Capital Markets clustering: An econometric approach

Álvaro de Campos Londres

Abstract

P. Samuelson and later in the 60's E. Fama presented the Efficient Market Hypothesis Model which is still referred to in discussion of financial efficiency. Later, Mandelbrot observed that large (small) price changes in the capital markets were usually followed by large (small) price changes. The result is that volatility comes together around certain periods in time. Using an econometric approach, this project uses financial data of the Portuguese, Spanish and UK capital markets to prove that this effect is statistically significant while providing some reasoning regarding its origins and consequences and their relation to market liquidity.

Keywords: market efficiency, random walk, fair game, liquidity

Introduction

This research project demonstrates that it is possible to estimate how a certain shock on an asset price will affect its future price variations, in terms of size and duration.

The starting point of this work is the Efficient Market Hypothesis Model (EMH). This work will briefly describe the theory and return to it several times over the work. In section 1.2 the work explains the relevance of my research to the theme and briefly outlines the objectives and hypothesis to be tested. The expected results will also be mentioned.

Section 2 undertakes the data analysis, description and explains the rational behind it.

After discussing the data, section 3 presents the econometric methodology used in the process and briefly describes all the statistical models, tests and steps. Some time will then be spent, in section 4, on the comments and interpretation of the results obtained by the tests and models, given the EMH.

Finally, section 5, provides the conclusions and highlights some topics for further research.

1.1 The Efficient Market Hypothesis

Ever since the capital markets appeared, market players have tried to make profit from it. It was only in the 50's, however, that data on these issues started to be saved and analysed. By that time, Chartist theories ruled the academic and professional opinion. The most important Chartist theory is called the *Dow Theory*. Developed by Charles Dow the theory used graphical and technical analysis to infer about futures prices.

When, due to technological advances, this large amount of data started to be saved, economists found that this theory could not provide significant returns when compared to other simpler strategies like the *buy-and-hold* or the *one security and cash*. Economists began to question about this issue and it was only in 1970 that one theory gathered some consensus.

Eugene F. Fama was only a young unknown professor when he wrote his innovative paper[1]. In his article he defines an efficient market as "*a market in which prices always "fully reflect" available information*" [Fama, 1970]. He also presents three different degrees of efficiency. First, the *weak form*, in which the information set is equal to the historical prices. The *semi-strong form* deals with price adjustments to publicly available information like annual earnings announcements or stock splits. Finally, the *strong form*, considers the possibility of monopolistic access to relevant information, in which price is concerned. Clearly, the term *"fully reflect"* is as strong as it is broad and so Fama presents two models that bring further understanding to his theory.

The Random Walk Model and the Fair Game Model share most of the important financial characteristics; however they differ, on their statistical properties. According to Wooldridge [2] a Random Walk is *"A time series process where next period's value is obtained as this period's value, plus an independent (or at least uncorrelated) error term"* [Wooldridge, 2003]. If a group of investors thought, due to superior information for instance, that a price of a certain asset would rise in the near future, they buy it and obtain their trading profit. This movement would increase the equilibrium price until the price reaches the point where they do not earn anything for their move. This theory rules out any chance of arbitrage. Therefore, price changes are as unpredictable as white noise.

In 1953 Kendall [3] suggests, after examining the cotton and wheat spot prices, in very interesting terms: *"The series looks like a wandering one, almost as if once a week the Demon of Chance drew a random number from a symmetrical population of fixed dispersion and added it to the current price to determine the next week's price"* [Kendall, 1953]. However, if prices already reflect all available information, why do they change at all? Cootner [4] states that prices change whenever available information changes and also: *"Since there is no reason to expect that information to be non-random in appearance, the period-to-period price changes of a stock should be random movements, statistically independent of one another"* [Cootner, 1964].

To summarise, the Random Walk theory suggests that successive price changes are independent and identically distributed (iid) i.e. white noise.

The Fair Game Model is a broader model. Unlike the Random Walk Model, it does not require very strict statistical properties. The assumption that prices fully reflect all available information is still held. However, we can allow some weak form of dependence as long as that dependence cannot be used to obtain significant profit. In fact, in 1965, Fama [5] had already found that there may be some sort of short-run dependence between price changes but, given their intrinsic risk and the transaction commissions, this was not enough to generate significant trading profit. This more relaxed model is only concerned with the chance of arbitrage. In other words, if there is no room for arbitrage, the Fair Game Model is present. To conclude, the Random Walk model is a particular case of the Fair Game Model that may consider different transaction costs and risk taking preferences. However, the financial characteristics are, as mentioned before, quite similar.

