FINANCIAL ANALYSTS IMPACT ON STOCK VOLATILITY. A STUDY ON THE PHARMACEUTICAL SECTOR

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ABSTRACT

Financial analysts play a key role in distinguishing which news are relevant for the valuation of a particular asset, and the changes in their recommendations are signals of new information in the market.

This paper studies the impact those *buy* or *sell* recommendations have on volatility instead of the traditional focus on prices. Twenty stocks from pharmaceutical sector in NYSE are daily tracked for five years along with the recommendations given by financial analysts.

We have modeled stock returns by a Markov Regime Switching model as in (Schaller and van Norden, 1997) and found two states of low and high volatilities. We have also found strong evidence that the probability of being in the estate of high volatility increases when a Financial Analyst changes his recommendation.

INTRODUCTION

The aim of this paper is analyzing the impact on financial markets of the public recommendations given by Financial Analysts (FA). In this sense, the return and volatility of stocks are modeled by a Markov Regime Switching (MRS) Model, founding that transition probabilities between volatility regimes are dependent to changes in the recommendations of FA.

In a efficient market, share prices reflect the correct valuation with the available information. As a corollary, quote changes would be a consequence of the market reaction to the appearance of some relevant news. Unluckily, the identification of relevant news to the evaluation of the market is not straightforward. Although (Fama et al., 1969) concluded that the information is quickly incorporated in the prices and it is not possible distinguish between the non expected part of the news from the expected one, several papers try to find the incidence of the arrival of news in returns. For example, (Pearce and Roley, 1985) analyzes the reaction of quotations to the announcements about monetary supply, inflation, economic activity and the discount rate. Through the expected part of the announcements is possible to test the Efficient Market Hypothesis (EMH) because only the surprise part of the announcement moves prices and in addition, the non-expected part related to monetary policy have a significant effect. So, the difficult point is to distinguish the anticipated part of any news (Pearce and Roley, 1985).

Precisely, the role of FA is collecting all relevant information about an asset as well as evaluating its impact on the price, sending recommendations to the agents. So, changes in FA assessments can be seen as a proxy of the entrance of new and relevant information to the market. They also act as amplifiers of any announcement, spreading their knowledge among actual and potential investors, and therefore affecting the behavior of the asset price.

As stated by (Womack, 1996), the revision of the FA recommendation means that they have analyzed public available information and have reached the conclusion that the present price of the share is not correct. This author also finds a strong evidence that stock prices are significantly influenced by these changes in financial recommendations.

In fact, the companies englobed in the pharmaceutical and biotechnological sector in the USA are highly sensible to news and announcements such as the impact of the decisions about commercialization of a new medicine made by the Food and Drug Administration (FDA) because it could have serious effect on future cash flows. This feature makes them specially suited for the purpose of the present paper, where technical knowledge is needed for distinguishing the possibilities of new drug developments and their value for the company. Pharmaceutical sector has been studied through many points of view, most of them referred to aspects such as regulation (Danzon and Chao, 2000; Philipson, 2002), about the financial valuation of patents (Grabowski and Vernon, 2002) or drug development costs, such as (Grabowski and Vernon, 1990; Berndt, 2002; DiMasi et al., 2003). However, we cannot find so much lit-

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erature that studies the pharmaceutical sector and its stock exchange characteristics. This paper contributes to the analysis of this particular industry in this aspect.

Nevertheless, measuring the impact of FA recommendations previously requires to impose some hypothesis about the stochastic model governing the behavior of both financial asset's returns and volatilities. In this sense, a mixture of two or more normal distributions is often enough to account for typical skewness and leptokurtosis on returns (Kon, 1984). If the arrival of new information to the market makes greater volatility than in the absence of news, then this behavior would be reflected in two different distributions, one with low variance for the moments of no news and another one with higher variance when announcements are made and markets react to new information.

Additionally, we have to take into account a number of stylized facts about volatility of financial asset prices such as volatility clustering, mean reverting and persistence that has led to models such as the family of ARCH models (Engle, 1982; Bollerslev, 1986) or Markov-switching models introduced by (Hamilton, 1989, 1990). The regime-switching modeling approach was initially proposed as a characterization for economic and financial time series, in order to identify two separated regimes in business cycles. An extension of Hamilton's approach have been used to describe and analyze stock market returns in order to identify two regimes either in mean, variance or both. Some important papers that have used these technics to examine stock market returns are those of (Turner et al., 1989; Hamilton and Susmel, 1994; Schaller and van Norden, 1997).

