Assessment of the volatility of the Moroccan stock market

Abstract

There are certainly distinct allocation strategies depending on the assumed dynamics of risky asset prices. There was no clear pattern of structural increase in volatility on the Moroccan equity market, except for the appearance of significant instantaneous peaks. It is the consequence, more than the cause, of the instability of the Moroccan stock market. The development of arbitrage between investment instruments increases overall liquidity thus reducing volatility.

Keywords: volatility, GARCH, return, MASI index, empirical volatility

Introduction

In the Moroccan stock market, which is illiquid, it happens that the frequency of quotations decreases and therefore the stock prices remain unchanged over a certain period. In this case, low volatility should not be interpreted as a low market risk, but as a high liquidity risk. It is therefore clear that the analysis of volatility alone does not prove a complete control over the market risk suffered by the financial players. Volatility is an approximate and biased indicator of risk, whether it is an empirical volatility calculated from past prices (historical volatility) or an implied volatility estimated from the evolution of stock prices.

Market volatility also depends on practical implementation and institutional investor attitudes towards portfolio diversification, namely the holding of a variety of assets whose returns are not closely correlated with each other. For example, by choosing fixed asset allocations at regular intervals, these investors help stabilize securities prices as they tend to reduce (increase) their asset portfolios that have allocations at regular intervals, these investors help stabilize securities prices as they tend to reduce (increase) their asset portfolios that have recently depreciated (appreciated) considerably (Figure 1).

Figure 1 Evolution of the Liquidity Ratio and the volatility of MASI 2004-2014

In addition, institutional investors could theoretically influence markets by moving asset prices away from fundamentals, exacerbating price movements and therefore volatility. This view is based on the size of institutional holdings relative to individual investors (Scharfstein and Stein) and (Bikhchandani and Sharma (2000)).

The high price volatility is, therefore, due to this illiquidity, and not to a change in the fundamental value of the shares. In other words, the liquidity factor can be fundamental in interpreting volatility.

Financial series generally present several aspects that characterize the stochastic process associated with stock prices.

Exploratory analysis of the data

The time series data used to model the volatility of the Casablanca Stock Exchange is the daily closing price of the MASI Index. The daily profitability of MASI was calculated from its performance series which is the first difference in logarithm of the closing price of the index of two successive days:

\[ r_t = \log \left( \frac{I_t}{I_{t-1}} \right) \]

Where \( I_{t-1} \) and \( I_t \), and are, respectively, the closing index of the MASI of the current day and the previous day.

Before using the MASI Index series and its performance series, one must explore the characteristics that condition the validity and reliability of their interpretations.

The stochastic processes associated with asset prices are generally non-stationary in the sense of second-order stationarity, while the processes associated with returns are consistent with the second-order stationarity property. This characteristic is the central property of ARCH processes; they possess the properties of a homoscedastic white noise (Figure 2), but their conditional variance depends on time.

Clusters\(^1\) Volatility: It is empirically observed that large changes in yields are generally followed by small variations. There is thus a grouping of cluster extremes or volatility packages. Under these conditions, the process is conditionally heteroscedastic.

Stationarity study of the Rendement-MASI series

Unit root test (Unit Root Test) can detect the existence of non-
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stationarity and determine its type (TS or DS process) and are considered the best indication for stationarizing a series (Figure 3).

Figure 2 Evolution of the series of MASI returns between 2004 and 2014.

We reject because -12.59 <-2.87 and we accept because -1.13 <2.53

Figure 3 Augmented test Dickey -Fuller for the RMASI series.

The idea of a unit root test (Dickey Fuller) is to estimate the regression $t_t = \phi \cdot t_{t-1} + a_t$ and then $H_0: \phi = 1$ test using the Student’s statistic.

If we note $H_0$ the null hypothesis of non-stationarity, then: $H_0: \phi = 1$ rejects $H_0$ if ADF ADF <t-statistic t-statistic tabulated.

The hypothesis of the non-stationary of the series of returns of the MASI index is rejected. The RMASI series is stationary and is therefore predictable.

In summary, the MASI series checks all the properties of the financial series. We can move to ARMA modeling of the RMASI yield series. Similarly, volatility evolves over time, suggesting that an ARCH process could be adapted to modeling the RMASI series.

Estimation of volatility by ARCH models

Previous Exploratory Analysis Rationale for Using Family Models ARCH to estimate volatility. Nevertheless, one can make sure of this justification by using the ARCH test applied to the residuals.

