On the Statistical Validation of Technical Analysis

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Abstract
Technical analysis, or charting, aims on visually identifying geometrical patterns in price charts in order to anticipate price "trends". In this paper we revisit the issue of technical analysis validation which has been tackled in the literature without taking care for (i) the presence of heterogeneity and (ii) statistical dependence in the analyzed data – various agglutinated return time series from distinct financial securities. The main purpose here is to address the *first* cited problem by suggesting a validation methodology that also "homogenizes" the securities according to the finite dimensional probability distribution of their return series. The general steps go through the identification of the stochastic processes for the securities returns, the clustering of similar securities and, finally, the identification of presence, or absence, of informational content obtained from those price patterns. We illustrate the proposed methodology with a real data exercise including several securities of the global market. Our investigation shows that there is a statistically significant informational content in two out of three common patterns usually found through technical analysis, namely: triangle, rectangle and head & shoulders.

***Keywords*:** Technical analysis; pattern; information content; heterogeneity; homogeneity; $AR - GARCH$; clustering; chi-square test.

JEL codes: C12; G11; G14.

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Resumo
A análise técnica, ou grafismo, consiste na identificação visual de padrões geométricos em gráficos de séries de preços de mercado com o objetivo de antecipar "tendências" de preço. Este artigo revisita a questão da validação da análise técnica, a qual vem sido estudada na literatura sem os devidos cuidados com os problemas de (i) heterogeneidade e de (ii) dependência estatística dos dados analisados – séries de retorno referentes a diversos ativos financeiros distintos. O objetivo central consiste em resolver o primeiro problema citado, através de uma metodologia para "homogeneizar" os ativos no tocante às distribuições de probabilidades de suas séries de retorno. Os passos gerais desta metodologia passam pela identificação dos processos estocásticos geradores dos retornos dos ativos, pelo agrupamento de ativos semelhantes e, finalmente, pela identificação de presença, ou não, de conteúdo informativo advinda dos padrões de preços. Como ilustração, são analisadas séries de diversos ativos do mercado financeiro mundial. A investigação conduzida neste artigo demonstra que há presença de conteúdo informativo em dois de três padrões usualmente encontrados pela análise técnica: triângulo, retângulo e *head & shoulders*.

***Palavras-chave*:** Análise técnica; padrão geométrico; conteúdo informativo; homogeneidade.

1. Introduction

Technical analysis (or *charting*) is an old day and empirical practice whose central target is the identification and anticipation of trends in the prices of financial securities, by means of recognizing geometrical patterns in the price charts. Following Murphy (2000), p. 49, we "define" *trend* by the simple direction to where the market is going to. This practice, although fully adopted in many financial institutions across the world, has been neglected in the academy. The main reason for that is its lack on scientific formalization which could have been directly confronted to empirical evidences, something that has not happened along other investment analysis based on the finance orthodox theory, from which we can cite sovereign examples such as the Portfolio Selection Theory conceived by Harry M. Markowitz (Markowitz, 1959), William F. Sharpe's Capital Asset Pricing Model (CAPM) (Sharpe, 1964) and the Black & Scholes option pricing model developed by Fisher Black and Myron S. Scholes (Black and Scholes, 1973). As another responsible we recall the fact that the technical analysis was forgotten by the academy is the traditional financial theory which has been built on efficient markets theory (Fama, 1965) that is inspired on the random walk theory (Bachelier, 1900).

Nevertheless there are references on technical analysis since the existence of the very first incipient financial markets like the rice market in feudal Japan. Actually the books in this field used to be heuristic in style and lacked on formalism. It was only after the appearance of some studies rejecting the random walk theory (Lo and Mackinlay, 1988, 1999) that the first studies about this practice had appeared in the mainstream periodicals. With the increasing of the empirical results toward the validation of technical analysis, the academy has become more interested on this subject.

One of the papers that aimed on subjecting technical analysis to econometric framework is the one by Lo et al. (2000). That research turns to the mathematical formalization of the geometrical patterns, the automatization of the pattern identification and the validation of technical analysis by traditional Chi-Square and Kolmogorov-Smirnov goodness-of-fit[1] tests (De Groot, 1986). Focusing on the last contribution of their paper, the validation of technical analysis, Lo *et al.* compared, by means of the cited tests applied to various agglutinated return series of several distinct financial securities, the empirical distribution of the return series after the geometrical patterns (the *conditional returns*) to the empirical distribution of the returns of all the complete series (the *unconditional returns*). Once the null hypothesis that the empirical distribution of the later adequately fits the empirical distribution of the former has been rejected, they took this result as a statistical evidence that there was informational content in the identified patterns. Here we must make two important and somewhat obvious critics on this validation proposal. Firstly, it is well known that those tests presume statistical independence for the data, something that is trivially violated by financial data given the pretty established stylized fact of conditional heteroscedasticity (Engle, 1995, Mills, 1999). Secondly, and much more harmful, the agglutination of return series of *different* securities can very plausibly violate the first principle of identically distributed random variables, without which anything would make sense. In other simpler words: that paper applied traditional goodness-of-fit tests and analyzed the results using potentially dependent and/or heterogeneous data sets.

The central objective of this paper is to solve that problem of heterogeneity previously explained. We attempt to do this by stepping into some clustering device in order to collect series which appear to come from the same "world" or "population". In Section 2 we quickly present the general terms of the technical analysis, its assumptions and its practice. In Section 3 we formalize our methodology for the validation of technical analysis, while detailing the pertinent statistical framework, namely: the estimation of $AR-GARCH$ models, the principal component analysis aimed on visual clustering and the goodness-of-fit tests. In Section 4 we illustrate the proposed methodology with several return series from different securities of the global market. Finally, in Section 5 we discuss possible extensions of the methodology.

2. Foundations of Technical Analysis: A briefing

Technical analysis is based on the idea that prices move in *trends*, which are naively defined as the directions of the market prices (Murphy (2000), p.49). According to Murphy (2000), a trend has three directions: *uptrend*, *downtrend* and *sideways trend*. Each part of this decomposition is determined by the changing attitudes of investors toward everything that economically, politically and psycho-

[1] Even though the appropriate term would be *homogeneity*, we prefer to commit this digression because, as will become clear in the sequel, the aforementioned word is reserved to a different connotation in this paper.

logically can affect them. Another assumption to the effectiveness of technical analysis lies in the belief that *history tends to repeat itself*: investor's behavior is known by the presence of well-defined reactions to some stimulus. Every information that can impact prices is "translated" to investor's mind as greed or fear. The practice defends that recursive behavior of investors can be captured by the identification of geometrical patterns in price graphics.

Pring (1991) asserts that the art of technical analysis consists of identifying trend changes in the early stages in order to maintain the investment posture until technical evidences indicate that trend has reversed. There are two categories of price patterns: the *reversal* and the *continuation*. The former category is responsible for the reverse of a previous trend and its five most commonly examples: the *head & shoulders*, *triple tops and bottoms*, *double tops and bottoms*, *spike* (or *V*) *tops and bottoms*, and *rounding* (or *saucer*). The later category responds for the continuation of a previous trend and the most used types are: *triangles*, *flags & pennants*, and *rectangles*. After a pattern has been identified, the analyst earns insights on the direction of a trend (if it will maintain or will reverse) after the end of the formation, also known as the *rupture* or *breakout point*. Figure 1 shows a head & shoulders formation with the new trend delineated after the breakout point.