In the case of (Turner et al., 1989), using S&P monthly index data for the period $1946 - 1989$, they consider a Markov switching model in which either the mean, the variance or both may differ between two regimes with univariate specifications with constant transition probabilities. (Hamilton and Susmel, 1994) propose a model with sudden discrete changes in the process that governs volatility. They find that a Markov switching model provides a better statistical fit to the data than ARCH models without switching. (Schaller and van Norden, 1997), in a result close to (Turner et al., 1989), extend their approach in several aspects, i.e. examining whether stock market returns are predictable, even after accounting for Markov switching behavior, as well as whether the transition probabilities of the Markov chain vary over time in response to changes in economic variables. In particular, they look at whether the transition probabilities are influenced by the price/dividend ratio finding an asymmetric response to the past price/dividend ratio.

This paper has modeled stock returns by a Markov Regime Switching model as in (Schaller and van Norden, 1997) to twenty companies during five years along with the recommendations given by FA. We have found two states of low and high volatilities and strong evidence that the probability of being in the estate of high volatility increases when a FA changes his recommendation. Traditionally, literature has concentrated on the impact of FA recommendations on prices and the novelty is that we concentrate on the analysis of the impact of FA recommendations on volatility.

So, a MRS model would allow us to reproduce the main characteristics of stock returns, along with the identification of periods of low and high volatilities. The probabilities of being in each regime can be linked to the chances of appearance of new information in the market at an specific moment, and thereafter, FA recommendations would modify such probabilities.

The rest of the paper is organized as follows: in section we describe the sector selected and the data collected for our analysis. In section , MRS models are estimated founding evidence of different volatility regimes. FA recommendation are added to the model in section while section concludes.

DATA DESCRIPTION

The Pharmaceutical Sector

The pharmaceutical industry is a dynamic sector because of its capacity to reinvent itself in the face of changing market models and government regulation. Currently, the industry is seeking to improve its results from an increasing demand from an ageing population, at the same time that increases its investments in R&D. In particular, genomic research could generate new therapeutic and diagnose products in the next years. As part of this effort, the leading pharmaceutical companies are aggressively moving to form joint-ventures with small biotechnological companies to develop new generations of drugs.

Although these developments involve important challenges and strong investment in risky projects, the pharmaceutical industry is a healthy and profitable one. A great share of the global pharmaceutical market is controlled by companies that are quoted in the New York Stock Exchange, making it an appropriate market to follow.

We can find in the literature several papers that study the process of the life cycle of the discovery and development of new drugs (Grabowski and Vernon, 2002; Berndt, 2002; DiMasi et al., 1991), or the average cost of developing an innovative new drug (DiMasi et al., 2003). However, we cannot find papers that analyze the evolution of this sort of companies in stock markets.

All of these companies depend on the last decision from the FDA, and the not approval in an intermediate phase involves the huge costs that the company

will have to assume. Once the FDA is next to announce its decision, rumors and news appear making stock prices to vary widely. FA base their recommendations on the successes and failures of the company, given that the FDA approval of a new drug will ensure new cash-flows for the company.

Stock Returns and Volatilities

The New York Stock Exchange (NYSE) defines companies to be part of the pharmaceutical industry if they are manufacturers of prescription or over-the-counter drugs, such as aspirin or cold remedies. Since 2004, this sector has its own index called *NYSE Health Care Index*. This index includes companies classified in the Health Care sector according to the Industry Classification Benchmark.

Companies included in this index are pharmaceutical and biotechnological that have an important weight in the market capitalization of this sector. The market capitalization in march 2008 was 1246.3 billion dollars, where the 74.7% has an American origin. The five more important companies included in this Index in 31*st* July 2006 are Johnson&Johnson (9.82% weight), Pfizer Inc. (7.97%), GlaxoSmithKline PLC (7.15%), Novartis AG (6.91%) and Merck (6.51%).

For the present paper we selected the pharmaceutical and biotechnological companies that quoted in the NYSE in January of 2007, during the period 2001 to 2005. We obtained from NYSE/TAQ the closing quotations data. We have chosen those companies with more than $400,000$ operations in order to assure they are liquid enough to be covered by a sufficient number of FA following the companies, and the prices correspond to efficiently-enough markets. The final sample of companies have 20 pharmaceuticals and 3 biotechnologicals companies.