So, if prices reflect all the available information and information is a random variable, is it possible to predict anything at all? And make some profit out of it? The answer this project provides is yes and maybe.

1.2 Objectives

As mentioned previously, one of the characteristics of the Random Walk is that price changes are iid. When studying the distribution of price changes, Mandelbrot [6] discovered that this was not a Normal Gaussian one. In fact, the tails of the distribution were consistently longer and higher, meaning that extreme values were somewhat more probable when compared to the Normal distribution. Mandelbrot suggested that there might be some sort of dependence, not on prices but on price changes, that could partially account for the longer and higher tails. He found that large price changes tend to be followed by large price changes, of random sign, whereas small changes tend to be followed by small changes. This kind of effect is called Volatility Clustering (VC) and this is what the project will explore. He appoints the rationale behind this dependence too. He states that the while information becomes available instantly (randomly but instantly), the market takes its time to incorporate this new information in the new price. While some analysts might be too impetuous and overprice the asset, others might be too conservative and underestimate it. This uncertainty will make prices very sensible and it will last until price reaches its new “fair” level. This is especially true if we consider that everyday new information is out. The information is out instantly and analysts are required to take instant decisions regarding it. A more experienced analyst should, therefore, be the one that can accurately anticipate information and correctly value it.

This effect can be easily observed in a graph of daily returns. The following graph presents the daily returns of Cimpor’s stock.

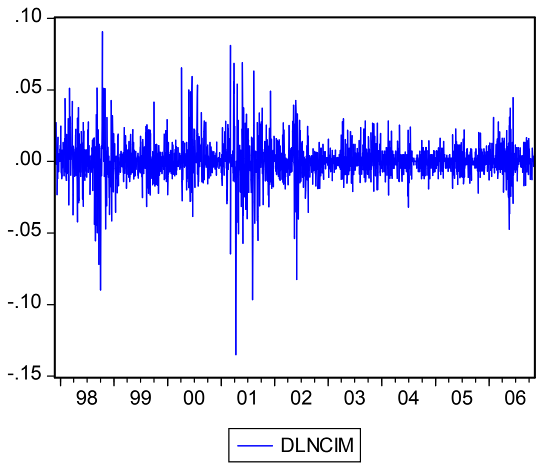

Figure 1: Cimpor’s daily returns. 1998-2006.

The graphical analysis we can clearly present periods where the returns where very volatile, in 2001, while other periods where quite calm, 2004 and 2005.

As Mandelbrot did in the 60's, this work will test if this effect - VC - still occurs in some European markets. To do this, the Portuguese, Spanish and UK capital markets will be analysed. Unlike Mandelbrot, this research will not be concerned about the distribution of price changes. Rather, it will focus on this odd phenomenon and try to understand its causes and consequences as well as its persistence and strength. The project's methodology will also differ from Mandelbrot's.

2. Data

In order to achieve the aforementioned aims, the daily closing prices of four major listed companies in Portugal, Spain and the UK as well their indexes were gathered. The data collected from Bloomberg runs from 01/12/97 to 31/10/06, excluding weekends and national holidays.

I have chosen Portugal for reasons of nationality, Spain due to its proximity and cultural similarities and the UK because it is commonly appointed as the most efficient capital market in Europe.

The chosen companies operate in the banking, telecommunication, industrial, electrical and oil sectors. The historical prices are financially correct from capital issuing, stock splits and dividends to absorb any artificial jumps in the series.

Although the indexes are computed in slightly different way within countries and the companies selected possess different relative weigh in their countries index, I will ignore these differences, as they are not truly important to the development of my work.

The selected companies and indexes are presented in the table (1) below:

Portugal	PSI20	Millennium BCP	PT	EDP	Cimpor
Spain	IBEX35	Banco Santander	Telefónica	Endesa	Repsol
UK	FTSE100	HSBC	Vodafone	Glaxo Smith Kline	BP

Table 1: Selected companies and indexes

The prices of the English companies are in pounds (£) and the others are in euros (€). As described later I will only be using one-day returns so this distinction will not make any difference.

