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EVALUATING MARKET SUPERVISION THROUGH AN OVERVIEW OF TRADING HALTS IN THE PORTUGUESE STOCK MARKET

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EVALUATING MARKET SUPERVISION THROUGH AN OVERVIEW OF TRADING HALT IN THE PORTUGUESE STOCK MARKET

João Duque and Ana Rita Fazenda¹

Abstract

In this study we analyse security-trading halts in the Portuguese capital market to measure the goodness of trading halts imposed by market authorities as well as its timing ability on both interrupting and restarting trading.

A sample of 54 equities whose trading has been halted from some hours to some days between 1992 and 1999 was collected. We used stock price returns, abnormal returns and volatility to compare and test the significance of differences for pre and post-halt periods. Firstly we consider the global sample to analyse stock abnormal returns and afterwards we split it into good and bad news halts. Concerning volatility, we applied t-test as a GARCH (1,1) model to complete volatility analysis. The GARCH(1,1) model has two additive dummy variables on the independent term of the mean and variance equations.

We found that justification for trading halts tend to increase as event window size increases, suggesting that supervisory authorities tend to spot better the dominant changes (mainly for the latest years considered in this research). In fact, when very short time sampling periods are used we found weaker justifications for stock halting. We also found a GARCH (1,1) model useful and a more sensitive instrument on justifying trading halts.

The opportunity of market authorities to interrupt trading seems to be increasing, but in terms of timing, we found that they seem to be most of the times retarded when imposing trading halts or anticipated when authorizing restart trading. Nevertheless when considering "good" news, although the halt tends to be late, the restart seems to be on time.

Additionally we found that the methods under scope in this study are not redundant and should be jointly used by stock watch departments of supervision authorities for detecting trading under asymmetric information.

Keywords: Market supervision, capital markets, trading halts, stock price returns, volatility and GARCH models.

JEL classification: G14, G18, and G28.

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1. INTRODUCTION

Market efficiency is a vital topic in organised and well-established capital markets. This is the only way to keep investment flow and economic activity in open economies based on strong capital markets. In these markets information becomes the most important resource in the creation of expectations that lead to price formation. This turns the regulator's activity, particularly its supervision, into one of its most important activities. Regulators devote significant financial, human and technical resources to this supervisory activity. Investors and financial institutions through taxes, rates or financial contributions, according to the system that takes place in each jurisdiction, do the financing of this activity directly or indirectly. Financial literature has been quite interested in analysing and testing the market efficiency of investors and financial intermediaries, but this has scarcely been applied to regulators.

One of the major concerns of regulators is preventing crime related to market information. In this category of crime we may include lack of information, false, dubious, unclear, incomplete, confusing information and the transmission of information out of the appropriated context. All these factors may lead to information asymmetry. Market regulators also look for information exaggeration or with strong tendencies for fictitious trading that may lead to the formation of expectations on prices or volumes that are false. In preventing the spread of such symptoms that may lead to unfair trading, supervisory authorities tend to suspend trading in individual securities during a certain period of time, during which information has to be released in order to overcome the noticed bias (trading halts). With this mechanism, the main purpose of the authorities is to give investors a chance to react to new information and to help the formation of a consensus price. In what share trading in organised exchanges may concern, the power to impose trading halts is concentrated on financial regulators or exchanges or even split into both, according to each jurisdiction.

Besides trading halts, there are also circuit breakers², another market mechanism ordered by the authorities and studied in the literature to moderate excessive volatility and to allow for fair spread and absorption of information by all market participants. Nevertheless, in this paper we will only focus on trading halts imposed by surveillance bodies (regulators and exchanges) resulting from uncertain information surrounding trading³.

² These are market-wide approach to managing volatility by stopping trading in the entire market during normal business hours.

³ While the arguments and evidence in this paper can likely be extended to the case of market-wide halts (or circuit breakers), our analysis will focus exclusively news related halts on individual securities.

1.1. REGULATORY AND INSTITUTIONAL DETAILS

Until 1991 the financial supervision of the incipient Portuguese stock market was run by a governmental body working under the administration of the Portuguese Ministry of Finance. In 1991 a new Finance Act and a new and independent regulatory body was created (CMVM - Comissão do Mercado de Valores Mobiliários). Ten years after, we feel that some attention should focus on how its activity has been developed. In order to do so, we thought that analysing trading halts could be just a start.

According to the law that regulates the Portuguese capital market since 1991, the regulator (CMVM) could impose trading halts on any security based on its initiative, by suggestion of the exchange, or even by proposal of the quoted company itself⁴. However, within the mechanism that was established in the Act, both the stock exchange and the regulator (CMVM) shared the power to suspend trading on stocks listed on the Market with Official Quotations (the blue chip stocks)⁵. For many years the information that was released concerning halts was unclear about its origin, i.e., who took the initiative that led to the decreed interruption on trading. Therefore, trading halt analysis could be significantly biased when used to infer about the regulator's efficiency in terms of its supervisory activity. Even though, the analysis of trading halts may be a good way to study the efficiency of the supervisory activity of the whole system where regulators and exchanges have the most significant role to play.

With the review of the Act and the implementation of the new Act issued in 2000 the power to impose trading halts is much more concentrated on the exchange. But as this research only collects and treats data before this new Act was approved and enforced, we will consider this analysis as a way of testing the efficiency of the supervisory system taken as a whole, in terms of timing (opportunity) and extension (durability) of trading halts⁶.

In order to do so, we explore stock price returns, abnormal returns and volatility using the event study methodology as in previous research papers but, differently, we use a GARCH model to explore in depth, volatility behaviour surrounding the events.

This paper is organised as follows. Section 2 reviews the literature on trading halts. Section 3 presents the theoretical model, section 4 the research design and section 5 the data collected. Section 6 explores some characteristics of trading halt activity in the Portuguese market and then we show the empirical results from the methodology used. Final comments are included in section 7 at the end of this document.

⁴ Articles 177° and 448° of the Decree of Law 142-A/91, published on April 10, 1991.

⁵ Although for the purpose of the law a distinction may be made, we will not distinguish between trading suspension and trading interruption.

⁶ The supervisory system will be considered as the regulator and the exchange altogether.

2. LITERATURE REVIEW

The basic literature starts with Roberts [1967], later reviewed by Fama [1970], when defining efficient capital markets in its semi-strong form. When new public and relevant information arrives, it should be spread around in order to be available to all investors and supposed to be incorporated in the new price formation process. There are two major ways to let market agents assimilate this information: i) by interpreting price behaviour as trades occur, or ii) by evaluating revealed information during forced trading halts⁷. The literature has presented a list of reasons for and against both procedures.

Several authors presented strong suspicions about the benefits of trading halts, suggesting that they may actually reduce the informative content of stock prices.

The model suggested by Glosten and Milgrom [1985] allows, by opposition to the Copeland and Galai [1983] model, a gradual information absorption process as a result of market activity. Therefore, trading prices would tend to reveal information and trading activity turned to be an efficient way to convert information into prices. According to Glosten and Milgrom [1985] when markets are opened, the expectations of informed and uninformed traders tend to converge as information is disseminated into the market prices. But when trading is halted, prices become unobservable and price sensitive information cannot be "released" by this mechanism. As reinforced by Grossman [1990] "... it merely prevents consenting adults from carrying out their desires on the floor of the stock exchange!" Other studies stand on the same line as Miller [1990], McMillan [1990], Grundy and McNichols [1989], Brown and Jennings [1989] or Dow and Gorton [1989]. These studies suggest that not only trading halts impose a liquidity cost on traders and a loss of opportunities, but also that information will not be readily revealed during a halt as through continuous trading. Furthermore, Ferguson [1988] argues that trading halts may cause market instability and an increasing cost for holding securities. If sellers perceive that a halt is to be imposed they will anticipate the move placing selling orders earlier, where before there was no reason for it, and bringing chaos to markets. Additionally, holding securities that are likely to be subject to trading halts will require an extra premium. This is the only way to compensate security holders for not selling, when thought appropriate. And, *ceteris paribus*, prices should decrease! The same reasons that tend to be applied when markets characteristics are moving down may be used for the reverse direction.

Hopewell and Schwartz [1978] studied daily abnormal returns around NYSE trading halts and also found large price changes over the day of the halt. This change increases with the halt time length.

⁷ We include in the first category the absence of trading due to very large bid-ask spreads quoted by specialists.

During the pre halt period prices tend to anticipate the halt, particularly when good news are observed. Post halt returns tend to be negligible except on the very short-term period (day +1).

Fabozzi and Ma [1988] showed that the first transaction price on the over-the-counter (OTC) market during the halt tends to be an unbiased estimate of the NYSE reopening price resulting in no apparent opportunities for arbitrage profits during NYSE halts. Schwartz [1982] and King et al. [1991] also supported this price learning process even when markets are closed. Therefore, if this is the case, why close the market if in the OTC market, on average, all participants tend to react adequately and fast to new and relevant information?

Other series of studies such as Grundy and McNichols [1989], Brown and Jennings [1989] or Dow and Gorton [1989] suggested models where trading is necessary in order to reveal and disseminate heterogeneous information. Amihud and Mendelson [1987] or Gerety and Mulherin [1992] supported the same idea showing that the reopening price is relatively noisy after regular breaks. The pressure to trade close to the market close or to the market opening is a way that investors use to avoid exposure to risk when markets are shut down. However, these studies used regular breaks based on exchange schedules, which is not the case under consideration. But if their conclusions were transposed to trading halts, its effects would tend to be negative. In the same line Lee et al. [1994] and Corwin and Lipson [2000] found, empirically, that trading halts do not reduce either trading or price volatility. On the contrary, in the post halt period volatility and trading volume tend to increase. This is presented as a result of the batch reopening mechanism employed by NYSE and therefore the paper tends to support the "learning through trading" class of models.

Kryzanowski and Nemiroff [1998] also presented empirical findings on which volatility and trading volume increase before and after trading halts, but return to the basic level after a while when information is completely incorporated into prices. These results support other findings such as Ferris, Kumar and Wolfe [1992]. Tanner and Pritchett [1992] also documented an increase in abnormal returns for stocks that experienced a delayed opening in NYSE, which seems to be inconsistent with the hypothesis that trading halts increase market efficiency.

However, using different approaches, several studies suggested models implying that non-trading periods can provide an opportunity for normal information transmission and, therefore, volatility and volume should decrease after trading halts. These are the cases of Stein [1987], Greenwald and Stein [1988], Kodres and O'Brien [1991], Goldman and Sosin [1979] or Greenwald and Stein [1991]⁸. Engelen and Kabir [2001] studied abnormal returns surrounding Brussels Stock Exchange trading halts and found that there is no significant abnormal return pattern before or after the suspension. They concluded that there is a complete and instantaneous adjustment to the newly released information, which would mean a support in favour trading suspensions. More recently Christie,

Corwin and Harris [2002] found empirical evidences that non-trading periods are a positive way for market agents absorb and digest information claiming for extended halts. And, of course, in favour of trading halts we find the major market regulators and exchange boards.

The great majority of the papers use traditional techniques to compare the behaviour of the variables under study which are among others price returns, trading volume, volatility, number of trades, quote depth, spreads, submissions and cancellations. Brailsford [1995] was one of the few authors that used a GARCH model to examine the relation between trading halts and volatility. Using Australian stock market data collected from 1974 to 1991, he studied the impact of trading halts on conditional volatility. When market closes or stops for any reason trading is interrupted but information flow does not cease. Using a GARCH-M model with a dummy variable on each day of the week, he found that Monday was the only day where the increase on volatility was significant after a trading break (the previous weekend). This seemed to confirm the hypothesis that information production during the close of the market has some impact on volatility that only has a visible consequence at the beginning of the week.

As a conclusion, we find two different positions when looking at security trading halts: i) from one side we have those that support the mechanism, considering that trading halts are beneficial. The underlying assumption is that traders are not able to obtain enough information about market conditions to encourage trading. ii) From the other side those that oppose suggesting models that support continuous trading. They implicitly assume that all market participants immediately observe market prices (which embody all market information in these models).

3. THE THEORETICAL APPROACH

The rational for market authorities to interrupt normal trading is the suspicion or the knowledge that information asymmetry exists, leading to irregular trading. Market authorities do not interrupt trading without a basis, and events, information or accusations from market participants are usually used as reasons. And when that happens we expect breaks on trading to go along with price behaviour changes. Otherwise unjustified trading halts promoted by market authorities may risk to be considered harmful, volatility prone and costly.

By increasing the subjective probability of halts, the security premium for holding stocks would increase and prices expected to be punished. Therefore, when supervisory authorities impose a break on market activity they must be convinced that the profit from breaking is higher than its

⁸All their models argue that, on average, market quality is higher if "informative" halts are allowed.

cost, which is the same as saying that, the cost of price discovery as a result of market activity is higher than its profit.

When trading is halted, price discovery through trading ceases. This will prevent informed traders from getting abnormal and illegal returns from others. But when this happens, several agents can be seriously penalised: for instance, people that strongly need to sell for liquidity or portfolio readjustment purposes in order to face compromises in other markets. If they are unable to sell the security in a market, some effect is expected on other markets⁹. This may seriously hit both players and other markets. The same happens with short sellers who may strongly need to close down their positions on the asset. Adding to that, when the market is closed, all the additional market agents find no way to learn from trading activity as documented in previous research.

We may argue that preventing trading will help sellers and buyers to get "fairer prices" than they would get if trading is continuous, although with a certain probability of not getting the relevant information. But this means delayed cash-in and the assumption that market prices may be "unfair", which is a reason difficult to sustain.

Therefore, whatever the decision to interrupt or to keep the market flow, we always find a significant number of market participants suffering some sort of potential damage and supervisory authorities must be absolutely convinced that social profits exceed the social costs.

But we may ask why to halt trading if all variables are unchanged when comparing pre to post halt periods. It may seem strange if there is no significant change in at least one of the market characteristics of the asset after the revelation of price sensitive information. This does not mean that all price characteristics should change when a halt is declared. But if they change after the release of new and significant information (or confirmation), this means that market authority had at least a reason to invoke the halt as an effective way to prevent unfair trading.

As a consequence, we start by making two basic assumptions: i) if no changes are noticed on market characteristics of the asset, we may infer that there was no reason for the trading halt and that market authorities may have reacted inopportunistly; ii) if changes are noticed we may confirm the fears of market authorities and trading halts were justified.

Using a modified version of the visual approach suggested by Haugen [1997], we might say that in efficient markets, efficient reactions should follow new information arrival and a new state of stable conditions should be observed. We are not specifically talking about prices, but about any

⁹ We may think on a market for a different asset such as the bond market, the real estate market or the market for another security where compromises have been assumed.

abstract stock characteristic that we may define as variable Ψ ¹⁰. We will assume that variable Ψ conditional under the information environment Ω is a martingale. When Ω changes (from Ω_{1-} to Ω_{1+}) as a result of the arrival of the information piece E at time t_1 , this will imply a new level of Ψ (passing from $\Psi_{1-} = A$ to $\Psi_{1+} = B$ in Figure 1). The new environmental information set will be:

$$\Omega_{1+} = \Omega_{1-} \cup E$$

The new level of variable of Ψ will be:

$$\Psi_{1+} | \Omega_{1+} \neq \Psi_{1-} | \Omega_{1-}$$

And its expected value will differ:

$$E[\Psi_{1+} | \Omega_{1+}] \neq E[\Psi_{1-} | \Omega_{1-}]$$

Figure 1 shows the efficient market reaction on variable Ψ to the arrival of new information conducting to a jump from level A to level B. If variable Ψ reacts differently we may suspect of some form of inefficiency, possibly caused by inefficient spread or absorption of the new bit of information E .