Financial Analyst Recommendations

On the other hand, we obtained recommendations of individual analysts jointly with their corresponding dates and the consensus recommendations. This information were not available in all the detail required for all companies selected and this is the reason why some of the original companies had been droped from the sample. So, the companies finally analyzed have been 18 pharmaceuticals and 2 biotechnological companies. All of these information have been obtained from I/B/E/S. As each house of analysis has a different category in its recommendations, I/B/E/S turn all the data to a single category with 5 different levels, assigning to each one a numerical value: (1) strong buy, (2) buy, (3) hold, (4) under-perform and (5) sell. In general they are biased to positive recommendations founding very few selling recommendations, although this can be sensible to the period considered. For example, in the case of Novartis,

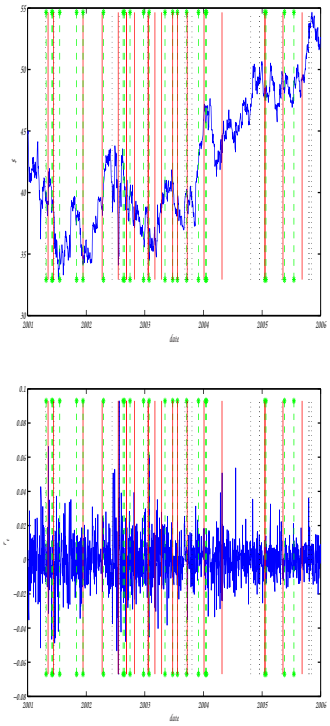


Figure 1: NVS Individual recommendations over prices and returns

there are more recommendations with values 2 (buy) and 3 (hold).

In a first approach, we can see in Figure 1 each individual recommendation over prices, returns, variance and volume for Novartis. Dashed green color with a star represents the case of a recommendation improvement respect to the previous, in solid red if it is worse and in dotted black if it is equal.

We encoded the values of the recommendations to move in the range -2 to 2. This five values corresponds to: strong sell (-2), sell (-1), hold (0), buy (1) and strong buy (2). We have made some new variables in order to test the effect of the recommendations on stock returns. These new variables are the following:

- *Recommendation*: Dummy variable indicating if this day a new analyst recommendation has been published. If this is the case, then it could imply higher volatility in the stock, since this new information will require the market to react.

- *Value*: Value of the new recommendation. The five possible values correspond to: strong sell (-2), sell (-1), hold (0), buy (1) and strong buy (2). It will take into account if the sense of the recommendation has a differential effect on returns (i.e. reactions are stronger after selling recommendations).

- *Absolute_value*: Absolute value of the new recommendation. It makes no differences between sell or buy orders, just the intensity of the recommendation (buy/sell, 1 or strong buy/strong sell, 2). This variable tries to capture the sensitivity of strong recommendations.

- *Variation*: It is the change in the value of the recommendation of the analyst with respect to his previous recommendation value. This variable takes into account that the effect on the market will be different if an analyst changes from buy to sell or viceversa, or if he publishes a new recommendation but maintains it as buy or sell.

- *N_analysts*: Number of analysts that follows a company. This variable changes along the sample and proxies the power of a given analyst. If very few analysts track a given company, the recommendation given by one of them has greater impact than would have had if he just was one more of a pretty crowd.

- *Consensus*: Daily mean of the last recommendations made by each analyst. It represents the mean of the analysts feelings about the company. The higher the value of this variable, the higher the recommendations to buy and viceversa.

- *Consensus_change*: Difference of the Consensus with respect to previous day. It takes into account that the importance could be not in the value of the recommendations given, but on the changes produced.

- *Absolute_consensus_change*: Absolute value of Consensus_change. The importance is given in this variable to the intensity of the change in consensus and not to the sense of the movement.

- *Agreement*: Standard deviation of the recommendations on the Consensus. A value 0 means that all analysts agree in the recommendations, and an increase in this variable indicates a higher degree of disagreement. The lower the value of this variable would imply less uncertainty about the company and lower volatility in the stock.

- *Agreement_change*: Differences in the value of variable *Agreement* from previous day. It indicates a momentum of increasing or decreasing uncertainty.

- *Absolute_agreement_change*: The absolute value of previous variable *Agreement_change*. It gives the intensity in the increase or reduction on uncertainty never mind the sense of this movement.

