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Switching regime in investors' risk perception

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Abstract: Financial assets' risk is considered as heteroskedastic, and is generally modelled with GARCH models. However, this risk is perceived in the same manner, only external events change, such as returns and historical risk. The way these events are treated by investors, is assumed static. Some scholars explain that risk perception is subject to structural breaks, which are not taken under consideration in GARCH models. For this reason, this paper aims to develop the switching regime GARCH model SWGARCH. Results clearly show that the SWGARCH can capture the risk dynamics of the studied indexes better than classical models.

Keywords: Switching Regime, GARCH, Risk Perception, Index

1. Introduction

Financial instability is, undeniably, the most prominent effect in the global economy. Consequently, forecasting volatility has become a leading subject for financial analysts, since many countries were victims of this financial perturbation, mainly due to structural changes, e.g., financial crisis, market fluctuation … etc. Hence, scholars have grown a real interest in analyzing and modeling the financial risk, especially to be able to provide good forecasts.

Since then, volatility has become an important concept in financial markets; it is a crucial element in financial decisions, especially when knowing that acting agents in financial markets react according to this measure. Indeed, a high volatility is a sign of market turbulences, which indicates a pessimistic behavior and lack of confidence in investors' actions. In contrary, a low volatility imply that the investors act confidently and are optimistic. Financial market movements are sensitive to good or bad news; consequently, prices move down in presence of bad news, which are the cause of high volatility.

Modeling the volatility of the stock market occupies a very important place for researchers, because the stock market is influenced by many changes in the global financial and economic systems. Therefore, during the last decades, the market is not stable and the risk dominates. Investors seek to understand the risk to minimize it. Hence, it is important to study and tend to have specific measures to this uncertainty. Risk measures are different, but the most used is the volatility. The volatility is not constant but its variation is a function of other factors namely the time factor, the type and interpretation of information... etc. For this reason, we focus in this research to study the perception of risk in the stock market in the case of regime change. Indeed, Abdymomunov [1] argues that volatility is subject to two regimes: normal and high, where the period of high volatility is very close to financial crises.

ARCH models [2] and GARCH models [3] are an extension to the linear model when the conditional variance of the error term changes over time. They have the advantage that they take into account the heteroskedasticity of the volatility and fat tails that characterize most financial series. However, they have a major drawback, that they do not explain a large excess kurtosis and more specifically those where the error follows a normal distribution. In addition, rare events cause and without discussion an excess kurtosis in the data, that justifies the presence of a non-normal situation for these data. Data asymmetry has become another important criterion besides the excess kurtosis in the studied data. Moreover, the persistence of volatility in GARCH models is the result of structural changes and investors' risk perception [4].

Through this work, we use GARCH models to analyze the perception of risk in the stock market in case of regime change, and in which we try to answer the following question: "Do investors in financial market perceive risk in the same way after a regime change?" The remainder of this paper is organized as follow: Section 2 presents a review of the literature, Section 3 discusses the model and methodology, Section 4 presents the main results, and finally we conclude in Section 5.

2. Review of the Literature

Modeling time series is a process consisting of iterative steps. It is interesting to check the stationarity of the time series as a fundamental step. Scholars have devoted numerous studies to analyze and predict the volatility; for this reason, they have made the use of GARCH models, which have become popular as a mean to risk measure and volatility forecasting.

GARCH models are used in many areas of finance including foreign exchange rates, interest rates, inflations rates, commodity prices, equity indices. The GARCH process is a predominant technique used to analyze the change in the volatility of financial and security markets. The financial market is designing a direct funding circuit, in addition to its primary market activity; it is responsible for the production of secondary market financial assets and transformation of industrial structures.

Beyond that, the operation of the financial market is based on the activity of two compartments whose functions are different and complementary: the primary market and the stock market or secondary market. As the primary market, the exchange can transform household savings in long-term resources for the public and private communities. This fundraiser can be estimated through the evolution of securities issued and the part they play in the volume of investments. As a secondary market, the financial market guarantees the liquidity and change in savings.

Therefore, in this research we present some previous work that are interested in modeling the volatility as a fundamental characteristic of the return of financial assets. Thus, we can distinguish the main factors that have an impact on this modeling. We can distinguish the contribution of these events in the estimation of data using the standard GARCH and GARCH models with regime change, knowing that this estimate plays an essential role in decision-making.