PLEASE INSERT FIGURE 1 HERE

Let us assume that variable Ψ reacts according to the inefficient path (b) of Figure 1 that resembles a delayed reaction. If that was the case as earlier market authorities react, interrupting trading, the better. This would correspond to a trading halt starting at time t_1 . But stock watch departments of exchanges and regulators, the typical departments that induce trading halts, base their interventions, much of the time, on historical price behaviour observations. Therefore, only when time passes they are able to spot a significant change, reacting accordingly. This corresponds to interrupt trading at time t_2 . At time t_2 market supervisors may observe, and confirm, that variable

¹⁰ Stock price returns, volatility, duration, delta, skewness of price returns, etc.. For instance, Glosten and Milgrom [1985] suggest trading volume as a variable with potential for insider activity signalling. Lee et al. [1994] use trading volume and volatility; Kryzanowski and Nemiroff [1998] study volatility and the number of trades; Kryzanowski and Nemiroff [2001] study quote depth, spreads and spread component costs; Corwin and Lipson [2000] use depth, number of orders sent and cancelled and spreads; and Christie, Corwin and Harris [2002] use spreads, abnormal returns, number of quote revisions, share volume, number of trades and average trade size.

Ψ has changed, basing their observation on the comparison of the information set φ_2 against the information set φ_3 . Information sets φ_i are composed by a collection of observations of variable Ψ .

After the halt has started a new decision has to be made: when should trading be restarted? If market authority suspicions were proved to be groundless, the earlier trading restarts the better. But if they were correct, the timing for the restart of the trading becomes a new problem. The rationale for trading halts is to avoid trading based on asymmetric information. And the big issue becomes when has the market already absorbed the new set of information. Returning to Figure 1 if trading restarted at time t_3 it is clear that the start would be too early. But this is only confirmed after comparing the sets φ_4 with φ_5 . Clearly, the optimal time decision would be to restart trading at time t_4 when variable φ shows signs of stability, confirmed by the comparison of information sets φ_5 with φ_6 .

Therefore **opportunity** may be measured by comparing levels of Ψ (particularly $\Psi(t < t_1)$ compared with $\Psi(t > t_4)$) and **timing** by comparing information sets φ_i with φ_{i+1} either before the halt either after the halt¹¹.

Hence, the theoretical model is based on the path of some variable(s) that may be a significant indicator(s) of stock price characteristics and that may lead to express some statement on how information has been absorbed by market participants when trade occurs.

4. RESEARCH DESIGN

In order to test whether trading halts ordered by market authorities were somehow related to a significant change on market price behaviour, we observed prices around the dates of the events. Two main methodologies were used: firstly we used average stock price returns and secondly volatility. For both variables we started by comparing the periods before with after the event date. In relation to volatility, we also tried to fit a GARCH (1,1) model into the stock price returns around the dates of the event. These two variables (stock price returns and volatility) were commonly used in similar studies such as Lee et al. [1994], Kryzanowski and Nemiroff [1998].

We started by defining a time window of 40 days before the first day of the trading halt (event) and 40 days after the last day of that same event. In some cases we observed that the same company

¹¹ This approach has two drawbacks in the absence of an over-the-counter market: i) it is impossible to disguise too early halts from interruptions on time or too late restarts from restarts on time; ii) if halts are due to false rumours even halts and restarts are on time they are not spot as if they were justified.

had two consecutive breaks on its share trading. Whenever these consecutive breaks occurred within a 6 days period we assumed they were still related with the first halt. Therefore, in these cases, we assumed that trading has been suspended from the start of the first break until the end of the second. This would mean that we treated it as a single event.

We defined "Test 1" as the statistical test that compares the 5 daily observations previous to the event with the 5 daily observations after the event (observe Figure 2), testing the **opportunity** of trading halts imposed by market supervisory authorities, as explained before. In order to check whether possible changes in price behaviour could already be reflected on prices previously to the trading halt, we defined "Test 2" that compares two consecutive time periods of 5 days before the date of the event. Accordingly, in order to check whether the trading halt had a sufficient time extension, we defined "Test 3" that compares two consecutive time periods of 5 days each, both after the date of the event. Therefore, "Test 2" and "Test 3" became our method of testing **timing** ability of market supervisory authorities, because they reflect how the moment chosen to impose trading halts and to restart trading suites changes on price characteristics.

PLEASE INSERT FIGURE 2 HERE

We chose 5 days-time periods because we thought this would be a reasonable balance between the minimum data required to get significant results when testing, and the short-term impact that we want to analyse. Furthermore, other studies where information absorption is studied, similar time windows are used. This is the case of Antoniou, Galariotis and Spyrou [2001] that used one week of data. When a longer time window is used we increase the likelihood of including other undesirable effects that could contaminate the sample, but results may be interesting to compile.

In fact we have also repeated the three tests using the same approach with a 10 and 20 days time windows. We selected these time periods also based on previous research about testing events or market reaction to news absorption. Kryzanowski and Nemiroff [2001] studied the effect around trading halts using a 10 days maximum window and Cox and Peterson [1994] or Ratner and Leal [1998] suggested time periods from one week to 20 days maximum. Although these are overreaction tests, they are also concerned with processes governing information absorption in trading prices.

4.1. STOCK PRICE RETURNS ANALYSIS

4.1.1 Individual Analysis of Stock Price Returns

We started by choosing stock price returns as one of the variables that could characterise assets and therefore that could show some evidence of the information arrival. This would result in an expected significant impact of trading halts on stock price returns.

Afterwards we collected 80 prices around the date of the event and managed to compute 39 instantaneous daily rates of return before and 39 instantaneous daily rates of return after each event:

$$R_{i,t} = \ln \left(\frac{P_{i,t}}{P_{i,t-1}} \right)$$

where $R_{i,t}$ stands for the daily instantaneous rate of return of asset i on day t and $P_{i,t}$ represents the closing price of asset i on day t . We assumed random variables, independent, identically distributed following a normal distribution in order to use a t-test¹² for comparing average rates of return before and after the event ("Test 1").

$$H_0 : \bar{R}_{B,i} = \bar{R}_{A,i} \quad \text{vs} \quad H_0 : \bar{R}_{B,i} \neq \bar{R}_{A,i}$$

Where, for testing purpose, $\bar{R}_{B,i}$ represents the average instantaneous rate of return of stock i for the time period of 5 days before the event and $\bar{R}_{A,i}$ represents the mean instantaneous rate of return of stock i for the time period of 5 days after the event:

$$\bar{R}_{B,i} = \sum_{t=-5}^{-1} \frac{R_{i,t}}{5} \quad \text{and} \quad \bar{R}_{A,i} = \sum_{t=+1}^{+5} \frac{R_{i,t}}{5}$$

As explained earlier, we also compared two consecutive periods both before the event ("Test 2"). This would give us a way of measuring the timing ability of market supervision authorities when interrupting trading.

$$H_0 : \bar{R}_{BB,i} = \bar{R}_{B,i} \quad \text{vs} \quad H_0 : \bar{R}_{BB,i} \neq \bar{R}_{B,i}$$

where, for testing purpose, $\bar{R}_{BB,i}$ represents the average instantaneous rate of return of stock i from day [-10] to day [-6] (before the event):

$$\bar{R}_{BB,i} = \sum_{t=-10}^{-6} \frac{R_{i,t}}{5}$$

If the average return were significantly different for the two previous periods, we may ask why not interrupt trading before the moment when actually happened? Would this mean a delayed reaction from supervisory authorities or simply a result of the supervision mechanism that is based on stock market observations?

As a way of testing the time extension of the trading halt we compared two consecutive 5-days windows after the event ("Test 3"):

$$H_0 : \bar{R}_{A,i} = \bar{R}_{AA,i} \quad \text{vs} \quad H_0 : \bar{R}_{A,i} \neq \bar{R}_{AA,i}$$

where, for testing purpose, $\bar{R}_{AA,i}$ represents the average instantaneous rate of return of stock i from day [+6] to day [+10] after the event:

$$\bar{R}_{AA,i} = \sum_{t=+6}^{+10} \frac{R_{i,t}}{5}$$

The rationale for this test relies on the assumption that if significant differences are still observed on the two consecutive time periods after the event, the restart of trading may be too soon. Therefore, this test also reflects the timing ability of market supervision authorities.

Later we repeated the tests using a 10 and a 20-days time window.

4.1.2 Individual Analysis of Abnormal Returns

In order to analyse stock price return behaviour surrounding trading suspensions, we also analysed abnormal stock price returns.

¹² We used, $t = \frac{(\bar{R}_{A,i} - \bar{R}_{B,i})}{\sqrt{\frac{\sigma_{A,i}^2}{n_A} + \frac{\sigma_{B,i}^2}{n_B}}}$ where $\sigma_{A,i}^2$ and $\sigma_{B,i}^2$ are the corresponding variances and n_A and n_B

represent the number of observations.

Individual abnormal stock price returns are measured as the difference between the daily return on stock i at day t ($R_{i,t}$), and its expected return ($E[R_{i,t}]$):

$$AR_{i,t} = R_{i,t} - E[R_{i,t}]$$

We used the market-adjusted return model to estimate the expected stock price return as in Engelen and Kabir [2001]¹³:

$$E[R_{i,t}] = R_{m,t}$$

where $R_{m,t}$ stands for the daily market instantaneous rate of return on day t ¹⁴.

We used the same methodology as in the stock price returns analysis, that is, we compared average abnormal returns before and after the suspension, assuming again independent normally distributed random variables in order to use a t-test.

$$H_0 : \overline{AR}_{B,i} = \overline{AR}_{A,i} \text{ vs } H_1 : \overline{AR}_{B,i} \neq \overline{AR}_{A,i}$$

For example, the 5-days average abnormal return of stock i after the event is calculated by the statistic:

$$\overline{AR}_{A,i} = \frac{1}{5} \sum_{t=+1}^{+5} AR_{i,t}$$

Then, we compared average abnormal returns in two consecutive periods before and after the suspension using:

$$H_0 : \overline{AR}_{BB,i} = \overline{AR}_{B,i} \text{ vs } H_1 : \overline{AR}_{BB,i} \neq \overline{AR}_{B,i}$$

and $H_0 : \overline{AR}_{A,i} = \overline{AR}_{AA,i} \text{ vs } H_1 : \overline{AR}_{A,i} \neq \overline{AR}_{AA,i}$ respectively.

As we used a 41-days window event, we only made these tests for 5 and 10-days time windows.

¹³ Engelen and Kabir [2001] also used this model to measure expected stock returns in order to analyse stock returns behaviour around trading suspensions.

4.1.3 Aggregated Abnormal Returns Analysis

In order to draw overall inferences we aggregated the abnormal return observations, testing whether the average abnormal return of the sample for each day ($\overline{AR}_t$) of the event window equals zero. The hypothesis tested is expressed as follows:

$$H_0 : \overline{AR}_t = 0 \text{ vs } H_1 : \overline{AR}_t \neq 0$$

The average abnormal return on each day (from $t=-20$ to $t=+20$) was calculated by aggregating individual stock abnormal returns lined up on the same day:

$$\overline{AR}_t = \frac{1}{n} \sum_{i=1}^n AR_{i,t}$$

where n is the number of stocks in the sample.

We analysed a 41-days event window that includes the event day and twenty trading days before and after suspension. We defined the event day (day [0]) as the day on which trading suspension occurs, day [-1] as the day immediately before the day of the suspension, and day [+1] as the day immediately after the end of the suspension. The return of day [0] is calculated using the last closing price before suspension and the first closing price after suspension. Similarly, the return of day [+1] is calculated as the return from the first closing price of the stock after the trading suspension to the next closing price. Many trading halts are single day suspensions but some are multiple day suspensions. So, in order to obtain a comparable daily return on the event day, the multiple day return over the suspension period is scaled down by the number of suspension days. And whenever there were two consecutive suspensions we calculated the average of daily returns within that event period.

Then we calculated the cumulative abnormal return $CAR_i(t_1, t_2)$ for stock i from time t_1 to t_2 , and the cumulative average abnormal return $\overline{CAR}_i(t_1, t_2)$ as follows:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \quad \overline{CAR}_i(t_1, t_2) = \frac{1}{n} \sum_{t=t_1}^{t_2} AR_{i,t}$$

Some halts are due to impending "good" news and some are due to impending "bad" news. As mentioned before, these two cases should be separated, otherwise we may get biased conclusions. Considering that 50% of the sample was good news and the other half was bad news, we would

¹⁴ We used the PSI Geral index produced by Euronext Lisbon in order to compute the market instantaneous rate of return.

risk getting on average, no significant changes. So, conclusions obtained by the previous methodology may be biased and therefore in the next section (4.1.4) we will analyse good and bad news separately.

4.1.4 Aggregated Abnormal Returns Analysis- "good" news vs "bad" news

As previously referred, we weren't able to collect information about the reasons for all the trading halts included in sample. To overcome this gap we used the following methodology to qualify them according to the price change signal as in Christie, Corwin and Harris [2002]:

- i) When the instantaneous rate of return of stock i on day $[0]$ was positive we classified it as "good" news;
- ii) When the instantaneous rate of return of stock i on day $[0]$ was negative we classified it as "bad" news.

Afterwards the tests and the methodology explained in 4.1.3 were repeated.

4.2. VOLATILITY ANALYSIS

4.2.1 Volatility

As a second variable we selected volatility measured by the classic estimator:

$$\sigma_{B,i} = \left[\sum_{t=-5}^{-1} \frac{(R_{i,t} - \bar{R}_i)^2}{4} \right]^{1/2} \quad \text{and} \quad \sigma_{A,i} = \left[\sum_{t=1}^{+5} \frac{(R_{i,t} - \bar{R}_i)^2}{4} \right]^{1/2}$$

where $\sigma_{B,i}$ represents the historical volatility of the 5 days previous to the event and $\sigma_{A,i}$ represents the forward volatility of the 5 days period after the event.

