the systematic crises periods.Several studies have supposed that volatility cannot be stable but change over time, the observation of this latter gives us an idea regarding the factors of its variation. It is in fact important to observe the volatility and its potential factors on the financial markets before seeking to quantify it.We analyze in this paper the volatility at the financial market; we analyze the case of the French market. We first discuss the measures of the volatility. Then, we illustrate our work, we base on the deterministic autoregressive dynamics models. Then, experimental results are presented. Finally, we present our related work and our conclusions.
Keywords: Financial French Market – Autoregressive Conditional Heteroscedasticity Models – the volatility measurements.

Introduction

A report on the increased volatility published by the financial council of the French markets shows that volatility at the financial French market has begun to increase since 1997 until the summer 2002, when it recorded important historical peaks with a record 31%. Its level is decreased at the end of the year 2003 to 19%, then at 11% on 2004 to reach 10% in 2005. This increase was related to the speculative bubble, it was not stronger than that of the 1987 crisis but rather more durable. This level has decreased at the end of the year 2003 to 19%, then at 11% on 2004 to reach 10% in 2005. This increase was related to the speculative bubble, it was not stronger than that of the 1987 crisis but rather more durable. Several other factors explain the volatility variation until our days, several events marked the disasters days of the Parisian market namely suicide bombings of September 11 th, 2001 for new York and Washington. The eviction of Mikhail Gorbatchev, on the top of the Soviet Union by proponents of "hardliners" within the communist party on august 19 th, 1991. The abandonment of the acquisition of American United Airlines by its staff, based on the crisis of confidence started by the Enron business, which issued in October 08th, 2001, a press release announcing the accounting manipulations which contributed to overestimate the benefits. The announcement of falsified account's of Enron, in November 08th, 2001 and the Woldcoms have caused changes in securities CAC40. Also the subprime crisis (the famous crisis of the real estate credits in the U.S.A in September 2008,) has severely beaten the stability of the financial French market when the CAC40 index lost more than 14%, and others.

1.Volatility measurements at the financial market.

Volatility is defined as a measure of risk commonly used in portfolio management, or as measure of risk of each asset as well as those markets where they are negotiated, and it is generally defined as a measure of a market uncertainty. It indicates in which amplitude the performance of assets can deviate upwards or downwards from its average performance, it increases when the prices drop and decreases as prices remain near their average. We talk about a stagnant market where the action is not very volatile; it can be neither bullish nor bearish tendency. The concepts of bull and bear markets are very largely related to the notion of volatility; low volatility means that the price has remained near to the average, while a high volatility means that the price was much deviated from the average

Soaring stock prices and their subsequent fall may indicate the existence of a speculative bubble; the latter can be explained by the role of financial behavior, such as opinions divergences, the irrationality of the various stakeholders and others. Several phenomena have shook financial markets worldwide, the most notable are the stock market crash. Several sectors related to financial engineering have experienced very strong movements and became more volatile. The rise of the prices can also be born from the traders speculation. Kindelberger (1978) assumed that the initial rise of the prices generates anticipations of ulterior rises, and attracts new buyers, mainly speculators interested in capital gains on assets rather than the future income. Shwertz (1990) has shown that performance can interfere in explaining volatility, high volatility of the market involves to high yields in spite of the risks which it generates. Thus, the investor agrees to buy assets that had a high volatility when performance is high, and in this case prices fall allowing the buyer to anticipate a higher volatility. Vennet and Crombez (2000) find that stock returns are highly correlated to market movements, and they have found a conditional relationship between returns and risk. Gatfaoui (2004) affirms that "volatility is sensitive to the political, economical and financial events which explain partly it varies over time often with a phenomenon of non-stationarity.

The precise volatility estimation became crucial for making decision related to the assets allocation, or risks management. A better specification of the process of profitability consists in knowing its variability, and its forecast it is become thus the current stake of the modern finance.

2.Review of empirical literature

The calculating method of the volatility presume that the future evolution is inspired from the passed evolution, but getting a good future estimation of volatility is not often easy, and that its approximation can not be always reliable, and this, owing to the fact that volatility cannot be constant but changes stochastically through time. Javahary (2004) supposes that the randomness aspect of the volatility has visible consequences on the returns distribution, it can be indeed so normal conditional distribution returns are thus asymmetrical and leptokurtique. This refers to the sixties works of Samuelson and Mandelbrot who have described the randomness of the variance distribution, and later in the seventies with works of Merton which have supposed the existence of great jumps among the fluctuations of the underlying assets and that the volatility does not remain constant over time. Forecasting volatility is the main topical issue in the modern finance. The expected markets volatility is the variable key of the financial investment decisions. An accurate estimation of volatility is of a fundamental importance for decision making related to the assets allocation or of risk management, but its measure poses problems.

The volatility is defined as a simple instrument to measure the risks or uncertainties of a financial asset. Thus and for its measure, it is important to separate the variability of the standard deviation, and the concept of risk. More specifically financial variability often refers to the standard deviation of the prices relative variations or to the variance calculated as follow:

$$\sigma^2 = \frac{1}{N}\sum_{T-1}^{N}(R-\bar{R})^2$$

In this case, volatility is a measure of the average deviation from the mean. While, and for a small number of observations, the average of the sample cannot predict with precision the effective time of the average series and thus the volatility estimation will be inaccurate. Consequently a current practice consisting to carry out the deviations of the observations from zero in rather that starting from the average, knowing that the daily and weekly outputs on the markets are very close to zero, and then, several empirical research like that of Figlewski (1997) confirms that this method increases the precision of the volatility forecast. It is thus important to note that the standard deviation is judiciously used as measure of risk which does not refer to any particular distribution. The dispersion index is only valid for normal and log- normals distributions, and they can not discriminate between positive and negative deviations. And it is since critics of Jansen (1989) that we distinguish the measures of conditional and unconditionally variance. The principle is to reconsider the problem of the Fisher's linear discriminents.

