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ASYMMETRIC INFORMATION AND SHOCK AS PORTFOLIO SELECTION CRITERIA: CASE OF THE DJIM 50 US PORTFOLIO

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Abstract:
Volatility is an important variable in portfolio management. Generally, it is the level of risk in the market. The purpose of this article is to measure the impact of good and bad news on the evolution and risk associated with these securities in the financial market. To do so, we proceeded to use the EGARCH model (generalized autoregressive heteroskedasticity condition model), the data used in this study correspond to the portfolio Dow Jones Islamic Market 50 US. The results show that good and bad news has different impacts on assets.

Keywords: modeling, ARCH, GARCH, EGARCH, news impact curve, innovations

1. Background of the Study

Volatility is a main variable that characterize most financial instruments and plays a central role in many areas of finance. From an empirical point of view, it is important to carefully model any variation in the volatility process. Depending on the leverage effect, a reduction in the value of the shares would increase the debt ratio, thus increasing the risk of the company, as evidenced by the increase in future volatility. As a result, future volatility will be negatively related to the current share price performance.

In this paper, volatility will be estimated to mirror the insight that good and bad news affect the market in a different way, and that news in a bull market is different from that in a bear market. This article quantifies the asymmetric impact of good and bad news on the stock market, specifically the asymmetric response to news in a Bear and Bull market situation. In the case of a purchase strategy, investors only benefit from the up-value of assets while the down value of assets is useless and vice versa, our goal is to

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measure the impact of the good and bad news for the 50 stocks that make up the Dow Jones Islamic Market Titans 50 US portfolio. The distinction between asset characteristics as well as the dominant regime (bull or bear) for each asset can be a raw material for leading a portfolio management strategy that takes into account the effect of information asymmetry and the impact of shocks on the evolution of assets. After a brief introduction, the second section will deal with literature review. The third section will contain the methodology, data and a presentation of the model for our analysis. Then the fourth section will contain the results and interpretations for our management model. Finally, the last section will be devoted to the conclusion.

2. Literature Review

Volatility is a latent variable derived from the returns of the securities or deducted from the market prices of derivative instruments. In well-developed equity markets that operate "normally", the volatility of the equities may serve as a forecaster of future fluctuations. These measures give the statistical difference (these differences are also weighted) to the extent to which returns deviate daily from their average over a given period. Generally, stock market returns are heavy and prone to outliers are basic knowledge of finance Poon and Granger (2003); Clements and Hendry (2008). However, a chart of market returns shows that volatility is not constant. There are periods of serenity in markets where volatility seems constant. Similarly, there are times when markets are turbulent and volatility can rise and remain at a level for a long time on what the markets call volatility clustering. Thus, the use of historical estimates to capture these regimes will underestimate the volatility of ex-ante decisions, regardless if it is the pricing of the multitude of financial instruments, stock selection decisions or calculation of risk measures in modern risk management. On the other hand, the implied volatility derived from the trading of derivative contracts on inventories using a model. One of these models is the Black-Scholes for call and put options Black & Scholes (1973). When such data is available, derivative volatility reflects current market sentiment and expectations. Implied volatility is generally not flat, because it reflects buying and selling decisions of market participants, which can be influenced by a variety of factors. We know that market players have difficulty deciphering the true meaning of these factors in most cases. Indeed, Jorion (1995) found ample evidence that implicit volatility derived from models can have significant bias. Fleming (1998) also documents biases in the estimation of implied volatility in the price volatility forecasts of the S&P index options. Fleming (1998) also, documents biases in the estimation of implied volatility in the price volatility forecasts of derivatives of S&P index. However, other researchers have criticized implicit volatility as model-dependent, Choi and Wohar (1992); Britten-Jones and Neuberger (2000); Christensen and Hansen (2002).

There are therefore potential problems with using implied volatility to make ex-ante investment decisions. Historical volatility and implied volatility may therefore not work properly when markets are nervous. In calm market conditions, both will likely lead to the same result. But in a situation where markets are disrupted, historical volatility is likely to underestimate the actual level of volatility, while implied volatility is more than likely to overestimate the pace of the market. The presence of significant noise inevitably confuses real signals related to the actual behavior of asset prices Black (1986). Price declines can lead to alternating wild volatility between much higher and lower levels. For example, geopolitical developments may lead to greater volatility in the short run than in the long run. Underestimating this short-term volatility in equity markets may result in undervaluation of risks, which may result in positions that have significant consequences for the investor, De Goede (2001); MacKenzie (2003); Carmassi et al. (2009).

In general, this period of heightened volatility is reflected in a series of clusters on the time series plot of returns. Such behavior is best modeled using the autoregressive conditional heteroscedasticity (GARCH) proposed by Engle (1982) and generalized by Bollerslev (1986). Alexander (2008) argues that GARCH models provide short and medium-term volatility forecasts based on econometric models that are "correctly" specified. The GARCH model is interested in the evolution of "standard deviation". Unlike historical and implied volatility, the GARCH model doesn't assume that returns are independent and distributed identically. This essential feature is at the heart of the time-varying volatility that the GARCH model seeks to capture. It is observed empirically that significant negative returns tend to increase volatility relative to positive returns of the same magnitude. The ARCH model and its various extensions have proved very effective tools in this direction.