As we assumed daily instantaneous rates of return following independent normal distributions, we used F-tests to compare the significance of volatility change around the date of the event:

$$H_0 : \sigma_{B,i}^2 = \sigma_{A,i}^2 \quad \text{vs} \quad H_1 : \sigma_{B,i}^2 \neq \sigma_{A,i}^2$$

We followed a similar procedure with volatility as with the instantaneous rate of return. Applying "Test 2" we compared two consecutive periods, both before the event:

$$H_0 : \sigma_{BB,i}^2 = \sigma_{B,i}^2 \quad \text{vs} \quad H_1 : \sigma_{BB,i}^2 \neq \sigma_{B,i}^2$$

where $\sigma_{BB,i}$ represents the volatility of stock i from day [-10] to [-6] (before the event):

$$\sigma_{BB,i} = \left[\sum_{t=-10}^{-6} \frac{(R_{i,t} - \bar{R}_i)^2}{4} \right]^{1/2}$$

And similarly to what was tested for stock price returns we tested two 5-days time periods volatility, consecutive to the event:

$$H_0 : \sigma_{AA,i}^2 = \sigma_{A,i}^2 \quad \text{vs} \quad H_1 : \sigma_{AA,i}^2 \neq \sigma_{A,i}^2$$

where $\sigma_{AA,i}$ represents the volatility of stock i from day [+6] to day [+10] (after the event):

$$\sigma_{AA,i} = \left[\sum_{t=+6}^{+10} \frac{(R_{i,t} - \bar{R}_i)^2}{4} \right]^{1/2}$$

And once again we repeated the tests for a 10 and a 20 days time window.

The volatility in the charts (Appendix 2) is the standard deviation of a 20-days period. For example, the volatility on day [-2] was computed as follows:

$$\sigma_{-2,i} = \left[\sqrt{\sum_{t=-21}^{-2} \frac{(R_{i,t} - \bar{R}_i)^2}{20}} \right]^{1/2},$$

and on the day [+3]:

$$\sigma_{+3,i} = \left[\sqrt{\sum_{t=+3}^{+22} \frac{(R_{i,t} - \bar{R}_i)^2}{20}} \right]^{1/2}$$

4.2.2 GARCH (1,1) Model

Lastly, as in Brailsford [1995] we tested whether volatility had changed its path after the halt. As suggested in previous literature, stock price volatility tends to show signs of cluster behaviour:

high volatilities tend to follow high volatilities and low volatility periods tend to follow low volatilities. This means that conditional volatility may be a good way to model market behaviour for volatility and GARCH (1,1) models seem to fit well (Bollerslev [1986]). The GARCH model has some advantages in relation to the previous volatility analysis (F-tests). For instance: i) it assumes a time varying volatility; ii) there are no assumptions on the independence and normality of stock returns.

Therefore, we hypothesise that a GARCH (1,1) model fits and that it may possibly "match" the behaviour of trading halts volatility.

Starting with a simple GARCH (1,1) model as:

$$\begin{cases} R_t = \mu + u_t, & u_t | \Omega \sim N(0, \sigma_t^2) \\ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2, & \alpha_0 > 0, \alpha_1, \beta_1 \geq 0 \end{cases}$$

the GARCH(1,1) process is wide-sense stationary with $E(u_t) = 0$, $Var(u_t) = \alpha_0(1 - \alpha_1 - \beta_1)^{-1}$ and $Cov(u_t, u_s) = 0$ for $t \neq s$ if and only if $\alpha_1 + \beta_1 < 1$ (see Theorem 1 in Bollerslev [1986]).

We then added two dummy variables to the independent term of the mean equation (ϕ_B and ϕ_A) and to the variance equation (ϕ_1 and ϕ_2). ϕ_B e ϕ_1 represent the time period before the event in each equation and ϕ_A and ϕ_2 the period after the event (using 80 observations¹⁵). The equations of the mean and the variance were then converted into:

$$\begin{cases} R_t = \mu + \phi_B d_{1t} + \phi_A d_{2t} + u_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \phi_1 d_{1t} + \phi_2 d_{2t} \end{cases}$$

$$\text{where } d_{1t} = \begin{cases} 1, & -5 \leq t \leq -1 \\ 0, & t < -5 \vee t > +1 \end{cases} \quad \text{and} \quad d_{2t} = \begin{cases} 1, & +1 \leq t \leq +5 \\ 0, & t < -1 \vee t > +5 \end{cases}$$

In order to find the parameters of the GARCH model we used the following maximum likelihood logarithm:

$$l(\theta) = -\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma_t^2) - \frac{u_t^2}{2\sigma_t^2}$$

¹⁵ As larger the sample size (n) the lower is the volatility associated with ϕ_1 and ϕ_2 estimates (although from a certain dimension the gain is almost null). So, if n is relatively high it is possible to gain some efficiency on estimating ϕ_1 and ϕ_2 even with a small window (5 observations before and 5 after the event).

Brailsford [1995] suggested a similar approach when testing the weekend effect as an information absorption process.

Then we tested if the parameters of each dummy variable in the mean and variance equations differ:

$$H_0 : \phi_B = \phi_A \text{ vs } H_1 : \phi_B \neq \phi_A$$

$$H_0 : \phi_1 = \phi_2 \text{ vs } H_1 : \phi_1 \neq \phi_2$$

The parameters affecting the dummy variables (in the mean and variance equation) measure how sensitive is the model on the approach of the trading halt (dummies B and 1) and how sensitive is the model on fading the effect of the trading halt (dummies A and 2). This methodology is supposed to conclude on a more sensitive basis around the event because we use a larger time window with 80 price observations for each stock. We may argue that a 5 days time window for each dummy variable could be insufficient to spot significant differences, but we wanted to compare this methodology with the previous one. It could be used a larger time window for the dummy variables (10 or 20 days) but the proportional increase in the total sampling period would have a very strong impact on the significance of the conclusions since we increase the probability of including other relevant effects on results.

5. DATA

We started by observing all interruptions of companies listed in the Euronext Lisbon¹⁶ between January 1991 and December 1999. We gathered information on the start and the end of the suspension period. Stock prices were collected immediately before and after trading suspension, but the reasons for suspension weren't available for all stocks. The information about these events was collected using different sources, namely monthly reports of the Lisbon Stock Exchange, the Department of Markets Surveillance of CMVM and the database *Dathis*¹⁷.

As observed in Table 1 there were 331 news related suspensions during the period January 1991 and December 1999. Among these there are single and intra-day suspensions but also multiple day suspensions.

¹⁶ By the time the data was collected the stock exchange was called BVLP - Lisbon and Oporto Stock Exchange.

¹⁷ Prices were collected from this database and consist of closing prices adjusted for dividends, stock splits and other similar price sensitive events.

PLEASE INSERT TABLE 1 HERE

After a significant increase either in terms of number of breaks or in terms of days consumed in halts, the tendency has been a decrease for both variables until 1999. In 1999 we observed another increase that is still to be confirmed if it stands as a new trend or if it is just an outlier. The same conclusion is extended to the average time of the halt, which dropped significantly since the analysis started. Compared with the average of 5.2 days, recent data shows that the average halt only lasts a bit above 1.5 days. The reasons for this decrease may be related to the speed of the processes based on the triviality of the act, the increased quality of communications between the regulator, the exchange and the issuing firms and the speed of response that is taken by these firms when questioned by the supervising authorities. Nevertheless, this is still a huge time period once Christie, Corwin and Harris [2002] report an average trading halt in Nasdaq of about 54 minutes for the late nineties.

Although we could determine with precision all the events under scope, we selected a smaller sample to carry this research. The reason to do so relates to the methodology in use. In order to apply the methodologies presented earlier, we needed to collect prices for a limited number of days to insure that only one event could be the main cause of a change in the price behaviour. Hence, the time window selected to collect prices should be sufficiently small in order to guarantee the single effect assumption, but sufficiently large in order to grasp a significantly large number of prices that would turn significant any statistical test. We chose an 80 days time window centred on the event.

If the trading halt took only one or part of a day, we collected the previous 40 closing prices of the event, as well as the following 40 closing prices after the same event. Whenever the trading halt took more than one day the procedure was similar with the necessary adjustment as if the event was compressed into a single moment in time.

As a consequence we only selected to the sample all the halt (events) that passed, simultaneously, the two following criteria:

- i. The stock should price at least 76 days within the time window of 80 days;
- ii. There was no other trading halt observed on that specific stock within the time window. Exceptions: we considered cases that observed another trading halt within a 6 days time. In these cases we assumed that the halt was still related with the first trading halt and the whole period from the first to the second trading halt was considered as a

single event¹⁸. Prices were then collected for the 40 days previous to the start of the first trading halt and for the 40 days subsequent to the end of the second trading halt.

After applying these criteria a sample of 54 events was selected. Appendix 1 lists the sample used in this study. For the earlier cases in the sample we could not recover the specific moment within the day when share trading was interrupted (at least for some of them).

Table 2 summarises the sample size per year and compares it with the universe.

PLEASE INSERT TABLE 2 HERE

In general terms we would say that the sample goes along with the universe either in terms of number of events or in terms of time extension per trading halt. We also underline that the sample tends to be more representative of the universe as we approach the most recent years.

6. EMPIRICAL RESULTS

We started by observing the charts of daily prices, stock returns and volatilities computed as described in the methodology, for each of the 54 trading halts included in the sample and presented in Appendix 2. For a reasonable number of cases we visually observe a quite remarkable difference on market price behaviour when comparing before with the corresponding time period after the event.

6.1. COMPARING STOCK PRICE RETURNS

6.1.1. *Comparing Individual Rates of Return*

We started by comparing the sample stock price returns around trading halts and found that, on average, they were statistically significant with an average of 3.64% and a standard deviation of 7.77%.

Then we compared individual average stock price returns using "Test 1", as explained before. We observed that only in a very small number of cases average stock price returns were significantly

¹⁸ Four events in this situation were included in the sample (see Appendix 1).

different when comparing before with after trading halts. From a total sample of 54 cases we only found 4, 6 and 4 cases with statistically different average returns when using respectively 5, 10 and 20 days of observations¹⁹. The overall average increase on the rate of return was only 0.10% when comparing 5 days around the halt, 0.33% for the 10-days and 0.06% for the 20-days period. We also computed the absolute value of the average stock price returns (see Appendix 3).

We may conclude that instantaneous stock price returns seem insensitive to trading halts. The same conclusions were found when applying "Test 2" and "Test 3". Therefore and like many other authors, like Hopewell and Schwartz [1978], Tanner and Pritchett [1992], Engelen and Kabir [2001], we will try, instead, abnormal returns.

6.1.2. Comparing Individual Abnormal Returns

Then we compared individual average abnormal stock price returns using the same methodology as for stock price returns. The number of cases for which the average abnormal stock price returns were significantly different when comparing before with after trading halts was even smaller than the results found for stock price return analysis. From a sample of 54 stocks we found respectively 2, 5 and 5 cases with statistically significant different average returns when using 5, 10 and 20 days of observations. But the overall average increase on the abnormal returns was much higher: 0.79% when comparing 5 days around the halt; 0.56% for the 10-days; and 0.53% for the 20-days period. We also computed the absolute value of the average abnormal returns (see Appendix 4). In addition the same conclusions were found when applying "Test 2" and "Test 3".

When we analyse stock price returns and average abnormal returns they seem insensitive to trading halts²⁰. Based exclusively on these variables we could argue that either market authorities tend to interrupt trading on an unfounded basis, or those variables are not appropriate for the purpose. Nevertheless, we obtained better results when aggregating abnormal returns of all stocks (see 6.1.3.).

¹⁹ Please refer to Appendix 3 that shows the tests of the differences on average returns and their absolute values.

²⁰ Although the overall average abnormal return increase around the halts ("Test 1") is higher than the similar increase in the overall average stock price return for all the windows considered (5, 10 and 20-days), the number of individual abnormal returns with statistically significant differences is lesser than the similar number found when studying stock price returns (equivalent conclusion was found when applying "Test 2" and "Test 3").

6.1.3. Comparing Aggregated Abnormal Returns – Global Sample

After comparing abnormal price returns around trading halts we found that on average they were not statistically significantly with an average of 1.36% and a standard deviation of 7.93%²¹ - see Figure 3 and Table 3. Therefore we could not confirm the findings of Hopewell and Schwartz [1978] nor Engelen and Kabir [2001] when studying daily abnormal returns around trading halts.

PLEASE INSERT TABLE 3 HERE

PLEASE INSERT FIGURE 3 HERE

Abnormal stock returns seem to increase during the days preceding trading halts, but they are relatively small in magnitude and also statistically insignificant. Therefore, there seems to be no signs of information leakage during the pre halt period.

The adjustment of prices to the newly released information only happens on the day after the event (day [+1]), where average abnormal return ($\overline{AR}$) is the highest (1.61%) and also statistically significant. After the restart of trading we observe small and insignificant abnormal returns. Therefore, as in Hopewell and Schwartz [1978], we also observed statistically significant average abnormal returns on the very short period (day +1) which may result from the fact that for some sample observations, the release of new information was only publicised at the end of a session, or after the market close. If that was the case information could only be incorporated in stock prices on day [+1].

When analysing average cumulative abnormal returns ($\overline{CAR}$) we found that it increases as the day of the event approaches – see Table 3 and Figure 4. However, we reject the hypotheses of these values being statistically significant in the pre halt period and even on day [0]. It seems that no information leakage was released on that period. But as we pass the event day cumulative abnormal returns become statistically significant, although not permanently. These findings are consistent with Engelen and Kabir [2001] but contradictory to those presented by Hopewell and Schwartz [1978].

²¹ See Table 3 – Annex.

PLEASE INSERT FIGURE 4 HERE

Figure 4 shows an increase in $\overline{CAR}$ after the restart of trading that extends up to day [+4], followed by an unstable behaviour till the end of the period. Assuming that there was no additional release of relevant information, this may suggest two different conclusions: i) the Portuguese stock market is not efficient in a semi-strong informational form, because the relevant information wasn't fully incorporated in the day it was publicly revealed²²; ii) market regulators authorised the restart of trading too early.

These weak and unclear results until now are also a possible consequence of having mixing up until now, in the same sample, good with bad news. In the next section we explore the possibility and present the results after having split up the sample into good and bad news (section 4.1.4.).

6.1.4. Comparing Aggregated Abnormal Returns - "good" news vs "bad" news

From a global sample of 54 halts, we were able to select 39 good news and 15 bad news²³. And as we can see from the following figures, in both cases there is a complete and instantaneous adjustment of prices to the newly released information on the day of the halt (day [0]).

PLEASE INSERT FIGURE 5 HERE

Apart day zero [0], we observed, for both sub-samples, a relatively stable and statistically insignificant average abnormal return²⁴, either on pre halt period or post halt period. T-tests are significantly different from zero on day [0], presenting the highest value of the sample (+3.83%) on the "good" news day and the lowest (-5.05%) on the "bad" news day (please refer to Table 4). Having split the sample into good and bad news we manage to found consistent results with those presented by Hopewell and Schwartz [1978] and Engelen and Kabir [2001].

²² Stocks observe some price volatility in the post halt period.

²³ Although "good" and "bad" news were defined by stock price returns the results did not differ if instead abnormal returns were used.

²⁴ Excluding day [0], in "good" news halts only days [-7] and [-3] are statistically significant and in "bad" news only days [-18], [-11], [6], [13] e [18].