Figure 1
Head & shoulders formation

There is also a specific rule according to each pattern, which defines the minimum size trend after the formation. So, the analyst can also determine the minimum target price of the new trend, as illustrated in Figure 2.

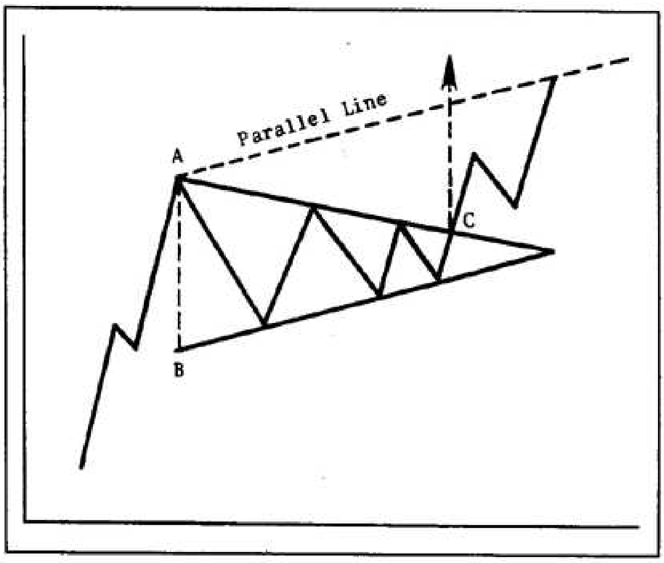

Figure 2
Representation of a pattern known as triangle. The rule to measure the minimum size of the posterior trend consists on draw a parallel line upward from the top of the baseline (A) parallel to the lower line in the triangle.

Authors in the field have recently made difference between the tools used by a technical analyst: charting, technical or sentimental indicators and oscillators, statistical analysis, and black box approach. Although this increased specialization urges distinctions between these many tools, it is common sense that all of them but charting are secondary or tertiary elements in the practice. So we will follow the classical approach considering technical analysis as charting.

Despite the fact that most of papers rejecting technical analysis were based in random walk theory, there are works with different conclusions about the practice. Saffi (2003) found results disapproving the use of technical indicators and oscillators as a methodology to achieve returns above the market. On the other hand, Neftci (1991) investigated the ability of Technical Analysis to get algorithmically implemented and to explain stock price movements better than *Wiener-Kolmogorov predictors*; sometimes the ability has been confirmed in that paper. Finally, Ratner and Leal (1999) found results that partially support specific technical indicator, based on *moving averages*, in some emerging markets.

The main critics on the practice lie in the highly subjective nature on the identification of geometrical patterns in price charts and also in the fact that there is no scientific evidence about the validation of such patterns. Those critics were considered in a pioneering way by Lo et al. (2000).

3. A Methodology for Statistical Validation of Technical Analysis: Searching for Homogeneity

3.1 The validation proposal of Lo *et al.*

We start by discussing the part of Lo et al. (2000) concerned on the validation of technical analysis by verifying the existence of informational content in the patterns extracted from price charts. We first detail their methodology and, after, stress its statistical drawbacks.

3.1.1 The original methodology

Firstly, we quote some terminology supervened from Lo et al. (2000). By *conditional returns* we mean the parts from the agglutinated return time series which follow after the identification of a given pattern in the correspondent portion of the price series. Figure 3 illustrates this concept within the geometrical pattern known as *flags* & *pennants*. And by *unconditional returns* we mean *all* the observations from *all* agglutinated return time series.

Figure 3
Price chart with detach to the portion (circled) which shall generate the conditional returns

In their work, Lo *et al.* chose the goodness-of-fit testing framework to find out when technical analysis produces potentially useful information. One of the appropriate tests is the popular Chi-Square test (De Groot, 1986). Its correspondent statistic, already adapted to the actual problem, is

$$Q = \sum_{i=1}^{10} \frac{(Y_i - (0,1)\,n)^2}{(0,1)\,n} \tag{1}$$

where Y_i represents the total of conditional returns assuming values between the i^{th} and the $i-1^{th}$ decile of the empirical distribution of the unconditional returns, n is the number of unconditional returns (that is, the number of observations from all series) and $(0,1)\,n$ is the expected absolute frequency of conditional returns to appear in some decile under this null hypothesis H_0: "*The theoretical distribution of the conditional returns is the same as the empirical distribution of the unconditional returns*". On rejecting this null hypothesis (the adopted asymptotic null distribution is the usual Chi-Square with $10-1=9$ degrees of freedom), Lo *et al.* conclude that the distributions of the conditional returns and the unconditional returns would not be the same and interpret this as some empirical evidence supporting an informational content identified by technical analysis.

The other test used by Lo *et al.* is the one due to Kolmogorov and Sminorv, which, in this context, has the same null hypothesis and aims at comparing the empirical distribution function of the conditional returns to the corresponding one of the unconditional returns. This is actually a traditional goodness-of-fit test and its details can be studied in De Groot (1986).

3.1.2 Statistical problems

We first should note that both Chi-Square and Kolmogorov-Sminorv tests have as basic presuppositions the independence and the homogeneity of data generating processes (for short: the data must be *i.i.d.*). Both conditions are trivially violated by the data considered in those applications of Lo *et al.*. Let us concentrate on this point for a while.

It is a well known fact that daily return series are not independent. They could be at most uncorrelated in time, but surely present at least some form of conditional heteroscedasticity. The *conditional volatility* is vastly discussed in the literature; see for instance Hamilton (1994), Engle (1995) and Mills (1999). Stepping further, we affirm that this dependence shall earn complexity whenever different series are agglutinated, since observations from different series from the same market (or even from different markets sometimes) sometimes evince high pairwise correlations besides other complicated types of dependence.

Secondly, the most important: the agglutination of different series and the treatment of all the observations as if they came from the same distribution is strongly criticizable, since the most plausible conclusion would be that this agglutination very possibly violates the distributional homogeneity.

Actually, Lo *et al.* (2000), p.1728, called the attention for these two issues and suggested that they would extend their analysis for the non *i.i.d.* framework. Here, in our paper, we concentrate on the most important second problem and propose an alternative methodology for attenuating the homogeneity violation. We leave the other problem (dependence of the data) for future research.

3.2 Preliminaries for an alternative methodology

We now present some general statistical background which are going to be used in the methodology to be presented in subsection 3.3. Quite briefly, the techniques are: (i) $AR - GARCH$ modelling; (ii) visual clustering under principal component analysis; and (iii) goodness-of-fit tests.

3.2.1 $AR - GARCH$ Models

The $AR(1){-}GARCH(1,1)$ model (Engle (1995), for a quite exhaustive treatment on the subject) is quoted as

$$\begin{aligned} R_t &= \phi_0 + \phi_1 R_{t-1} + h^{1/2}\varepsilon_t \;\;,\;\; \varepsilon_t \sim i.i.d.(0,1) \\ h_t &= \omega_0 + \alpha\left(R_{t-1} - \phi_0 - \phi_1 R_{t-2}\right)^2 + \beta h_{t-1} \end{aligned} \tag{2}$$

where R_t is the stochastic process representing some security daily return and, obviously, $h_t = Var\left(R_t | R_{t-1}, R_{t-1}, \ldots\right)$. By Nelson (1990), sufficient conditions for the ergodicity of the model in (2) would be $|\phi_1| < 1$, $\omega_0 > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta \leq 1$.