The stock market is driven by the news (information). Good news, in a good day, lead the market to the rise. The bad news, in a good day, restrains growth. The effect is not symmetrical. Good news has less influence on the market than bad news. This phenomenon has a plausible economic explanation. This is the leverage effect suggested by Black (1976) and further elaborated by Christie (1982). The GARCH linear model (p, q) is not able to capture this type of dynamic model since the conditional variance is only related to past conditional variances and squared innovations. So, the sign of returns plays no role in volatility. This limitation of the standard ARCH formulation is one of the main motivations of the EGARCH model developed by Nelson (1991), while the latter model detects the effect of information on the evolution of the financial markets, several studies have largely underestimated the impact of good and bad news on volatility and price evolution Ewing, Ewing & Malik (2017) The empirical results of their work suggest that it is preferable to include both asymmetric effects and structural breaks in a model in order to accurately estimate the dynamics of price volatility. Also, the work of Korkpoe end al. (2018) explains that in the emerging markets deprived of information, investors may be surprised by the news, the reaction of the market to positive news has only a small effect on market volatility.

Investors are concerned about the brutal reactions to the negative news that characterizes the data. The market will attract uninformed traders at this stage of its

development. These traders are probably generating what will appear to be a high reaction to the news as they try to reduce their losses at the first signs of trouble.
Veronesi (1999) and DeLong et al. (1988) have documented this phenomenon extensively in their studies. Investors may be forced to protect themselves from this "noise" in the market, as this could hurt their previous earnings. While the work of Korkpoe and al. (2018) on the Johannesburg Stock Exchange has incorporated the explicit impact of the information in the analysis of the variable volatility of returns.

3. Material and Methods

The data used originated from the financial market, they correspond to Dow Jones Islamic Market Titans 50 US portfolio. We use daily data of the 53 stocks that make up the portfolio for a 2-years period, 504 observations from January 1, 2015 to December 31, 2016, to cover as many regimes as possible.

$$\mathrm{r}_{i,t} = \Delta \log (p_i)$$

3.1. Descriptive statistics

The following table represents the descriptive statistics of the shares making our portfolio.

Table 1: DJIMT 50 US Portfolio Descriptive Statistics

Assets	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	ADF test	Jarque-Bera	Prob
AAPL	0.00019	0.06294	-0.06797	0.01582	-0.18594	5.51179	-21.97744	135.1258	0
ABBV	-0.0001	0.09598	-0.10902	0.01886	-0.38583	7.92409	-22.81561	520.6486	0
ABT	-0.00022	0.04173	-0.09751	0.01459	-1.3938	10.05811	-22.57968	1206.942	0
ACN	0.00065	0.06538	-0.06479	0.01316	-0.1606	7.08268	-23.07566	351.5012	0
BIIB	-0.00037	0.09682	-0.24949	0.02462	-1.93191	25.87208	-22.55874	11276.86	0
BMY	0.00005	0.0588	-0.17418	0.01719	-2.45626	26.66662	-22.01242	12244.73	0
CELG	0.00004	0.10179	-0.05958	0.02051	0.32991	5.05444	-22.85788	97.58378	0
CL	-0.00002	0.05831	-0.04775	0.0106	-0.20348	6.98362	-24.801	336.0639	0
COP	-0.00049	0.09257	-0.09664	0.02363	0.01877	4.49968	-21.38635	47.16594	0
CVS	-0.00031	0.05229	-0.12584	0.01319	-1.75767	19.80909	-25.86448	6180.674	0
CVX	0.00026	0.06039	-0.05015	0.0161	0.15454	4.11569	-22.05728	28.09018	0
DDPA	0.00017	0.04574	-0.05736	0.01265	-0.20541	5.57695	-16.35944	142.7151	0
EBAY	0.00045	0.13033	-0.13299	0.01805	-0.38115	19.06227	-22.56877	5419.357	0
EME	0.00098	0.06306	-0.03951	0.01434	0.26404	4.75847	-23.98376	70.65242	0
EOG	0.00022	0.1035	-0.07775	0.02189	0.22109	4.70695	-23.41564	65.16346	0
FB	0.00076	0.14429	-0.05986	0.01687	1.02172	14.13053	-21.01727	2684.016	0
GILD	-0.00049	0.05811	-0.09499	0.01741	-0.84277	7.3033	-22.64522	447.6577	0
GOOG	0.00078	0.14887	-0.05465	0.01562	1.87812	20.77058	-20.64885	6914.214	0
GOOGL	0.0008	0.15065	-0.05566	0.01544	1.83203	21.59186	-20.568	7525.772	0
HAL	0.00069	0.10517	-0.06154	0.02151	0.40044	4.54747	-21.51324	63.63073	0
HD	0.0006	0.04373	-0.04895	0.01226	-0.08941	4.49475	-22.19064	47.49668	0
HON	0.00038	0.05541	-0.07796	0.0119	-0.18602	8.63568	-23.39699	668.5569	0
IBM	0.00022	0.04913	-0.06038	0.01298	-0.7337	6.49045	-22.21969	300.4699	0
INTC	0.00012	0.06188	-0.09543	0.01485	-0.60282	7.44454	-22.76032	444.4731	0
JNJ	0.00019	0.0484	-0.03324	0.0095	0.27065	5.84784	-23.94903	176.1173	0
KO	0.0001	0.02798	-0.04904	0.00902	-0.56675	5.57953	-22.91803	166.3846	0
LLY	0.00022	0.06343	-0.11109	0.01618	-0.57302	9.78211	-24.51762	991.5475	0
LOW	0.00016	0.05295	-0.06392	0.01345	-0.44978	5.32991	-23.29738	130.7316	0