Nevertheless, when analysing $\overline{CAR}$ we concluded differently. As presented in Table 5, only "good" news reveals an average cumulative abnormal return statistically significant on day [0] (+6.88%). For the "bad" news, only day [-18] shows an average cumulative abnormal return significantly different from zero (see Figure 6)²⁵. Therefore we could not confirm the findings of Hopewell and Schwartz [1978] who suggested that in the pre halt periods prices tend to anticipate the halt, particularly when "good" news were observed

PLEASE INSERT FIGURE 6 HERE

Therefore, according to the theoretical model, we may conclude that both "good" news and "bad" news show significant changes around trading halts. When a "good new" is to be released, we found that $\overline{CAR}$ starts to increase on day [-5], only stabilizing on the day following the event. From day [+1] till the next 19 days there was a small decrease in cumulative abnormal return behaviour and then some stability. This empirical finding is in general consistent with market efficiency hypothesis, considering that profits obtained on day [0] do not seem to persist for long and the regulator's activity seems fully justified. When observing "bad" news $\overline{CAR}$ reveals not even a single statistically significant figure (not even on the event day) and then we could raise doubts on the goodness of the regulator's intervention.

6.2. COMPARING VOLATILITY

6.2.1. Volatility

As with the analysis of stock price returns, we started by comparing volatility applying "Test 1" to compare two consecutive 5-days periods. As a first look to Appendix 5 shows a significant increase in the number of cases where volatility significantly changes after the event (10, 18 and 27 for the 5, 10 and 20 days of observations). This means that although, on average, changes are not severe, volatility seems to change with statistical significance after the halts. Most of the differences are observed in the most recent years under analysis and, interestingly, as we increase the time period for analysis, the number of significant differences increases. This means that: i) volatility seems to be a more efficient variable to detect why regulators tend to halt trading; and ii) regulators seem to spot more accurately structural changes on volatility than short-term changes.

²⁵ Therefore we could not confirm Hopewell and Schwartz [1978] findings when suggesting that pre halt

Although halts seem to be justified by volatility analysis, we still have market supervisors' timing ability to test. In order to test the timing ability, we started by selecting exclusively those observations where we observed a difference on volatility when comparing stock price returns before and after the halt. If either before or after the two consecutive periods presented similar levels of volatility than, the timing for interrupting and suspending was perfect. Otherwise we may ask about the timing suitability.

We started with the "Test 1" applied to the 5-days window. We found 10 observations where volatility observed a significant change comparing before the halt and after the halt. Then we applied "Test 2" and "Test 3" to these 10 observations. Table 6A summarises the results whose data comes from Appendix 5. Table 6A reflects those 10 observations where we found significant differences on volatility when comparing the volatility of 5 days before with 5 days after the trading halt. As observed, only for 2 out of 10 observations we found having an appropriate timing ability either for trading suspensions, either for trading restarts. For the remaining 8 observations market supervision fails to be on timing.

For the remaining 44 observations we failed to reject different levels of volatility when comparing pre with post halt windows ("Test 1"). In such a situation we may wonder why interrupt trading if no significant differences were found? In addition the question seems to have even a more difficult answer when checking the timing of these occurrences. And in fact, for 26 observations there were no differences on volatility for any of the three tests we developed and for 18 observations we found the halt to show signs of timing unsuitability (see Table 6B).

When repeating the analysis for 10 and 20 days of observations the conclusions reverse! The number of observations that show a justification for interruption increases when we use higher time windows, reaching 50% (27 out of 54 when using the 20 days time period - Table 6E). And within those 27, we found 8 cases (29.6%) where the timing for interruption seemed to be suited either in terms of stop trading or in terms of restart trading. This means a significant increase in percentage terms.

Trading halts can be lately imposed as a result of two major reasons. Firstly because market supervision authorities observe historical prices as a supervisory instrument, reacting frequently as a result of some unusual price movement. If this is the case we may observe a delayed stop on trading, particularly when we use small time periods for testing. But when longer time periods for testing are used this excuse should not be applied because market authorities have a quite long time for considering intervention. Secondly we may hypothesise that market authorities are inefficient when interrupting trading.

period prices tend to anticipate the halt, particularly when "good" news are observed.

Therefore, if we neglect the analysis on the starting of trading halts, considering only the post halt period, the conclusions did not change much: most of the times market authorities seem out of timing when restart trading, suspending the halt apparently too early (around 60% of the times for 5, 10 and 20 days of sampling). If this is the case we may well argue why to interfere on the market?

PLEASE INSERT TABLE 6 HERE

6.2.2. *Using a GARCH Model*

GARCH (1,1) models were found a useful and appropriate tool by a vast number of researchers when studying stock price volatility. This good modelling performance applies either to stock price returns forecasting or to stock price volatility behaviour.

We are particularly interested on studying both the stock returns and stock volatility. When we tested the GARCH (1,1) model as described earlier we found an increase on the number of situations where market authorities seemed to have a clear reason for interruption. Instead of 10 cases we found 20 cases where we could reject the hypothesis that both dummies of the variance equation were equal. This means that for 20 observations the sensitivity of volatility when trading halts approach differs from similar sensitivity when trading restarts.

PLEASE INSERT TABLE 7 HERE

But most interestingly from those 20 cases, 6 were observed in 1998 and 7 were observed in 1999, representing almost 50% of the cases of those years. In addition to the fact that the average time length of the halts has been reduced since 1992, this means that GARCH (1,1) model seems more appropriate to study the information absorption processes under scope. Additionally we may infer that the accuracy of market authorities has increased on the opportunity for interrupting trading.

As the meaning of this research method is different from the previous method used when comparing volatilities it is not inconsistent if cases do not match on the same conclusion. Instead of competing, we think that both methods should complement each other. Nevertheless we found 9 cases in common by both methods (GARCH (1,1) model and volatility comparisons) - 1 in 1997, 4

in 1998 and 4 in 1999. Therefore, GARCH (1,1) methodology may represent an instrument with increased power to detect and justify trading halts imposed by market authorities. And it seems to be more helpful as halts become shorter.

6.3. USING ALL THE METHODS

When we use all the methods to study the opportunity for halting trade we found that larger time windows reveal more clearly reasons to suspend trading. As Table 8 shows, when using a 5-days window even working with three different methods the opportunity for trading halt is only spot in 24% of the cases. However, when increasing the window size for 10 and 20 days we observe a significant increase in the percentage of cases where interruption seems plausible (44% and 56% correspondingly). When on top of that we use all the methods, including the GARCH (1,1) methodology, with all the time windows available we increased to 70% the percentage of cases where trading halts seem justified. Therefore, based on our empirical evidence, we would advise stock watch departments of market authorities to use combined methods, namely those used in this study, in search for signs on trading under information asymmetry.

PLEASE INSERT TABLE 7 HERE

7. CONCLUSION

Trading halts are frequently imposed on listed companies by supervisory authorities. These are usually justified on a basis of presumed asymmetric information among market players. In the literature we find two very opposite positions when looking at security trading halts: those that support the mechanism and those that oppose. Both sides base their perspectives on economic reasons, theoretical models and empirical findings.

We used the Portuguese market to observe and test how prices behave around trading halts looking for signs of timely and appropriate intervention of market supervising authorities. A sample of 54 observations was compiled covering the period between 1992 and 1999, a homogeneous period in regulatory terms. During this period, both, the stock exchange and the regulator had the power to suggest and/or impose the trading breaks that are under scope.

We used two variables to study these effects (stock price returns and volatility). When analysing each trading halt we soon found that only volatility could bring some insight to the research.

Therefore we observed that trading halts are much more related with "dominant" changes in volatility than with very short-term changes. This may lead one to conclude that market authorities tend to disguise better volatility changes as the time window increases, denoting some incapacity to detect changes *ex-ante*. We may consider this a result of methods employed for market supervision but also as a consequence of some delayed reaction (this timing incapacity was also confirmed when observing the end of the trading halts).

We then used a GARCH(1,1) model with two added dummy variables (in the mean and variance equations) in order to study very short-term volatility changes in more detail. We concluded a superior ability of the GARCH(1,1) model to associate trading halts to volatility changes. This superior ability was dominant in most of the recent years of the sample. In 1999 the GARCH model confirmed almost 50% (7 out of 15) of the cases where volatility changed from pre to post halt periods. We found this methodology a very useful complement of previous methodology for comparing impacts on volatility.

From the aggregated abnormal returns analysis of the global sample we didn't find any significant changes around the day of the event and we also concluded that market regulators timing on restarting trading was not appropriate. By splitting the sample, we found significant changes over the day of the halt on "good" news, although the moment chosen to halt the trading seems behind time. Nevertheless the restart seemed to be appropriated and on time. Concerning "bad" news we also observed abnormal losses around the halt, though it is not possible to draw reasonable conclusions about the timing of market authorities.

In conclusion, from all the methodologies used, we couldn't find consistent signs of an increase in volatility after halts occurred, but we found consistent changes in volatility. We conclude for an increased ability of Portuguese market supervising authorities, for the opportunity of halts, but consistently out of timing as Christie, Corwin and Harris [2002] also found. Nevertheless, we found in "good" news that although the halt tends to be late, the restart seems to be on time. Additionally we found that the methods under scope in this study are not redundant and should be jointly used by stock watch departments of supervision authorities for detecting trading under asymmetric information.

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TABLES AND FIGURES

Figure 1 – Different market reactions to the arrival of new information

Figure 2 – Description of "Test 1", "Test 2" and "Test 3"

Table 1 - Annual Number and Extension of Trading halts

	Number of Trading halts	Number of Days	Average Number of Days per Trading halt
1992	30	155	5.2
1993	70	414	5.9
1994	42	170	4.0
1995	50	164	3.3
1996	27	55	2.0
1997	27	47	1.7
1998	26	39	1.5
1999	59	101	1.7
Total	331	1145	3.5
Mean	41	143	

Source: CMVM, Euronext Lisboa.

Table 2 - Sample Size and Characteristics

	Number of Trading halts	Number of Days	Average Number of Days per Trading halt
1992	2	11	5.5
1993	5	24	4.0
1994	8	26	3.3
1995	1	1	1.0
1996	4	8	2.0
1997	5	10	2.0
1998	14	17	1.2
1999	15	27	1.5
Total	54	124	2.3
Mean	6.75	15.5	

Source: CMVM, Euronext Lisboa.

Table 3 - Average AR and CAR, AR and CAR Standard Deviations

Day	Average AR (%)	AR Standard Deviation (%)	t -test	Average CAR (%)	CAR Standard Deviation (%)	t- test
-20	0.36%	1.75%	1.529	0.36%	1.75%	1.529
-19	0.09%	1.71%	0.366	0.45%	2.32%	1.424
-18	0.30%	1.75%	1.247	0.75%	2.69%	2.042*
-17	0.39%	1.49%	1.909	1.13%	3.30%	2.527*
-16	0.04%	1.69%	0.188	1.18%	4.15%	2.088*
-15	-0.14%	1.44%	-0.712	1.04%	3.82%	1.996
-14	-0.33%	1.46%	-1.640	0.71%	4.24%	1.232
-13	0.03%	1.83%	0.107	0.74%	4.71%	1.152
-12	0.08%	2.55%	0.238	0.82%	5.66%	1.066
-11	-0.14%	2.24%	-0.465	0.68%	5.96%	0.837
-10	0.40%	2.28%	1.297	1.08%	6.08%	1.307
-9	-0.02%	1.46%	-0.124	1.06%	6.36%	1.221
-8	0.08%	1.47%	0.409	1.14%	6.60%	1.267
-7	-0.22%	1.63%	-0.977	0.92%	6.51%	1.040
-6	-0.01%	1.79%	-0.056	0.91%	6.98%	0.955
-5	-0.39%	3.20%	-0.885	0.52%	9.29%	0.413
-4	0.22%	2.03%	0.809	0.75%	9.69%	0.565
-3	0.31%	1.91%	1.172	1.05%	10.06%	0.767
-2	0.23%	1.72%	0.972	1.28%	10.60%	0.886
-1	0.59%	2.41%	1.795	1.87%	11.80%	1.163
0	1.36%	7.93%	1.261	3.23%	16.61%	1.429
1	1.61%	5.54%	2.129*	4.83%	16.61%	2.139*
2	0.32%	3.62%	0.657	5.16%	16.06%	2.360*
3	-0.07%	2.84%	-0.185	5.09%	14.78%	2.529*
4	-0.28%	2.31%	-0.906	4.80%	15.94%	2.213*
5	-0.26%	3.60%	-0.523	4.54%	18.24%	1.831
6	-0.45%	1.35%	-2.483*	4.09%	18.70%	1.607
7	-0.58%	2.71%	-1.566	3.51%	19.82%	1.302
8	0.23%	2.21%	0.766	3.74%	20.78%	1.323
9	0.41%	2.93%	1.019	4.15%	19.75%	1.543
10	0.25%	2.71%	0.665	4.39%	20.09%	1.607
11	-0.02%	2.31%	-0.076	4.37%	19.68%	1.631
12	0.35%	1.93%	1.331	4.72%	19.62%	1.767
13	-0.63%	1.88%	-2.451*	4.09%	20.34%	1.479
14	-0.15%	2.30%	-0.496	3.94%	20.47%	1.414
15	-0.06%	2.14%	-0.215	3.88%	20.59%	1.383
16	0.07%	2.27%	0.212	3.94%	20.21%	1.433
17	-0.40%	2.06%	-1.428	3.54%	20.18%	1.290
18	-0.45%	1.57%	-2.093*	3.09%	20.28%	1.120
19	0.09%	1.67%	0.377	3.18%	20.65%	1.131
20	0.03%	2.84%	0.087	3.21%	21.02%	1.123

Note: * represent parameters that are statistically significant at a 5% confidence level.