Table 1: Descriptive statistics

	CV	skew	kurt	JB (pv)
Abbott Laboratories (ABT)	107.6	-0.8	14.4	6918.9 (0)
Allergan Inc. (AGN)	155.8	-0.1	6.1	501.4 (0)
Alpharma Inc. (ALO)	118.1	-0.2	31.4	42144.4 (0)
AstraZeneca Group (AZN)	511.3	-0.5	13.2	5536.4 (0)
Bristol Myers Squibb (BMY)	20.5	-1.3	13.2	5865.0 (0)
Pharmaceuticals, Inc. (BRL)	41.4	-0.2	5.8	430.7 (0)
Biovail Corporation (BVF)	91.7	-0.6	12.2	4537.1 (0)
Applera-Celera (CRA)	36.1	0.4	5.2	278.0 (0)
Charles River Lab (CRL)	60.8	-0.5	9.7	2370.5 (0)
Genentech, Inc (DNA)	43.3	1.8	28.1	33387.4 (0)
FOREST LABS INC (FRX)	115.2	-0.4	7.6	1139.9 (0)
GlaxoSmithKline (GSK)	193.5	-0.0	5.4	314.4 (0)
Johnson & Johnson. (JNJ)	105.7	-1.4	25.2	26186.1 (0)
King Pharmaceuticals (KG)	47.4	-0.9	15.9	8816.2 (0)
Eli Lilly and Company (LLY)	43.2	0.0	5.1	231.4 (0)
Merck & Co Inc. (MRK)	22.8	-3.4	56.3	150400.9 (0)
Medicis Pharmaceutical (MRX)	207.6	0.1	6.5	644.1 (0)
Mylan Laboratories (MYL)	44.2	-0.5	11.0	3394.2 (0)
Novartis (NVS)	109.3	0.3	6.6	713.7 (0)
Pfizer Inc. (PFE)	32.1	-0.4	7.2	963.8 (0)
Pharmaceutical Resources (PRX)	27.6	-1.1	28.4	33827.2 (0)
Schering Plough Corp. (SGP)	27.5	-0.8	7.8	1306.1 (0)
Watson Pharmaceuticals (WPI)	80.1	-6.2	126.7	805521.7 (0)

These variables have been defined for all the companies in the sample of section . With the data on stock returns and recommendations we can define a model that relates both set of variables.

REFERENCE MODEL

Normality hypothesis is usually rejected in the context of financial asset returns. Since the works of (Mandelbrot, 1963) and (Fama, 1965), three characteristics are highlighted to diverge from a gaussian distribution.

1. Extreme values in the distribution. The tails of the distributions concentrate more probability than is supposed on a Gaussian distribution.

2. Extreme movements are more frequent in the left side of the distribution, as a consequence of market's higher sensibility to bad news.

3. Clusters of volatility. Days with high volatility tends to be followed by high volatility also in next days.

The first feature leads to a leptokurtic distribution, while the second one to the presence of skewness in the distribution. This abnormalities are usually attributed to outliers that are distributed as fat tails.

As can be seen in Table 1, skewness coefficients are mostly negative and kurtosis values are greater than 3 in all cases. Both are evidences of non-gaussian distributions, a fact confirmed by Jarque-Bera test, presenting pvalues close to zero for all the companies, rejecting the null of normality.

Moreover, in financial returns we can observe persistence in volatility and volatility clustering, mean reverting. The study of the autocorrelation function for Novartis shows, weak evidence of dependence on the mean (Figure 2 a.), assuming a constant mean. At the same time, in the correlogram of the squared returns (Figure 2 b.s) all the autocorrelation coefficients are positive and with significant and slow pos-

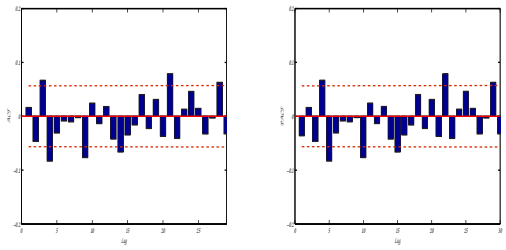
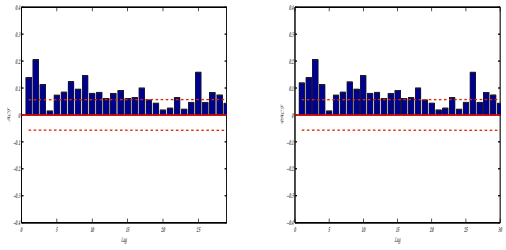


Figure 2: a. NVS Autocorrelation function for returns



b. NVS Autocorrelation function for squared returns

itive decay which indicates an important dependence of past values of the volatility.

Observations of this type in financial time series have led, in many cases, to the use of ARCH family models in financial forecasting and derivatives pricing, such as ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models. The main idea behind these widely-used models is that volatility is dependent upon past realizations of the asset process and related volatility process. This is a more precise formulation of the intuition that asset volatility tends to revert to some mean rather than remaining constant or moving in monotonic fashion over time.