This model, which is a very particular case of a general $ARMA(p,q) - GARCH(s,t)$ structure, is in its own place here since there are plenty of practical evidences that it captures fairly well the dynamics of many return series. In practice the AR(1) structure is used to be "weak" in the sense that $\phi_1 \approx 0$. This latter stylized fact should be interpreted as some device to account the lack of efficiency of the subjacent financial market, but not as something to rely on if one attempts to make forecasts.

In general the estimation of $AR(1){-}GARCH(1,1)$ models is consistently accomplished by *quasi* maximum likelihood estimation (Bollerslev and Wooldridge (1992) where the adopted *quasi* likelihood is usually Gaussian (Greene (2000), p. 802-807, for analytical expressions and derivatives used in numerical optimizations).

3.2.2 Principal component analysis

Visual clustering by means of *principal component analysis* (Johnson and Wichern, 1998, ch. 8) consists on visually grouping experimental units with similar values for the first components, precisely those whose variances account for great part of the variability came from the original variables. This is some kind of dimensional reduction where main and few orthogonal components (say, the very first, or the first and the second together) replace the original variables, permitting therefore a graphical depict of the experimental units. Surely, the technique would be only valuable and recommended if the adopted components "satisfactorily" represent the data and a crucial condition for this shall be moderated correlations among the original variables.

Consider that there are p variables observed on n desirably independent individuals (the experimental units). So we have $X_i = (X_{i1}, \ldots, X_{ip})'\,, i = 1 \ldots n$. We define the j^{th} principal component of the i^{th} individual as the scalar product of the normalized eigenvector associated with the j^{th} greatest eigenvalue from the sample covariance matriz of the original variables. That is,

$$Y_{ij} = e_j' X_i = e_{j1} X_{i1} + \cdots + e_{jp} X_{ip}, i = 1, \ldots, n \text{ and } j = 1, \ldots, p \quad (3)$$

By Johnson and Wichern (1998), ch.8, the sample variance of the j^{th} component is given by the j^{th} greatest eigenvalue:

$$\hat{Var}\,(Y_j) = \hat{\lambda}_j, j = 1, \ldots, p \quad (4)$$

Those readers interested on more theoretical and methodological material concerning principal component analysis are referred to Johnson and Wichern (1998), ch.8.

3.2.3 Goodness-of-fit tests

As already specified in the subsection 3.1.1, the statistic given in (1) is used to compare the empirical distributions of the conditional and unconditional returns. Under the null, those squared differences $(Y_i - (0,1)\,n)^2$ would assume "small" values. Details on that test and on the Kolmogorov-Smirnov test, which was also discussed before and will be used here in this paper, can be found in De Groot (1986).

3.3 The methodology itself

Once formalized, those statistical techniques discussed along subsection 3.2 must be combined to form our methodology, which is given in the following 9-step algorithm:

1. Obtain a relatively large number of price series from securities. This would be the *raw data*.

2. Estimate by *quasi* maximum likelihood $AR(1) - GARCH(1,1)$ models, as given in (2), for each of the return series calculated from the prices.

3. Consider as the new data set the 5 estimated coefficients (these are the variables!) from all securities. Then, explanatorily search for outliers (that is, estimated coefficients values that are "strange" as compared to the majority of the securities). This can be done by descriptives graphical devices, some "3-sigma" strategy and/or *provisory* principal component analysis. Once the outliers are found, remove the correspondent securities from the data and go to the next step.

4. Use the "outliers-free" data set to implement a *definitive* principal component analysis with those 5 variables (the estimated coefficients) in order to get a reduction from 5 to, let us say, 2 dimensions. Interpretation of components is optional.

5. Use the adopted principal components to realize a visual clustering attempt in order to obtain some homogeneous groups of securities in terms of the principal components values - and, consequently, in terms of the estimated coefficients values.

6. Without loss of generality, let us consider that the last step has produced one cluster. Within this cluster, search descriptively for "sub-clusters" by looking at the values of the original variables, the estimated coefficients, in the data set.

7. Use the securities from the (sub-)clusters to realize a technical analysis in order to find potential geometrical patterns.

8. For each type of geometrical pattern found in the technical analysis (cf. section 2 for the possible types), group the parts from the clustered return series which follow after the identification of a given pattern. These are the conditional returns. Observe that the number of data sets formed with conditional returns equals to the number of patterns found in the last step. Also construct the correspondent data sets formed with the unconditional returns.

9. In this final step, perform the goodness-of-fit tests within each pattern. To say once more: the null is that the theoretical probability distribution of the conditional returns is adequately fitted by the empirical distribution raised by the unconditional returns. If the null is rejected, interpret this as an evidence of informational content came from that particular pattern.

A technical word. The so-searched and important homogeneity is just supposed to be tackled in steps 2 to 6. The strict stationarity of the AR(1)-GARCH(1,1) already discussed in subsection 3.2.1 is the building block of everything: the random variables associated with those processes with close estimated coefficient values are believed to have the "same" distribution (even though still presenting a rather complicated statistical dependence).

4. An Application

4.1 General points

Along this section we are going to illustrate the proposed methodology of the last section with real financial data. Each step(s) of the methodology, whenever passed through, is (are) indicated in the following subsections. The same is done on specific computational frameworks. All the implementations have been performed on a Pentium 4 with 3.2 GHz and 512 Mb RAM.

4.2 1st step: obtention of the data

We chose to work with daily series, each one comprising 1000 observations from 62 worldwide securities, such as stocks, commodities, several indexes and exchange rates. The period of analysis ranges from December, 20^{th}, 2001 till December, 9^{th}, 2005. Appendix A offers a table with general information on those securities. The data were obtained from *Reuters* (www.reuters.com).

4.3 2nd step: estimation of the $AR(1) - GARCH(1,1)$ models

We estimated $AR(1) - GARCH(1,1)$ models using *quasi* maximum likelihood for the 62 return series and stored the 5 estimated coefficients for each security. The implementation of this step has been accomplished in Ox language (www.oxmetrics.net) with the use of the package G@RCH (Laurent and Peters, 2006) and the computational time was 13 seconds. Appendix B shows the estimated coefficients, their associated t statistics and the corresponding p-values. We observe that, for all the securities but AL.N CLose (Appendix B), the Bonferroni conjoint significance test indicated that at least one of the theoretical coefficients is different from zero at the level of 1%.

4.4 3rd step: eliminating outliers

This step was performed in Minitab 12.1 (www.minitab.com). Although we do not detail the whole procedure in this paper, it should be mentioned that the data on estimated coefficients have been scrutinized under all the suggested devices listed in our methodology's 3rd step. The conclusion was that the securities listed in Table 1 were quite discordant in terms of their values. By using the remaining 50 securities, we move on.

Table 1
Excluded securities

1	BLS.N
2	AT.N
3	.ITH
4	CSX.N
5	LUV.N
6	AL.N
7	MRK.N
8	LLY.N
9	SGP.N
10	ORCL.
11	INTC.
12	KCc1

4.5 4th and 5th steps: principal component analysis and clustering

Consider the data set with 5 estimated coefficients from the 50 securities, which is actually the data presented in Appendix B without the 12 lines corresponding to the excluded securities listed in Table 1. Now we present the details of the definitive principal component analysis, whose main output is in Table 2. Implementation has been done in Minitab 12.1.