Figure 3 - Daily Average Abnormal Returns and t-tests

Figure 4 - Average Cumulative Abnormal Returns and t-tests

Figure 5 - Average Abnormal Returns

("good" news vs "bad" news)

Table 4 - Average AR and t ratios ("good" news vs "bad" news)

Day	"good" news			"bad" news		
	Average AR (%)	AR Standard Deviation (%)	t-test	Average AR (%)	AR Standard Deviation (%)	t-test
-20	0.31%	1.69%	1.147	0.51%	1.97%	0.998
-19	0.11%	1.73%	0.387	0.03%	1.72%	0.065
-18	0.00%	1.60%	-0.006	1.08%	1.94%	2.147*
-17	0.36%	1.46%	1.522	0.47%	1.62%	1.123
-16	-0.05%	1.37%	-0.240	0.29%	2.38%	0.477
-15	-0.16%	1.21%	-0.825	-0.09%	1.97%	-0.171
-14	-0.40%	1.40%	-1.784	-0.14%	1.65%	-0.318
-13	0.16%	1.68%	0.593	-0.32%	2.18%	-0.568
-12	0.31%	1.90%	1.017	-0.51%	3.79%	-0.521
-11	0.39%	2.00%	1.232	-1.53%	2.29%	-2.589*
-10	0.61%	2.19%	1.727	-0.13%	2.48%	-0.203
-9	-0.01%	1.60%	-0.028	-0.07%	1.04%	-0.261
-8	0.11%	1.52%	0.458	0.00%	1.37%	0.013
-7	-0.49%	1.43%	-2.138*	0.49%	1.95%	0.973
-6	0.07%	1.94%	0.222	-0.23%	1.38%	-0.642
-5	-0.17%	1.68%	-0.642	-0.94%	5.55%	-0.657
-4	0.26%	2.20%	0.747	0.12%	1.60%	0.297
-3	0.62%	1.68%	2.286*	-0.50%	2.28%	-0.856
-2	0.39%	1.55%	1.585	-0.21%	2.09%	-0.380
-1	0.64%	2.33%	1.717	0.45%	2.69%	0.654
0	3.83%	6.29%	3.802*	-5.05%	8.37%	-2.338*
1	1.80%	6.12%	1.837	1.10%	3.77%	1.129
2	-0.02%	3.93%	-0.025	1.21%	2.55%	1.834
3	-0.31%	1.66%	-1.156	0.54%	4.75%	0.440
4	-0.16%	2.11%	-0.460	-0.62%	2.82%	-0.853
5	-0.07%	2.04%	-0.200	-0.75%	6.12%	-0.477
6	-0.26%	1.19%	-1.380	-0.95%	1.62%	-2.274*
7	-0.31%	2.49%	-0.784	-1.27%	3.20%	-1.532
8	0.41%	2.38%	1.067	-0.23%	1.66%	-0.536
9	0.27%	2.10%	0.792	0.77%	4.50%	0.661
10	0.13%	2.86%	0.275	0.56%	2.34%	0.919
11	-0.16%	2.30%	-0.438	0.33%	2.39%	0.540
12	0.11%	1.70%	0.400	0.98%	2.38%	1.587
13	-0.48%	1.88%	-1.597	-1.00%	1.88%	-2.064*
14	-0.29%	2.52%	-0.726	0.20%	1.60%	0.493
15	-0.14%	2.12%	-0.411	0.14%	2.25%	0.236
16	-0.09%	2.24%	-0.237	0.46%	2.37%	0.748
17	-0.48%	2.12%	-1.414	-0.19%	1.94%	-0.382
18	-0.31%	1.73%	-1.111	-0.82%	1.04%	-3.036*
19	0.10%	1.79%	0.341	0.05%	1.38%	0.154
20	-0.15%	1.75%	-0.534	0.51%	4.68%	0.422

Note: * represent parameters that are statistically significant at a 5% confidence level.

Table 5 - Average CAR and t ratios ("good" news vs "bad" news)

Day	"good" news			"bad" news		
	Average CAR (%)	CAR Standard Deviation (%)	t-test	Average CAR (%)	CAR Standard Deviation (%)	t-test
-20	0.31%	1.69%	1.147	0.51%	1.97%	0.998
-19	0.42%	2.49%	1.046	0.54%	1.90%	1.093
-18	0.42%	2.60%	0.999	1.61%	2.83%	2.205*
-17	0.77%	2.91%	1.652	2.08%	4.10%	1.964
-16	0.72%	3.30%	1.358	2.37%	5.77%	1.592
-15	0.56%	3.39%	1.027	2.29%	4.66%	1.899
-14	0.16%	3.70%	0.266	2.15%	5.29%	1.574
-13	0.32%	3.79%	0.523	1.83%	6.56%	1.081
-12	0.63%	4.41%	0.889	1.32%	8.25%	0.621
-11	1.02%	4.87%	1.310	-0.21%	8.31%	-0.099
-10	1.63%	4.72%	2.153*	-0.34%	8.74%	-0.151
-9	1.62%	5.03%	2.013*	-0.41%	9.01%	-0.177
-8	1.73%	5.31%	2.038*	-0.41%	9.21%	-0.171
-7	1.24%	5.47%	1.420	0.08%	8.85%	0.036
-6	1.31%	5.82%	1.410	-0.15%	9.55%	-0.059
-5	1.14%	6.63%	1.074	-1.09%	14.26%	-0.295
-4	1.40%	7.00%	1.253	-0.96%	14.78%	-0.253
-3	2.02%	7.49%	1.684	-1.47%	14.89%	-0.382
-2	2.41%	7.77%	1.939	-1.67%	15.77%	-0.411
-1	3.05%	8.56%	2.229*	-1.22%	17.72%	-0.266
0	6.88%	10.03%	4.285*	-6.27%	25.24%	-0.962
1	8.68%	12.28%	4.416*	-5.17%	22.05%	-0.908
2	8.67%	12.91%	4.191*	-3.96%	20.01%	-0.767
3	8.36%	12.92%	4.040*	-3.42%	16.31%	-0.813
4	8.20%	13.71%	3.737*	-4.05%	18.33%	-0.855
5	8.14%	14.48%	3.510*	-4.80%	23.67%	-0.785
6	7.88%	14.63%	3.361*	-5.75%	24.48%	-0.910
7	7.56%	14.45%	3.269*	-7.02%	27.49%	-0.989
8	7.97%	15.39%	3.234*	-7.25%	28.52%	-0.984
9	8.24%	16.23%	3.169*	-6.48%	24.39%	-1.029
10	8.36%	17.96%	2.907*	-5.92%	22.23%	-1.032
11	8.20%	18.28%	2.801*	-5.59%	20.30%	-1.067
12	8.31%	19.01%	2.729*	-4.61%	18.63%	-0.959
13	7.83%	19.50%	2.508*	-5.62%	19.85%	-1.096
14	7.54%	19.99%	2.354*	-5.42%	19.29%	-1.088
15	7.40%	20.09%	2.300*	-5.28%	19.63%	-1.042
16	7.31%	19.95%	2.288*	-4.82%	18.75%	-0.996
17	6.83%	19.94%	2.139*	-5.01%	18.81%	-1.032
18	6.52%	19.81%	2.056*	-5.83%	19.34%	-1.167
19	6.62%	20.11%	2.056*	-5.77%	19.91%	-1.123
20	6.47%	20.03%	2.018*	-5.26%	21.84%	-0.933

Note: * represent parameters that are statistically significant at a 5% confidence level.

Figure 6 - Average Abnormal Returns

("good" news vs "bad" news)

Table 6 - Testing Variances - Number of Sample Cases After Applying "Test 1" According to Different Sampling Time Length Around Trading Halts

Table 6 A - Number of Cases when Testing Timing ("Test 2" and "Test 3") Using Variances for Periods of 5 Days, having Rejected H_0 of "Test 1"

Testing 5B with 5A Reject H_0 (Significant Differences)		Testing 5A with 5AA		Total
Testing 5BB with 5B	No Differences Found	Interruption Justified and on Timing 2	Interruption Justified and on Time but Restarting Early 4	6
	⚡ (Differences Found)	Interruption Justified although Late but Restarting on Time 2	Interruption Justified although Late but Restarting Early 2	4
	Total	4	6	10

Table 6 B - Number of Cases when Testing Timing ("Test 2" and "Test 3") Using Variances for Periods of 5 Days, Failing to Reject H_0 of "Test 1"

Testing 5B with 5A Accept H_0 (No Significant Differences)		Testing 5A with 5AA		Total
Testing 5BB with 5B	No Differences Found	Why? 26	Why to Interrupt if Restarting so Early? 6	32
	⚡ (Differences Found)	Why to Interrupt if Interrupting so Late? 11	Why to Interrupt if Interrupting so Late and Restarting so Early 1	12
	Total	37	7	44

Table 6 C - Number of Cases when Testing Timing ("Test 2" and "Test 3") Using Variances for Periods of 10 Days, having Rejected H_0 of "Test 1"

Testing 10B with 10A Reject H_0 (Significant Differences)		Testing 10A with 10AA		Total
Testing 10BB with 10B	No Differences Found	Interruption Justified and on Timing 5	Interruption Justified and on Time but Restarting Early 8	13
	⚡ (Differences Found)	Interruption Justified although Late but Restarting on Time 4	Interruption Justified although Late but Restarting Early 1	5
	Total	9	9	18

Table 6 D - Number of Cases when Testing Timing ("Test 2" and "Test 3") Using Variances for Periods of 10 Days, Failing to Reject H_0 of "Test 1"

Testing 10B with 10A Accept H_0 (No Significant Differences)		Testing 10A with 10AA		Total
		No Differences Found	⚡ (Differences Found)	
Testing 10BB with 10B	No Differences Found	Why? 19	Why to Interrupt if Restarting so Early? 7	26
	⚡ (Differences Found)	Why to Interrupt if Interrupting so Late? 5	Why to Interrupt if Interrupting so Late and Restarting so Early 5	10
Total		24	12	36

Table 6 E - Number of Cases when Testing Timing ("Test 2" and "Test 3") Using Variances for Periods of 20 Days, having Rejected H_0 of "Test 1"

Testing 20B with 20A Reject H_0 (Significant Differences)		Testing 20A with 20AA		Total
		No Differences Found	⚡ (Differences Found)	
Testing 20BB with 20B	No Differences Found	Interruption Justified and on Timing 8	Interruption Justified and on Time but Restarting Early 3	11
	⚡ (Differences Found)	Interruption Justified although Late but Restarting on Time 4	Interruption Justified although Late but Restarting Early 12	16
Total		12	15	27

Table 6 F - Number of Cases when Testing Timing ("Test 2" and "Test 3") Using Variances for Periods of 20 Days, Failing to Reject H_0 of "Test 1"

Testing 20B with 20A Accept H_0 (No Significant Differences)		Testing 20A with 20AA		Total
		No Differences Found	⚡ (Differences Found)	
Testing 20BB with 20B	No Differences Found	Why? 6	Why to Interrupt if Restarting so Early? 5	11
	⚡ (Differences Found)	Why to Interrupt if Interrupting so Late? 8	Why to Interrupt if Interrupting so Late and Restarting so Early 8	16
Total		14	13	27

Table 7 - Testing a GARCH (1,1) model

		H ₀ : $\phi_A = \phi_B$ vs H ₁ : $\phi_A \neq \phi_B$		H ₀ : $\phi_1 = \phi_2$ vs H ₁ : $\phi_1 \neq \phi_2$	
		Test Statistic	p-value	Test Statistic	p-value
Unicer	1992	0,142	0,707	0,023	0,880
BES	1992	-23,826	1,000	-23,292	1,000
BPI	1993	31,137*	0,000	13,546*	0,000
BPA	1993	-7,201	1,000	2,351	0,130
Lusotur	1993	1,295	0,255	1,345	0,250
Sonae Ind.	1993	1,256	0,262	1,113	0,290
Sonae SGPS	1993	7,960*	0,005	14,539*	0,000
Lisnave	1994	0,497	0,481	0,281	0,600
Modelo	1994	1,396	0,237	1,257	0,260
BTA	1994	1,306	0,253	0,369	0,540
BCP	1994	2,495	0,114	2,438	0,120
BES	1994	-10,952	1,000	1,181	0,280
Efacec	1994	0,115	0,735	17,796*	0,000
Cort. Amorim	1994	0,333	0,855	0,030	0,860
BTA 2	1994	27,478*	0,000	23,844*	0,000
Reditus	1995	1,708	0,191	2,017	0,160
BFE	1996	3,472	0,062	0,031	0,860
CPP	1996	6,650*	0,010	-20,598	1,000
BFE 2	1996	0,040	0,950	17,564*	0,000
BPI	1996	11,060*	0,001	27,603*	0,000
Cerexport	1997	1,112	0,292	0,306	0,580
Reditus	1997	1,161	0,281	1,556	0,210
JM	1997	1,152	0,283	0,380	0,540
Inparsi	1997	3,888*	0,049	1,903	0,170
CPP	1997	8,789*	0,003	8,419*	0,000
AXA	1998	3,808	0,051	-87,397	1,000
BCP	1998	0,421	0,517	0,291	0,590
BPI	1998	13,320*	0,000	13,626*	0,000
BANIF	1998	8,670*	0,003	8,521*	0,000
CPP	1998	11,397*	0,001	3,736*	0,050
BPSM	1998	0,131	0,718	0,124	0,730
BTA	1998	12,972*	0,000	12,804*	0,000
CSMC	1998	0,586	0,444	0,151	0,700
Caima	1998	23,021*	0,000	10,468*	0,000
BTA 2	1998	1,325	0,250	1,167	0,280
CPP 2	1998	8,891*	0,003	-4,079	1,000
BPSM 2	1998	1,367	0,242	1,647	0,200
CSMC 2	1998	0,126	0,723	9,440*	0,000
Cimpor	1998	12,516*	0,000	-5,040	1,000
Mota&Comp.	1999	2,420	0,120	1,835	0,180
Mota&Engil	1999	-5,009	1,000	9,137*	0,000
EDP	1999	1,049	0,306	1,914	0,170
Inparsi	1999	20,546*	0,000	17,806*	0,000
Cofina	1999	24,520*	0,000	-1,014	1,000
BPA	1999	-5,093	1,000	0,010	0,750
Sonae Ind.	1999	2,088	0,148	1,926	0,170
Colep	1999	1,410	0,235	5,689*	0,020
BPI	1999	-4,870	1,000	9,135*	0,000
BCP	1999	-23,612	1,000	-22,937	1,000
BFSM	1999	3,899*	0,048	3,846*	0,050
BTA	1999	1,918	0,166	2,675	0,100
CSMC	1999	26,611*	0,000	25,044*	0,000
CPP	1999	0,112	0,737	0,068	0,790
Pararede	1999	4,670*	0,031	5,082*	0,020

Note: The shadowed cells represent the invalid statistics and * represent parameters that are statistically significant at a 5% confidence level.