Regime Switching Model

Previously to the analysis of recommendation impact on stock returns, we need a benchmark model for the later variable. Financial returns are usually modeled using stochastic volatility models like GARCH family of (Engle, 1982) and (Bollerslev, 1986). Although this models allows to take into account volatility clustering they are not fully able to explain fat tails and skewness. Some modifications on this models could help to introduce such features in the model but had the drawback of their increasing complexity.

Alternative modeling of return distribution via Extreme Values Theory (see (Embrechts et al., 1997) for a detailed description). has similar disadvantages and becomes difficult to conciliate them with financial theory. Nevertheless a simplest way of reaching similar results are the mixture of normal distributions, each one representing a different situation of the market.

We can find the origin of this model in the work of (Clark, 1973), that uses the concept of subordinated stochastic process and interpreted the leptokurtic behavior as a signal that the negotiation activity is not distributed uniformly during the period of negotiation.

Another important work that applied a mixture of normals to explain the indicated problems (fat tails, kurtosis and asymmetry) is the one of (Kon, 1984). He proposed a mixture of normal discrete distributions and indicated that although the hypothesis of a model with stationary normal distribution is empirically rejected, the gaussian hypothesis has great importance in financial theory.

The model presented by (Kon, 1984) was formed by a discrete mixture of four normal distributions for stock-exchange returns of 30 shares quoting in the Dow Jones. His results showed that it was a superior model than the student alternative, allowing to explain the asymmetry and kurtosis observed in the analyzed data. (Gonzalez and Gimeno, 2006) also showed that with a mixture of just two normal distribution it is possible to explain leptokurtosis and skewness of 30 worldwide stock indexes.

Nevertheless, a mixture of normal distributions is not able to explain the clusters of volatility in stock returns. In this sense, (Schwert, 1989) consider a model with two normal distributions with different variance in which transitions between variances are governed by a two-state Markov process. (Turner et al., 1989) generalized the model to allow both mean and variance to change between regimes, capturing the skewness in the distribution with different impacts on mean returns of states of low or high volatility. Finally, (Hamilton and Susmel, 1994) showed that a Markov regime switching (MRS) model provides a better statistical fitting than ARCH models.

This MRS model, originally proposed by (Hamilton, 1989), would allow us to distinguish the existence of different regimes in financial assets. Although MRS models can be quite flexible in the mean equation of each regime, we have selected a restricted version with a constant similar to (Turner et al., 1989),

$$r_t = \begin{cases} \mu_1 + \epsilon_{1t} & if \quad s_t = 1 \quad \epsilon_{1t} \sim N(0, \sigma_1) \\ \mu_2 + \epsilon_{2t} & if \quad s_t = 2 \quad \epsilon_{2t} \sim N(0, \sigma_2) \end{cases} \quad (1)$$

Model 1 has two different regimes ($s_t = 1$ and $s_t = 2$), one of them with low volatility (σ_1) and other one with high volatility (σ_2) that could be linked to the turmoil after the entrance of new information on the market. Skewness would be consequence of different means (μ_1 and μ_2) between regimes, since markets tends to react stronger upon bad news.

Each of the regimes in equation 1 are normally distributed, so the model can be considered as a mixture of normal distributions. Additionally, state variable (s_t) is a Markov chain with a transition matrix P (equation 2) that gives the probabilities of

being in any regime conditioned to the regime in previous period.

$$P = (p_{ij}) = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{pmatrix} \quad (2)$$

In equation 2, p_{11} denotes the probability of being in regime 1 ($s_t = 1$), conditioned to having been also in regime 1 the day before ($P(s_t = 1|s_{t-1} = 1)$), whereas p_{22} plays the same role for the second regime. Values of p_{22}, linked to the regime of high volatility, close to one will implied volatility persistence and produce clusters of volatility as the ones found in financial time series.

Parameter estimations of both equations 1 and 2 are obtained via maximum likelihood (see (Hamilton, 1989)). Nevertheless, the function we have to optimize is not linear, being sensible to the initial parameters in the model. To accelerate the optimization process we select initial values for the parameters (μ_1, μ_2, σ_1, σ_2, p_{11}, p_{22} and the probability of being on regime 1 in the first period p_0), following the methodology of (Gonzalez and Gimeno, 2006).

We roughly identify the days of high volatility to compute both μ_i and σ_i in each regime. The methodology consist in an iterative procedure that successively test normality hypothesis though Jarque-Bera test (Jarque and Bera, 1980) and drop the data with higher absolute daily returns, until a sub-sample is reached where normality hypothesis is not rejected. The returns in this sub-sample are initially considered as generated by the distribution with lower volatility of regime 1, whereas the dropped ones would be identified as days with high volatility.