MA01	0.0004	0.06497	-0.04531	0.01313	-0.0396	5.20752	-23.41667	102.264	0
MCD	0.00066	0.07811	-0.04569	0.01087	0.64008	10.31284	-22.43374	1155.15	0
MDT	0.00008	0.05369	-0.04843	0.01315	0.17592	5.23198	-22.34549	107.0029	0
MMM	0.00006	0.04605	-0.09061	0.01272	-0.78471	8.76258	-23.16054	747.5927	0
MON	0.00027	0.05108	-0.06216	0.01056	-0.24136	7.10954	-25.92045	358.8338	0
MRK	-0.00017	0.08219	-0.08093	0.01487	0.27551	9.33592	-22.07741	847.7119	0
MSFT	0.00019	0.09901	-0.05365	0.01341	0.87467	10.62299	-23.48582	1282.024	0
NKE	0.00067	0.09941	-0.0971	0.01607	0.23587	11.7364	-21.9474	1604.303	0
ORCL	0.00021	0.08521	-0.05115	0.01416	0.34898	6.38801	-22.45163	250.7818	0
OXY	-0.00023	0.04036	-0.05223	0.01286	-0.43156	5.09359	-24.26344	107.476	0
PCLN	-0.00008	0.05789	-0.05512	0.01642	0.0917	4.06914	-23.09647	24.66172	0
PEP	0.0005	0.10655	-0.1207	0.01789	-0.55919	12.6526	-19.68265	1978.957	0
PFE	0.00032	0.0313	-0.04701	0.00913	-0.31839	5.22362	-22.41604	112.1262	0
PG	0.00021	0.06828	-0.04295	0.01215	0.59595	5.87464	-20.96722	202.9634	0
QCOM	-0.00002	0.03561	-0.04089	0.00956	-0.24515	5.12758	-22.5461	99.9077	0
SLB	-0.00013	0.07105	-0.16547	0.01904	-2.04204	18.6527	-23.0577	5484.52	0
TSM	0.00007	0.05953	-0.04963	0.01604	0.25125	4.19185	-22.96142	35.06337	0
TXN	0.00064	0.08333	-0.05538	0.01546	0.30124	5.46146	-23.31939	134.5897	0
UNP	0.00072	0.11268	-0.07072	0.01522	0.54268	10.70758	-22.66086	1269.757	0
UPS	-0.00017	0.04637	-0.06905	0.01546	-0.27148	4.51868	-21.26289	54.51663	0
V	0.00019	0.04943	-0.10434	0.01056	-1.74977	22.80064	-22.85026	8473.708	0
WBA	0.00037	0.07179	-0.05414	0.01372	0.06796	5.6536	-24.06086	147.9673	0
WMT	0.00017	0.06155	-0.1135	0.01545	-0.43696	9.50725	-23.13806	903.4711	0
XOM	-0.00032	0.09149	-0.10581	0.01266	-0.64305	17.74374	-23.17982	4590.542	0

Note: ADF Test critical values: 1%; level t-Statistic =-3.443149.

The stocks in this portfolio are characterized by asymmetric distributions (Skewness is different from 0), and fat tails (kurtosis greater than 3). Also, we can argue that daily returns are strongly non-Gaussian with the excess of Kurtosis and the existence of asymmetry.

Combined with the property on the tails, the Jarque-Bera test also leads to reject the assumption of a normal distribution (reject the null hypothesis). The zero probability of the Jarque-Bera statistic leads us to reject the hypothesis H_0 of the normality of the distribution (Prob Jarque-Bera <0.05).

Also, the ADF test of stationarity shows that all the series of stocks are stationary within the critical values of 1% with all probability values is less than 5%.

3.2. Heteroscedasticity test:

With this test, we will conform if our series of returns is homoscedasticity or heteroscedastic, all that based on the ARCH test.