3. Econometric Methodology

To begin with the methodology it is important to recall the main purpose of the research. The aim of this project is to account for the presence of VC, as described before. In econometric terms, if there is statistical evidence for VC, we are facing a case of heteroscedasticity in the volatility of the stock. According to Brooks [7] *"if the variance of the errors is not constant, this would be known as heteroscedasticity"*. However, Mandelbrot did not only say that the errors are heteroscedastic, he also said that the errors depend, not in terms of sign but in terms of size, on previous errors. Note that I moved from price changes to errors due to the characteristics of the models that will be estimated. This will be explained in a while. If the sizes of the error terms depend on its past values, but not on their signs, the model to apply is an autoregressive heteroscedastic one. The Autoregressive Conditionally Heteroscedastic (ARCH) model is exactly what I will use for my research.

As Mandelbrot mentioned, large price changes tend to be followed by large price changes. The first model I will use is an autoregressive one for the daily returns. This model, an AR(q), is defined as follows:

$$returns_t = \beta_0 + \beta_1 returns_{t-1} + \beta_2 returns_{t-2} + \cdots + \beta_q returns_{t-q} + u_t$$

Equation 1: Autoregressive model of order q for the returns
of a given stock price where u_t is a traditional error term.

In this model the u_t term acts as a shock term. Whenever there is new information available, this term is different from zero. Remember that the theory of the Random Walk suggests that price changes are not related in time. Therefore, it can be expected that in more efficient markets, such as the UK, the best AR(q) will be an AR(0), explained only by a close-to-zero constant and the erratic term, generator of the white noise. If this is true we can conclude that the price series are a random walk.

After estimating all the optimal models for all the companies and indexes, the residuals for each equation will be saved and squared in order to estimate the second model that follows the next equation:

$$\hat{u}_t^{\ 2} = \beta_0 + \beta_1 \hat{u}_{t-1}^{\ 2} + \beta_2 \hat{u}_{t-2}^{\ 2} + \cdots + \beta_q \hat{u}_{t-q}^{\ 2} + v_t$$

Equation 2: ARCH model of order q. The variable v_t is a traditional error term.

Like before, the best ARCH model will be chosen following the Schwarz criterium.

Once the optimal ARCH is chosen and the estimators calculated it will be possible to make the ARCH test. The joint null hypothesis (H_0) of this test is that all q lags of the squared residuals have coefficient values that are not significantly different from zero. The alternative hypothesis (H_1) is that at least one of them is significant. It is expected that for all the companies and indexes the tests will strongly reject H_0, thus validating the presence of VC.

Assuming these are the results obtained, this work will continue by estimating the Impulse Response (IR) and Accumulated Response (AR) of a shock of 1 in period 0.

These two functions provide important information regarding the dimension and duration of the ARCH effect.

The IR function accounts for the effect at a given period that a shock of 1 in period 0 causes. If for a given t=5 the IR is 0.2 this means that a shock of 1 in period 0 is estimated to cause a 0.2 response 5 periods later.

The accumulated sum of the IR function gives us the AR of a shock of 1 in period 0. If the AR is 1.5 at period 4, this means that a shock of 1 in period 0 is estimated to have caused a total response of 0.5 divided between the periods 1 and 4. The difference between the AR at period 4 and period 5 will, therefore, correspond to the IR in period 5.

As the ARCH effects tend to be considerably high in the periods after the shock but lower as time goes by, it might also be interesting to investigate on when the effect disappears. Besides the AR and IR I will also look at the period in which the ARCH effects become insignificant. There is no general rule on what constitutes insignificance so, for the purpose of this study, insignificant will be when, at a given period t, the effect of a shock of 1 in period 0 causes a shock smaller than 0.01, i.e. the $IR_t<0.01$.

The results will be presented in section 4. I Comments on the findings, some reasoning and financial intuition to will also be presented to support results.

4.1 Results Obtained

Generally speaking, the results obtained from the previously presented tests and models are, in my opinion, both strong and expected.

Regarding the first estimated model (see Equation 1), the AR(q) for the returns, the optimal lag structure is presented below for every company and index.

	Portugal					Spain					UK				
	BCP	Cimpor	EDP	PT	PSI20	Sant.	Repsol	Endesa	Telef.	IBEX35	HSBC	GSK	BP	Vodaf.	FTSE100
Optimal Lag Structure	1	1	0	2	1	0	0	0	1	0	0	0	0	0	0

Table 2: Optimal lag structure of the AR(q) for the returns.