Through this procedure we will obtain two groups of returns, that can be assigned to regime 1 and 2. Once we have separate the data, we can obtain the initial mean and variance values for each of the states. Transition matrix is also easily estimated once we have tentative regimes for each day, whereas p_0 is set to be equal to 0 or 1 depending on the first return classification.

This values are just tentative, and final parameters are estimated via maximum likelihood (Table 2). As can be seen, regime 2 is assigned to the distribution with higher standard deviation (tipically three times higher). The probability of remaining in the same regime are also high in both states, and reinforce the evidence on clusters of volatility.

Figure 3 represents the stock returns of Novartis plotted with different color depending on the results of the probabilities of being in each regime. It is possible to see how the probabilities of being in the first regime (in green color) or in the second one (in red color with star points) change along the time and coincide with the periods of high and low volatility in the returns.

Table 2: Estimated values of MRS parameters

	μ_1	σ_1	μ_2	σ_2	p_{01}	p_{11}	p_{22}
ABT	0.01%	1.14%	-0.07%	2.77%	1.00	0.97	0.92
ALO	0.05%	2.32%	-0.57%	11.70%	1.00	0.96	0.36
AGN	0.03%	1.02%	0.02%	2.68%	0.00	0.94	0.90
AZN	-0.03%	1.30%	0.15%	3.25%	1.00	0.97	0.89
BMY	-0.01%	1.04%	-0.20%	2.62%	0.00	0.98	0.96
BRL	0.07%	1.40%	0.03%	3.17%	1.00	0.93	0.83
BVF	0.08%	1.94%	-0.47%	5.87%	0.00	0.92	0.67
CRA	-0.10%	2.29%	-0.12%	4.21%	0.00	0.99	0.98
DNA	0.06%	1.76%	0.22%	4.94%	1.00	0.97	0.92
FRX	0.06%	1.51%	-0.10%	3.71%	0.00	0.92	0.71
GSK	-0.01%	1.12%	0.00%	2.36%	1.00	0.98	0.95
JNJ	0.01%	0.87%	0.04%	2.21%	0.00	0.96	0.89
KG	0.10%	1.67%	-0.49%	5.20%	0.00	0.91	0.74
LLY	-0.05%	1.20%	0.04%	2.47%	0.00	0.98	0.95
MRK	0.02%	1.24%	-0.73%	4.44%	0.00	0.96	0.68
MYL	0.01%	1.34%	0.21%	3.56%	0.00	0.90	0.67
NVS	0.01%	0.99%	0.07%	2.24%	1.00	0.97	0.88
PFE	-0.06%	1.21%	-0.01%	2.82%	0.00	0.98	0.93
SGP	-0.01%	1.42%	-0.20%	3.01%	0.00	0.97	0.94
WPI	0.01%	1.52%	-0.80%	7.72%	0.00	0.96	0.46

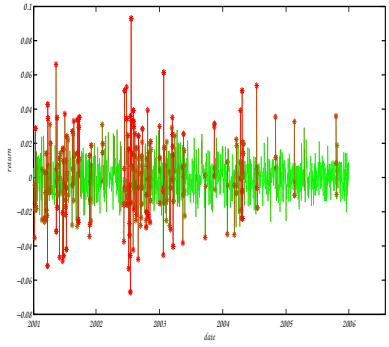


Figure 3: NVS Posteriori probabilities over returns

In Table 3 and 4 we present the results of likelihood ratio tests (see (Engle, 1984) for a general description and (Hansen, 1992) for its application on MRS models) on the estimated model for each company. The test on the null hypothesis of equal means in both regimes (column 2) are accepted in all but two companies, as well as being equal to zero (Table 3 columns 4, 5 and Table 4 column 2) in all but one case. This results imply that there is no forecasting opportunity on stock returns, as is generally found in the financial literature. Nevertheless, in the case of σ_i parameters, the null hypothesis is rejected (Table 3 column 3), reinforcing the idea of the two regimes related with low and high volatility. Finally, the null of no regime switching is also rejected in all cases (Table 4 column 3).

In addition, we have proceed to calculate the standardized residuals of the model. When we compare the moments of the original return distribution with the ones obtained from the residuals of the MRS model (Table 5), both skewness and leptokurtosis are dramatically reduced (80%-90% of reduction). In terms of normality, the reduction is even higher in the Jarque-Bera statistic, and in half of the cases the reduction is enough to accept the normality hypothesis.

