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Modeling volatility of the French stock market

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Abstract

This paper aims to investigate the volatility of the French stock market using the CAC40 index on daily and monthly frequencies. For this purpose, we use linear and nonlinear ARCH models to check whether the magnitude of volatility can be explained by data frequency and cyclical nonlinearity. Our findings reveal that the EGARCH model outperforms the TGARCH model in capturing volatility for both daily and monthly data.

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1. Introduction

Market volatility can be defined as a statistical measure of the risk inherent to portfolio management. It is commonly defined as a measure of the uncertainty of a market or more precisely as a measure of the risk of a given security. Higher volatility leads to large variations of returns and as a consequence higher risk. Thus, estimating volatility has become the focus of much research in modern finance since financial investment decisions depend in most part on the expected volatility. Therefore, an accurate estimation of volatility is of fundamental importance for asset allocation or risk management decision making, but its measurement raises some problems. Indeed, there are several estimation methods of volatility but unfortunately their results are controversial. We often distinguish between historical, stochastic and implied volatility. Historical volatility takes into account only the past and it does not consider the processes followed such as ARCH and GARCH. This historical volatility is considered as a naive conditional prediction method. However, a good estimation method of future volatility is often not easy and this procedure cannot always be reliable. Indeed, several studies have shown that volatility is not constant but changes stochastically over time. Mandelbrot (1966) and Samuelson (1965) are the pioneers who argue that volatility is non-deterministic and it is normally distributed only under some conditions. Guyon (2002) assumes that volatility can be considered as a random quantity since it seems to exhibit stochastic behavior. He argues that modeling volatility by a stochastic process is in fact recognizing that quantifying risk by a constant volatility parameter is insufficient to explain certain market phenomena since the volatility of securities is not constant but changes stochastically over time. Javaheri (2004) assumes that the randomness of volatility has visible consequences on the distribution of returns, and this volatility is normally distributed only under some conditions. The distribution of returns is thus asymmetric and leptokurtic. Unlike the historical volatility which is about the past, and stochastic volatility which consists in using GARCH-type models, implied volatility looks forward and forecasts the future volatility of a market. Christensen and Prabhala (1998), Szakmary et al. (2003), Jorion (1995) consider implied volatility as a better predictor of future volatility. Fleming (1999) assumes that implied volatility can be used as an essential component in asset valuation models.

Given the importance of an accurate estimation of volatility, a wide variety of theoretical and empirical approaches have been employed by researchers in financial markets. However, there is no consensus on an appropriate model. The present paper provides additional evidence on volatility in the French stock market. The study of time-varying volatility in the French context deserves a particular attention since it presents a huge instability compared to the American case (Le Bris, 2012). The main contribution of this paper consists in considering two data frequencies contrary to previous studies in the French context. Our findings reveal the existence of nonlinearity and asymmetry phenomenon in the volatility of the CAC40. In addition, we find that the EGARCH model outperforms the others for both daily and monthly data.

The remainder of this article is structured as follows. Section 2 discusses the main previous literature on stock market volatility. In section 3, we present data and we attempt to capture the volatility of the French stock market through the CAC40 index. Section 4 concludes.

2. Literature Review

The ARCH model introduced by Engle (1982) and generalized (GARCH) later by Bollerslev (1986) is the most widely used to capture the volatility of stock markets. The GARCH model proposes an explicit modeling of the variance of returns by adding an autoregressive term to the equation of variance. These models are largely employed to estimate stochastic volatility by suggesting that returns are not always normally distributed. Several extensions of ARCH and GARCH models were developed such as GARCH-M and EGARCH (Nelson, 1991), NGARCH (Higgins and Bera, 1992), QGARCH (Sentana, 1995), TGARCH (Zakoian, 1994), FIGARCH (Baillie et al. 1996), etc… However, there is no consensus on the best model for modeling and forecasting time-varying financial market volatility.

Omar and Halim (2015) attempt to model volatility of Malaysian stock market using daily index return. The results given by GARCH (1,1) indicate the presence of volatility clustering and persistence effects on the stock market volatility. They also find that the EGARCH and TGARCH models capture the leverage effects in the data series. The comparison between these models reveals that EGARCH model outperforms the two other models.

Lim and Sek (2013) compare the performance of GARCH-type models in capturing volatility in Malaysian stock market. They conclude that, in normal periods (pre and post-crisis) symmetric GARCH model outperforms the asymmetric GARCH, whereas this latter seems more appropriate in fluctuation period (crisis period). Similarly, Tripathy and Gil-Alana (2015) investigate the effects of the recent global financial crisis on the time-varying volatility of the Indian stock market. Using symmetric and asymmetric GARCH models, they point out that the volatility of the Indian stock market is persistent and asymmetric and increases during crisis period.