Table 8 - Trading Halt Opportunity Revealed by different Methods

		5-day Stock Return	5-day abn. Ret.	10day Stock Return	10-day abn. Ret.	20day Stock Return	20-day abn. Ret.	5-day volatility	10-day volatility	20-day volatility	GARCH (1,1)	Methods with 5-Day	Methods with 10-Day	Methods with 20-Day	ALL METHODS
Unicer	1992									X				X	X
BES	1992														
BPI	1993									X	X			X	X
BPA	1993								X	X			X	X	X
Lusotur	1993														
Sonae Ind.	1993									X				X	X
Sonae SGPS	1993									X	X			X	X
Lisnave	1994														
Modelo	1994									X				X	X
BTA	1994														
BCP	1994														
BES	1994							X		X		X		X	X
Efacec	1994										X				X
Cort. Amorim	1994									X				X	X
BTA 2	1994			X	X	X	X				X		X	X	X
Reditus	1995								X	X			X	X	X
BFE	1996														
CPP	1996														
BFE 2	1996										X				X
BPI	1996								X	X	X		X	X	X
Cerexport	1997	X		X					X			X	X		X
Reditus	1997														
IM	1997			X		X	X			X			X	X	X
Inpansa	1997	X							X	X		X	X	X	X
CPP	1997							X			X	X			X
AXA	1998								X	X			X	X	X
BCP	1998														
BPI	1998							X		X	X	X		X	X
BANIF	1998							X	X	X	X	X	X	X	X
CPP	1998							X	X	X	X	X	X	X	X
BPSM	1998														
BTA	1998							X	X	X	X	X	X	X	X
CSMC	1998	X	X	X	X			X				X	X	X	X
Caixa	1998			X	X	X	X				X		X	X	X
BTA 2	1998														
CPP 2	1998														
BPSM 2	1998														
CSMC 2	1998			X		X	X				X		X	X	X
Cimpor	1998								X				X		X
Mota&Comp.	1999								X	X			X	X	X
Mota&Engil	1999										X				X
EDP	1999								X	X			X	X	X
Inpansa	1999							X	X	X	X	X	X	X	X
Cofina	1999								X	X			X	X	X
BPA	1999														
Sonae Ind.	1999								X	X			X	X	X
Colep	1999							X			X	X			X
BPI	1999								X	X	X		X	X	X
BCP	1999									X				X	X
BPSM	1999	X	X		X				X	X	X	X	X	X	X
BTA	1999														
CSMC	1999								X	X	X		X	X	X
CPP	1999														
Pararede	1999				X			X		X	X	X	X	X	X
Total Sample		54	54	54	54	54	54	54	54	54	54	54	54	54	54
# Observations		4	2	6	5	4	4	10	18	27	20	13	24	30	38
#/Tot Sample		7%	4%	11%	9%	7%	7%	19%	33%	50%	37%	24%	44%	56%	70%

APPENDIX 1

Sample used in the study

N.	Firm	Year	Halt Starting Date	Time	Halt Ending Date	Time	N. of Days
1	Unicer-União Cerv.-Nom	1992	09-04-92	-	09-14-92	-	6
2	B.Espirito Santo-Nom.	1992	09-08-92	-	09-15-92	-	5
3	B.Português Atlântico-Nom	1993	02-01-93	-	02-09-93	-	6
4	BPI-Nom.	1993	04-13-93	-	04-19-93	-	4
5	Lusotur-Soc.Fin.Turismo	1993	10-18-93	-	10-21-93	-	4
6	Sonae Indústria-SGPS	1993	11-19-93	-	11-25-93	-	4
7	Sonae-SGPS	1993	12-17-93	-	05-22-93	-	3
7	Sonae-SGPS	1993	12-27-93	-	12-30-93	-	3
8	Lisnave-Estal.Nav.Lisboa	1994	01-03-94	-	01-04-94	-	1
9	Modelo-SGPS	1994	02-10-94	-	02-17-94	-	4
10	B.Totta & Açores-Nom	1994	03-30-94	-	04-05-94	-	2
11	B.Comercial Português-Nom	1994	04-08-94	-	04-15-94	-	5
12	BES Nom	1994	04-18-94	-	04-22-94	-	5
13	Efacec-E.F.Máq.Eléctricas	1994	08-16-94	-	08-22-94	-	4
14	Corticeira Amorim-SGPS	1994	10-17-94	-	10-21-94	-	4
15	B.Totta & Açores-Nom	1994	12-29-94	-	12-30-94	-	1
16	Reditus-SGPS	1995	05-09-95	-	05-10-95	-	1
17	B.Fomento Exterior-Nom	1996	01-19-96	-	01-22-96	-	1
18	Crédito Predial Port.-Nom	1996	07-04-96	9:10	07-05-96	-	1
19	B.Fomento Exterior-Nom	1996	08-22-96	10:38	08-28-96	9:00	3
20	BPI-SGPS-Nom	1996	08-23-96	-	08-28-96	-	3
21	Cerexport-Cer.Exportação	1997	01-15-97	-	01-20-97	-	3
22	Jerónimo Martins-SGPS	1997	02-03-97	-	02-07-97	-	4
23	Reditus-SGPS	1997	02-27-97	-	02-28-97	-	1
24	Inparsa-Ind.Part.SGPS	1997	07-10-97	9:15	07-11-97	9:00	1
25	Crédito Predial Port.-Nom	1997	07-29-97	-	07-30-97	-	1
26	BPI	1998	01-23-98	9:20	01-23-98	11:05	1
27	Crédito Predial Port.-Nom	1998	02-11-98	18:00	02-12-98	14:00	1
28	B.Pinto Sotto Mayor-Nom	1998	02-11-98	18:00	02-12-98	14:00	1
29	B.Totta & Açores-Nom	1998	02-11-98	18:00	02-12-98	14:00	1
30	C.S.Mundial Confiança-Nom	1998	02-11-98	18:00	02-12-98	14:00	1
31	Caima - Comp. de celulose	1998	03-25-98	9:30	03-25-98	12:00	1
32	AXA Portugal-Comp.S.-Nom.	1998	04-01-98	17:12	04-02-98	11:30	1
33	Banif-Nom	1998	07-23-98	-	07-29-98	-	4
34	Crédito Predial Port.-Nom	1998	11-13-98	8:35	11-13-98	12:00	1
35	BCP	1998	11-13-98	8:35	11-13-98	12:00	1
36	B.Pinto Sotto Mayor-Nom	1998	11-13-98	8:35	11-13-98	12:00	1
37	B.Totta & Açores-Nom	1998	11-13-98	8:35	11-13-98	12:00	1
38	C.S.Mundial Confiança-Nom	1998	11-13-98	8:35	11-13-98	12:00	1
39	Cimpor	1998	11-13-98	8:35	11-13-98	12:00	1
40	Inparsa-Ind.Part.SGPS	1999	02-26-99	9:12	02-26-99	13:15	1
41	Sonae Indústria	1999	02-26-99	9:12	02-26-99	13:15	1
42	Mota-Engil, SGPS	1999	07-23-99	15:45	07-26-99	8:55	3
43	Mota & Companhia	1999	07-23-99	15:55	07-26-99	8:55	1
43	Mota & Companhia	1999	07-29-99	14:56	07-30-99	8:43	1
44	BPI	1999	08-17-99	11:27	08-17-99	14:15	1
45	Cofina	1999	08-17-99	11:27	08-17-99	14:15	1
46	B.Comercial Português-Nom	1999	11-11-99	11:20	11-15-99	9:00	2
47	B.Pinto Sotto Mayor-Nom	1999	11-11-99	9:00	11-15-99	9:00	2
47	B.Pinto Sotto Mayor-Nom	1999	11-18-99	9:16	11-19-99	8:32	1
48	B.Português Atlântico-Nom	1999	11-11-99	11:20	11-15-99	9:00	2
49	B.Totta & Açores-Nom	1999	11-11-99	9:00	11-15-99	9:00	2
50	C.S.Mundial Confiança-Nom	1999	11-11-99	9:00	11-15-99	9:00	2
51	Crédito Predial Port.-Nom	1999	11-11-99	9:00	11-15-99	9:00	2
52	Pararede - SGPS	1999	11-12-99	11:12	11-15-99	10:10	1
53	Colep Port-Emb.Prod.E.Eq.	1999	12-03-99	9:15	12-06-99	8:46	1
53	Colep Port-Emb.Prod.E.Eq.	1999	12-15-99	15:24	12-17-99	8:54	2
54	EDP	1999	12-22-99	9:15	12-22-99	13:00	1

APPENDIX 2

Charts for Prices, Returns and Volatility for each Trading halt in the Sample

Modelo (1994)

— Closing Price — Instant Returns (IR) — Volatility

BTA (1994)

— Closing Price — Instant Returns (IR) — Volatility

BCP (1994)

— Closing Price — Instant Returns (IR) — Volatility

BES (1994)

— Closing Price — Instant Returns (IR) — Volatility

Efacec (1994)

— Closing Price — Instant Returns (IR) — Volatility

Corticeira Amorim (1994)

— Closing Price — Instant Returns (IR) — Volatility

BTA2 (1994)

— Closing Price — Instant Returns (IR) — Volatility

Reditus (1995)

— Closing Price — Instant Returns (IR) — Volatility

CPP (1997)

BPI (1998)

CPP (1998)

BPSM (1998)

BTA (1998)

CSMC (1998)

Caima (1998)

AXA (1998)

Banif (1998)

CPP2 (1998)

BCP (1998)

BPSM2 (1998)

BTA2 (1998)

CSMC2 (1998)

Cimpor (1998)

Inparsa (1999)

Sonae Indústria (1999)

Mota&Engil (1999)

Mota&Companhia (1999)

BPI (1999)

Cofina (1999)

BCP (1999)

BPSM (1999)

BPA (1999)

APPENDIX 3

Stock Price Returns around Trading halts

Firm	N.º	Year	5 Days					10 Days					20 Days				
			BB	BA	Difference	Absolute %	AA	BB	BA	Difference	Absolute %	AA	BB	BA	Difference	Absolute %	AA
Unicer	1	1992	-0,2139	0,0075	0,00%	0,00%	0,5048	0,1321	0,3596	-0,15%	0,15%	0,6057	0,0778	0,9033	-0,48%	0,48%	-0,3867
Bes Nom	2	1992	0,5316	1,4411	-1,34%	1,34%	-0,5453	-1,9614	1,5318	-1,38%	1,38%	0,2962	0,0596	0,9035	-0,64%	0,64%	-1,7066
Average 1992					-0,67%	0,67%				-0,76%	0,76%				-0,56%	0,56%	
BPA Nom	3	1993	-0,0159	1,2333	-1,61%	1,61%	-2,4096	-0,4318	-0,8531	1,21%	1,21%	1,5165	0,0115	-0,1593	0,13%	0,13%	-0,1651
BPI Nom	4	1993	0,7708	-1,5815	1,01%	1,01%	3,0588*	0,4989	0,0411	-0,02%	0,02%	-0,4549	-0,3920	-0,1096	0,07%	0,07%	-0,9003
Lusotur	5	1993	-0,9450	0,0363	-0,02%	0,02%	0,6991	-0,2779	0,9042	-0,72%	0,72%	-0,3377	1,5505	0,7121	-0,45%	0,45%	0,2588
Sonae Indústria, SGPS	6	1993	0,0000	0,8017	-0,58%	0,58%	-1,8240	0,7188	-0,3428	0,19%	0,19%	0,5425	0,4936	0,5915	-0,37%	0,37%	-2,5399
Sonae SGPS	7	1993	1,3968	-1,4706	2,49%	2,49%	0,0350	-1,1316	-0,9404	1,24%	1,24%	0,4099	-0,1129	-1,4345	1,44%	1,44%	1,1217
Average 1993					0,26%	1,14%				0,38%	0,68%				0,16%	0,49%	
Lisnave	8	1994	-0,6612	1,0411	-1,03%	1,03%	0,0344	0,2959	0,9346	-0,66%	0,66%	0,9202	-1,2914	2,0009	-1,07%	1,07%	-0,7681
Modelo SGPS	9	1994	0,0997	1,0774	-0,80%	0,80%	-0,7958	1,7644	0,3521	-0,35%	0,35%	-1,1454	0,2329	1,2980	-0,88%	0,88%	0,2625
BTA Nom	10	1994	0,0000	0,6112	-0,42%	0,42%	-0,7494	-0,0682	0,4947	-0,18%	0,18%	-0,3144	-0,6383	0,1682	-0,08%	0,08%	1,9149
BCP Nom	11	1994	0,8951	-0,7656	0,48%	0,48%	0,3765	1,0556	-0,1262	0,06%	0,06%	0,2195	0,0051	0,6666	-0,22%	0,22%	-1,0153
BES Nom	12	1994	-0,2980	0,1099	-0,08%	0,08%	2,5562*	0,6689	0,9125	-0,38%	0,38%	-0,8397	0,7596	0,5963	-0,23%	0,23%	0,1225
Efacec	13	1994	1,0703	-0,9488	1,11%	1,11%	0,4141	0,8112	-0,3465	0,27%	0,27%	1,2668	0,2352	0,8873	-0,48%	0,48%	0,4459
Corticeira Amorim	14	1994	-0,8108	0,8985	-0,69%	0,69%	-0,3989	-0,8223	0,3571	-0,19%	0,19%	0,6579	-0,7972	0,1713	-0,06%	0,06%	2,8802*
BTA (2) Nom	15	1994	-0,0267	2,1469	-1,55%	1,55%	0,1521	-1,0259	2,2546*	-1,59%	1,59%	-0,3665	-0,3550	2,6443*	-1,16%	1,16%	-2,6460
Average 1994					-0,37%	0,77%				-0,38%	0,46%				-0,52%	0,52%	
Reditus, SGPS	16	1995	1,7512	-0,6299	4,74%	4,74%	-0,6003	0,8034	-1,0098	4,53%	4,53%	0,2504	1,7765	-1,3375	3,14%	3,14%	0,1708
Average 1995					4,74%	4,74%				4,53%	4,53%				3,14%	3,14%	
BFE Nom	17	1996	0,4176	0,3810	-0,37%	0,37%	-0,7257	-0,0208	0,0525	-0,04%	0,04%	-0,1447	-0,9747	-0,1288	0,07%	0,07%	-0,3691
CPP Nom	18	1996	-0,6112	0,9752	-1,71%	1,71%	-1,7690	0,3904	0,394	-0,37%	0,37%	0,9033	-1,2011	1,5833	-0,80%	0,80%	-0,5898
BFE (2) Nom	19	1996	-1,4669	0,7227	-0,27%	0,27%	0,1702	-1,2631	0,4333	-0,12%	0,12%	0,0967	1,8941	0,0971	-0,02%	0,02%	-0,0114
BPI Nom	20	1996	-0,9083	0,8586	-0,92%	0,92%	0,5886	-0,7545	0,8701	-0,51%	0,51%	3,0154*	-1,1466	1,9638	-0,69%	0,69%	-1,3240
Average 1996					-0,82%	0,82%				-0,25%	0,26%				-0,35%	0,39%	
Cerxport	21	1997	-1,7037	2,3807*	-3,60%	3,60%	0,6275	-2,7194*	2,3931*	-2,54%	2,54%	-0,4994	-1,5907	1,5644	-1,06%	1,06%	-0,9116
Jer. Martins, SGPS	22	1997	0,8562	1,3915	-1,04%	1,04%	-0,8722	1,1049	2,2267*	-0,95%	0,95%	-0,0877	-0,4292	3,2431*	-1,30%	1,30%	-1,7163
Reditus, SGPS	23	1997	1,1500	-0,2846	0,48%	0,48%	-1,0675	1,3663	-0,0155	0,02%	0,02%	-0,1986	-0,7136	0,7952	-0,68%	0,68%	-0,4934
Inparisa	24	1997	-1,4179	3,3464*	-3,95%	3,95%	-2,9618	-1,2958	-0,5695	1,15%	1,15%	1,2401	-2,9956	-0,4173	0,49%	0,49%	1,2535
CPP Nom	25	1997	-1,4636	1,7787	-1,95%	1,95%	-0,7715	0,4663	-0,072	0,10%	0,10%	0,6863	-0,0735	0,6947	-0,61%	0,61%	0,5287
Average 1997					-2,01%	2,20%				-0,44%	0,95%				-0,63%	0,82%	
BPI	26	1998	-3,1917	0,8298	-0,95%	0,95%	0,6054	0,359	0,6098	-0,49%	0,49%	-0,2971	-1,9338	0,8689	-0,45%	0,45%	-0,1449
CPP Nom	27	1998	0,6883	0,3825	-1,17%	1,17%	-0,4575	-1,159	1,1666	-1,91%	1,91%	-0,0388	-1,2998	1,1793	-0,99%	0,99%	-2,0200
BPSM Nom	28	1998	-0,1357	-0,4897	0,38%	0,38%	-1,3338	3,3351*	-1,5147	1,32%	1,32%	-0,1495	-1,1020	0,0971	-0,07%	0,07%	-0,5596
BTA Nom	29	1998	0,5922	-0,6568	0,97%	0,97%	-0,5920	0,6511	-0,9382	0,74%	0,74%	0,0727	-0,4955	-0,6047	0,37%	0,37%	-0,9874
CSMC Nom	30	1998	0,3900	-2,3064	2,03%	2,03%	-0,3394	2,1677*	-3,3271*	2,02%	2,02%	2,2675*	-0,0069	-0,5532	0,33%	0,33%	-0,5284
Caima - Comp. de Celulose	31	1998	-0,6842	1,8029	-3,31%	3,31%	0,1078	-1,6426	2,7165*	-2,77%	2,77%	0,6099	-0,6024	2,8266*	-2,18%	2,18%	-1,4526
AXA Portugal Nom	32	1998	-0,5162	0,8874	-1,42%	1,42%	-0,8150	-0,746	0,9615	-0,75%	0,75%	-1,3208	0,9647	0,2717	-0,14%	0,14%	-0,0227
BANIF Nom	33	1998	1,0889	-0,4230	0,76%	0,76%	0,1798	1,2845	-0,1864	0,20%	0,20%	-0,1256	-1,2615	0,3480	-0,28%	0,28%	0,8008
CPP (2) Nom	34	1998	1,3136	-1,3206	1,88%	1,88%	1,0492	0,4047	-0,014	0,02%	0,02%	0,6197	-0,0769	0,7048	-0,56%	0,56%	-0,4959
BCP	35	1998	0,6989	-0,0410	0,04%	0,04%	-0,2586	1,4519	0,1625	-0,10%	0,10%	0,2490	-0,4420	1,2839	-0,60%	0,60%	-1,2799
BPSM (2) Nom	36	1998	2,8434*	-0,9127	1,50%	1,50%	0,6368	0,2941	0,5912	-0,66%	0,66%	-0,7695	0,1047	0,5970	-0,41%	0,41%	-1,1372
BTA (2) Nom	37	1998	1,6737	-0,6946	1,05%	1,05%	0,2738	0,6902	0,2094	-0,20%	0,20%	0,0246	0,4207	0,8311	-0,59%	0,59%	-0,1006
CSMC (2) Nom	38	1998	0,2088	1,2049	-2,12%	2,12%	0,0204	0,2937	2,1905*	-2,33%	2,33%	-0,1821	-1,9674	3,4610*	-2,41%	2,41%	-1,3608
Cimpor	39	1998	0,7542	-1,3785	1,10%	1,10%	1,0434	1,7626	-0,1426	0,13%	0,13%	0,2390	-0,3793	1,2929	-0,90%	0,90%	-0,2402
Average 1998					0,05%	1,33%				-0,34%	0,97%				-0,64%	0,73%	
Inparisa	40	1999	1,0735	1,2089	-1,05%	1,05%	-0,1856	-1,0162	1,5492	-1,23%	1,23%	-1,1213	0,7135	0,2260	-0,18%	0,18%	-0,2765
Sonae Indústria	41	1999	0,9794	-0,1029	0,07%	0,07%	-0,1836	0,6347	-0,0183	0,02%	0,02%	0,2449	0,6534	0,3750	-0,23%	0,23%	0,0121
Mota & Engil, SGPS	42	1999	-0,1864	2,0190	-1,66%	1,66%	-2,6994*	0,8195	-1,0753	1,77%	1,77%	-0,2357	0,6039	0,0141	0,00%	0,00%	-2,2111
Mota & Companhia	43	1999	0,2383	1,9399	-1,16%	1,16%	-1,4390	-0,3796	1,187	-0,96%	0,96%	-1,2076	-1,0249	0,3298	-0,26%	0,26%	0,8608
BPI	44	1999	-3,0674	1,1305	-1,50%	1,50%	1,5797	-0,8878	0,115	-0,11%	0,11%	1,5268	0,1033	0,0141	-0,01%	0,01%	-0,6569
Cofina	45	1999	-0,2210	-0,7363	3,07%	3,07%	0,6529	-0,9452	-0,7496	1,65%	1,65%	0,9518	-0,7114	-0,6208	0,72%	0,72%	0,6948
BCP Nom	46	1999	-0,8108	-1,0016	0,55%	0,55%	2,7880*	-0,2737	-0,1617	0,06%	0,06%	2,1605*	-0,2423	1,3086	-0,37%	0,37%	-1,0038
BPSM Nom	47	1999	-2,5936	2,5160*	-1,49%	1,49%	0,6163	-1,1209	1,4173	-0,68%	0,68%	-1,1800	1,0508	0,4441	-0,16%	0,16%	-3,0809
BPA Nom	48	1999	0,3149	-1,3715	0,93%	0,93%	1,7321	-0,7305	-0,3922	0,21%	0,21%	1,4667	1,2170	-0,1202	0,04%	0,04%	1,4247
BTA Nom	49	1999	-0,9434	0,5653	-0,94%	0,94%	-0,3149	-0,9706	0,1081	-0,10%	0,10%	0,6357	1,1367	-0,1657	0,10%	0,10%	-0,5851
CSMC Nom	50	1999	-4,4377	-0,3567	1,00%	1,00%	0,6063	-0,794	-0,6213	0,86%	0,86%	1,0449	0,8813	-0,4784	0,36%	0,36%	0,5991
CPP Nom	51	1999	-1,2601	0,7887	-0,90%	0,90%	-0,0327	-1,4641	0,6865	-0,40%	0,40%	-0,0586	0,8924	0,0141	-0,01%	0,01%	-0,7753
Parade, SGPS	52	1999	0,4707	0,7058	-0,53%	0,53%	0,3361	-0,4824	1,8065	-0,77%	0,77%	-1,6535	-1,0094	0,2266	-0,10%	0,10%	-0,6890
Colep Port	53	1999	-1,3316	1,2666	-2,34%	2,34%	-0,7878	-0,0694	0,5452	-0,53%	0,53%	-0,1024	-0,8927	0,6105	-0,44%	0,44%	-0,1258
EDP	54	1999	0,9349	0,3030	-0,22%	0,22%	0,0190	-0,1719	1,0086	-1,32%	1,32%	-0,4890	-1,2002	1,4070	-1,03%	1,03%	-1,4979
Average 1999					-0,41%	1,16%				-0,10%	0,71%				-0,11%	0,27%	
Global Average					0,10%	1,60%				0,33%	1,17%				0,06%	0,67%	