In Figures 4 a) and 4 b) we present the correlation and partial correlation function for both the residuals of the MRS model as well as the squared

Table 3: LR tests on MRS models (a)

	μ_1=μ_2		$\sigma_1 = \sigma_2$		$\mu_1 = 0$	$\mu_2 = 0$	
ABT	0.21		287.4	***	0.04	0.19	
AGN	0.00		295.4	***	0.41	0.02	
ALO	0.16		345.2	***	0.52	0.14	
AZN	0.61		263.0	***	0.40	0.47	
BMY	2.06		228.7	***	0.06	2.63	
BRL	0.04		157.1	***	1.26	0.01	
BVF	1.63		200.0	***	1.12	1.33	
CRA	0.00		156.7	***	1.32	0.34	
DNA	0.31		418.5	***	0.75	0.61	
FRX	0.34		160.1	***	1.16	0.15	
GSK	0.00		204.6	***	0.02	0.00	
JNJ	0.04		303.7	***	0.16	0.10	
KG	3.17	*	240.5	***	2.26	2.46	
LLY	0.31		181.8	***	1.43	0.06	
MRK	3.64	*	265.0	***	0.18	3.60	*
MYL	0.18		131.4	***	0.01	0.34	
NVS	0.12		124.2	***	0.08	0.21	
PFE	0.06		258.3	***	1.89	0.00	
SGP	1.32		199.9	***	0.00	1.72	
WPI	0.82		241.7	***	0.07	0.81	

With $***$ for those values with pvalue$<$ 0.01,
with $**$ for pvalue$<$ 0.05and $*$ for pvalue$<$ 0.1

Table 4: LR tests on MRS models (b)

	$\mu_1 = \mu_2 = 0$	$s_t(1) = s_t(2)$	
ABT	0.22	287.5	***
AGN	0.48	303.6	***
ALO	0.62	587.7	***
AZN	0.78	263.0	***
BMY	2.76	369.7	***
BRL	1.52	157.3	***
BVF	2.00	357.5	***
CRA	1.80	157.8	***
DNA	1.50	419.7	***
FRX	1.16	197.7	***
GSK	0.02	204.6	***
JNJ	0.33	303.9	***
KG	4.01	417.8	***
LLY	1.43	183.3	***
MRK	3.64	497.7	***
MYL	0.95	245.0	***
NVS	0.37	190.6	***
PFE	1.94	258.6	***
SGP	1.80	201.0	***
WPI	0.84	707.3	***

With $***$ for those values with
pvalue$<$ 0.01, with $**$ for
pvalue$<$ 0.05 and $*$ for pvalue$<$ 0.1

Table 5: Normality test

	SKEWNESS		KURTOSIS		JARQUE-BERA TEST			
	r1	rs	r1	rs	r1		rs	
ABT	-0.8	-0.2	14.4	4.1	6918.9	***	68.4	***
AGN	-0.1	0.0	6.1	2.7	501.4	***	4.8	*
ALO	-0.1	0.0	31.5	2.7	42144.4	***	3.4	
AZN	-0.5	-0.2	13.3	3.4	5536.4	***	12.5	***
BMY	-1.3	-0.4	13.3	4.9	5865.1	***	214.5	***
BRL	-0.2	0.0	5.9	2.6	430.7	***	6.8	**
BVF	-0.6	0.1	12.3	2.8	4537.2	***	4.3	
CRA	0.4	0.2	5.2	3.2	278.0	***	10.7	***
DNA	1.8	0.4	28.1	5.7	33387.5	***	418.9	***
FRX	-0.4	-0.0	7.6	2.6	1139.9	***	9.3	***
GSK	-0.0	-0.0	5.5	2.8	314.5	***	2.2	
JNJ	-1.4	-0.4	25.3	6.1	26186.1	***	524.7	***
KG	-0.9	-0.1	15.9	3.4	8816.2	***	11.2	***
LLY	0.0	-0.1	5.1	2.6	231.4	***	11.4	***
MRK	-3.4	-0.1	56.3	4.2	150400.9	***	82.9	***
MYL	-0.5	-0.2	11.0	3.1	3394.2	***	7.9	**
NVS	0.3	0.1	6.7	2.7	713.7	***	4.1	
PFE	-0.4	-0.1	7.3	2.9	963.8	***	1.9	
SGP	-0.9	-0.2	7.8	3.4	1306.1	***	15.1	***
WPI	-6.2	-0.1	126.7	3.8	805521.8	***	39.2	***

With $***$ for those values with pvalue$<$ 0.01,
with $**$ for pvalue$<$ 0.05 and $*$ for pvalue$<$ 0.1
r_1 represents stock returns while r_s are MRS standardized resids