Table 2
Principal component analysis

Eigenvalue	2,5237	1,2790	0,7678	0,4125	0,0171
Proportion	0,505	0,256	0,154	0,082	0,003
Cumulative	0,505	0,761	0,914	0,997	1,000
Variable	CP1	CP2	CP3	CP4	CP5
c	0,035	0,677	0,729	-0,090	0,038
ar	-0,123	0,680	-0,663	-0,285	0,047
$alpha\,0$	0,511	0,265	-0,163	0,744	-0,298
$arch$	-0,623	0,038	0,049	0,118	-0,771
$garch$	0,578	-0,090	0,013	-0,587	-0,560

By looking at the output of the analysis, we find out that the two first principal components respond for 76,1% of the total variance of the original variables, the estimated coefficients. Interpretation of the components is direct. The first one, as it is more strongly weighted on the $GARCH$ coefficients, is called *GARCH Effect*, and the second one, once being more strongly weighted on the AR coefficients, is called *AR Effect*.

With these two adopted and interpreted components, we tackle the visual clustering of securities. The following scatter plot in Figure 4 for the two components is an appropriate place to start.

Looking at the scatter plot, which "photographs"/projects the securities onto two dimentions, we decided to pick some points up, while respecting the following ranges: $-1.5 < GARCH\ Effect < -0.5$ and $-0.4 < AR\ Effect < 0.3$. The selected securities are circled in the scatter plot and have their names displayed in Table 3.

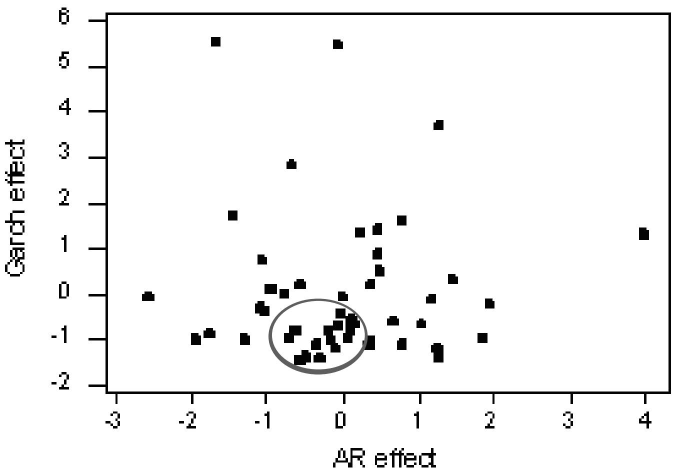

Figure 4
Scatter plot for the two first principal components detaching the first clustering attempt

The clustered securities have been put together by solely looking to the first two principal components. Some information from the original variables has therefore been neglected. In order to remedy this, we refine this clustering process in the next step.

Table 3
General cluster

MWD
JPM
RUT
MCD
EURJPY
XAU
EMR
GBPCHF
BAC
COST
KSS
KO
SPX
DJI

4.6 6th step: sub-clustering

From the securities of Table 3, we extracted two sub-clusters by carefully looking at the values of the estimated coefficients. For the interested, we re-mention Appendix B with the complete data set. The two homogenous groups are listed in Tables 4 and 5, together with their estimated AR-GARCH coefficients.

Table 4
First cluster formed from the estimated coefficients.

series	c	ar	$alfa\,0$	$garch$	$arch$
MWD.N Close(Last Trade)	0,000419	-0,020685	0,0000014	0,951418	0,044894
JPM.N Close(Last Trade)	0,0003682	-0,001257	0,0000007	0,943139	0,054871
.RUT Close(Last Trade)	0,0006923	-0,043158	0,0000025	0,939550	0,043546
.SPX Close(Last Trade)	0,0004121	-0,075118	0,0000005	0,941578	0,053121
.DJI Close(Last Trade)	0,0003233	-0,071565	0,0000006	0,936283	0,057318
MCD.N Close(Last Trade)	0,0007783	-0,037495	0,0000019	0,953246	0,041723

Table 5
Second cluster formed from the estimated coefficients.

series	c	ar	$alfa\,0$	$garch$	$arch$
GBPCHF=R Close(Bid)	-0,000049	-0,014575	0,0000000	0,980384	0,018629
BAC.N Close(Last Trade)	0,0002801	-0,026154	0,0000004	0,980532	0,016194
COST.O Close(Last Trade)	0,0004386	-0,052422	0,0000008	0,984596	0,012819
GPS.N Close(Last Trade)	0,0001368	-0,029704	0,0000009	0,985106	0,012204

After this search for homogeneity in all the return series, we admit that there are strong similarity on the $AR(1) - GARCH(1,1)$ data generating processes for this two final clusters. This would necessarily imply in the returns tending to be identically distributed (albeit still dependent!).

4.7 7th step: technical analysis

At this stage, geometrical patterns were extracted within technical analysis over the price time series due to the securities clustered in Tables 4 and 5. We would like to thank the JGP staff (www.jgp.com.br) from whom we obtained these charting results. In Table 6 we enumerate the types of identified patterns and their respective frequencies for each security. Additional information on the beginning and on the breakout points of these patterns, as well the raw material on the performed technical analysis – which is characterized by scrutinized price charts –, can be found in the appendix of Lorenzoni (2006).

Table 6
General information on the occurrence of the geometrical patterns along the securities from both clusters

Asset	Cluster	Triangles	Rectangles	H&S
JPM	1	1	0	1
MWD	1	2	1	0
RUT	1	1	1	1
DJI	1	1	1	1
SPX	1	0	2	1
MCD	1	4	1	0
BAC	2	2	1	0
GPS	2	2	1	0
GBPCHS	2	1	2	0
COST	2	3	3	0

4.8 8th and 9th steps: grouping return observations and the goodness-of-fit tests

For each of the patterns given in Table 6 we have grouped together the parts of all the return series corresponding to the conditional returns. These would be compared to all the agglutinated return series, the unconditional returns. Then we get everything needed for the application of the Chi-Square and Kolmogorov-Smirnov tests, whose implementation has been executed in Ox language; the computational time was derisive (much less than a second).

Tables 7 and 8 give information on the tests applied to the first cluster. By reading those tables we see that the triangle is the most uninformative pattern (see "big" p-values). In the other hand we find evidence on the presence of informational content came from rectangles and head & shoulders (see "small" p-values).

Table 7
Goodness-of-fit tests for the first cluster

Pattern	χ^2 statistic	χ^2 p-value	*K-S* statistic	*K-S* p-value
Triangle	5,0195	0,8326	0,9491	0.3286
Rectangle	30,5849	0,0003*	1,3451	0.0536*
H&S	25,1342	0,0028*	1,5661	0.0514*

* Significant at the level of 10%.

Table 8
Number of observations used in the tests for the first cluster

Pattern	Number of observations	Conditional observations
Triangle	6000	307
Rectangle	6000	265
H& S	6000	745

Now we concentrate on the second cluster. Information from Table 9 tells us that both patterns, triangle and rectangle, are informative by at least one of the tests (see the p-values). We better mention that, although suggesting the effectiveness from the rectangle, care must be exercised on interpreting this result since the number of observations on conditional returns is not that large (only 122 observations); cf. Table 10.