ARCH model is due to its founder Engle [2], it is an appropriate solution to describe the history of the conditional variance with the rejection of constant volatility hypothesis, such as ARMA model. The idea of Engle is that the actual conditional variance depends on the square of past chocks. Bollerslev [3] proposed an extension, which is the conditionally heteroskedastic generalized autoregressive GARCH model; this model came as a solution to the problem of high order of the ARCH model. Therefore, the GARCH model offers fewer parameters to estimate than the ARCH model, it expresses the conditional variance as a function of the square innovations delayed and conditional past variance.

GARCH models are able to capture certain characteristics of financial time series including the presence of heteroskedasticity, return asymmetry, flattening and instability of the second conditional moment, and volatility clustering: periods of high volatility are followed by periods of high volatility. These properties represent basis drawbacks in ARMA modeling.

Switching regime GARCH model is developed by Marcucci [5]. The idea behind this model lies in the structure of the conditional variance. The estimated GARCH model with switching regime is effective in explaining volatility persistence. For this reason, Marcucci [5] estimated the conditional distribution of the S&P 100's return. Coefficients are different for each regime. The estimated GARCH model with regime change requires a special algorithm for solving the maximum likelihood optimization.

We can conclude that volatility is a fundamental characteristic of financial markets. It explains the psychological aspect of the market; investors' decisions are based on this concept. Anderson and Bollerslev [6] showed that the use of the return squared gives good results. However, GARCH models and their extensions are unable to consider structural breaks such as the case of a crisis. It gives false estimates and leads to wrong decisions. It is clear that with the switching regime GARCH cures the drawback described by standard GARCH models. This new model explains in a clear manner the phenomenon of persistence, and minimizes its effect.

The literature focusing on regime change in volatility has been recently developed. It is divided into two branches; (i) some authors suggest that the risk evolves according to several regimes, but is constant in each regime [7, 8]; (ii) others suggest that the volatility is heteroskedastic in several regimes [5, 9, 10].

3. Methodology

3.1. GARCH (1, 1) Model

In this research, we begin by estimating the GARCH (1,1) standard model. This model is made of two equations as described in the previous part of this paper. However, we are interested in modeling the volatility so we will limit ourselves to the second equation and we assume that our dependent variable is random. This is why we encourage the use of a model that does not contain the average return [6].

The model is represented as follow:

$$\begin{cases} r_t = \varepsilon_t \\ \varepsilon_t = \sigma_t z_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{cases} \tag{1}$$

Where z_t is an independently and identically distributed variable.

r_t denotes the endogenous variable, which is the return of the market index. Given that the variance is a positive operator, the positivity condition of this operator is imposed on the coefficients of the variance equation. α_0 must be strictly greater than zero, α_1 and β_1 must be greater than or equal to zero. For the unconditional variance to exist and be defined, it requires that the sum $\alpha_1 + \beta_1$ is strictly less than 1 [11]. This sum measures the volatility persistence in time, the more the sum approaches one, the higher the persistence of the volatility; and the more it approaches zero, the more the volatility converges rapidly and therefore no sign of fear for the investor. In practice, the persistence condition is usually violated, especially for daily data. Some authors propose a solution and they explain that this persistence is due to the presence of structural change that the GARCH model does not take into consideration. Consequently, the GARCH model with switching regime allows to clearly explaining the phenomenon of persistence and can distinguish two states of the volatility of the same sample.

3.2. Switching Regime GARCH (1,1) Model

We choose to estimate a model with switching regime where changes are occasional, since we are interested in modeling the volatility in case of random or extreme events, such as the case of financial crisis. These events are probabilistic but they have a very significant impact on data analysis. Therefore, it seems interesting to implement a model that meets both events, and which models the variance in the time variable, the switching regime GARCH model. The parameters of this model are based on a Markov chain to better describe extreme events.

We are therefore faced with two equations of the conditional variance. A first one is for the first regime, and a second one for the second regime; and each can be interpreted separately. The structural form of the conditional heteroskedastic variance is more efficient than the fixed form. A fixed form leads to erroneous results and is difficult to interpret in case we are dealing with an explosive process. In a structure that is not fixed, the coefficients of the model are different in each regime, to reflect the status of the dependent studied variable during the sample period. The model that we are interested in estimating has the following form:

$$\begin{cases} r_t = \sigma_t z_t \\ \sigma_t^2 = \alpha_{0,s_j} + \alpha_{1,s_j} r_{t-1}^2 + \beta_{1,s_j} \sigma_{t-1}^2 \end{cases} \quad (2)$$

Where s_j is the unobserved state variable for regime "j".