We then talk about historical or unconditional volatility when the present prices fluctuation, is based on the previous prices during a given period. The measure of prices fluctuations in a finished times, uses historical prices data (daily, weekly, monthly, quarterly, or annual) to measure empirically the volatility, which is defined as the average over uniforms periods of measure. It indicates the value deviation degree of its average, and more this deviation degree is elevated, more the risk is great. Experience has shown that volatility can fluctuate significantly, and to calculate this volatility we should start to identify the average and calculate standard deviation.

Several studies showed that volatility is not constant but changes stochastically through time. Guyon (2002) supposed that there is good reason to consider the volatility as a random quantity, and it appears to have a stochastic behavior. The volatilities of financial assets are not constant but changes stochastically over time. In fact a stochastic variable varies over time. Referring to the Mandelbrot and Samuelson work, which have described the randomness of the variance, they have supposed that the volatility is not deterministic, and that it can not be normal as conditionally. Empirical studies, such as; Shiller (1981), Schwertz (1989), French and Roll (1986) have suggested that the volatility can be defined as the sum of the volatility caused by the noises traders, and the unperceived fundamental volatility caused by the stochastic information. The historical volatility as its name indicates, reflects only the historical past and makes it possible to its operator to project the future variance; it does not take into account the processes followed standard ARCH and GARCH. Several authors criticized this volatility by supposing that it is about a naive conditional forecast mode.

Several models have the limits ones: of historical volatility, and normal distributions of returns. In the eighties, the models of conditional volatility were widely used in the theories of modern portfolio, they are based on the principal which suppose that past performance of securities are used to determinate the extended of future returns, assuming that the volatility of a period depends on the previous changes to which random factors are added. These models consider volatility observed in the past and make predictions in the future, by describing volatility on the basis of available information. They had to describe the characteristic of second order moment of the distribution, they are based on the principal which suppose that the variance is known at a given date as a function of past variances and in practice, high volatility is followed of a high volatility, and that a low volatility is followed of a low volatility. These models show a good predictor of profitability, resulting in a more predictable distribution of net returns. The linear models of ARCH types (Autoregressive Conditionnal Heteroscedasticity), and GARCH (Generalized ARCH) models are more or less popular for the estimate of stochastic volatility, they had proposed to take into account the conditional variances, time dependant. Their principle is to challenge the ownership of homoscedasticity restraint in the linear model, to describe the heteroscedasticity phenomena and the persistence of volatility. These models introduced by Engle (1982) show the descriptive power of the series, and are generalized by Bollerslev (1986) who introduces an explicit modeling of the variance of returns, by adding an autoregressive term in the equation of the variance.

Traditional ARCH model

Engle (1982) introduced the ARCH process to highlight the dependence of the variance at the whole of available information and in time, and to make operational the idea that "The recent past provides information about variance forecasts". In its standard form, this model allows to the conditional variance to change over time as a linear function of the square residual. Its contribution induces changes in the volatility of time series which may be predictable and result from a nonlinear dependence in the changes of structural variables. The original model is based on modeling the dynamic of moments of a profitability of conditional distribution to the available information. To evaluate and study the movements of the volatility from ARCH models, Engle (1982) used an autoregressive representation of the conditional variance in the information passed. This model consists of two equations; the first, highlights the performance and the variables that explain it, and the second modeled the conditional variance of residuals. It looks like this:

$$Y_T = X\beta + \varepsilon_T$$

X: represents the variables that explain returns.

$$\varepsilon_t \big| I_{t-1} N(0, h_t)$$

I_{T-1} : refers to all available information until t $_{-1}$.

The process $\varepsilon_t = z_t \sqrt{ht}$

With: $h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}{}^2$

$VAR(\varepsilon_t) = E(\varepsilon_t ? = \alpha_0 + \alpha_1 E(\varepsilon^2{}_{t-1})$

With: $\alpha_0 > 0$ and $0 \leq \alpha i < 1$.

$$IE(\varepsilon_t / \Omega_{t-1}) = E[\varepsilon_t] = 0$$
$$V(\varepsilon_t / \Omega_{t-1}) = E(\varepsilon^2 / \Omega_{t-1}) = \sigma^2$$

The model realizes that the variance is conditional to the available information and there is a dependency of the variance with previous returns. The conditional volatility varies over time, this variation is caused by the autocorrelation between the square of random shocks on the endogenous variable.

The ARCH model allows considering the symmetrical clusters of volatility, is that the variations in prices are followed by other variations in prices and the low price changes are followed by other low price changes. But the problem is the fact that volatility is predicted by the square of innovations and the sign can not be predictive, and this is the case when the number of data becomes large, and that the conditional variances tend to be negative. The returns and variance of assets tend to be negatively correlated, hence the extension of ARCH model to the GARCH models.