Aggrawal et al. (1999) analyze the determinants of volatility in emerging stock markets. They provide evidence that the large changes in volatility in these markets may be explained by country specific political, social and economic events. In addition, they find that daily returns are more volatile than weekly and monthly returns.

Audrino and Trojani (2006) consider daily (log) return series of nine major stock indices (such as the French CAC40 index). They find strong evidence for more than one multivariate threshold (more than two regimes) in conditional means and variances of global equity index returns.

Miloudi et al. (2016) investigate the relationship between trading volume, stock returns and volatility in the French stock market. Using the EGARCH (1,1) to measure the monthly conditional market volatility, they provide evidence that current conditional market volatility is positively associated with the market turnover and stock market returns. Arisoy (2010) finds that volatility is an important factor that investors take into account while pricing stocks on the French market. The author also finds that the value premium observed in the French stock market depends on the systematic volatility risk. Le Bris (2012) points out that the monthly volatility of the French stock market exhibits high variations over time and it can be explained by the monetary instability and the magnitude of public deficit. Cousin and De Launois (2006) investigate whether information flow affects stock price volatility using a sample of French firms pertaining to the CAC40 index. They provide evidence that public information flows strongly affect the stock returns distribution and that news frequency seems to be largely responsible for the persistence volatility effect, and its impact on the volatility level is important. Using daily data, Capelle-Blancard and Havrylchyk (2016) provide evidence that securities transaction tax has no significant impact on the volatility of the French stock market.

Examining the existing literature, overviewed above, we notice that there is no study on the French market has so far attempted to test whether the performance of volatility models depends on data frequency. Therefore, the current paper aims to fill this gap by assessing the time-varying volatility in the French stock market using both daily and monthly data.

3. Empirical analysis and data

3.1. Data

In this article we attempt to study the volatility in the French stock market through the CAC40 index during the period from January 2013 to December 2015 on monthly frequencies. We will also identify the source of this volatility and the causes of vulnerability of this index on daily data from January 1, 2011, to December 31, 2015. The data are taken from Datastream. We begin by conducting various tests on our data to ensure that they reflect market conditions. In particular, when there was no exchange on a security, the Datastream database reports the closing price of the previous day. This is not only the case for all securities on public holidays on the Paris Stock Exchange, but also for the stocks that had been suspended from listing on whole days. These days could be identified because the closing price was the only data reported. It is essential for our study to exclude these data which are not the result of investor transactions and artificially increase proportion of zero returns.

3.2. Preliminary analysis

3.2.1. Descriptive statistics

Table 1 displays the descriptive statistics for the log of the CAC40 index on daily and monthly frequencies. The results of the descriptive analysis of the CAC40 index, over the period 2013-2015, on monthly frequencies suggest the symmetry of the French stock market. This symmetry is detected from the Kurtosis which is equal to (2.270393), and which is less than 3. The CAC40 follows a normal distribution, since the statistics of Jarque and Bera, which is equal to (4.210261), is less than the critical value of the Chi-square distribution with two degrees of freedom (5.991). In contrast, the daily data of the CAC40 index covering the period 2011 to 2015 are not normally distributed since the statistics of Jarque and Bera equals 57.56429.

Table 1. Descriptive statistics

Statistics / LCAC40	Mean	Median	St. Dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera
LCAC40 monthly data	7.186	7.137	0.286	6.669	7.762	0.1759	2.270	4.210
LCAC40 daily data	4.408	4.372	0.882	2.519	6.168	0.1312	1.953	57.564***

Notes: LCAC40 represents the natural logarithm of the CAC40 index. *** denotes 1% level of significance.

3.2.2. Stationarity tests

We verify the stationarity of the CAC40 index by the tests of Dickey-Fuller (1979-1981) in level and in first difference. For this, we use the sequential procedure to determine the optimal number of lags of this index on monthly and daily frequencies. Results reported in table 2 indicate that both series have a unit root since t-statistics are higher in level than the tabulated value of Mackinnon (1996). This unitary root disappeared after a single differencing. Hence, the CAC40 index on monthly and daily frequencies is integrated of order 1. The unitary root for the CAC40 index on daily data is detected by the Dickey-Fuller test (1979) while the Dickey-Fuller-Augmented test (1981) is used to identify the existence of a unit root of the CAC40 index on monthly frequencies.