Legend: BB represents Test 2; BA the Test 1 and AA the Test 3. The values below are the statistical tests.

Note: The shadowed cells represent parameters that are statistically significant at a 5% confidence level.

APPENDIX 4

Abnormal returns around trading halts

Item	N°	Year	5 Days					10 Days					20 Days				
			BB	BA	Difference	Absolute A	AA	BB	BA	Difference	Absolute A	AA	BB	BA	Difference	Absolute A	AA
Unicer	1	1992	-0,1314	-0,1599	0,10%	0,10%	0,3423	0,7019	0,0098	0,00%	0,00%	-0,0656	0,2827	-0,14%	0,14%		
Bes Nom	2	1992	0,4300	1,1396	-1,04%	1,04%	-0,8383	-1,6064	1,0550	-0,90%	0,90%	-0,0548	0,1414	-0,10%	0,10%		
Average 1992					-0,47%	0,57%				-0,45%	0,45%				0,12%		
BPA Nom	3	1993	-0,6889	1,2690	-1,74%	1,74%	-2,4533	1,1471	-0,8190	1,13%	1,13%	0,9847	-0,4738	0,37%	0,37%		
BPI Nom	4	1993	0,2894	-0,8292	0,52%	0,52%	1,8488	0,4438	0,0956	-0,04%	0,04%	-0,1347	0,5797	-0,29%	0,29%		
Lusotur	5	1993	-0,9240	0,3623	-0,36%	0,36%	0,6307	0,2494	0,3286	-0,24%	0,24%	-0,1485	0,1284	-0,07%	0,07%		
Sonae Indústria, SGPS	6	1993	0,2731	-0,3124	0,28%	0,28%	-0,3380	0,7339	-0,6193	0,35%	0,35%	0,6019	0,1313	-0,08%	0,08%		
Sonae SGPS	7	1993	1,3834	-1,4505	2,09%	2,09%	0,1099	-0,9770	-0,6918	0,81%	0,81%	0,4917	-0,8877	0,87%	0,87%		
Average 1993					0,16%	1,00%				0,40%	0,51%				0,34%		
Lisnave	8	1994	-0,1100	0,6545	-0,57%	0,57%	0,5147	-0,0576	0,8937	-0,67%	0,67%	0,6233	1,3704	-0,82%	0,82%		
Modelo SGPS	9	1994	0,3466	0,0982	-0,07%	0,07%	-1,3062	1,5633	-0,3558	0,29%	0,29%	-0,0049	0,8521	-0,52%	0,52%		
BTA Nom	10	1994	-0,4344	0,4584	-0,26%	0,26%	-0,5787	0,0832	0,0868	-0,03%	0,03%	-0,7301	-0,2178	0,07%	0,07%		
BCP Nom	11	1994	0,2104	0,2518	-0,13%	0,13%	-0,3441	0,3726	0,2779	-0,09%	0,09%	-1,4851	-0,8997	0,23%	0,23%		
BES Nom	12	1994	0,3807	-0,0635	0,04%	0,04%	-0,7099	0,2869	-0,1113	0,05%	0,05%	-0,0577	-0,0078	0,00%	0,00%		
Efacec	13	1994	0,2078	-1,2985	0,99%	0,99%	0,6625	0,9754	-0,8232	0,55%	0,55%	-0,5380	-0,9909	0,61%	0,61%		
Corticeira Amorim	14	1994	-0,6806	0,7106	-0,49%	0,49%	-0,0487	-0,5723	0,3173	-0,16%	0,16%	0,9960	0,5854	-0,21%	0,21%		
BTA (2) Nom	15	1994	0,1782	1,9998	-1,38%	1,38%	0,3724	-1,4219	2,5289	-1,61%	1,61%	-0,8691	2,3359	-0,97%	0,97%		
Average 1994					-0,23%	0,49%				-0,21%	0,43%				0,43%		
Reditus, SGPS	16	1995	1,7244	-1,0664	8,43%	8,43%	0,0696	0,8571	-1,1649	5,30%	5,30%	0,1367	-1,5452	3,76%	3,76%		
Average 1995					8,43%	8,43%				5,30%	5,30%				3,76%		
BFE Nom	17	1996	0,8781	0,1950	-0,15%	0,15%	-1,0420	0,3004	-0,1924	0,15%	0,15%	-0,4768	-0,6944	0,35%	0,35%		
CPP Nom	18	1996	-0,5367	0,7099	-1,26%	1,26%	-1,6754	0,5754	-0,0017	0,00%	0,00%	0,8458	0,5766	-0,28%	0,28%		
BFE (2) Nom	19	1996	-2,3004	1,3492	-0,57%	0,57%	0,9999	-0,4773	1,2887	-0,36%	0,36%	-1,0235	0,4496	-0,08%	0,08%		
BPI Nom	20	1996	-1,0427	1,1222	-1,15%	1,15%	0,3501	-0,7032	1,0728	-0,64%	0,64%	2,2838	2,0456	-0,75%	0,75%		
Average 1996					-0,78%	0,78%				-0,21%	0,29%				-0,19%	0,37%	
Cerexport	21	1997	-2,0200	2,1266	-2,76%	2,76%	0,5683	-2,2572	2,0443	-1,73%	1,73%	0,0645	1,5289	-0,99%	0,99%		
Jer. Martins, SGPS	22	1997	0,6755	1,5376	-1,13%	1,13%	-1,4101	-0,0337	1,6575	-0,77%	0,77%	0,3182	2,2391	-0,83%	0,83%		
Reditus, SGPS	23	1997	0,7155	0,1137	-0,20%	0,20%	-1,4334	0,9096	0,0987	-0,10%	0,10%	-0,5191	0,6162	-0,51%	0,51%		
Imparsa	24	1997	-0,7420	2,2684	-2,20%	2,20%	-3,0650	-0,8288	-1,1133	2,01%	2,01%	1,5664	-0,7992	0,92%	0,92%		
CPP Nom	25	1997	-1,1795	0,0177	-0,04%	0,04%	0,7306	0,0380	0,0118	-0,01%	0,01%	-0,3400	-0,3142	0,23%	0,23%		
Average 1997					-1,27%	1,27%				-0,12%	0,92%				-0,24%	0,70%	
BPI	26	1998	-2,2069	0,4866	-0,49%	0,49%	0,9037	-0,3292	0,6008	-0,36%	0,36%	0,0017	1,0810	-0,37%	0,37%		
CPP Nom	27	1998	0,4256	0,3361	-0,87%	0,87%	1,4468	-1,8515	1,5721	-2,24%	2,24%	0,1904	1,5304	-1,24%	1,24%		
BPSM Nom	28	1998	-1,2491	0,2176	-0,12%	0,12%	-0,3546	0,1768	-0,9736	0,51%	0,51%	-1,4789	0,1895	-0,10%	0,10%		
BTA Nom	29	1998	0,0066	0,5279	-0,42%	0,42%	-0,9267	0,0347	0,2635	-0,17%	0,17%	-1,0748	-0,3856	0,23%	0,23%		
CSMC Nom	30	1998	-0,5828	-2,8015	1,57%	1,57%	1,6617	1,6799	-2,5083	1,26%	1,26%	1,8159	-0,9916	0,17%	0,17%		
Caixa - Comp. de Celulose	31	1998	-0,7459	1,2785	-2,69%	2,69%	1,0477	-1,7997	2,5301	-2,86%	2,86%	0,4784	3,2161	-2,46%	2,46%		
AXA Portugal Nom	32	1998	-1,2541	0,9791	-1,72%	1,72%	-0,2735	-0,0400	0,6302	-0,60%	0,60%	-1,2370	-0,4391	0,36%	0,36%		
BANIF Nom	33	1998	-0,3527	-0,6852	1,04%	1,04%	0,6385	0,5177	-0,8176	0,67%	0,67%	-0,0800	-0,2917	0,16%	0,16%		
CPF (2) Nom	34	1998	0,3988	-1,1453	1,10%	1,10%	1,1678	-0,0237	-0,5759	0,38%	0,38%	0,7009	-0,0481	0,03%	0,03%		
BCP	35	1998	-1,9251	1,2595	-1,01%	1,01%	-0,7519	0,5437	0,1828	-0,09%	0,09%	-0,2078	0,2632	-0,09%	0,09%		
BPSM (2) Nom	36	1998	1,7924	-1,4111	1,69%	1,69%	1,5319	-0,4104	-0,0292	0,02%	0,02%	-0,2863	-0,3529	0,19%	0,19%		
BTA (2) Nom	37	1998	0,8377	-0,6292	1,17%	1,17%	0,3954	0,0794	-0,2613	0,26%	0,26%	-0,0650	-0,4515	0,32%	0,32%		
CSMC (2) Nom	38	1998	-0,9659	0,2752	-0,76%	0,76%	1,0246	-0,1980	0,8479	-1,25%	1,25%	0,3726	3,1441	-1,90%	1,90%		
Cimpor	39	1998	-0,5263	0,6970	-0,53%	0,53%	-0,7717	1,6429	-0,1260	0,09%	0,09%	-0,5763	0,2511	-0,15%	0,15%		
Average 1998					-0,15%	1,08%				-0,31%	0,77%				-0,35%	0,55%	
Imparsa	40	1999	1,0017	0,4882	-0,40%	0,40%	-0,2183	-0,8688	1,0253	-0,56%	0,56%	-0,6814	0,3028	-0,19%	0,19%		
Sonae Indústria	41	1999	0,7904	0,1955	-0,09%	0,09%	-1,0210	0,6626	-0,5159	0,34%	0,34%	1,2437	0,5867	-0,27%	0,27%		
Mota & Engil, SGPS	42	1999	-0,2425	-1,7109	10,02%	10,02%	1,5733	0,8827	-1,5680	5,40%	5,40%	1,6214	-0,4952	0,49%	0,49%		
Mota & Companhia	43	1999	0,8097	-0,3095	0,22%	0,22%	0,4192	-0,3576	0,6495	-0,52%	0,52%	-0,3712	-0,0417	0,03%	0,03%		
BPI	44	1999	-3,6435	1,5030	-1,64%	1,64%	1,0115	-0,8638	0,5281	-0,43%	0,43%	-0,1532	-0,2118	0,11%	0,11%		
Cofina	45	1999	0,6289	-1,3223	5,90%	5,90%	1,3076	-0,0745	-1,0010	2,51%	2,51%	0,8415	-0,6440	0,80%	0,80%		
BCP Nom	46	1999	-0,0509	0,2116	-0,13%	0,13%	1,9673	-0,7557	1,6979	-0,62%	0,62%	1,9193	3,1909	-1,05%	1,05%		
BPSM Nom	47	1999	-1,6274	2,8034	-1,36%	1,36%	0,5490	-0,7996	2,4708	-1,07%	1,07%	-1,2521	1,3468	-0,45%	0,45%		
BPA Nom	48	1999	0,9945	-0,1314	0,11%	0,11%	1,0650	-1,0949	1,2098	-0,57%	0,57%	1,2237	1,7857	-0,59%	0,59%		
BTA Nom	49	1999	-0,7098	0,9348	-1,44%	1,44%	-0,4533	-1,2271	0,7608	-0,68%	0,68%	0,5905	1,4586	-0,78%	0,78%		
CSMC Nom	50	1999	-2,6803	-0,5158	1,31%	1,31%	1,0032	-1,1716	-0,4531	0,59%	0,59%	1,4391	0,4249	-0,32%	0,32%		
CPP Nom	51	1999	-0,8309	1,1843	-1,40%	1,40%	-0,1914	-1,8428	1,6497	-0,98%	0,98%	-0,0374	1,4709	-0,62%	0,62%		
Pararede, SGPS	52	1999	0,2571	2,0289	-1,80%	1,80%	-0,7238	-0,6375	2,7805	-1,53%	1,53%	-1,7733	1,7716	-0,77%	0,77%		
Colep Port	53	1999	-1,4340	0,1678	-0,46%	0,46%	0,7497	-0,0368	0,0524	-0,08%	0,08%	-0,0878	0,4294	-0,37%	0,37%		
EDF	54	1999	0,8182	-0,1460	0,08%	0,08%	0,5041	-0,4970	0,8739	-0,85%	0,85%	0,6823	1,2856	-0,81%	0,81%		
Average 1999					0,59%	1,76%				0,06%	1,11%				-0,32%	0,51%	
Global Average					0,79%	1,92%				0,50%	1,22%				0,53%	0,85%	