Table 2: Heteroskedasticity Test: ARCH

	ARCH effect		
Assets	**F-statistic**	**Obs*R²**	**Probability**
AAPL	5.984407	5.937283	0.0148
ABBV	18.20585	17.63650	0.0000
ABT	5.250813	5.217029	0.0224
CL	16.52200	16.05748	0.0001
COP	31.75696	29.97985	0.0000
CVS	4.518595	4.496038	0.0340
CVX	46.67921	42.86419	0.0000

DDPA	9.547597	9.406174	0.0021
HD	12.81732	12.54695	0.0004
JNJ	8.449779	8.342592	0.0038
KO	6.382670	6.327429	0.0118
MA01	5.205787	5.172754	0.0229
MDT	11.34322	11.13596	0.0008
MMM	5.378339	5.342386	0.0208
MRK	7.313797	7.237190	0.0071
MSFT	4.279737	4.260389	0.0391
ORCL	6.563918	6.504780	0.0107
PFE	24.42048	23.37643	0.0000
PG	41.52423	38.49350	0.0000
QCOM	6.121657	6.071804	0.0137
TSM	4.683324	4.658424	0.0309
WBA	5.198926	5.166006	0.0230
WMT	23.04737	22.11995	0.0000

Note: F-statistic and Obs*R² have the same probability value.

Heteroskedasticity test ARCH shows that correspond probability value is less than 5%, so we reject null hypothesis (H0: our model is homoscedastic) and we can accept the alternative hypothesis (hypothesis H1: our model is heteroscedastic). Only 23 of our assets are heteroscedastic, the rest of the assets will be excluded from our studies.

3.4. Asymmetric information modeling

After testing the return's stationarity of our portfolio. The ADF test confirm the stationarity of the returns of all series,

The GARCH model (p, q):

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_{t-1}^2.$$

This simple structure imposes significant limitations on GARCH models. The negative correlation between stock returns and changes in the volatility of returns, ie volatility tends to increase in response to "bad news" (excess returns below expectations) and fall in response to "good news "(excess returns exceeding expectations).

The GARCH models assume, however, that only the magnitude and not the positivity or negativity of the unexpected excess returns determine the characteristic σ_t^2 ,If the distribution of z_t is symmetric, the variance change in (t + 1) is conditionally uncorrelated with the excess returns in (t) Nelson (1991).

If we write σ_t^2 as a function of lagged σ_t^2 . Or

$$\varepsilon_t^2 = z_t^2\sigma_t^2$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_j \, z_{t-j}^2\sigma_{t-j}^2 + \sum_{i=1}^{p} \beta_i\sigma_{t-i}^2$$

It is obvious that the conditional variance is invariant to the changes of sign of the z_t moreover, the innovations $z_{t-j}^2\sigma_{t-j}^2$ Are not independently and identically distributed. Another limitation of the GARCH models results from the constraints of no negativity on ω^* and ϕ_k In the following equation.

$$\sigma_t^2 = \left(1 - \sum_{i=1}^{p} \beta_i L_i\right)^{-1} \left[\omega + \sum_{j=1}^{q} \alpha_i \varepsilon_{t-j}^2\right] = \omega^* + \sum_{k=0}^{\infty} \phi_k \varepsilon_{t-k-1}^2$$

It is two imposed parameters to ensure that σ_t^2 Remains non-negative for all t with a probability equal to 1. These constraints imply that the increase of z_t^2 in any period increases σ_{t+m}^2 for all $m \geq 1$, excluding the behaviors of the random oscillations in the process σ_t^2. The GARCH models are not able to explain the observed covariance between ε_t^2 and ε_{t-j}. This is only possible if the conditional variance is expressed as an asymmetric function of ε_{t-j}.

In the GARCH model (1,1), shocks can persist in one norm and disappear into another, so that the conditional moments of GARCH (1,1) can explode even when the process is strictly stationary and ergodic.

GARCH models essentially specify the behavior of squared data. In this case, broad observations may dominate the sample asymmetric models provide an explanation for leverage, i.e. an unexpected price decreases increase volatility more than an unexpected price increase. The EGARCH (p, q) model (Exponential GARCH (p, q)) put forward by Nelson (1991) provides a first explanation of σ_t^2 Which depends on both size and sign and delayed residues.

This is the first example of an asymmetric model:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2) + \sum_{i=1}^{q} \alpha_j \left[\phi\, z_{t-j}^2 + \psi(|z_{t-i}| - \mathrm{E}|z_{t-i}|\right]$$

$$\alpha_1 \equiv 1, \mathrm{E}|z_t| = \left(2/\pi\right)^{1/2} \text{ Of which, } z_t \sim (0,1)$$

and where the parameters $\omega, \beta_i, \alpha_i$, are not limited to being non-negative.

$$g(z_t) \equiv \phi z_t + \psi[|z_t| - \mathrm{E}|z_t|]$$

By construction $\{g(z_t)\}_{t=-\infty}^{\infty}$ Has a null means, and it is independently and identically distributed. The components of $g(z_t)$ are ϕz_t *and* $\psi[|z_t| - \mathrm{E}|z_t|]$ Each with zero means.

If the distribution of z_t Is symmetric, the components are orthogonal, although they are not independent. $0 < z_t < +\infty$, $g(z_t)$ is linear in z_t with the slope given by $\phi + \psi$, and for $-\infty < z_t < 0$, $g(z_t)$ is linear with the slope given by $\phi - \psi$.