Table 9
Goodness-of-fit tests for the second cluster.

Pattern	χ^2 statistic	χ^2 p-value	*K-S* statistic	*K-S* p-value
Triangle	22,7826	0,0067*	0,9586	0,3170
Rectangle	21,9344	0,0091*	1,7785	0,0036*

* Significant at the level of 10%.

Table 10
Number of observations used in the tests for the second cluster.

Pattern	Number of observations	Conditional observations
Triangle	4000	553
Rectangle	4000	122

4.9 Complementary analysis

The results from the application of the proposed methodology indicated, by remaining on the considered data set, two potentially important patterns (rectangle and head & shoulders), and rejected the triangle.

Although we are anchored at limited empirical evidence, triangles' failure seems to be corroborated by several technical analysts who frequently agree on the inconstancy of this particular geometrical pattern. On the other two accepted patterns, we understand that those results could go through the direction of prior belief on possible trend anticipation in price charts.

5. Discussion

In this paper's final section we attempt to further debate on the proposed methodology by suggesting extensions. We however advertise that the dependence issue is not entering in what follows; the next two subsections in fact deal with (i) an econometrically more rigorous framework for improving the sub-clustering 6th step of our methodology and (ii) possible advances on the understanding about how the real informational content statistically influences the conditional returns whenever it is uncovered by the goodness-of-fit tests.

5.1 A statistical test for homogeneity

Recall the 5th and 6th steps of the prosed methodology. They prove to be crucial to the whole work, since they try to overcome the undesirable distributional differences of the data by collecting together securities that seem to present homogeneous statistical properties.

However, some readers may find the elected clustering device somewhat subjective in the sense that one can understand that the formed clusters, visualized by another, are not appropriate and vice-versa. But we stick to the simple fact that *any clustering attempt is subjective*, regardless of its nature being more visual or more automatic. If we for instance go to Mardia et al. (1979), or to Johnson and Wichern (1998), plentiful discussion can be found on how a swap in any clustering device can dramatically change the obtained groups of individuals.

So, as little can be done on the attenuation of subjectiveness came from cluster analysis, we could step to the *elimination* of it! Indeed, we could try an econometrically more compelling way to form a group of homogeneous securities in order to apply the goodness-of-fit tests. In fact, we are working in this task even though implementations have not been accomplished yet. But we can outline the general points of it and leave the empirical results to an upcoming paper.

Firstly we assume something quite reasonable: the sub-clustered securities – say k securities – harvested from the 6th step of the methodology have their dynamics adequately described by some kind of $VAR(1) - GARCH(1,1)$ model which necessarily admits $AR(1) - GARCH(1,1)$ models for each one of its components (the returns series for the securities). By denoting the vector of total parameters of the joint $VAR(1) - GARCH(1,1)$ model by ψ and the parameters of the marginal $AR(1) - GARCH(1,1)$ models by $\psi_j \equiv g_j(\psi)$, where g_j is an appropriate function, $j = 1, \ldots, k$, we formalize this presupposition by displaying

$$\begin{gathered} \mathbf{R}_t \equiv (R_{t1}, \ldots, R_{tk})' \sim VAR(1) - GARCH(1,1)(\psi) \\ R_{jt} \sim AR(1) - GARCH(1,1)(\psi_j) \\ j = 1, \ldots, k. \end{gathered} \tag{5}$$

Those acquainted with GARCH literature and its multivariate extensions certainly knowledge that not every multivariate GARCH structure leads to marginal univariate GARCH structures, this not happening with the proposed model by Bollerslev (1990). So the latter could be an alternative.

Secondly we would establish the grounds for the estimation of the adequate multivariate GARCH model in (5) with the data on returns for the k securities. And we do this by (*quasi*) maximum likelihood framework. Within this set up it becomes possible to test the following hypothesis:

$$\begin{gathered} H_0 : \psi_1 = \cdots = \psi_k \\ H_1 : \text{The null fails.} \end{gathered} \tag{6}$$

Accepting the null in (6) is actually everything we need because this would reveal to us the lack of evidence came from the data against the fact that *the securities present strictly the same marginal processes driving their dynamics*. This implies in $R_{11}, \ldots, R_{1k}, \ldots, R_{T1}, \ldots, R_{Tk}$ being identically distributed, and therefore we are done: homogeneity has rigourously been achieved.

There are two issues to be considered. The first is on the test that should be evoked and performed to lead us on deciding between H_0 and H_1. Since multivariate GARCH proposals usually contemplate lots of parameters, a smart choice would lead to the LM type tests owing to their sole necessity for estimation of reduced - and more parsimonious - models. Maybe some changes on the original test statistic due to *quasi* likelihood framework would be important (White, 1994). The second issue is on the distribution to be chosen for the multivariate error term associated to the $VAR(1)-GARCH(1,1)$ model. This is rather relevant because additional parameters coming from fat-tailed distributions (*e.g.* the degrees of freedom of multivariate *t*-Student distributions) could be used as additional variables in the clustering process.

5.2 Comparison of moments

When the null hypothesis is rejected by the goodness-of-fit tests, the data prove to furnish evidence on some differences between the probability distributions of the conditional and unconditional returns. Quoting the interpretation given in Lo et al. (2000) for this found, we say that, in such case, there is informational content came from the technical analysis. But, what is exactly this "informational content"? Is this latter connected to decisions made by technical analysts on their daily routines in banks, brokers, asset management and investment clubs?

Some work shall be done in order to answer those last two questions. In fact, Narasimhan Jegadeesh already tried to step to this point in the discussion of Lo et al. (2000) by statistically testing if there were differences on the means of the conditional and unconditional returns. Although did the adopted tests not found evidences against differences between both means, this is not too relevant because, in practice, financial decisions are rarely made on basis of first order moments of return distributions. On the contrary, they actually have their grounds on the behavior of moments of greater orders. Even more, since the tests applied by Jegadeesh have used the same data sets from Lo *et al.*, we are tended to unconsider those conclusions because the data still share the same heterogeneity problems.

Our suggestion for future research is the comparison between higher order moments from both conditional and unconditional returns *with securities clustered by this paper's methodology*. As an example of what could be uncovered, we cite possible differences on skewness (third order moments) which would certainly lead to better use of derivative strategies.