The GARCH models

For a better representation of the conditional volatility process, and the estimated variances of portfolio returns, Bollerslev (1986) generalized the original ARCH- type model by introducing an autoregressive dynamic. The use of GARCH -type models assume that the residue is a time series composed of variables random, and the terms of this series are auto correlated. This model is based on the idea that volatility in each passed moment depends on the volatility of different passed moments and of the past shocks on the endogenous variable, the sum of squared residuals explains the crashes of the volatility. Because when a shock comes at a past time, the endogenous variable's changes, and the residue will be larges, the square of this residue is involved in the conditional variance and the past shock will be transmitted from the present moment. The GARCH models are as follows:

Supposing that: $\varepsilon_t = z_t \sqrt{h_t}$

The conditional variance equation of a GARCH process given that:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j}$$

The coefficient: α represents the transmission of previous shocks in the variance, and β represents the persistent character of the volatility described by Mandelbrot.

It is therefore clear that these models impose a quadratic relationship between the error and the conditional variance, and this is the case when the analysed changes are from the same sign. The general GARCH model assumes that the conditional variance is positive and that any impact whatever its sign always has a positive impact on volatility. These formulations are restrictive when it comes to changes in opposite sense, as it is the case when volatility tends to rise in response to the bad news and fall in response to the good news. Nelson (1991) has discussed the non negativity constraint, imposed on the model parameters. he has supposed that this mechanism of asymmetry is modelled by a nonlinear ARCH process, and this is the case where the specifications of the variance were proposed namely asymmetrical GARCH models; like EGARCH (exponential GARCH), models ARCH with Threshold, TGARCH (Thresheld GARCH) which take into account the asymmetrical effects according to nature of information which occurs . QGARCH model introduced by Engle and Ng (1993) and Sentana (1995), Duan and Al. (2004) use an expansion of Egeworth to obtain analytical approximations for GJR-GARCH models, these models reject the assumption of symmetry.

We make often distinguish between; historical volatility, stochastic volatility and implied volatility. Although the historical volatility, deals with the past and stochastic volatility consists in the use of the GARCH models. The implied volatility deals with the future and is regarded as representation of the forecast of the future volatility of a market. More precisely the investors anticipate what will be the future volatility of the price of the underlying. The latter observation reflects all available information on the market that could affect future volatility. Several studies, have considered this volatility which anticipates the level of realized volatility over a future period as preacher more powerful than historical volatility, and than it allows out performing the same if used jointly with the models of temporal series. These, since it makes it measures the risk of an instrument or a portfolio at a given time on the past, which is the case for historical volatility. The studies of Christensen and Prabhala (1998), Fleming (1998), Szakmary and al (2003), and of Jorion (1995) suppose that implied volatility is a better predictor of future volatility than models based on the historical volatility. Fleming (1998) supposes that implied volatility can be used as essential component in the models of assets pricing .And it is from these principals that the researchers have focused on providing the best estimators.

3. Data and methodology

In order to measure the volatility in the financial market we retain the case of the French market. We retain as sample, the constituent assets of CAC40 index, from1997 to 2009 on monthly frequencies, and from 2004 to 2009 on daily frequencies .We perform various tests on these primary data to ensure that they represent the market conditions. In particular, when there was not trade in a security database, Thomson Financial Datastream defers the closing rates of the day before. It is the case for the whole asset in the holidays at the Paris stock exchange, but also for the asset which was suspended from trading during the whole days. For our study, it is essential to exclude these data which are not the result of the investor’s transactions and which artificially increase the proportions of null returns.

We analyze the volatility in the financial French market by means of the autoregressive conditional heteroscedastic models. Several linear and non linear ARCH models are used to appreciate the volatility of the CAC40 index.

Linear ARCH model

Engle (1982) was the first who proposed an endogenous specification of the conditional variance called ARCH (q) .This model is based on a quadratic parametrization of the conditional variance, it appears as a linear function of q past values of the square process innovations:

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha(L)\,\hat{\varepsilon}_t^2 + \nu_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \hat{\varepsilon}_{t-j}^2 + \nu_t \quad A\text{vec } \alpha_0 \succ 0; \alpha_j \succ 0 \ \forall \ j = 1,\ldots\ldots, q$$

$$h_t = Var(\hat{\varepsilon}_t / \underline{\varepsilon}_{t-1}) = E(\hat{\varepsilon}_t / \underline{\varepsilon}_{t-1}) = \alpha_0 + \sum_{j=1}^{q} \alpha_j \hat{\varepsilon}_{t-j}^2$$

With: $\underline{\varepsilon}_{t-1} = \{\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots, \varepsilon_0\}$

If we assume that: $W_t = \{1, \hat{\varepsilon}_{t-1}^2, \ldots\ldots\ldots, \hat{\varepsilon}_{t-q}^2\}$ et $\alpha' = (\alpha_0, \alpha_1, \ldots\ldots, \alpha_q)$ we find the classic form of heteroscedasticity .Indeed, in the case of AR(1).

$$Y_t = \phi_1 \, Y_{t-1} + \varepsilon_t.$$

This process follows a normal distribution of mean and variance covariance matrix. This model is called autoregressive process of first order with errors ARCH (q).By introduction a specification and not AR ARMA noise. Bollerslev (1988) proposed a general GARCH (p,q):

$$Var\,(\hat{\varepsilon}_t / \underline{\varepsilon}_{t-1}) = E(\hat{\varepsilon}_t^2 / \underline{\varepsilon}_{t-1}) = \alpha_0 + \sum_{j=1}^{q} \alpha_j \hat{\varepsilon}_{t-j}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}; \text{avec } \alpha_0 \succ 0,\ \alpha_j \geq 0 \text{ et } \beta_j \geq 0$$

$$\hat{\varepsilon}_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \hat{\varepsilon}_{t-j}^2 + \sum_{j=1}^{p} \beta_j (\hat{\varepsilon}_{t-j}^2 - \nu_{t-j}) = \alpha_0 + \sum_{j=1}^{Max(p,q)} (\alpha_j + \beta_j)\hat{\varepsilon}_{t-j}^2 - \sum_{j=1}^{p} \beta_j \, \nu_{t-j}$$

$$\left(1 - \sum_{j=1}^{Max(p,q)} (\alpha_j + \beta_j) L^j \hat{\varepsilon}_t^2\right) = \alpha_0 - \sum_{j=1}^{p} \beta_j L^j \, \nu_t$$

$$(1 - (\alpha(L) + \beta(L)))\,\hat{\varepsilon}_t^2 = \alpha_0 + \beta(L)\nu_t$$