Thus, $g(z_t)$ allows the conditional variance process $\{\sigma_t^2\}$ to respond asymmetrically to increases and decreases in the share price. The term $\psi[|z_t| - \mathrm{E}|z_t|]$ Represents an effect of amplitudes. If $\psi > 0$ *and* $\phi = 0$, innovation in $\ln(\sigma_t^2)$ is positive (negative) when the amplitude of z_t is greater (smaller) than its expected value.

If $\psi = 0$ and $\phi < 0$,, the innovation in the conditional variance is now positive (negative) when the innovations are negative (positive).

A negative shock on yields, which would increase the debt ratio and therefore increase the uncertainty of future returns, could be taken into account when $\alpha_i > 0$ and $\phi < 0$. In the EGARCH model, $\ln(\sigma_{t+1}^2)$ is homoscedastic conditional on σ_t^2, and the partial correlation between z_t and $\ln(\sigma_{t+1}^2)$ is constant conditional on σ_t^2. A possible alternative specification of the news impact curve is as follows Bollerslev, Engle and Nelson (1994).

$$g(z_t, \sigma_t^2) = \sigma_t^{-2\theta_0} \frac{\theta_1}{1+\theta_2|z_t|} + \sigma_t^{-2\gamma_0} \left[\frac{\gamma_1|z_t|^p}{1+\gamma_2|z_t|^p} - E_t\left(\frac{\gamma_1|z_t|^p}{1+\gamma_2|z_t|^p}\right)\right]$$

Parameters γ_0 and θ_0 allow both the conditional variance of $\ln(\sigma_{t+1}^2)$ and its conditional correlation with z_t to vary with the level of σ_t^2. If $\theta_1 < 0$ then $\mathrm{Corr}_t(\ln(\sigma_{t+1}^2), z_t)$ <0: is the leverage effect. The constraints of the EGARCH model $\gamma_0 = \theta_0 = 0$, so that the conditional correlation is constant, as well as the conditional variance of $\ln(\sigma_t^2)$. The parameters ρ, γ_2, and θ_2 give the model the flexibility of the weight to be attributed to the tail observations: for example, $\gamma_2 > 0$, $\theta_2 > 0$, the model has $|z_t|$ Widely in low weight.

3.5. The impact curve news

The information has asymmetrical effects on volatility. In asymmetric volatility models, good and bad news has different predictability for future volatility. The impact curve of the information characterizes the impact of past yield shocks on the implied volatility of return in a volatility model.

By constantly keeping the information dated from $(t-2)$ and earlier, we can examine the implicit relation between ε_{t-1} and σ_t^2, with $\sigma_{t-i}^2 = \sigma^2$ with $i = 1, \ldots, p$. This curve is called, with all the delayed conditional variances evaluated at the level of the unconditional variance, the news impact curve because it relates past (information) yield shocks to current volatility. This curve measures how new information is incorporated into volatility estimates.

For the GARCH model, the News Impact Curve is centered at $\varepsilon_{t-1} = 0$. In the case of the EGARCH model, the curve has its minimum at $\varepsilon_{t-1} = 0$ and increases exponentially in both directions, but with different parameters.

GARCH (1,1):

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

The impact curve of the news to the following expression:

$$\sigma_t^2 = A + \alpha\varepsilon_{t-1}^2$$

$A \equiv \omega + \beta\sigma^2$

EGARCH (1,1):

$$\ln(\sigma_t^2) = \omega + \beta_i \ln(\sigma_{t-i}^2) + \phi\, z_{t-1} + \psi(|z_{t-1}| - \mathrm{E}|z_{t-1}|]$$

or

$$z_t = \frac{\varepsilon_t}{\sigma_t}.$$

The impact curve of the news is given by:

$$\sigma_t^2 = \begin{cases} A\, exp\left[\frac{\phi+\psi}{\sigma}\varepsilon_{t-1}\right] pour\ \ \varepsilon_{t-1} > 0 \\ A\, exp\left[\frac{\phi-\psi}{\sigma}\varepsilon_{t-1}\right] pour\ \ \varepsilon_{t-1} < 0 \end{cases}$$

$$A \equiv \sigma^{2\beta} exp\left[\omega - \psi\sqrt{2/\pi}\right]$$

$$\phi < 0 \quad , \quad \phi + \psi > 0$$

The EGARCH model allows good news and bad news to have a different impact on volatility, unlike the GARCH model. The EGARCH model allows big news or information to have a bigger impact on volatility than the GARCH model.
The EGARCH model would have higher variances in both directions because the exponential curve dominates the quadrature.

4. Results and Discussions

in this section, we will proceed to apply EGARCH model on the stocks which have shown the existence of the heteroscedasticity, all the parameters are giving in the following table (Table 3).