In Eq. (2), the coefficients of variance equation are not constant, they are a function of a state parameter s_j. Empirically, we analyze this equation in two ways. For the variance to exist and be defined, it is necessary that $\alpha_{0,s_j} > 0$, $\alpha_{1,s_j} \geq 0$, and $\beta_{1,s_j} \geq 0$ the existence of the second order moment is examined for each regime.

3. Data and Results

In this study, we focus on the modeling the volatility of the returns of the S&P 500, Nikkei 225 and CAC 40. We choose these indices due to their explanatory power of the financial markets, as they represent the largest companies in the United States, Japan and France; and this leads us to virtually visit and analyze these markets given that they are more dynamic compared to other markets. The data are daily returns collected from www.yahoo.finance. Returns are calculated based on daily closing prices for the period starting from January 3, 2006 to December 30, 2012. The choice of this period is justified by the presence of rare events.

4.1. Descriptive Statistics

We will begin by presenting some descriptive statistics of the series. Descriptive statistics are necessary to distinguish the characteristics of our data. The statistics are presented in Table 1.

Table 1. *Descriptive statistics*

Return	S&P 500	Nikkei 225	CAC 40
Mean	6.82E-05	-0.00029	-0.00015
Standard deviation	0.014743	0.016749	0.016228
Variance	0.000217	0.000281	0.000263
Kurtosis	8.670894	8.6714	5.655952
Skewness	-0.28534	-0.52503	0.094254
Minimum	-0.0947	-0.12111	-0.09472
Maximum	0.109572	0.132346	0.105946
Number of observation	1755	1712	1787

We observe that the asymmetry coefficients are different from zero, so the data distributions are asymmetric. We note that the skewness is negative for the American and Japanese market; *i.e.*, a drop in prices is more likely than an increase. In addition, it is positive for the French market, *i.e.*, a rise in prices is more likely than a decrease. Kurtoses are greater than 3, the distributions are leptokurtic, or with thicker than normal tails.

4.2. Results with a Single Regime

First, we try to distinguish the significance of the parameters in case where the error term follows a normal and a Student distribution, respectively. Next, we analyze the stationarity condition of the volatility based on these parameters. Bollerslev [12] supports the use of the Student distribution than the normal distribution.

Table 2. *Results with a single regime under the Normal distribution*

Coefficients	S&P 500	Nikkei 225	CAC 40
α_0	1.9989E-6 (5.8325) *	6.5681E-6 (4.0866)*	3.3345E-6 (4.1472)*
α_1	0.9669 (9.5157)*	0.12535 (10.4636)*	0.1099 (9.7725)*
β_1	0.89204 (80.5195)*	0.84809 (51.3779)*	0.88006 (71.3944)*
Maximum likelihood	5415.97	4897.85	5127.71
Schwartz criterion	-10809.5	-9773.35	-10233

* Significant at 5% level.

All coefficients α_0, α_1 and β_1 are statistically significant at 5% level.

Table 3. *Results with a single regime under the Student distribution*

Coefficients	S&P 500	Nikkei 225	CAC 40
α_0	1.1991E-6 (2.3933)*	5.0499E-6 (3.1026)*	2.925E-6 (2.6705)*
α_1	0.098076 (6.2016)*	0.10058 (6.3555)*	0.098418 (6.4891)*
β_1	0.90192 (63.9080)*	0.87769 (43.8609)*	0.89228 (56.2414)*
Degree of freedom	5.4744 (6.2994)*	13.86 (3.4849)*	9.0118 (5.2901)*
Maximum likelihood	5455.47	4905.37	5147.62
Schwartz criterion	-10881.1	-9780.97	-10265.3

* Significant at 5% level.

For the model using a single regime with Student *t* distribution, we observe that all the coefficients α_0, α_1 and β_1 are statistically significant at 5% level. We also note that the degree of freedom is statistically significant. In Table 3, the Schwartz criterion shows that the t distribution is the most effective.

4.3. Results with Switching Regime

The algorithm used in the numerical estimation is based on a direct method. In addition to the coefficients of each regime, we also estimate the transition matrix containing the probability of transition from regime 1 to the regime 2 (P1), and the transition from regime 2 to regime 1 (P2).