Table 2. Dickey-Fuller (1979-1981) test

Tests DF - ADF / LCAC40	Lags	t-statistic in level	Model	Critical values in level	t-Statistic in difference	Critical values in difference	Integration order
Daily data	2	-0.054	M1	-1.941	-37.916***	-1.941	I (1)
Monthly data	1	-1.977	M2	-2.881	-8.178***	-2.881	I (1)

*** denotes 1% level of significance.

The large size of our sample might generate a problem of heterogeneity. The existence of a problem of heteroskedasticity and autocorrelation can lead to a weakness of the Dickey-Fuller test (1979-1981) in the detection of the unit roots in level of the CAC40 index for both frequencies. In order to overcome the deficiency of this stationarity test, we use the Phillips and Perron test which takes into account the existence of autocorrelation and heteroskedasticity problems in time series. The results of the Phillips and Perron test reported in table 3 confirm the existence of a unit root for each series of CAC40, and the use of the difference remains necessary in order to stabilize the first and second moments for each series of CAC40.

Table 3. Phillips and Perron test (1988)

PP test / LCAC40	Lags	t-statistic in level	Model	Critical values in level	t-statistic in difference	Critical values in difference	Integration order
Monthly data	3	-1.955	M2	-2.880	-10.329***	-2.881	I (1)
Daily data	3	-0.016	M1	1.941	38.134***	-1.941	I (1)

*** denotes 1% level of significance.

3.2.3. ARIMA modeling

The estimation of ARIMA models assumes that the series are stationary. This means that both the mean and the variance of the series are constant over time. The proper method for eliminating any trend is to differentiate, that is, to replace the original series by the series of first differences. A time series that needs to be differenced to reach stationarity is considered as integrated process. The correction of non-stationarity of the variance can be achieved by logarithmic transformations. These transformations must be carried out before differencing. After the differencing step to stabilize CAC40 series, we apply an autoregressive model of order 1 (AR(1)) to monthly data and an ARIMA model (1 ; 1 ; 1) to daily data. Table 4 shows that the CAC40 index is volatile, whether on monthly or daily frequencies.

Table 4. ARIMA modeling

ARIMA / ΔLCAC40	ARIMA	Constant	AR	MA
Monthly data	(1 ; 1 ; 0)	0.004 (0.728)	0.164^{**} (2.0364)	
Daily data	(1 ; 1 ; 1)	6.64×10^{5} (0.1703)	0.299 (1.328)	-0.408^{*} (-1.888)

Notes: Numbers in parentheses are t-statistics. ** and * denote 5% and 10% level of significance, respectively.

The following figures illustrate the volatility of the CAC40 index. As can be seen, volatility is well detected on daily data of the CAC40 index than on monthly data. This evidence is similar to what found by Aggrawal et al. (1999) for a sample of emerging markets.

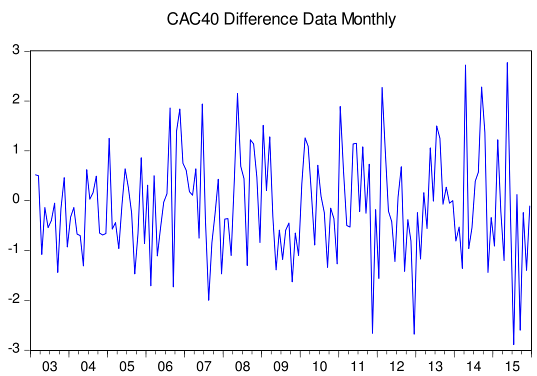

Figure 1. CAC40 monthly volatility

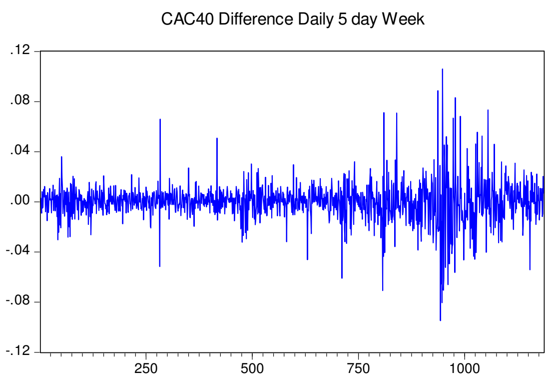

Figure 2. CAC40 daily volatility

3.2.4. Heteroskedasticity test

The instability of the variance of this index is essentially due to residual heteroskedasticity. In order to check the heterogeneity of this variance, we use the White test based on the likelihood ratio statistic or the Fisher statistic. The results of the heterogeneity test of the CAC40 variance on daily and monthly frequencies are reported in table 5.