Table 3: GARCH model parameter for our portfolio

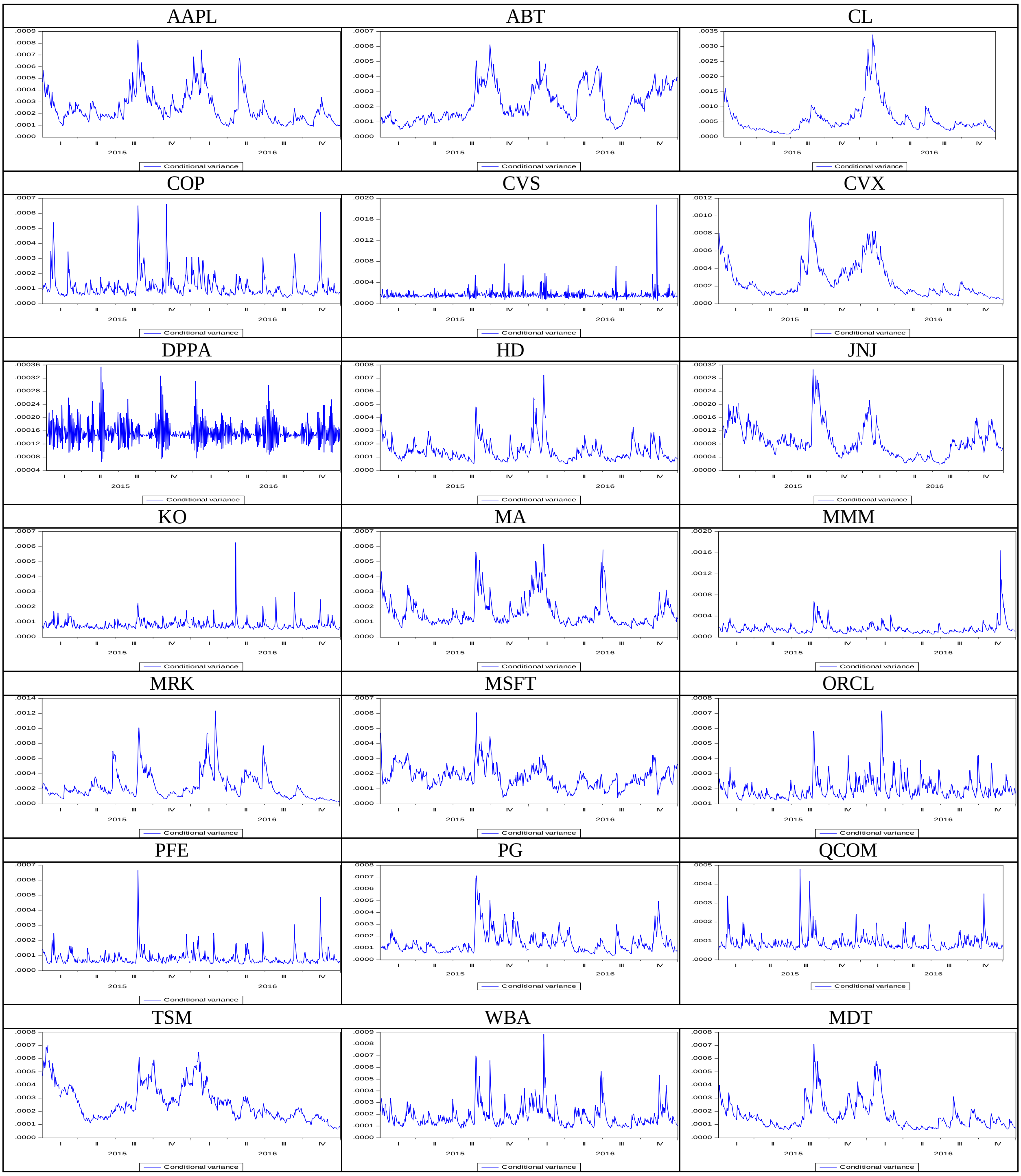
Assets		Parameters			
		ω	α	γ	β
AAPL	Coefficient	-0.4213	0.0917	-0.1308	0.9583
	Probability	0.0002	0.0041	0.0000	0.0000
ABBV	Coefficient	-7.9429	0.0100	0.0100	0.0100
	Probability	0.6348	0.7552	0.6438	0.9962
ABT	Coefficient	-0.1814	-0.0542	-0.1336	0.9735
	Probability	0.0000	0.0000	0.0000	0.0000
CL	Coefficient	-2.5544	0.4217	-0.0656	0.7561
	Probability	0.0000	0.0000	0.1096	0.0000
COP	Coefficient	-0.2107	0.1582	-0.0804	0.9886
	Probability	0.0048	0.0000	0.0045	0.0000