This relationship allows defining the necessary and sufficient condition for a weak stationarity, which means the variance is independent of the time:

$$\alpha(1) + \beta(1) = \sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j \prec 1$$

Nelson (1990) defined the necessary and sufficient condition for the strict stationarity using a transformation of conditional variance. Indeed, if we ask, $\varepsilon_t = \sigma Z_t$, is an independent and identically distributed from zero mean and variance without autocorrelations , the unitary representation GARCH(p,q) becomes:

$$Var(\hat{\varepsilon}_t / \underline{\varepsilon}_{t-1}) = \alpha_0 + \sum_{j=1}^{Max(p,q)} (\alpha_j + \beta_j)\sigma^2 Z_{t-j} - \sum_{j=1}^{p} \beta_j \nu_{t-j}$$

Non linear ARCH models

According to some authors, the ARCH and GARCH formulations are very restrictive because they impose a quadratic relationship between error and the conditional variances. The GARCH model may be insufficient to Nelson (1991) for two reasons according:

- The choice of a quadratic form for the conditional variance has important consequences on the time path of the typical series. If the series are characterized by periods of high and low volatility, or in the case of economic series, volatility tends to be higher after a decline, than after the increase, the choice of symmetrical form of the conditional variance can provide a better model for this phenomenon.

- The traditional ARCH models require that their parameters are positive; GARCH models also, remain heavily constrained that their movements should always be conditionally positive. Consequently, the Shock whatever its nature always has a positive effect on the current volatility. What makes the linear ARCH model and GARCH models inadequate to express the oscillatory behavior of cyclical volatility

These criticisms have led to the developpement of three processes: the EGARCH model (exponential GARCH), TGARCH model (Threshold GARCH) and QGARCH model (Quadratic GARCH).These models differ from the usual ARCH models is that they reject. The hypothesis of symmetry associated with the quadratic specification of the conditional variance.

- ***EGARCH Model***

This is a log linear model introduced by Nelson (1991) and Gewek and Pantula (1988) to avoid the constraints imposed on positives coefficients.

The EGARCH model is presented in the form of the following equation:

$$Log[Var(\varepsilon_t / \underline{\varepsilon}_{t-1})] = \alpha_0 + \sum_{j=1}^{q} \alpha_j \{ \gamma Z_{t-j} + \delta [|Z_{t-j}| + E|Z_{t-j}|] \} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2)$$

With : $Z_{\text{t-j}} = \dfrac{\varepsilon_{t-j}}{\sigma_{t-j}}$

In the exponential GARCH model coefficients can be positive or negative. Let the standard form of the following EGARCH models:

$$g(Z_t) = \phi Z_t + [|Z_{t-j}| + E|Z_{t-j}|]$$

If $Z_t \succ 0$, then $g(Zt)$is a function of slope and if, then $g(Zt)$ is a function of slope $\gamma - \phi$. The conditional variance responds asymmetrical to the signs Zt-j. The signs and amplitudes are respectively taken into account by the coefficients γ and ϕ .The choice of standardized variables Zt-j instead achieves weak stationarity conditions relating solely to the polynomial $\beta(L)$

TGARCH Model

Also as part of the specification of asymmetric volatility, Zakoin and Threshold (1994) proposed the Threshold GARCH model or the quadratic form is replaced by a linear function by piece depending on the sign of the shock and the standard deviation of conditional the previous period. This model specifies the asymmetry on the standard deviation rather than on the conditional variance. Rabemanajara and Zakoian (1993), speculate that "it is possible to relax the positivity conditions on parameters, allowing an oscillatory behavior of the conditional standard deviation (in absolute value) relative to the value shock of previous period."

The Threshold GARCH (TGARCH (p,q)) expresses the conditional variance as a quadratic function piece by past values crude

$$\sigma^2 = \left[\alpha_0 + \sum_{j=1}^{q} \left(\alpha_j^+ \varepsilon_{t-j}^+ - \alpha_j^- \varepsilon_{t-j}^- \right) \right] + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 = \alpha_0 + \alpha^+(L)\varepsilon_t^+ - \alpha^-(L)\varepsilon_t^- + \beta(L)\sigma_t^2$$

With: $\varepsilon_t^+ = \max(\varepsilon_t, 0)$; $\varepsilon_t^- = \min(\varepsilon_t, 0)$,; $\alpha_0 \succ 0; \alpha_{\text{j}}^+ \geq 0$ et $\alpha_{\text{j}}^- \geq 0$

The model covers TGARCH conditional variance while EGARCH model relates the logarithm of the conditional variance.