As we can see, with the exception of EDP, the optimal q, the number of lags on the AR model for the Portuguese capital markets' returns, is bigger than zero. The returns are not iid, thus the Random Walk is not present, as the results suggest that one day returns are correlated to previous returns. However, this sort of short term dependence, which was already mentioned before, could under certain conditions, not question the efficiency of the Portuguese capital market in its weak form. The Fair Game states that there can be dependence while still holding the financial efficiency characteristics, rather than statistical.

Regarding the Spanish and UK's capital markets we can probably conclude that they are closest to the most pure sort of weak form of efficiency, the Random Walk, as there is no strong evidence for daily dependence, i.e. the returns appear to be iid. The only exception is Telefonica with an optimal lag of one.

UK's Capital Market is commonly referred to as one of the most sophisticated in Europe. Therefore, it would be expected that the returns would easily pass the Random Walk test, as they did. On the other extreme we saw that the Portuguese capital market might not be as efficient, at least with regard to statistical independence. The Spanish market appears to be somewhere in between but closer to the UK.

The second model (see Equation 2) used, the ARCH(q), presented the following optimal lag structure:

	Portugal					Spain					UK				
ARCH(q)	BCP	Cimpor	EDP	PT	PSI20	Sant.	Repsol	Endesa	Telef.	IBEX35	HSBC	GSK	BP	Vodaf.	FTSE100
Optimal Lag Structure	2	9	1	4	9	12	5	7	9	15	9	1	5	10	8

Table 3: Optimal Lag Structure of the ARCH(q) model.

Conclusions on the results of this model will not be drawn as the relevant indicators are the ARCH tests, the IR and the AR functions that were calculated based on this model.

The ARCH test, already described in footnote 4, gives us the global idea of the presence of ARCH effects. This test is not meant to explain or describe the effect. Its only purpose is to account for its presence.

The ARCH test p-value, the AR and the duration of the ARCH effect for all companies and indexes are presented below:

	Portugal					Spain					UK				
ARCH effect	BCP	Cimpor	EDP	PT	PSI20	Sant.	Repsol	Endesa	Telef.	IBEX35	HSBC	GSK	BP	Vod.	FTSE100
AR	1.519	2.277	1.208	1.465	2.887	3.738	1.609	2.262	2.848	4.697	2.364	1.082	1.897	2.458	3.705
Duration	6	28	2	8	41	56	11	21	38	87	28	1	15	31	46
p-value,TR^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4: Accumulated Response, Duration and p-value of the TR^2 for the ARCH effect.

The first and probably the most notable result obtained is that the ARCH effect is very strong and significant for all companies and indexes across the three countries. By looking at the p-value of the ARCH test we can be sure that we reject the previously mentioned H_0 with a confidence of at least 99,999%. Thus, we can clearly conclude that there is strong evidence towards the existence of Autoregressive Conditional Heteroscedasticity and VC is fully validated. The statistical implication of these results is that the conditional probability that tomorrow's price change will be large, given that today's price change was large, is higher than the unconditional probability of a large price change. Loosely speaking, it is possible to predict the size of future price changes and therefore, future volatility. I will talk about the financial implications of this result in section 4.2.

What is not so clear is how big and long the effect is between companies and indexes.

A rough analysis will suggest that companies that present longer ARCH effects will also present higher AR. The longest lasting effect is in the IBEX35 (87 days) and it is also the series with a higher AC (4.697) while in Glaxo Smith Klein the effect is only strong for the following day and its total effect appears to be quite small. This is quite easy to accept and rather intuitive.

The comparison between countries itself suggests that these effects are stronger in Spain than in the UK and stronger in the UK than in Portugal. This result probably rules out the chance that these effects are augmented in less efficient capital markets.

There does not appear to be any relation between the results I obtained and the industry sector of the selected companies as some might expect. For instance, the Portuguese bank, BCP, has an AC of approximately 1.52 over 6 following days while the Spanish, Santander, presents an AC of approximately 3.74 over 56 following days.

Finally, the conclusion that I will focus on, is that the national indexes present consistently higher AR and duration, when compared to the companies of the same country that are, in fact, also included in the index.

In fact, the indexes present, on average, about 82.7% higher AC compared to company average and 198.1% longer duration. As this project suggests below, this is a consequence of liquidity, or the lack of it.

As mentioned, the selected companies are all members of their national indexes. They are also some of the most important, in terms of relative weight, of the indexes. In Portugal, for example, the four selected companies account for about 59% of the index. In Spain they weight about 46% while in the UK they still hold 25%. In that sense, given that the index is basically a weighted average of a group of companies, the other companies that were not selected should be the ones pushing the ARCH effects up.