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Appendix A

List of the 62 Chosen Securities and Pertinent Information

Assets	Asset Type	Sector	Country
BLS.N Close(Last Trade)	Equity	Telecommunications	U.S.A.
AT.N Close(Last Trade)	Equity	Telecommunications	U.S.A.
.ITH Close(Last Trade)	Index	Telecommunications	U.S.A.
CSX.N Close(Last Trade)	Equity		U.S.A.
LUV.N Close(Last Trade)	Equity	Transportation (aviEquity)	U.S.A.
R.N Close(Last Trade)	Equity	Transportation	U.S.A.
/.HSI Close(Last Trade)	Index	Stocks	Hong Kong
EWW.A Close(Last Trade)	Index	Stocks	Mexico
XOM.N Close(Last Trade)	Equity	Oil & Gas	U.S.A.
CVX.N Close(Last Trade)	Equity	Oil Company	U.S.A.
SLB.N Close(Last Trade)	Equity	Oil Company	U.S.A.
AIG.N Close(Last Trade)	Equity	Financial Sector	U.S.A.
MWD.N Close(Last Trade)	Equity	Financial Sector	U.S.A.
JPM.N Close(Last Trade)	Equity	Financial Sector	U.S.A.
CHF= Close(Bid)	Exchange Rate	Dollar x Swiss Franc	-
GBPCHF=R Close(Bid)	Exchange Rate	British pound x Swiss Franc	-
EURJPY=R Close(Bid)	Exchange Rate	Euro x Yen	-
XAU= Close(Bid)	Commoditie	Gold	-
XAG= Close(Bid)	Commoditie	Silver	-
CLc1 Close(Last Quote)	Commoditie	Crude Oil	-
Sc1 Close(Last Trade)	Commoditie	Soybean	-
KCc1 Close(Last Trade)	Commoditie	Coffee	-
.SPX Close(Last Trade)	Index	Stocks	U.S.A.
.RUT Close(Last Trade)	Index	Small cap. Stocks	U.S.A.
.DJI Close(Last Trade)	Index	Stocks	U.S.A.
.FTSE Close(Last Trade)	Index	Stocks	England
.SOXX Close(Last Trade)	Index	Semmiconductor stocks	U.S.A.
.STOXX50 Close(Last Trade)	Index	European stock Stocks	Europa
.N225 Close(Last Trade)	Index	Stocks	Japan
.GDAX Close(Last Trade)	Index	Stocks	Germany
.DXY Close(Last Trade)	Index	Dollar x another currency	-
EUR= Close(Bid)	Exchange Rate	Euro x Dollar	-
BAC.N Close(Last Trade)	Equity	Financial Sector	U.S.A.
Q.N Close(Last Trade)	Equity	Telecommunications	U.S.A.
AA.N Close(Last Trade)	Equity	Basic Materials	U.S.A.
AL.N Close(Last Trade)	Equity	Basic Materials	U.S.A.
APD.N Close(Last Trade)	Equity	Basic Materials	U.S.A.
PD.N Close(Last Trade)	Equity	Basic Materials	U.S.A.
PX.N Close(Last Trade)	Equity	Basic Materials	U.S.A.
GE.N Close(Last Trade)	Equity	Capital Goods	U.S.A.
BA.N Close(Last Trade)	Equity	Transportation (aviEquity)	U.S.A.
MMM.N Close(Last Trade)	Equity	Capital Goods	U.S.A.
EMR.N Close(Last Trade)	Equity	Capital Goods	U.S.A.
WMT.N Close(Last Trade)	Equity	Retail	U.S.A.
TXN.N Close(Last Trade)	Equity	Semiconductors	U.S.A.
GM.N Close(Last Trade)	Equity	Car Plants	U.S.A.
F.N Close(Last Trade)	Equity	Automotive	U.S.A.
LOW.N Close(Last Trade)	Equity	Retail	U.S.A.

Continued on next page

Assets	Asset Type	Sector	Country
COST.O Close(Last Trade)	Equity	Retail	U.S.A.
MAT.N Close(Last Trade)	Equity	Retail	U.S.A.
KSS.N Close(Last Trade)	Equity	Retail	U.S.A.
KO.N Close(Last Trade)	Equity	Staples	U.S.A.
DIS.N Close(Last Trade)	Equity	Staples	U.S.A.
PEP.N Close(Last Trade)	Equity	Staples	U.S.A.
BUD.N Close(Last Trade)	Equity	Staples	U.S.A.
MCD.N Close(Last Trade)	Equity	Staples	U.S.A.
GPS.N Close(Last Trade)	Equity	Retail	U.S.A.
PFE.N Close(Last Trade)	Equity	Pharmaceutical	U.S.A.
MRK.N Close(Last Trade)	Equity	Pharmaceutical	U.S.A.
JNJ.N Close(Last Trade)	Equity	Pharmaceutical	U.S.A.
LLY.N Close(Last Trade)	Equity	Pharmaceutical	U.S.A.
SGP.N Close(Last Trade)	Equity	Pharmaceutical	U.S.A.
ORCL.O Close(Last Trade)	Equity	Technology	U.S.A.
INTC.O Close(Last Trade)	Equity	Semiconductors	U.S.A.

Appendix B

$\mathrm{AR}(1) - \mathrm{GARCH}(1,1)$ Estimated Coefficients for the 62 Chosen Securities

Assets	c	ar	alfa0	garch	arch
BLS.N Close(Last Trade)	0,00015	-0,01559	0,00000	0,95691	0,04308
	(0,37300)	(-0,42620)	(0,58300)	(36,34000)	(1,48500)
	[0,70920]	[0,67010]	[0,28000]	[0,00000]	[0,06890]
AT.N Close(Last Trade)	0,00054	-0,02841	0,00000	0,96685	0,02845
	(1,42100)	(-0,83330)	(1,43700)	(114,40000)	(3,67800)
	[0,15570]	[0,40490]	[0,07555]	[0,00000]	[0,00010]
.ITH Close(Last Trade)	0,00000	-0,00393	0,00000	0,95271	0,04509
	(-0,01601)	(-0,11200)	(0,85590)	(38,17000)	(1,77500)
	[0,98720]	[0,91080]	[0,19610]	[0,00000]	[0,03810]
CSX.N Close(Last Trade)	0,00100	-0,12183	0,00000	0,92457	0,06060
	(2,00900)	(-3,54300)	(0,89800)	(18,59000)	(1,49500)
	[0,04480]	[0,00040]	[0,18470]	[0,00000]	[0,06765]
LUV.N Close(Last Trade)	0,00033	-0,13318	0,00000	0,94817	0,04169
	(0,55820)	(-3,71900)	(1,04200)	(34,11000)	(2,04000)
	[0,57680]	[0,00020]	[0,14890]	[0,00000]	[0,02080]
R.N Close(Last Trade)	0,00076	-0,03335	0,00004	0,79381	0,07595
	(1,38200)	(-0,95540)	(2,16600)	(10,89000)	(2,91100)
	[0,16720]	[0,33960]	[0,01525]	[0,00000]	[0,00185]
/.HSI Close(Last Trade)	0,00043	0,06036	0,00000	0,96918	0,02617
	(1,36600)	(1,99000)	(0,97120)	(78,51000)	(2,56700)
	[0,17220]	[0,04680]	[0,16585]	[0,00000]	[0,00520]
EWW.A Close(Last Trade)	0,00154	0,00810	0,00000	0,92963	0,05300
	(3,62700)	(0,25340)	(1,63900)	(41,38000)	(3,40800)
	[0,00030]	[0,80000]	[0,05080]	[0,00000]	[0,00035]
XOM.N Close(Last Trade)	0,00090	-0,09108	0,00000	0,92033	0,06324
	(2,41200)	(-2,84000)	(1,65400)	(35,64000)	(3,16000)
	[0,01600]	[0,00460]	[0,04925]	[0,00000]	[0,00080]
CVX.N Close(Last Trade)	0,00081	-0,03993	0,00001	0,86017	0,09388
	(2,21300)	(-1,22100)	(1,88900)	(19,46000)	(3,84600)
	[0,02710]	[0,22230]	[0,02960]	[0,00000]	[0,00005]
SLB.N Close(Last Trade)	0,00112	-0,01801	0,00000	0,95418	0,03262
	(2,07000)	(-0,54430)	(1,39800)	(49,87000)	(2,62700)
	[0,03880]	[0,58630]	[0,08125]	[0,00000]	[0,00440]
AIG.N Close(Last Trade)	0,00056	0,01250	0,00001	0,85774	0,11400
	(1,29900)	(0,37710)	(1,67100)	(26,71000)	(4,23600)
	[0,19420]	[0,70620]	[0,04750]	[0,00000]	[0,00000]
MWD.N Close(Last Trade)	0,00042	-0,02069	0,00000	0,95142	0,04489
	(0,78740)	(-0,61450)	(0,99850)	(52,57000)	(2,60000)
	[0,43130]	[0,53900]	[0,15915]	[0,00000]	[0,00475]
JPM.N Close(Last Trade)	0,00037	-0,00126	0,00000	0,94314	0,05487
	(0,93950)	(-0,04393)	(1,12300)	(49,60000)	(2,53000)
	[0,34770]	[0,96500]	[0,13075]	[0,00000]	[0,00580]
CHF= Close(Bid)	-0,00030	-0,07872	0,00000	0,96120	0,02065
	(-1,34100)	(-2,54300)	(1,48800)	(68,63000)	(2,39600)
	[0,18030]	[0,01110]	[0,06850]	[0,00000]	[0,00840]
GBPCHF=R Close(Bid)	-0,00005	-0,01458	0,00000	0,98038	0,01863
	(-0,37990)	(-0,42960)	(0,38350)	(47,19000)	(1,56800)
	[0,70410]	[0,66760]	[0,35070]	[0,00000]	[0,05860]