The definition of an ARCH process involves the notion of conditional variance. We have seen that the conditional variance makes it possible to model the local variance of the process at each instant $t$, according to previous observations.

This notion can be extended at any time in the time series. Thus, the conditional expectation of the process $\{X_t\}$ at time $t$ is the expected mean value of the process at time $t$ calculated taking into account the values of the process observed in the past. To illustrate this concept, consider the random walk (Table 1).

Table 1 Heteroskedasticity Test ARCH

| Variable | Coefficient | Std. error | t-Statistic | Prob. |
|----------|-------------|------------|------------|-------|
| C        | -116030.3   | 26204.88   | 4.427812   | 0     |
| RESID^2   | 0.226483    | 0.086091   | 2.630743   | 0.0096|

We reject $H_0$ because -12.59 <-2.87 and we accept $H_0$ because -1.13 <2.53

Author Calculations

$p = 0.0098$ which we reject the null hypothesis (There is no ARCH effect) and we accept the alternative hypothesis. Volatility can be estimated by the ARCH model.

We will develop an ARCH, GARCH, EGARCH and PGARCH modeling. Then we will compare these models to retain the most appropriate data used. The decision rule used will be the AIC and SIC criteria (lowest).

This family of models is widely used in both practice and academic discourse. The model is very useful for modeling the behavior of the conditional variance of the random term of an econometric equation over time and for capturing the effect of volatility on stock prices. This model captures the dynamic characteristics of volatility according to the equation (Table 2):

$$\sigma_t^2 = \gamma_0 + \alpha^2 \cdot \sigma_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$$

Table 2 Appropriate model choice

| Estimated model | Akaike info criterion & Schwarz |
|-----------------|---------------------------------|
| ARCH 5 GARCH 0  | AIC 14.65 SIC 14.80             |
| GARCH (1,1)     | AIC 14.69 SIC 14.77             |
| TARCH or GJR-GARCH | AIC 14.70 SIC 14.81         |
| PGARCH          | AIC 14.67 SIC 14.81             |

Author Calculations

After estimating all these models and testing for heteroscedasticity and the autocorrelation of the residuals we retain the PGARCH.

There is a growing volatility of the MASI index which becomes significant from 2007, while yields of the index turned negative. This situation obviously diverts institutional investors from equity investments (Table 3).

Table 3

| Variable | Coefficient | Std. error | z-Statistic | Prob. |
|----------|-------------|------------|------------|-------|
| C        | -55.24304   | 15.31553   | 3.607035   | 0.0003|
| R- squared | -0.01756    | Mean dependent var | 0.0003      |
| Adjusted R- squared | -0.01756 | SD dependent var | 387.6786    |

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Dependent variable: MASI DTC

Method: ML ARCH - Normal Distribution (BFGS / Marquardt steps)

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The volatility of the Casablanca Stock Exchange remains low in comparison with other stock markets of emerging countries or similar economies. Indeed, it was around 12% on average of ten years, while it exceeded 29% in Turkey and 16% in South Africa.

The fall in stock prices since the crisis therefore accentuates the decorrelation between prices and fundamentals, which is reflected in the evolution of the MASI index and the PERs of listed companies. Gains posted on the tailings correlogramme (in annexes) show I I ny no car horn relationship between residues. This result improves the validity of the estimated PGARCH model.

Note that P = 0.4628 <5%, so we can conclude that there is no ARCH effect in the residuals of the estimated PGARCH model.

Indeed, the AR (1) process is a Gaussian process: the tails of distribution are less thick than the tails observed on the variance of the MASI index and we do not observe a period of high volatility. ARCH models (simulated below) allow them to better take into account this kind of behavior (Table 4).

Table 4 Heteroscedasticity of residues

| Heteroscedasticity test: ARCH |
|-------------------------------|
| F- statistic                  | 0.533046 |
| Prob. F (1,128)               | 0.4667   |
| Obs * R- squared              | 0.53913  |
| Prob. Chi-Square (1)          | 0.4628   |
| Variable                      |          |
| Coefficient                   |          |
| Std. error                    |          |
| t- Statistic                  |          |
| Prob.                         |          |
| C                             | 0.940641 |
| 0.157115                      |
| 5.986945                      |
| 0                             |
| WGT_RESID ^ 2 (-1)            | 0.064371 |
| 0.088167                      |
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