Table 4. *Results with switching regime under the normal distribution*

Normal distribution	Coefficients	S&P 500	Nikkei 225	CAC 40
Regime 1	α_0	1.0547E-06 (2.3718)*	8.1885E-05 (0.8402)	4.6093E-05 (0.6451)
	α_1	0.10052 (8.7139)*	0.41503 (2.7440)*	0.11728 (1.3017)
	β_1	0.89948 (75.6987)*	0.58497 (2.5745)*	0.88272 (5.7605)*
	Expected duration (days)	187.24	9.15	6.63
Regime 2	α_0	5.621E-05 (0.7047)	2.1378E-06 (2.6082)*	1.6368E-06 (2.4402)*
	α_1	0 (0.0000)	0.041976 (3.8945)*	0.062713 (4.5974)*
	β_1	0 (0.0000)	0.93778 (69.4074)*	0.92042 (65.6152)*
	Expected duration (days)	36.11	85.98	86.96
Transition matrix	P_1 (regime 1 to 2)	0.9947 (36.36)*	0.8908 (8.327)*	0.8491 (6.514)*
	P_2 (regime 2 to 1)	0.9723 (23.99)*	0.9884 (35.58)*	0.9885 (37.83)*
Maximum likelihood		5426.52	4915.85	5144.37
Schwartz criterion		-10778.3	-9757.25	-10213.8

* Significant at 5% level.

From Table 4 we see that the coefficients of the GARCH (1,1) are statistically significant at the 5% level. We also note that all probabilities are significant, which confirms the hypothesis of regime change, and hence the change of the risk perception of investors.

Table 5. *Results with switching regime under the Student distribution*

Student *t* distribution	Coefficients	S&P 500	Nikkei 225	CAC 40
Regime 1	α_0	3.0213e-06 (1.6967)**	0.00018037 (0.8801)	2.5162e-06 (1.8773)*
	α_1	0.088936 (4.2406)*	0.4808 (1.2782)	0.1024 (5.2513)*
	β_1	0.90637 (37.7805)*	7.8166e-21 (0.0000)	0.8976 (54.4419)*
	Degree of freedom	11.456 (1.8533)**	5.2104 (0.5188)	150.42 (607130.8647)*
	Expected duration (days)	77.8	21.9	3.42
Regime 2	α_0	1.5329e-06 (1.5321)	3.2903e-06 (2.5301)*	3.7338e-05 (0.3629)
	α_1	0.037365 (1.2128)	0.085058 (6.2975)*	0.18889 (0.4018)
	β_1	0.93743 (32.2816)*	0.89891 (54.1746)*	0.73768 (2.4757)*
	Degree of freedom	3.1057 (4.8994)*	25.365 (17.9554)*	2.2513 (3.0166)*
	Expected duration (days)	48.09	434.81	1.00

Student *t* distribution	**Coefficients**	**S&P 500**	**Nikkei 225**	**CAC 40**
Transition matrix	P_1 (regime 1 to 2)	0.9871 (32.91)*	0.9543 (7.171)*	0.7074 (5.977)*
	P_2 (regime 2 to 1)	0.9792 (27.16)*	0.9977 (39.23)*	0.0000 (0.00)
Maximum likelihood		5463.79	4913.03	5156.76
Schwartz criterion		-10837.9	-9736.71	-10223.7

* Significant at 5% level.
** Significant at 10% level.

From Table 5, we note that all probabilities are significant, which confirms the hypothesis of regime change, and hence the change of the risk perception of investors.

For switching regime models, they perform better than single regime models (based on the maximum likelihood). Moreover, they can explain the volatility better than the model without regime change.

4. Conclusion

The study of the returns of the stock indices S&P 500, Nikkei 225 and CAC 40 over the years 2006 to 2012 shows that their behavior is nonlinear. It is clear that during this period there is a variability of returns described empirically by the existence of periods of high and low volatility. With the presence of extreme events, the model that most describe and predict the volatility is the GARCH model.

It is clear that the volatility describes the behavior of the market in which agents' decisions are produced. For this reason, several authors discuss this problem and verify that these models are unable to support for such a random change that undergoes the data. We showed in our study that switching regime GARCH model could better describe the returns of S&P 500, Nikkei 225 and CAC 40. It takes into consideration of such probabilistic change. This change is unobservable, but has a huge fluctuation. The switching regime GARCH model is able to consider this event and distinguishes between two regimes, the first with high risk, and the second with lower risk. Therefore, the perception of investors towards risk is changing.

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