Just like Mandelbrot suggested, the ARCH effects are a consequence of the incapacity to fully reflect the new information in prices instantly. Analysts have to introduce the new information in their models, maybe even construct a new model from the start. However, analysts do not follow all companies in the world: it would be impossible to do so. Typically they follow only a sector, a country or even one single company. They tend to follow bigger companies as these are the ones with high free-floats, big turnovers, major M&A deals and financial restructurings that can boost the trader's profits. These are also the companies that generate more information: public information for legal reasons as well as business plans, company releases, newspapers, elevator rumours… The consequence of this particularity is that big companies are regularly traded in the capital markets while smaller caps are somehow forgotten. Big companies are liquid, smaller companies are not.

The point of this project is that the ARCH effect, or VC for what that matter, is closely related to market liquidity. If a company is heavily traded every day in the stock market it is because there are several players betting on their performance, weather it is good or bad. If so, they must, therefore, have good information and good valuation methods. On the other hand, if a company is obscure, unknown, traders will think twice before buying it. Any relevant information available concerning that company will tend to be ignored by most of the analysts and the price will take longer to adjust. Also, since there are fewer players trading it, the price will float more as a consequence of the relative power that the small number of traders have. They become more price makers than price takers.

To confirm this theory, it is important to check if the selected companies are really liquid, when compared to other companies in the index. To do so, one extra company per country was added to the previous list of companies. To quantify liquidity, a commonly used financial indicator, the bid-ask spread is presented. If the spread between bids and asks is bigger, less transactions will occur, making the asset less liquid.

The following table presents the ask-bid spreads for all the 15 companies.

	Portugal					Spain					UK				
Liquidity	BCP	Cimpor	EDP	PT	**Pararede**	Sant.	Repsol	Endesa	Telef.	**Iberia**	HSBC	GSK	BP	Vodaf.	**Kingfisher**
Bid-ask spread	0.42%	0.45%	0.45%	0.26%	**2.68%**	0.20%	0.16%	0.18%	0.16%	**0.66%**	0.20%	0.17%	0.18%	0.25%	**0.44%**

Table 5: Bid-Ask spread for all companies, daily data from 1998-2006, simple average.

Newly selected companies appear in **Bold**.

It is clear to see that within countries the liquidity varies. Interestingly, the new companies show higher spreads than the previously selected companies and thus, less liquidity. This is especially true for smaller markets, such as the Portuguese. Also, for every country, the less liquid of the originally selected are the ones that present more ARCH effect: Cimpor, Santander and Vodafone.

Loosely speaking, this shows that there is a negative correlation between liquidity and ARCH effects. The results of the indexes provide support to this argument.

4.2 Consequences of the findings

Until now this work has shown that there is strong evidence to support the existence of VC, through ARCH effects, and that by knowing this fact we can make more precise estimations regarding future price changes. As mentioned before, the conditional probability that tomorrow's price change will be large, given that today's price change was large, is higher than the unconditional probability of a large price change.

Does this finding question the EMH presented in section 1.1?

Fama's work concerns the capital markets efficiency. He defended that, in a Random Walk Model or a Fair Game Model, it was impossible to deliver significant profits from trading without facing significant risk. No matter what kind of strategy or investment filter there is no chance for arbitrage.

The model involved in this work can help estimating the size of future price changes. However, it has no bearing on the sign of this change. In that sense, any trader that would use these findings could be betting on a bullish move and the market could respond with a bearish one. On average no significant profit would be made and probably he would even increase his portfolio risk.

However, pure trading is not the only way to generate profit out of the capital markets. In fact, some players are only interested in volatility; buying and selling volatility.

The development of derivatives brought new options to the capital markets. Derivatives are contracts that resemble financial bets. Some of the simplest derivative products are called options. A call option is a contract that allows its buyer to obtain, in a contracted future, a certain asset at a certain strike price. Similarly, in a put option an investor buys the option to sell. With these two simple mechanisms it is possible to use volatility, or the lack of it, for profit. The pricing of these options is usually based on the current asset price, future strike price, maturity of the option and the volatility of the asset. A more volatile asset will be priced higher for both call and put options as the chances of becoming *in the money* are higher.