QGARCH Model

QGARCH processes have been by Sentana (1995), these models can be expressed as follows:

$$\sigma_t^2 = \sigma_z^2 + \phi' Z_{t-q} + Z'_{t-q} A Z_{t-q} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

With ϕ is a vector of parameters is the conditional variance of $Z_t = \dfrac{\varepsilon_t}{\sigma_t}$ and

$$Z_{t-q} = \left(Z_{t-1}, \ldots\ldots\ldots, Z_{t-q}\right)'$$

The asymmetry is considered by the intermediation of the linear term.A: is a matrix whose terms outside the main diagonal reflects the interaction effects of lagged values of Zt on the conditional variance. According to previous expression, we observe several configurations of non linear processes in variances:

- When ϕ =0, we get the process" Augmented GARCH, proposed by Bera and Lee (1990).
- When ϕ =0, β_j and A: is a diagonal matrix, we end up with ARCH models proposed by Engle (1982).
- When A: is a diagonal matrix, we find the expression of EGARCH models.

4.Empirical Results

We begin our analysis by pre-testing the data. In the first step, each series is individually examined under the null hypothesis of a unit root against the alternative of stationarity.

The table below represents a detailed descriptive analysis of CAC40 index if the data are monthly or daily:

Table1: Descriptive analysis of the CAC40 index

Indicateurs	Mean	Médian	σ	Minimum	Maximum	Skewness	Kurtosis	JB
CAC40 mensual Data	7,1855	7,137337	0,28637	6,66921	7,762327	0,175939	2,270393	4,210261
CAC40 daily data	1,462947	1,475106	0,204013	0,92386	1,819375	-0,17623	2,114179	44,91486

The results of the descriptive analysis of the CAC40 index on monthly frequencies validates the symmetry of the French financial market, which is detected starting from the kurtosis which is lower than 3. The CAC40 follows a normal distribution, since Jarque and Bera statistic is equal to 4.2102, and which are lower than (5.991). On the other hand, according to the results on daily data, the statistics of jarque Bera are higher than the statistics of khi-deux. From where, this index does not follow a normal distribution. Although thàt information (using daily data) runs symmetrically on the financial French market, statistics of Kurtosis is lower than 3.

The Dickey-Fuller (1979-1981) statistics designed to test the null hypothesis of non stationary process against the alternative hypothesis of stationary process. Their interest is with us about the need to differentiate the series studied. Before testing the stationarity from the first test of Dickey fuller (1979-1981), it proves to be necessary to determine the optimal number of delays, it will be obtained by the specific rule of Ng and Perron (1995), the table below will give the optimal order delays, as well as the test of, the stationarity in levels and in difference of Dickey Fuller (1979-1981)

Table2: Dickey fuller test on monthly and daily Data

Dickey-Fuller test							
Tests DF-ADF / LCAC40	Delays	T-Statistics In level	Chosen Model	Critical Values In level	T-Statistic In difference	Critical value in différence	Nomber of intégration
Mensual Data	1	-1.97659	M2	-2.8804	-8.17784	-2.88059	I (1)
daily Data	2	-0.05426	M1	-1.9410	-37.9158	-1.94109	I (1)

From this table, we can note that these two series have each one a unit root, since the T-statistics are higher than the tabulated values of Makinnon (1996). This unit root is disappeared after the only one differentiation, from where, the index of the financial French market on monthly or daily frequency is integrated of order one. Obtaining a unit root for the CAC40 index on daily data is detected from the test of Dickey Fuller (1979). But, we used a test of Dickey Fuller increased to have the existence of a unit root of the CAC40 index on monthly frequencies. The large size of the sample generates the problems of heteroscedasticity and autocorrelations, in our database. The existence of an heteroscedasticity and an autocorrolation problem in this database leads to a weak test of Dickey Fuller (1979-1981) in detecting the unit roots of our series study .To overcome this shortcoming, we use the test of Philips Perron (1988) . This model reflects the existence of autocorrelation s and heteroscedasticity problems, in macro or micro economics series.

Philips and Perron (1988) have proposed a non parametric correction of the Dickey Fuller (1979-1981) test, in order to regulate the problem of the autocorrelation and of the heteroscedasticity of errors. They have suggested associating an auto regression coefficient to the statistic of student, a factor with correction, based on consistent estimators of the parameters of harmful effect which eliminate this stochastic dependence.

The table below will present the Philips-Perron (1989) test for CAC40 index.

Table 3 : Philips & Perron (1988) test on monthly and daily Data.

Philips & Perron (1988) test							
Tests DF-ADF / LCAC40	Delays	T-Statistics In level	Chosen Model	Critical Values In level	T-Statistic In difference	Critical value in différence	Nomber of intégration
Monthly data	3	-1.955116	M2	-2.88033	-10.32874	-2.88046	I (1)
Daily Data	3	-0.016274	M1	-1.94109	-38,13416	-1.94109	I (1)

We then modelize the CAC40 index. The estimated ARIMA models require that we work on stationary series, which means that the mean and variance of a series are constant over time. The best method to eliminate any tendency is to differentiate, that is to say, to replace the original series, with the differences of the adjacent series. A time series that needs to be differentiated to achieve stationarity is considered an integrated version of a stationary series. The correction of non stationarity in terms of variance can be achieved by logarithmic transformation of type or the reverse exponential. These transformations must be performed before the differentiation. A temporal ARIMA model can be specified by the following equation:

$$\Delta CAC40_t = \alpha + \sum_{i=1}^{P} \beta_i \Delta CAC40_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j}$$

The identification of ARIMA process is based on the total autocorrelation functions which play a role in determining the optimal number of delays for the MA part of the process. If the autocorrelation is significant, this indicates that K terms of moving average must be added to the model. Considering that if the AR coefficients can be estimated by a multiple regression analysis, such an approach is impossible for the MA coefficients. First, because the prediction equation is nonlinear and other errors can be specified as independent variables. The errors must be calculated step by step according estimates of parameters. Considering that if the AR coefficients can be estimated by a multiple regression analysis, such an approach is impossible for the MA coefficients. First, because the prediction equation is nonlinear and other errors can be specified as an independent variables. The errors must be calculated step by step according estimates of parameters. So if MA is associated with à negative autocorrelation at lag 1, the series will be on differentiated .A slight over-differentiation may be compensated by adding a term moving average.