For each security, first number is the estimate, second is the t statistic and third is the p-value.

Assets	c	ar	alfa0	garch	arch
EURJPY=R Close(Bid)	0,00027	0,00324	0,00000	0,93970	0,03733
	(1,53900)	(0,09865)	(1,10600)	(25,39000)	(1,77000)
	[0,12420]	[0,92140]	[0,13450]	[0,00000]	[0,03850]
XAU= Close(Bid)	0,00061	-0,05597	0,00000	0,97024	0,02117
	(2,21300)	(-1,88100)	(1,27500)	(85,76000)	(2,80700)
	[0,02710]	[0,06030]	[0,10125]	[0,00000]	[0,00255]
XAG= Close(Bid)	0,00065	0,04003	0,00000	0,96538	0,02991
	(1,55800)	(1,20400)	(1,04700)	(84,33000)	(3,46900)
	[0,11950]	[0,22870]	[0,14770]	[0,00000]	[0,00025]
Sc1 Close(Last Trade)	0,00070	-0,01164	0,00001	0,90339	0,08214
	(1,50700)	(-0,32880)	(1,47500)	(28,28000)	(3,03600)
	[0,13200]	[0,74240]	[0,07020]	[0,00000]	[0,00125]
.SPX Close(Last Trade)	0,00041	-0,07512	0,00000	0,94158	0,05312
	(1,61700)	(-2,46800)	(1,31600)	(49,94000)	(3,10300)
	[0,10610]	[0,01380]	[0,09425]	[0,00000]	[0,00100]
.RUT Close(Last Trade)	0,00069	-0,04316	0,00000	0,93955	0,04355
	(1,87800)	(-1,40100)	(1,90600)	(53,34000)	(3,53100)
	[0,06070]	[0,16140]	[0,02850]	[0,00000]	[0,00020]
.DJI Close(Last Trade)	0,00032	-0,07157	0,00000	0,93628	0,05732
	(1,29100)	(-2,29700)	(1,26500)	(40,51000)	(2,72600)
	[0,19710]	[0,02180]	[0,10310]	[0,00000]	[0,00325]
.SOXX Close(Last Trade)	0,00075	-0,02083	0,00000	0,96695	0,03100
	(1,22300)	(-0,69130)	(0,73410)	(151,10000)	(4,85600)
	[0,22160]	[0,48960]	[0,23155]	[0,00000]	[0,00000]
.STOXX50 Close(Last Trade)	0,00050	-0,06534	0,00000	0,92277	0,06953
	(1,88100)	(-2,07400)	(1,91000)	(64,94000)	(5,13400)
	[0,06030]	[0,03830]	[0,02820]	[0,00000]	[0,00000]
.N225 Close(Last Trade)	0,00086	0,02485	0,00000	0,91959	0,07421
	(2,50400)	(0,80060)	(1,57100)	(48,29000)	(3,71900)
	[0,01240]	[0,42360]	[0,05820]	[0,00000]	[0,00010]
.GDAX Close(Last Trade)	0,00076	-0,03910	0,00000	0,92568	0,06868
	(2,27400)	(-1,26600)	(1,63600)	(65,79000)	(4,92400)
	[0,02320]	[0,20580]	[0,05105]	[0,00000]	[0,00000]
.DXY Close(Last Trade)	-0,00032	-0,06415	0,00000	0,94983	0,02577
	(-1,99400)	(-2,12500)	(2,06000)	(68,39000)	(2,88000)
	[0,04650]	[0,03380]	[0,01980]	[0,00000]	[0,00205]
EUR= Close(Bid)	0,00039	-0,05866	0,00000	0,95769	0,02378
	(2,02000)	(-1,99100)	(1,88700)	(77,53000)	(2,92700)
	[0,04360]	[0,04670]	[0,02975]	[0,00000]	[0,00175]
BAC.N Close(Last Trade)	0,00028	-0,02615	0,00000	0,98053	0,01619
	(0,83150)	(-0,34130)	(0,13440)	(15,79000)	(0,36210)
	[0,40590]	[0,73300]	[0,44655]	[0,00000]	[0,35865]
Q.N Close(Last Trade)	0,00107	0,00442	0,00001	0,93357	0,06643
	(0,89530)	(0,12030)	(1,00800)	(41,83000)	(2,11800)
	[0,37080]	[0,90430]	[0,15685]	[0,00000]	[0,01720]
AA.N Close(Last Trade)	0,00011	0,02712	0,00000	0,96469	0,02924
	(0,19260)	(0,86490)	(1,09700)	(91,22000)	(3,78900)
	[0,84730]	[0,38730]	[0,13650]	[0,00000]	[0,00010]
AL.N Close(Last Trade)	0,00063	0,06678	0,00007	0,69403	0,10513
	(1,11100)	(1,99800)	(0,66820)	(1,82100)	(1,13500)
	[0,26700]	[0,04600]	[0,25210]	[0,03440]	[0,12830]
APD.N Close(Last Trade)	0,00057	-0,00966	0,00001	0,85908	0,09560
	(1,35100)	(-0,28200)	(0,91730)	(7,35100)	(1,40600)
	[0,17700]	[0,77800]	[0,17960]	[0,00000]	[0,08000]

For each security, first number is the estimate, second is the t statistic and third is the p-value.