The findings presented in this project suggest that volatility can be estimated in a more accurate way than a simple but yet commonly used variance/standard deviation of past historical records. Furthermore, if one can use this information while other analysts hold to their simplistic estimations, it will be possible to obtain significant returns. For example, if an analyst would estimate that, given the current information, a certain asset's volatility is underestimated (reflected by the small price of a call or put) he would be able to buy a call and a put, *bottom straddle strategy*, cheaply, and get his profit once the maturity is over, as the real chances of ending *in the money* are higher than reflected in prices. On the other hand if the volatility is overestimated he will do the opposite: sell a call and a put, *top straddle strategy*, and bet on the price persistence. If all players use pure historical information on volatility as a proxy for future volatility they will end up with an efficient derivatives market. On the other hand, if all players understand and account for the presence of ARCH effects, the prices of the derivatives will reflect this common known information and the derivative market will still be efficient. However, as soon as some (not all) realize that unlike asset prices, volatility is somehow predictable, the model presented by this work shows that it will be possible to earn significant profit without incurring significant risk as the prices of these products will not reflect their fair value.

The model I developed does not remove the White Noise that information represents and therefore it cannot completely remove risk in such games. However, it can reduce it by providing information that apparently was hidden. Again, if the pricing of the derivatives does not fully reflect this type of information (and that will happen whenever market players ignore the ARCH effects) it is possible that the derivative market is not being completely efficient allowing some analysts to take advantage of this asymmetry in information and breaking the *strong form* of efficiency.

This approach and conclusions this work presents does not question Fama's view of efficiency. In fact, it even uses his definition of efficiency to provide discussion on the derivatives market.

5. Conclusions

In section 1.1 the project briefly described the EMH developed by Fama. It also presented the models that supported his theory, in particular the Random Walk model and the Fair Game.

Section 1.2 introduced Mandelbrot's work concerning distributional evidence and VC. Regarding the VC, this project did intensive testing on the Portuguese, Spanish and UK market. The approach used was rather econometrical and strongly in support of the presence of this effect. In particular, the project tested for autoregressive squared residuals. ARCH tests were made to provide evidence on the presence of VC while the Accumulated Response function was used to test for duration and power. The tests indicate that this effect is highly persistent and significant in all observed capital markets. They also indicated different duration and accumulated effect on returns. This particularity appears to be related to the degree of liquidity of stock used. The research suggests that more liquid companies are less sensitive to ARCH effects and supports this idea with financial intuition and reasoning.

At the end of the work some words are dedicated to the consequence of this effect on the financial markets. In particular, it is presented in a very simplistic way, how these models can be used to achieve profit from simple derivative products and strategies and how it might question the derivatives market.

Future research on this topic should include a different methodology, perhaps GARCH models or other estimation techniques unlike the traditional Ordinary Least Squares. Further works should also include less liquid companies in order to provide further support of the ideas presented in this project and optimally a greater geographical reach.

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Appendix

Portuguese companies and index

Best AR(q)
Lag Structure
Schwarz Criterium

Portugal

Lags	BCP	Cimpor	EDP	PT	PSI20
0	-5.4408	-5.7407	-5.5483	-4.9575	-6.2316
1	-5.4469	-5.7495	-5.5477	-4.9618	-6.2468
2	-5.4461	-5.7463	-5.5450	-4.9623	-6.2435
3	-5.4428	-5.7431	-5.5435	-4.9590	-6.2403
4	-5.4403	-5.7401	-5.5407	-4.9560	-6.2425
5	-5.4374	-5.7376	-5.5386	-4.9526	-6.2397

Best ARCH(q)
Lag Structure
Schwarz Criterium

Lags	BCP	Cimpor	EDP	PT	PSI20
1	-11.199	-11.818	-12.102	-10.948	-13.349
2	-11.223	-11.816	-12.102	-10.950	-13.356
3	-11.221	-11.813	-12.099	-10.956	-13.372
4	-11.218	-11.817	-12.097	-10.960	-13.378
5	-11.215	-11.816	-12.097	-10.958	-13.376
6	-11.213	-11.819	-12.094	-10.960	-13.373
7	-11.216	-11.820	-12.091	-10.957	-13.394
8	-11.213	-11.822	-12.091	-10.956	-13.429
9	-11.210	-11.839	-12.088	-10.955	-13.434
10	-11.212	-11.836	-12.086	-10.953	-13.431
11	-11.209	-11.839	-12.083	-10.953	-13.428
12	-11.205	-11.836	-12.079	-10.949	-13.425
13	-11.203	-11.833	-12.076	-10.948	-13.423
14	-11.200	-11.829	-12.073	-10.946	-13.420
15	-11.198	-11.828	-12.072	-10.946	-13.419
16	-11.195	-11.827	-12.069	-10.943	-13.421
17	-11.192	-11.825	-12.065	-10.940	-13.426
18	-11.191	-11.824	-12.062	-10.937	-13.424
19	-11.188	-11.820	-12.059	-10.934	-13.421
20	-11.186	-11.817	-12.055	-10.931	-13.419