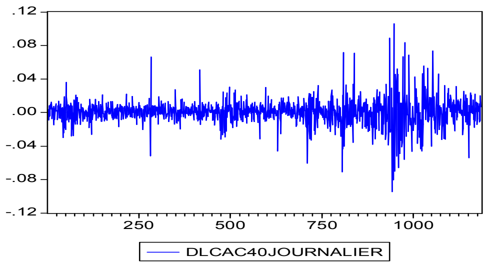
Modelling each of the CAC40 series is presented in the table below:

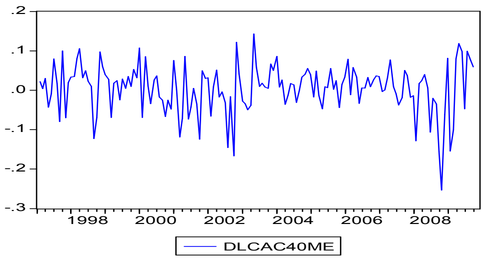
Table 4: Modelling CAC40

Modelling CAC40				
DF-ADF test / ΔLCAC40	ARIMA	Constant	AR	MA
Monthly data	(1 ; 1 ; 0)	0.004342	0.164412	
T student		(0.727966)	(2.036420)	
Daily Data	(1 ; 1 ; 1)	6.64×10^{5}	0.299691	-0.407663
T student		(0.170311)	(1.328097)	(-1.88748)

We modelled the CAC40 index on monthly frequencies from1997 to 2009 by a stationary autoregressive model of order1, and an ARIMA (1.1.1), on daily data.

We can see that the CAC40 index is volatile on monthly and daily frequency. The figures have validated the volatility of the index.





Graphe1: Observation of the daily index volatility **Graphe2: Observation of the monthly volatility of the index**

The volatility is detected on the daily data and the monthly data of the index. The instability of the variance of this index is mainly due to the residual heteroscedasticity. To check the heterogeneity of this variance, we use the White test statistic based on the likelihood ratio or the Fisher statistic. The table below shows the test of heterogeneity of variance of CAC40 on daily or monthly frequencies.

Table 5: The White (1980) test on the daily and monthly data.

The White (1980) test			
LR or F Statistic / ΔLCAC40	LR Statistic $n\times R^2$	Fisher statistic	
Monthly data	11, 93446 (0.002561)	6,347868 (0.002261)	Hétéroscédasticity Problem
daily Data	946.2585 (0.000000)	2350.307 (0.000000)	Hétéroscédasticity Problem

The value in parenthesis represents the gain or the probability of the first kind.

From this table we can see that there is an heteroscedasticity problem in the variance of the CAC40 index. This problem is detected by the test of White (1980).While the variance of residuals heteroscedastic; we can remodel the CAC40 index by linear or nonlinear ARCH models.

Before detecting the volatility of the CAC40 index on monthly or daily data, it is interesting to verify the existence of heterogeneity problem of residues of these two series. The table below shows the test of residuals variances heteroscedasticity of these two series.

Table 6 : Heteroscedasticity LM-ARCH test on daily and monthly data

Heteroscedasticity LM-ARCH test				
Statistique de LR / ΔLCAC40	**Statistique LR $n\times R^2$**	**Constant**	**Résidus$^2_{t-1}$**	**Résidus$^2_{t-4}$**
Mensual data	6.236230 (0.012516)	0.002991 (4, 75737)	0.203074 (2,533520)	
Daily data	200.1086 (0.000000)	9.77×10^5 (4,370568)	0,087002 (3,032862)	0.181901 (6,341112)

We see from this table that the probability associated with the statistical NR2 is very low, so we accept the alternative hypothesis of heteroscedasticity at the expense of the null hypothesis of homoscedasticity of the error term. Hence, the autoregressive coefficients of residues squared variables above are delayed significantly and different from zero.

Considering this ARCH effects, we present and estimate the equation of the conditional variance associated with modelling linear or nonlinear in variance terms. We use the maximum likelihood technique to estimate ARCH model parameters of CAC 40 index.

Table7: Estimated linear ARCH model by the maximum likelihood technique

Estimated linear ARCH model by the maximum likelihood technique				
Statistique of LR ou F / Δ**CAC40**	**Constant**	$\hat{\varepsilon}_{t-1}^2$	$\hat{\varepsilon}_{t-6}^2$	**Conclusion**
Mensuel data	0,002807 (7,940391)	0.249070 (2, 34553)		ARCH (1)
Daily data	5.16×10^5 (15.69640)	0.061609 (4.594451)	0.057830 (2.676763)	ARCH (6)

The results of this table show that the coefficients parameters of each autoregressive process of conditional heteroscedastic are positive, and significantly different from zero. Consequently, the coefficient of these processes validates the positivity constraints of the conditional variances. The ARCH (1) model is the candidate model for the representation of conditional variance, on the differential of the CAC40 index, in the daily data. This index is modelled by an ARCH (6) on the daily frequencies. The large size of the CAC 40 index, on daily data, requires a GARCH model to reduce the degree of freedom.