Assets	c	ar	alfa0	garch	arch
PD.N Close(Last Trade)	0,00203	0,04847	0,00002	0,90391	0,05186
	(2,88100)	(1,52400)	(2,17000)	(29,95000)	(2,85800)
	[0,00410]	[0,12790]	[0,01510]	[0,00000]	[0,00215]
PX.N Close(Last Trade)	0,00103	-0,02932	0,00000	0,94954	0,03787
	(2,20100)	(-0,84700)	(1,35200)	(45,64000)	(2,64100)
	[0,02800]	[0,39720]	[0,08840]	[0,00000]	[0,00420]
GE.N Close(Last Trade)	0,00033	-0,01578	0,00000	0,96991	0,02751
	(0,87390)	(-0,48220)	(0,91460)	(54,80000)	(4,38600)
	[0,38240]	[0,62980]	[0,18030]	[0,00000]	[0,00000]
BA.N Close(Last Trade)	0,00130	-0,13085	0,00000	0,97199	0,02418
	(2,59400)	(-3,80300)	(0,73800)	(57,48000)	(1,79300)
	[0,00960]	[0,00020]	[0,23035]	[0,00000]	[0,03665]
MMM.N Close(Last Trade)	0,00040	-0,04456	0,00003	0,67818	0,18391
	(1,02300)	(-1,14300)	(2,74800)	(7,78400)	(2,60100)
	[0,30640]	[0,25330]	[0,00305]	[0,00000]	[0,00470]
EMR.N Close(Last Trade)	0,00073	-0,03839	0,00000	0,96468	0,03134
	(1,77600)	(-1,16600)	(0,96540)	(69,03000)	(2,50900)
	[0,07610]	[0,24400]	[0,16730]	[0,00000]	[0,00615]
WMT.N Close(Last Trade)	-0,00017	-0,04931	0,00000	0,96373	0,03041
	(-0,44860)	(-1,43000)	(1,26900)	(77,23000)	(2,84900)
	[0,65380]	[0,15290]	[0,10230]	[0,00000]	[0,00225]
TXN.N Close(Last Trade)	0,00121	0,02620	0,00000	0,96406	0,03140
	(1,55300)	(0,85930)	(1,16900)	(89,94000)	(3,30000)
	[0,12080]	[0,39040]	[0,12135]	[0,00000]	[0,00050]
GM.N Close(Last Trade)	0,00008	0,02192	0,00001	0,92148	0,06399
	(0,15190)	(0,57020)	(1,32800)	(35,79000)	(3,94700)
	[0,87930]	[0,56870]	[0,09220]	[0,00000]	[0,00005]
F.N Close(Last Trade)	-0,00044	-0,01175	0,00001	0,92340	0,06649
	(-0,71080)	(-0,32720)	(1,44300)	(39,98000)	(3,36300)
	[0,47740]	[0,74360]	[0,07465]	[0,00000]	[0,00040]
LOW.N Close(Last Trade)	0,00070	0,00587	0,00000	0,96646	0,02900
	(1,34800)	(0,18710)	(0,97000)	(61,73000)	(2,30700)
	[0,17800]	[0,85160]	[0,16615]	[0,00000]	[0,01065]
COST.O Close(Last Trade)	0,00044	-0,05242	0,00000	0,98460	0,01282
	(0,83300)	(-1,41700)	(0,42550)	(67,82000)	(1,55800)
	[0,40500]	[0,15680]	[0,33530]	[0,00000]	[0,05980]
MAT.N Close(Last Trade)	0,00019	-0,07003	0,00002	0,82002	0,10558
	(0,37830)	(-1,84200)	(1,39400)	(8,80500)	(2,07800)
	[0,70530]	[0,06580]	[0,08185]	[0,00000]	[0,01895]
KSS.N Close(Last Trade)	0,00007	-0,00363	0,00000	0,96458	0,02756
	(0,12150)	(-0,11870)	(1,08900)	(48,77000)	(1,88500)
	[0,90330]	[0,90550]	[0,13815]	[0,00000]	[0,02985]
KO.N Close(Last Trade)	0,00025	-0,01457	0,00000	0,95203	0,03966
	(0,70270)	(-0,41810)	(0,88390)	(37,46000)	(1,96000)
	[0,48240]	[0,67600]	[0,18850]	[0,00000]	[0,02515]
DIS.N Close(Last Trade)	0,00060	-0,00299	0,00001	0,88891	0,10082
	(1,21900)	(-0,08117)	(1,63600)	(23,38000)	(2,42000)
	[0,22310]	[0,93530]	[0,05105]	[0,00000]	[0,00785]
PEP.N Close(Last Trade)	0,00048	-0,10896	0,00001	0,69359	0,26511
	(1,58600)	(-2,46200)	(1,41900)	(4,42500)	(1,72100)
	[0,11310]	[0,01400]	[0,07805]	[0,00000]	[0,04275]
BUD.N Close(Last Trade)	-0,00008	-0,13323	0,00000	0,93012	0,05170
	(-0,25110)	(-3,60200)	(0,87520)	(17,10000)	(1,29100)
	[0,80180]	[0,00030]	[0,19085]	[0,00000]	[0,09845]

For each security, first number is the estimate, second is the t statistic and third is the p-value.

Assets	c	ar	alfa0	garch	arch
MCD.N Close(Last Trade)	0,00078	-0,03750	0,00000	0,95325	0,04172
	(1,65600)	(-1,00400)	(1,21900)	(58,76000)	(2,65100)
	[0,09810]	[0,31550]	[0,11150]	[0,00000]	[0,00405]
GPS.N Close(Last Trade)	0,00014	-0,02970	0,00000	0,98511	0,01220
	(0,19600)	(-0,89920)	(0,70070)	(99,60000)	(1,54000)
	[0,84470]	[0,36880]	[0,24180]	[0,00000]	[0,06195]
PFE.N Close(Last Trade)	-0,00074	-0,02641	0,00001	0,85186	0,09637
	(-1,47300)	(-0,55180)	(1,26900)	(9,95900)	(1,76200)
	[0,14120]	[0,58120]	[0,10245]	[0,00000]	[0,03915]
MRK.N Close(Last Trade)	-0,00061	0,00834	0,00016	0,51784	0,05546
	(-1,01000)	(0,18850)	(2,33200)	(5,17800)	(1,06400)
	[0,31260]	[0,85050]	[0,00995]	[0,00000]	[0,14380]
JNJ.N Close(Last Trade)	0,00021	-0,05973	0,00000	0,89088	0,09499
	(0,60820)	(-1,79500)	(1,22900)	(17,46000)	(1,90800)
	[0,54320]	[0,07290]	[0,10965]	[0,00000]	[0,02835]
LLY.N Close(Last Trade)	-0,00057	0,00742	0,00000	0,91049	0,07680
	(-1,22500)	(0,20310)	(1,42200)	(27,00000)	(2,85300)
	[0,22080]	[0,83910]	[0,07770]	[0,00000]	[0,00220]
SGP.N Close(Last Trade)	-0,00007	0,04171	0,00000	0,97262	0,02463
	(-0,13690)	(1,22300)	(0,72230)	(70,68000)	(1,96800)
	[0,89110]	[0,22160]	[0,23515]	[0,00000]	[0,02465]
ORCL.O Close(Last Trade)	0,00020	-0,08944	0,00000	0,97518	0,02021
	(0,30660)	(-2,64600)	(1,20400)	(215,30000)	(4,52900)
	[0,75920]	[0,00830]	[0,11445]	[0,00000]	[0,00000]
INTC.O Close(Last Trade)	0,00052	-0,04654	0,00000	0,96933	0,02805
	(0,83640)	(-1,41400)	(1,04300)	(157,00000)	(3,61500)
	[0,40320]	[0,15760]	[0,14850]	[0,00000]	[0,00015]