We find that there is a problem of heteroskedasticity in the variance of the ΔCAC40 index. Since the variance of residuals is heteroskedastic, we can re-specify ΔCAC40 by linear or nonlinear ARCH models.

Table 5. The White test (1980)

Statistics of Likelihood ratio and Fisher / ∆LCAC40	Statistic LR n×R²	Statistic Fisher	Conclusion
Monthly data	11. 935*** (0.003)	6.348*** (0.002)	Heteroskedasticity problem
Daily data	946.259*** (0.000)	2350.307*** (0.000)	Heteroskedasticity problem

Notes: Numbers in parentheses are *p*-values. *** denotes 1% level of significance.

3.3. Volatility estimation

3.3.1. ARCH specification

Table 6 reports the results of the heteroskedasticity test of the variance of residuals for the CAC40 index on monthly and daily frequencies. Under the null hypothesis of homoscedasticity, the statistic nR^2 follows a Chi-squared distribution with q degrees of freedom, where n is the number of observations of the series $\hat{\varepsilon}_t^2$ and R^2 is the coefficient of determination associated with the estimation of the ARCH process. We notice from this table that the probability associated with the nR^2 statistic is very low. We therefore reject the null hypothesis of homoscedasticity and then we have heteroskedasticity of the error term. Hence, the autoregressive coefficients associated with the squared residuals are significantly different from zero. To account for this ARCH effect, our aim is to present and estimate the equation of the conditional variance associated with linear or nonlinear modeling in terms of variance. We use the maximum likelihood technique to estimate the parameters of the ARCH model of the CAC40 index.

Table 6. ARCH-LM test

Statistic LR / ∆LCAC40	Statistic LR n×R²	Constant	Residuals^2_{t-1}	Residuals^2_{t-4}
Monthly data	6.236*** (0.013)	0.003*** (4. 757)	0.203*** (2.534)	
Daily data	200.109*** (0.000)	9.77×10^{5}*** (4.371)	0.087*** (3.033)	0.182*** (6.341)

Notes: Numbers in parentheses for the statistic LR are *p*-values while those for other parameters are t-statistic. *** denotes 1% level of significance.

Table 7 shows that the coefficients of the parameters of both autoregressive conditional heteroskedastic (ARCH) processes are positive and significantly different from zero. The coefficients of these processes have validated the constraints of the positivity of the conditional variances. The ARCH (1) model is therefore the appropriate model for the representation of the conditional variances of the differential of the CAC40 index on monthly data while ARCH (6) is employed for daily frequencies.

Table 7: Estimating the linear ARCH model by the Maximum Likelihood technique.

ARCH / ΔLCAC40	Constant	$\hat{\varepsilon}^2_{t-1}$	$\hat{\varepsilon}^2_{t-6}$	Conclusion
Monthly data	0.003^{***} (7.940)	0.249^{***} (2. 3455)		ARCH (1)
Daily data	$5.16\times10^{5\ ***}$ (15.696)	0.062^{***} (4.595)	0.058^{***} (2.677)	ARCH (6)

*** denotes 1% level of significance.

3.3.2. GARCH models

The large size of the CAC40 index, on daily data, requires modeling it by a GARCH model in order to reduce the degree of freedom. As can be seen, the coefficients of the variance equation of the differential of the logarithm CAC40 are significant and positive. Consequently, the GARCH model (1,1) remains a proper model. Moreover, we notice that the sum of the coefficients ARCH (1) and GARCH (1) is very close to 1. This suggests a phenomenon of persistence in conditional variances which is frequently encountered for the CAC40 even if this index on daily data is modeled by GARCH (1; 2).

Table 8. Estimating the linear GARCH model by the Maximum Likelihood technique

GARCH / ΔLCAC40	Constant	$\hat{\varepsilon}^2_{t-1}$	h_{t-1}	Conclusion
Monthly data	0.001 (1.365)	0.163^{***} (2.705)	0.759^{***} 7.332	GARCH (1 ; 1)
Daily data	4.71×10^{6} *** (4.477)	0.0840^{***} (4.836)	1.258^{***} (7.964)	GARCH (1 ; 2)

*** denotes 1% level of significance.

3.3.3. Asymmetric GARCH models

Rejecting the quadratic specification of conditional variances and taking into account the asymmetry phenomenon, we therefore estimate the exponential GARCH (EGARCH) and the threshold GARCH (TGARCH) models.