CVS	Coefficient	-13.1482	0.4313	0.0299	-0.4710
	Probability	0.0000	0.0000	0.5235	0.0000
CVX	Coefficient	-0.2552	0.1479	-0.0943	0.9840
	Probability	0.0056	0.0006	0.0001	0.0000
DDPA	Coefficient	-16.6594	0.1117	0.0669	-0.8858
	Probability	0.0000	0.0000	0.0000	0.0000
HD	Coefficient	-0.9327	0.1438	-0.1845	0.9077
	Probability	0.0000	0.0002	0.0000	0.0000
JNJ	Coefficient	-0.3756	0.0752	-0.1395	0.9664
	Probability	0.0000	0.0049	0.0000	0.0000
KO	Coefficient	-5.0097	0.3682	-0.0489	0.4997
	Probability	0.0066	0.0000	0.3286	0.0089
MA01	Coefficient	-0.7365	0.1236	-0.1679	0.9270
	Probability	0.0008	0.0108	0.0000	0.0000
MMM	Coefficient	-1.0089	0.1366	-0.2191	0.8972
	Probability	0.0001	0.0078	0.0000	0.0000
MRK	Coefficient	-0.4342	0.2400	-0.1037	0.9697
	Probability	0.0000	0.0000	0.0000	0.0000
MSFT	Coefficient	-0.5313	-0.0363	-0.1907	0.9358
	Probability	0.0000	0.0402	0.0000	0.0000
ORCL	Coefficient	-2.1713	0.1923	-0.1419	0.7631
	Probability	0.0007	0.0072	0.0004	0.0000
PFE	Coefficient	-3.3401	0.3518	-0.1784	0.6767
	Probability	0.0004	0.0000	0.0006	0.0000
PG	Coefficient	-1.0002	0.3024	-0.1309	0.9138
	Probability	0.0000	0.0000	0.0001	0.0000
QCOM	Coefficient	-2.8316	0.2719	-0.1459	0.7193
	Probability	0.0022	0.0000	0.0024	0.0000
TSM	Coefficient	-0.0769	0.0258	-0.1031	0.9932
	Probability	0.0234	0.0970	0.0000	0.0000
WBA	Coefficient	-1.3498	0.1678	-0.2157	0.8591
	Probability	0.0021	0.0061	0.0000	0.0000
MDT	Coefficient	-0.5129	0.1866	-0.0957	0.9582
	Probability	0.0005	0.0000	0.0003	0.0000

After modeling with EGARCH model the asset ABBV will also be excluded from our study (probability value > 0.05).

The conditional volatility of each asset is giving by the following figure (Figure 1)

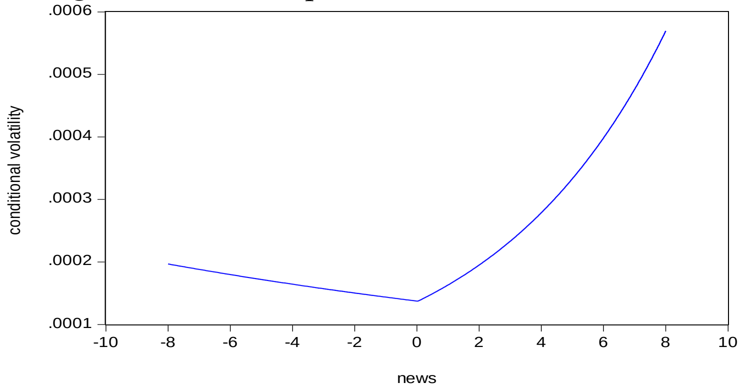
Figure 1: Conditional volatility of our assets
based on EGARCH model



All of conditional volatility shows the existence of volatility clustering, the leverage effect suggested by Black (1976) suggesting that Good news has less influence on the market than bad news. This suggestion will be analyzed using the NIC (News Impact Curve).

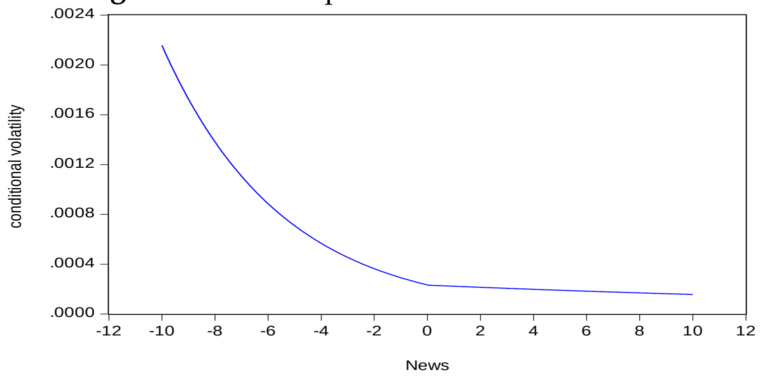
The news impact curve based on the parameters of the EGARCH model indicates that the information in the market has different impacts for each asset, in the following figure the asset DDPA shows that the good news is almost the only factor that pushes conditional volatility. Also, it is observable that there is a small impact for bad news, this indicates that in a good day in the market where values are rising, bad news (negative shocks) have a low impact on the asset and then cause less turbulence in the values during the day, in the other hand good news (positive shock) will trigger more volatility and more turbulence for DDPA assets.