Table 8: Estimated linear GARCH model with maximum likelihood technique.

Estimated linear GARCH model with maximum likelihood technique				
Statistique de LR ou F / Δ**LCAC40**	**Constant**	$\hat{\varepsilon}_{t-1}^2$	h_{t-1}	**Conclusion**
Mensuel data	0.000340 (1.364581)	0.163036 (2.704680)	0.758583 7.331807	GARCH (1 ; 1)
Daily data	4.71×10^6 (4.476796)	0.084016 (4.836124)	1.258055 (7.964191)	GARCH (1 ; 2)

Given this table, the coefficients of equation for the variance of the difference of the CAC40 logarithm were significant and positives. Therefore, the GARCH(1,1) is a candidate model .Moreover, we note that the total degree of ARCH (1) and GARCH (1) is very close to1.This reflects a persistence phenomenon in the conditional variances, a phenomenon frequently encountered in the French stock market index, although this index on daily data is modelled by the GARCH (1,2).

We then estimated two models that reject the quadratic specification of conditional variances and designed to reflect the phenomena of asymmetry: the exponential GARCH process, and the TGARCH model.

Table 9: Estimation of nonlinear EGARCH model

Estimation of nonlinear EGARCH model				
EGARCH / **ΔLCAC40**	**Constant**	α	γ	β
Mensuel data	-0.789754 (-1.76447)	0.085236 (0.807706)	-0.215653 (-3.47586)	0.874065 (11.77208)
Daily data	-0.367089 (-9.33693)	0.119802 (8.350024)	-0.162785 -12.75316	0.968153 (247.6703)

Given this table, we see that all the differential coefficients of the logarithm of the CAC40 index, in the equation for the variance are significantly different from zero. So there is a phenomenon of asymmetry, a phenomenon that could be highlighted through the linear models.

Table 10: Estimation of nonlinear TGARCH model.

Estimation of nonlinear TGARCH model				
EGARCH / ΔLCAC40	Constant	α^-	α^+	β
Mensuel data	0.000511 (1.987327)	-0.122142 (-1.84468)	0.302573 (3.218023)	0.803191 (8.330393)
Daily data	4.54×10^{6} (7.320263)	-0.017129 (-2.13487)	0.193217 (11.16927)	0.900305 (92.18780)

We note in table 10 that the average coefficients are significantly different from zero for the differential of the log CAC40. In addition, it exist the factors associated with different coefficients and indicating the presence of the asymmetry phenomenon.

Which model we can finally adopted for the modelling of conditional variances? To the extent that the phenomenon of asymmetry is present, we think that the most appropriate models are the EGARCH and TGARCH process. The choice between these two processes can be assessed using criteria for comparing models. For guidance, we also defer the criteria valued ARCH (1) and GARCH (1, 1). These values are given in the following table:

Table 11: Criteria for comparing models estimated

Criteria for comparing estimated models				
ΔLCAC40 mensuel data				
	ARCH (1)	**GARCH (1,1)**	**EGARCH (1,1)**	**TGARCH (1,1)**
R^2	0.021419	0.020433	0.025185	0.026056
LL	213.8520	218.1755	223.0411	222.9684
AIC	-2.761211	-2.804941	-2.855804	-2.854847
SC	-2.681635	-2.705472	-2.736440	-2.735484
ΔLCAC40 daily data				
	ARCH (6)	**GARCH (1,2)**	**EGARCH (1,1)**	**TGARCH (1,1)**
R^2	0.005433	0.006855	0.009198	0.009205
LL	3465.074	3462.515	3507.050	3499.825
AIC	-5.837963	-5.838708	-5.913935	-5.90173
SC	-5.799374	-5.812981	-5.888209	-5.876005

R^2 : coefficient of determination, LL : Log likelihood, AIC : Akaike info criterion et SC : Schwarz criterion

We Compared selection criteria between the various models, this that is led us to select the model's, EGARCH (1,1) process for the differential of the logarithm of the CAC 40 on the monthly data and the model's, TGARCH (1) for the differential of the logarithm of the daily frequency of the index.

We can from our empirical work validate the hypothesis of financial market volatility, and this by modelling a linear or nonlinear ARCH processes. This volatility is detected by both of good and bad news coming in the French stock market. The nonlinearity of the CAC40 index on monthly and daily frequencies is explained by the non stationarity of the index in terms of the mean and variance. This volatility is due to the asymmetry of information since that the kurtosis is exceeds 3.

Conclusion

From this work, we were able to exhibit the heteroscedastic movements of the large amplitudes, which explained the structural changes that have occurred in our business environment. The volatility is the result of these changes; his prediction has become essential to anticipate risk. Nowadays any investor is aware of events that introduced an element of risk in his portfolio, and thus it is recommended to choose the degree of risk exposure and to hedge against the adverse facts which may affect the markets.

Several studies have agreed that to combat volatility, we must diversify investments, including new assets in the portfolio, that allows the investor to gain risk and generate profits, greater diversification reduces the systematic risks and can find more effective responses to price shocks reached. He proved in fact that derivatives are instruments of choice to protect the portfolio during periods of volatility and abrupt reversals in equity markets. It is admitted fact that the options can be used as part of hedging strategy to protect portfolios against adverse movements in prices, or as a speculative asset that earns the expected changes in prices. In assessing the fair value of an option, or to protect from the market risk, investors must indicate their expectations of underlying assets. In assessing the fair value of options or to hedge the market risk investors are asked to specify their expectations by observing the future volatility. Therefore we can assume that randomness of the volatility can be observed twice, either from the abnormal returns on equity markets, or from an implied volatilities observed on the options markets.