Table 9. Estimating non-linear EGARCH model

EGARCH / ΔLCAC40	Constant	α	γ	β
Monthly data	-0.790* (-1.765)	0.085 (0.808)	-0.216*** (-3.476)	0.874*** (11.772)
Daily data	-0.367*** (-9.337)	0.119*** (8.350)	-0.163*** -12.753	0.968*** (247.670)

*** and * denote 1% and 10% levels of significance, respectively.

In Table 9, the coefficients α, γ and β of equations of the variances are the coefficients of the model EGARCH (1,1) described in the following form:

$$\ln(\sigma_t^2) = C + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\ln\sigma_{t-1}^2$$

Table 9 shows that all coefficients of the differential of the logarithm of the CAC40 index in the variance equation are significantly different from zero. There is thus a phenomenon of asymmetry which could not be detected by the ARCH linear modeling.

Table 10. Estimating non-linear TGARCH model

TGARCH / ΔLCAC40	Constant	α^-	α^+	β
Monthly data	0.001** (1.987)	-0.122* (-1.84)5	0.303*** (3.218)	0.803*** (8.330)
Daily data	4.54×10^6 *** (7.320)	-0.017** (-2.135)	0.193*** (11.169)	0.900*** (92.188)

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

The model TGARCH (1,1) estimated in Table 10 is written in the following form:

$$\sigma_t = C + \alpha_1^+\varepsilon_{t-1}^+ - \alpha_1^-\varepsilon_{t-1}^- + \beta\sigma_{t-1}$$

Table 10 shows that the coefficients of the mean are significantly different from zero for the differential of the logarithm of the CAC40. The coefficients associated with α_1^+ and α_1^- are different, indicating the presence of a phenomenon of asymmetry. Moreover, the change between the two regimes is significant, which suggests the existence of a slowly damping volatility problem (smooth change). However, we cannot use the QGARCH model (Quadratic GARCH) and we cannot assume quadratic nonlinearity because nonlinear volatility disappeared completely and there will be a risk of returning to linear ARCH models. Consequently, there is not a sudden change between the regimes and the nonlinearity cannot take a quadratic form. So, which model should we retain for modeling conditional volatility?

3.3.4. Performance of models

Given the existence of an asymmetry phenomenon, we assume that the most appropriate models are the EGARCH and TGARCH processes. The choice between these two processes can be made on the basis of comparison criteria. For information, we also report the values of the criteria for ARCH (1) and GARCH (1,1) models. These values are given in Table 11.

Table 11. Model comparison criteria

	ΔLCAC40 monthly data			
	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
R-squared	0.021	0.020	0.025	0.026
Log Likelihood	213.852	218.176	223.041	222.968
Akaike info criterion	-2.761	-2.805	-2.856	-2.855
Schwarz criterion	-2.682	-2.706	-2.736	-2.736
	ΔLCAC40 daily data			
	ARCH (6)	GARCH (1,2)	EGARCH (1,1)	TGARCH (1,1)
R-squared	0.005	0.007	0.009	0.009
Log Likelihood	3465.074	3462.515	3507.050	3499.825
Akaike info. criterion	-5.838	-5.839	-5.914	-5.902
Schwarz criterion	-5.799	-5.813	-5.888	-5.876

We rely on the Akaike info criterion (AIC) to define the most appropriate model for each series in order to capture the volatility phenomenon. The comparison of the selection criteria for the different models leads to select the process EGARCH (1,1) for both monthly and daily frequencies.

4. Conclusion

In this paper, we attempted to assess the volatility of the Paris stock exchange through the CAC40 index. Our preliminary analysis revealed that our data exhibit heteroskedastic aspect accompanied by important fluctuations whatever we focus on daily or monthly frequencies. We modeled the CAC40 index by an ARIMA model and we detected the volatility of this index by linear and nonlinear ARCH models. We documented that there is an asymmetric volatility phenomenon in the French stock market. Thus, we verified the volatility of the CAC40 index by the GARCH model and we found that the coefficients of volatility are significant at a 1% level. We also checked the non-linear of the CAC40 volatility and distinguished the good news and the bad news entering in the French stock market by the EGARCH model. We also detected the presence of a non-linear regime change in the volatility of the CAC40 index through the TGARCH model. The comparison of the performance of models revealed that the EGARCH model outperforms the others for both daily and monthly data.

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