Best ARCH(q)

Lag Coefficient	BCP	Cimpor	EDP	PT	PSI20
1	0.1834	0.2111	0.1767	0.1020	0.0848
2	0.1626	-0.0008		0.0561	0.0453
3		-0.0105		0.0872	0.1034
4		0.0609		0.0831	0.0555
5		0.0223			-0.0086
6		0.0641			-0.0103
7		0.0486			0.1220
8		0.0396			0.1862
9		0.1431			0.0917

Note that the Schwarz criterium is optimized in its minimum.

Spanish companies and index

Best AR(q)
Lag Structure
Schwarz Criterium

Lags	Santander	Repsol	Endesa	Telefonica	IBEX35
			Spain		
0	-4.8305	-5.3313	-5.3544	-4.8789	-5.7000
1	-4.8272	-5.3294	-5.3532	-4.8798	-5.6968
2	-4.8238	-5.3278	-5.3500	-4.8786	-5.6939
3	-4.8244	-5.3256	-5.3515	-4.8759	-5.6929
4	-4.8225	-5.3224	-5.3482	-4.8725	-5.6897
5	-4.8192	-5.3202	-5.3449	-4.8692	-5.6864

Best ARCH(q)
Lag Structure
Schwarz Criterium

Lags	Santander	Repsol	Endesa	Telefonica	IBEX35
1	-10.572	-11.652	-11.836	-11.106	-12.705
2	-10.579	-11.656	-11.862	-11.116	-12.733
3	-10.618	-11.659	-11.873	-11.151	-12.766
4	-10.629	-11.657	-11.872	-11.157	-12.783
5	-10.630	-11.669	-11.870	-11.154	-12.785
6	-10.655	-11.667	-11.878	-11.162	-12.804
7	-10.664	-11.665	-11.879	-11.175	-12.822
8	-10.673	-11.664	-11.876	-11.181	-12.838
9	-10.671	-11.668	-11.875	-11.187	-12.846
10	-10.674	-11.667	-11.874	-11.186	-12.849
11	-10.679	-11.668	-11.873	-11.183	-12.851
12	-10.680	-11.665	-11.870	-11.181	-12.852
13	-10.677	-11.662	-11.870	-11.177	-12.852
14	-10.676	-11.680	-11.867	-11.198	-12.857
15	-10.681	-11.676	-11.863	-11.195	-12.858
16	-10.678	-11.674	-11.860	-11.192	-12.856
17	-10.677	-11.670	-11.857	-11.196	-12.853
18	-10.674	-11.668	-11.854	-11.192	-12.850
19	-10.672	-11.665	-11.851	-11.189	-12.847
20	-10.669	-11.665	-11.848	-11.188	-12.846

Best ARCH(q)

Lag Coefficient	Santander	Repsol	Endesa	Telefonica	IBEX35
1	0.1071	0.1175	0.1506	0.0647	-0.0026
2	-0.0056	0.0655	0.1307	0.0461	0.0522
3	0.1098	0.0643	0.0934	0.1399	0.0931
4	0.0641	0.0228	0.0145	0.0635	0.0632
5	0.0106	0.1218	0.0198	-0.0188	0.0126
6	0.1460		0.0913	0.0701	0.1032
7	0.0815		0.0690	0.1158	0.1069
8	0.0973			0.0886	0.1114
9	0.0320			0.0957	0.0992
10	0.0700				0.0814
11	0.0992				0.0569
12	-0.0661				-0.0801
13					-0.0551

14		0.0911
15		0.0680

UK companies and index

Best AR(q)
Lag Structure
Schwarz Criterion

	UK				
Lags	HSBC	GSK	BP	Vodafone	FTSE100
0	-5.1785	-5.1355	-5.2499	-4.4857	-6.0813
1	-5.1751	-5.1321	-5.2469	-4.4823	-6.0781
2	-5.1734	-5.1341	-5.2476	-4.4835	-6.0772
3	-5.1705	-5.1308	-5.2490	-4.4853	-6.0809
4	-5.1674	-5.1279	-5.2460	-4.4820	-6.0779
5	-5.1687	-5.1271	-5.2450	-4.4786	-6.0770