References.

[1] - Alireza Javaheri, (2004), « The Volatility Process: A Study of Stock Market Dynamics via Parametric Stochastic Volatility Models and a Comparison to the Information embedded in the Option Prices" these de doctorat. Cerna, Centre d'économie industrielle Ecole Nationale Supérieure des Mines de Paris.

[2]- Anil K. Bera & Sangkyu Lee, 1990. « Information Matrix Test, Parameter Heterogeneity and ARCH: A Sunthesis" University of California at San Diego, Economics Working Paper Series 90-26, Departement of Economics, UC San Diego.

[3]-Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroscedasticity," Journal of Econometrics, 31, 307–327.

[4]-Christensen, B.J., and N.R. Prabhala, (1998), "The Relation between Implied and Realized Volatility," Journal of Financial Economics, 50,125-150.

[5]- Crombez.j and Vennet.R (2000) « Risk-return relationship conditional on market mouvement on the Brussels stock Exchange » Tijdschrift voor Economie en management, vol 45, pp 163-188.

[6]- Dickey, D.A. and W.A. Fuller (1979) "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," Journal of the American Statistical Association, 74, 427–431.

[7]- Engle, R. (1982) "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation". Econometrica, 50 :987–1008.

[8]- Duan, J.-C., Gauthier, G., Sasseville, C., Simonoto, J.-G., (2004). « Approximating the GJR-GARCH and EGARCH option pricing models analytically". Rotman School of Management, University of Toronto, unpublished manuscript.

[9]- Engle, R. And.V.Ng (1993), " Measuring and Testing the impact of News on Volatility" Journal of Finance, 48,1749-1778.

[10]-Figlewski (1997), "Forecasting volatility," Financial Markets; Institutions & Instruments 6(1), 1{88.

[11]-Fleming, J. (1998). "The quality of market volatility forecasts implied by S&P100 index option prices". Journal of Empirical Finance, 5, 317–345.

[12]- French, K.etR.Roll (1986) « Stock return Variances: The arrival of information and the reaction of orders » Journal of financial Economics,17,p.5-26.

[13]-Gatfaoui, Hayette, (2004) « Rôle et Impact de la Volatilité dans le Pricing d'Options et de ProduitsDérivés », Editions Publibook Universités, 2004.

[14]-Geweke, J. (1986), 'Modelling persistence in conditional variances: A comment', Econometric Reviews 5, 57–61.

[15]- Jansen , D. W. (1989) "Does Inflation Uncertainty Affect Output Growth?" The Federal Reserve Bank of

Saint Louis Review, July-August, pp.43-54.
[16]- Jorion, P. (1995). “Predicting volatility in the foreign exchange market”. Journal of Finance, 50, 507–528.
[17]-Julien Guyon (2002) « Volatilité stochastique : « L’étude d’un modèle ergodique ».
[18]-Kindelberger, Charles P., 1978, Manias, Panics and Crashes, Londers et Basingstoke, Macmillan Press.
[19]-MacKinnon, J. G. (1996), ‘Numerical distribution functions for unit root and cointegration tests’, Journal of Applied Econometrics, 11, 601–618.
[20]- Mandelbrot B. (1963). “The Variation of Certain Speculative Prices”, Journal of Business, 36, p. 349-419.
[21]-Nelson, D.B., (1990). “ARCH models as diffusion approximations”. Journal of Econometrics 45, 7–38.
[22]-Nelson, D. B (1991), "Conditional Heteroskedasicity in asset returns: a new approach",Econometrica, N°2 p.p 374-370.
[23]-NG, S., And P. Perron (1995): “Unit Root Tests in ARMA Models with Data-Dependent Methods for the Selection of the Truncation Lag,” Journal of the American Statistical Association, 90(429), 268–281.
[24]-Pantula, S. G. (1986), ‘Modelling persistence in conditional variances: A comment’, Econometric Reviews . 5, 71–74.
[25]-Phillips P.C.B et Perron P.(1988), "Testing for Unit Root in a Time Series Regression",Biometrika, Vol.75, pp.335-346.
[26]-Rabemananjara, R & Zakoian, J M, (1993). " Threshold Arch Models and Asymmetries in Volatility” Journal of Applied Econometrics, John Wiley et Sons, Ltd, Vol.8(1), pages 31-49, Jan-Marc
[28]-Samuelson, P.A. (1965) “theory of Warrant pricing.” Industriel Management Review 6 (1965),13-39.
[29]-Santana E.. (1995) “Quadratic ARCH Models”, Review of Economic Studies, , Vol.62: 636-661.
[30]-Schwert, W.G. (1990), “Stock Market Volatility”. Financial Analysts Journal, May-June, pp.23-34.
[31]-Schwert, W.G. (1989) “Why does stock market volatility change over time?”. Journal of Finance, 44, pp.1115-1153.
[32]-Shiller, Robert (1981). «Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends», American Economic Review, 71, pp. 421-436.
[33]- Szakmary, M., et al. (2003). “The predictive power of implied volatility: Evidence from 35 futures markets”. Journal of Banking and Finance, 27, 2151-2175.
[34]-White, H. (1980). «A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. » Econometrica, 48(4), 817– 838.
[35]-Zakoloin, J.M.Treshold (1994) « Heteroscedasticity models” .Journal of Economics Dynamics and Control 18 (1994), 931-955.