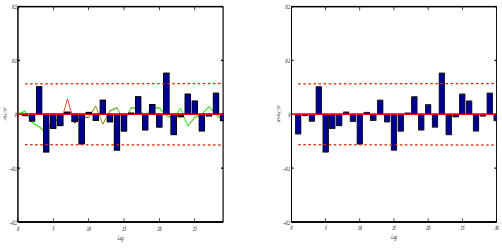
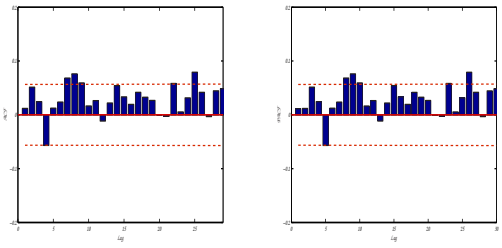


Figure 4: a. NVS Autocorrelation function for standardized RMS resids



b. NVS Autocorrelation function for squared standardized RMS resids

residuals. When compared with the ones obtained from the raw returns (Figures 2 a) and 2 b)) it is possible to see that although correlogram on the original variables are quite similar, in the case of the squared variables, that in the case of returns indicates the presence of conditional heterokedasticity, this evidence disappear in the residuals of the MRS model, indicating that GARCH modelling is no longer needed. Similar results are obtained for the other companies.

THE EFFECT OF FA RECOMMENDATIONS

Once we have a valid model to represent stock returns, we can measure the impact on volatility of FA recommendations. We follow (Schaller and van Norden, 1997), and consider that the transition probabilities on equation 2, instead of being constant, can be set to be a function of some exogenous variables,

$$\begin{aligned} p_{11} &= P(S_t = 1/s_{t-1} = 1, A_t) = \Phi(A_t\beta_1) \\ p_{22} &= P(S_t = 2/s_{t-1} = 2, A_t) = \Phi(A_t\beta_2) \end{aligned} \tag{3}$$

where A_t is, in our case, a vector containing the recommendation variables defined in section ((Schaller and van Norden, 1997) used the past price/dividend ratio)and $\Phi(\cdot)$ is a function that returns the cumulative probability of a normal distribution. Then the probabilities on (3), becomes Probit models (In fact, we used Probit estimations as initial values of the final model), and the transition matrix is redefined,

$$P = \begin{pmatrix} \Phi(A_t\beta_1) & 1 - \Phi(A_t\beta_1) \\ 1 - \Phi(A_t\beta_2) & \Phi(A_t\beta_2) \end{pmatrix} \tag{4}$$

Since A_t vector contains eleven variables, β vectors would add 22 extra parameters to the estimation.

Table 6: LR tests on the influence of FA over transition probabilities

	FA rec	
ABT	64.321	***
AGN	89.747	***
ALO	63.090	***
AZN	44.512	***
BMY	84.160	***
BRL	79.139	***
BVF	117.595	***
CRA	57.173	***
DNA	73.213	***
FRX	81.531	***
GSK	42.240	***
JNJ	62.860	***
KG	82.656	***
LLY	53.203	***
MRK	39.542	**
MYL	70.134	***
NVS	48.862	***
PFE	43.515	***
SGP	56.298	***
WPI	64.971	***

Where
$***$ indicates pvalue< 0.01,
$**$ for pvalue< 0.05
and $*$ for pvalue< 0.1

In Table 6, we present the LR test under the null of no effect of FA recommendations in the volatility regime. As can be seen, in all of the cases the null is rejected, and strong evidence is found of the effect of FA on the volatility. This result suggest that either the FA has direct effect on the market or that he has reach in its recommendation the same conclusion the market does.

CONCLUSIONS

In the present paper we have analyzed the effect of FA recommendations on the market volatility of Pharmaceutical and Biotechnological companies. This paper contributes to the literature because analyzes the sector and its stock exchange characteristics. Moreover, we study the impact of FA recommendations on volatility instead of the traditional literature that focuses on prices.

We have found in all of the 20 companies analyzed strong evidence of correlation between FA recommendations and changes in volatilities. This result may point out to the role of FA to extend new information about a company to the market, since such event is usually linked to higher volatility in a price discovery process.

We have also found that a mixture of simple two normal distributions with the same mean but different variance, with probabilities governed by a Markov chain (MRS model), is able to capture the main features of financial assets in a meaningful model. A MRS model is considerably more parsimonious than alternatives like GARCH models and extreme values distributions, but at the same time is able to take into account volatility clustering, leptokurtosis and skewness in financial returns.

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