Best ARCH(q)
Lag Structure
Schwarz Criterion

Lags	HSBC	GSK	BP	Vodafone	FTSE100
1	-11.233	-10.803	-11.904	-10.376	-13.507
2	-11.245	-10.801	-11.910	-10.389	-13.585
3	-11.254	-10.798	-11.912	-10.396	-13.622
4	-11.255	-10.799	-11.923	-10.405	-13.631
5	-11.259	-10.797	-11.950	-10.405	-13.640
6	-11.257	-10.796	-11.949	-10.410	-13.650
7	-11.271	-10.793	-11.946	-10.408	-13.650
8	-11.270	-10.791	-11.947	-10.406	-13.662
9	-11.272	-10.787	-11.944	-10.408	-13.659
10	-11.269	-10.785	-11.942	-10.412	-13.657
11	-11.266	-10.783	-11.943	-10.409	-13.656
12	-11.265	-10.780	-11.942	-10.410	-13.653
13	-11.263	-10.776	-11.949	-10.409	-13.653
14	-11.261	-10.773	-11.947	-10.407	-13.650
15	-11.257	-10.770	-11.946	-10.403	-13.648
16	-11.254	-10.844	-11.943	-10.401	-13.645
17	-11.251	-10.841	-11.940	-10.398	-13.642
18	-11.248	-10.838	-11.936	-10.395	-13.641
19	-11.248	-10.835	-11.934	-10.396	-13.638
20	-11.244	-10.831	-11.931	-10.394	-13.638

Best ARCH(q)

Lag Coefficient	HSBC	GSK	BP	Vodafone	FTSE100
1	0.1086	0.0818	0.1099	0.0987	0.0426
2	0.0667		0.0620	0.0763	0.1669
3	0.0793		0.0443	0.0556	0.1298
4	0.0306		0.0991	0.0830	0.0637
5	0.0629		0.1730	0.0285	0.0709
6	0.0125			0.0681	0.0908
7	0.1191			0.0332	0.0530
8	0.0419			0.0162	0.1233
9	0.0724			0.0662	
10				0.0854	

ARCH-LM tests

ARCH Test:			
BCP			
F-statistic	90.77270	P-value	0.00000
Obs*R-squared	168.47810	P-value	0.00000

ARCH Test:			
PT			
F-statistic	22.03970	P-value	0.00000
Obs*R-squared	85.08257	P-value	0.00000

ARCH Test:			
PSI 20			
F-statistic	40.72330	P-value	0.00000
Obs*R-squared	317.23050	P-value	0.00000

ARCH Test:			
SANTANDER			
F-statistic	50.88157	P-value	0.00000
Obs*R-squared	383.15130	P-value	0.00000

ARCH Test:			
TELEFONICA			
F-statistic	37.67573	P-value	0.00000
Obs*R-squared	296.55790	P-value	0.00000

ARCH Test:			
HSBC			
F-statistic	25.84001	P-value	0.00000
Obs*R-squared	212.00100	P-value	0.00000

ARCH Test:			
GSK			
F-statistic	15.49603	P-value	0.00009
Obs*R-squared	15.40575	P-value	0.00009

ARCH Test:			
FTSE			
F-statistic	73.65244	P-value	0.00000
Obs*R-squared	470.35630	P-value	0.00000

ARCH Test:			
EDP			
F-statistic	74.00564	P-value	0.00000
Obs*R-squared	71.76193	P-value	0.00000

ARCH Test:			
CIMPOR			
F-statistic	26.21591	P-value	0.00000
Obs*R-squared	214.79640	P-value	0.00000

ARCH Test:			
IBEX 35			
F-statistic	39.89366	P-value	0.00000
Obs*R-squared	477.03090	P-value	0.00000

ARCH Test:			
ENDESA			
F-statistic	40.90352	P-value	0.00000
Obs*R-squared	255.38050	P-value	0.00000

ARCH Test:			
REPSOL			
F-statistic	24.16904	P-value	0.00000
Obs*R-squared	115.09570	P-value	0.00000

ARCH Test:			
BP			
F-statistic	41.82468	P-value	0.00000
Obs*R-squared	192.14670	P-value	0.00000

ARCH Test:			
VODAFONE			
F-statistic	22.92911	P-value	0.00000
Obs*R-squared	209.36820	P-value	0.00000