Figure 2: News impact curves of asset 'DDPA'



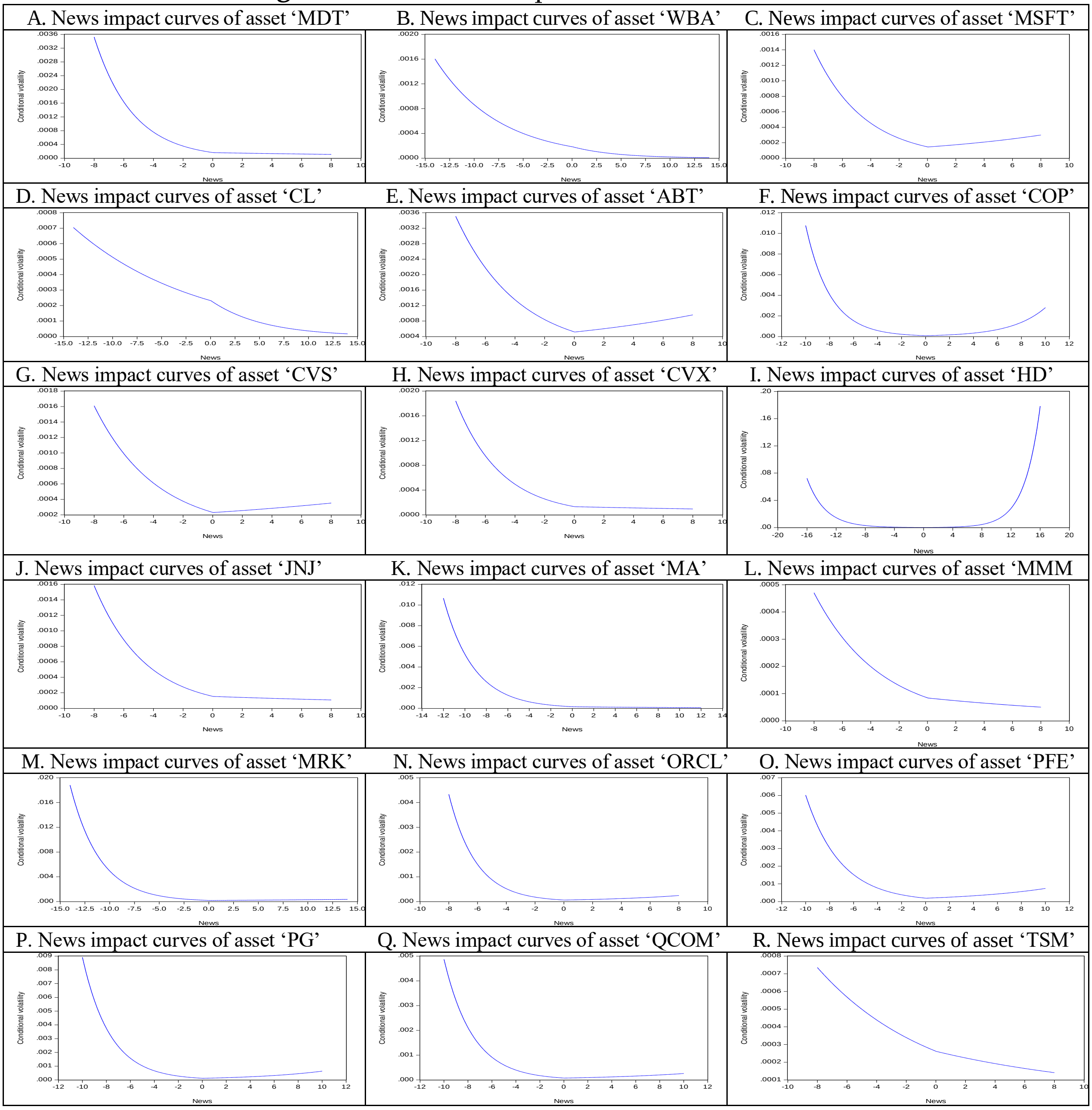
The situation is different for the company Apple Inc 'AAPL', the news impact curve that the bad news only has an impact on the conditional volatility, while good news (positive shocks) have the ability to calm the market and lower conditional volatility.

Figure 3: News impact curves of asset 'AAPL'



The EGARCH model has given the opportunity to differentiate between the impact of news or information on the market. For investors this data is very important, the behavior of assets is one of the keys to a successful portfolio management, a management based only on the mean-variance criteria is very limited, the assumption of normality in the financial market is already criticized by a large number of studies, the existence of asymmetric returns as well as heteroscedasticity, are all big motivation for our use of the EGARCH model with News Impact Curve. These models provide investors with a good understanding of the behavior of each stock in the financial markets.

Figure 4: The News Impact Curve for our assets



5. Conclusion

During this article we have applied EGARCH models to study the behavior of the DJIMT 50 US Portfolio's return series. The model used the normal distribution to capture the behavior of the tail. We also examined how investors can adapt their portfolios to a changing risk environment in the presence of unexpected information or news. Our work integrates the explicit impact of the information in the analysis of the volatility of the returns. Investors are concerned about the brutal reactions to negative information. These traders are probably generating what will appear to be a high reaction to information as they try to reduce their losses at the first signs of trouble. Veronesi (1999) and De Long and al. (1988) have documented this fact extensively in their studies. Investors may be forced to protect themselves from this "noise" in the market, as this could hurt their previous earnings. Our study has clarified the reaction of assets in the market, the action taken by investors will be different from asset to asset all according to their News Impact Curve, the measure of the impact of news on each asset will give investors more confidence in their choices.

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