Legend: BB represents "Test 2"; BA the "Test 2" and AA "Test 3". The values below are the statistical test.

Note: The shadowed cells represent parameters that are statistically significant at a 5% confidence level.

APPENDIX 5

Volatility around trading halts

Firm	N.	Year	5 Days					10 Days					20 Days				
			BB	BA	Difference	Absolute %	AA	BB	BA	Difference	Absolute %	AA	BB	BA	Difference	Absolute %	AA
Unicer	1	1992	0.2457	0.9199	0.00%	0.00%	0.4251	3.2634*	0.3331	0.01%	0.01%	0.1640*	4.2869*	0.1963*	0.04%	0.04%	2.1591
Bes Nom	2	1992	3.9012	0.8671	0.00%	0.00%	0.4327	0.8303	1.2813	-0.01%	0.01%	0.4809	0.0236*	0.9199	0.00%	0.00%	4.1576*
Average 1992					0.00%	0.00%				0.00%	0.01%				0.02%	0.02%	
BPA Nom	3	1993	0.0001*	0.3383	0.04%	0.04%	0.3770	0.3549	0.0500*	0.18%	0.18%	4.5626*	2.2670*	0.0468*	0.12%	0.12%	8.3272*
BPI Nom	4	1993	0.3242	2.5617	-0.01%	0.01%	0.7546	3.2082*	0.7225	0.00%	0.00%	0.1289*	1.9554	0.3480*	0.04%	0.04%	2.7649*
Lusotur	5	1993	4.5976	0.2374	0.04%	0.04%	3.8152	2.3742	1.1032	0.00%	0.00%	1.2466	1.9701	2.0613	-0.03%	0.03%	1.2721
Sonae Indústria, SGPS	6	1993	2.9660	0.2075	0.02%	0.02%	1.5664	16.4071*	0.3547	0.01%	0.01%	4.7118*	0.3570*	5.1548*	-0.05%	0.05%	0.1145*
Sonae SGPS	7	1993	2.4929	0.4295	0.06%	0.06%	0.9482	0.1749*	0.9080	0.01%	0.01%	0.4075	0.1463*	0.3261*	0.10%	0.10%	4.1338*
Average 1993					0.03%	0.03%				0.04%	0.04%				0.03%	0.07%	
Lisnave	8	1994	2.3551	0.7226	0.01%	0.01%	2.7939	1.5184	1.8827	-0.02%	0.02%	0.788	1.9996	2.0054	-0.02%	0.02%	0.3614*
Modelo SGPS	9	1994	15.1929*	0.3663	0.01%	0.01%	0.2917	1.1961	1.2427	-0.01%	0.01%	4.0695*	0.4694	2.9651*	-0.04%	0.04%	1.9211
BTA Nom	10	1994	0.5733	0.3423	0.01%	0.01%	7.3488*	12.6446*	0.4431	0.01%	0.01%	0.5365	1.7087*	2.0958	-0.01%	0.01%	0.6036
BCP Nom	11	1994	0.6463	4.2409	-0.01%	0.01%	0.3349	0.2958*	1.9770	-0.01%	0.01%	0.1189	1.6221*	0.6561	0.00%	0.00%	0.8023
BES Nom	12	1994	0.1860	42.9654*	-0.02%	0.02%	0.1209*	0.1913*	3.0600	-0.01%	0.01%	0.1046*	2.3618*	0.3405*	0.01%	0.01%	0.5657
Efacec	13	1994	0.2665	2.5833	-0.03%	0.03%	0.4017	1.3832	1.0502	0.00%	0.00%	3.5359*	1.5154	1.8591	-0.02%	0.02%	0.3489*
Corticeira Amorim	14	1994	1.7466	1.1473	0.00%	0.00%	3.0723	0.8334	2.5226	-0.01%	0.01%	1.4609	1.2019	2.7819*	-0.01%	0.01%	1.9024
BTA 2 Nom	15	1994	7.8190*	0.5530	0.01%	0.01%	1.2624	0.0376*	2.7236	-0.02%	0.02%	0.4886	0.4684	0.9740	0.00%	0.00%	1.6377
Average 1994					0.00%	0.01%				-0.01%	0.01%				-0.01%	0.02%	
Reditus, SGPS	16	1995	0.0365*	0.2096	1.85%	1.85%	1.7553	0.4379	0.1851*	1.40%	1.40%	10.6176*	0.7689	0.2461*	0.67%	0.67%	0.3038*
Average 1995					1.85%	1.85%				1.40%	1.40%				0.67%	0.67%	
BFE Nom	17	1996	0.2442	5.8382	-0.03%	0.03%	0.0583*	0.5457	0.4035	0.03%	0.03%	6.9881	0.1039*	0.5278	0.03%	0.03%	1.4091
CPP Nom	18	1996	0.0637*	3.4984	-0.09%	0.09%	3.0062	0.1706*	2.1601	-0.03%	0.03%	4.1192*	0.2013*	1.9961	-0.02%	0.02%	3.9482*
BFE 2 Nom	19	1996	0.1199*	0.8040	0.00%	0.00%	0.4491	0.7294	0.3528	0.00%	0.00%	2.4558	7.9977*	0.4718	0.00%	0.00%	2.9905*
BPI Nom	20	1996	0.2109	12.0302	-0.05%	0.05%	2.2587	0.2501*	10.6762*	-0.03%	0.03%	0.6345	0.5377	3.5512*	-0.01%	0.01%	1.0622
Average 1996					-0.04%	0.04%				-0.01%	0.01%				0.00%	0.01%	
Cerexport	21	1997	0.6980	1.8210	-0.03%	0.03%	12.5321*	0.1721*	3.7195*	-0.06%	0.06%	0.4476	0.6783	1.8759	-0.03%	0.03%	0.462
Jer. Martins, SGPS	22	1997	0.1930	0.5679	0.01%	0.01%	2.5409	1.7458	0.4846	0.01%	0.01%	1.6085	1.1055	2.4162*	-0.01%	0.01%	0.6027
Reditus, SGPS	23	1997	0.4527	2.6162	-0.06%	0.06%	3.9527	0.801	3.0939	-0.05%	0.05%	0.2063*	0.7886	1.0494	0.00%	0.00%	3.1176*
Inpsa	24	1997	6.1851	0.2637	0.04%	0.04%	0.1861	0.5294	0.1774*	0.29%	0.29%	3.9502*	0.5195	0.2761*	0.17%	0.17%	0.7305
CPP Nom	25	1997	1.2844	19.4910*	-0.05%	0.05%	0.0117*	1.5887	0.6068	0.05%	0.05%	21.8731*	0.1872*	1.4865	-0.03%	0.03%	16.4250*
Average 1997					-0.02%	0.04%				0.05%	0.09%				0.02%	0.05%	
BPI	26	1998	12.8724*	0.0177*	0.06%	0.06%	1.6673	1.0093	0.3335	0.03%	0.03%	1.3809	0.9711	0.3805*	0.02%	0.02%	1.0544
CPP Nom	27	1998	0.2505	6.4929*	-0.34%	0.34%	7.3073*	0.0370*	7.3219*	-0.20%	0.20%	8.5603*	0.0426*	7.3058*	-0.11%	0.11%	0.1027*
BPSM Nom	28	1998	3.1094	1.3878	0.00%	0.00%	0.1843	1.3507	0.7237	0.01%	0.01%	1.3296	0.2706*	1.5763	-0.02%	0.02%	0.4015
BTA Nom	29	1998	0.0233*	33.9470*	-0.10%	0.10%	0.0854*	1.2659	4.3434*	-0.04%	0.04%	0.416	0.2826*	2.9588*	-0.04%	0.04%	0.4351*
CSMC Nom	30	1998	1.5863	1.7715	-0.01%	0.01%	0.2200	0.9492	0.8301	0.01%	0.01%	1.3965	0.5172	0.9248	0.00%	0.00%	0.8902
Caixa - Comp. de Celulose	31	1998	0.3597	2.0817	-0.06%	0.06%	3.4950	0.6728	2.3263	-0.04%	0.04%	0.3976	1.0007	1.2473	-0.01%	0.01%	0.3681*
AXA Portugal Nom	32	1998	0.0257*	5.1684	-0.09%	0.09%	7.0917*	0.8131	4.4329*	-0.04%	0.04%	2.7731	26.2622*	5.5519*	-0.04%	0.04%	2.8045*
BANIF Nom	33	1998	2.1651	0.0448*	0.15%	0.15%	1.8076	6.1576*	0.1044*	0.10%	0.10%	1.2386	0.6283	0.4499*	0.05%	0.05%	1.8116
CPP 2 Nom	34	1998	1.3622	2.1146	-0.04%	0.04%	0.6324	0.7511	2.0681	-0.05%	0.05%	0.6024	2.8165*	1.3452	-0.02%	0.02%	2.8858*
BCP	35	1998	0.8510	0.5787	0.01%	0.01%	1.1452	0.9294	0.6017	0.01%	0.01%	0.8181	4.8980*	0.5816	0.01%	0.01%	1.0947
BPSM 2 Nom	36	1998	1.2173	0.2787	0.08%	0.08%	7.0035	0.5165	0.8870	0.01%	0.01%	1.7606	5.4715*	0.8346	0.01%	0.01%	0.6067
BTA 2 Nom	37	1998	1.8640	0.3259	0.06%	0.06%	11.0390*	1.4843	1.1448	-0.01%	0.01%	0.9921	1.0554	1.4528	-0.02%	0.02%	0.3725*
CSMC 2 Nom	38	1998	0.9694	1.3754	-0.02%	0.02%	5.5714	0.6003	2.3089	-0.04%	0.04%	0.7737	3.7339*	1.6166	-0.02%	0.02%	0.2742*
Cimpor	39	1998	4.6149	5.4095	-0.02%	0.02%	0.3699	0.5327	7.7330*	-0.06%	0.06%	0.1409*	2.8485*	1.7116	-0.03%	0.03%	0.8999
Average 1998					-0.02%	0.07%				-0.02%	0.05%				-0.01%	0.03%	
Inpsa	40	1999	12.7101*	0.0370*	0.04%	0.04%	0.4317	0.9969	0.1741*	0.04%	0.04%	0.2904*	23.4499*	0.0341*	0.11%	0.11%	3.2375*
Sonae Indústria	41	1999	0.7627	0.4013	0.01%	0.01%	0.0889*	0.5313	0.0644*	0.09%	0.09%	2.0942	7.7231*	0.0480*	0.06%	0.06%	3.0709*
Mota & Engil, SGPS	42	1999	2.1011	0.7078	0.01%	0.01%	0.7760	0.6162	0.5452	0.08%	0.08%	8.3781*	0.477	7.7355	0.00%	0.00%	1.4269
Mota & Companhia	43	1999	8.1058*	3.7343	-0.01%	0.01%	0.3482	2.5354	7.0254*	-0.05%	0.05%	0.1899*	0.2877*	3.6967*	-0.07%	0.07%	1.8635
BPI	44	1999	0.3303	2.5713	-0.04%	0.04%	6.0054	0.5957	4.8445*	-0.06%	0.06%	1.5601	0.2717*	4.3551*	-0.05%	0.05%	0.2668*
Cofina	45	1999	17.6128*	0.0010	0.87%	0.87%	5.5418	0.505	0.0148*	0.47%	0.47%	10.3684*	7.7891*	0.0304*	0.26%	0.26%	5.9286*
BCP Nom	46	1999	0.1411*	0.8711	0.00%	0.00%	2.7676	1.5216	0.4008	0.01%	0.01%	1.0099	0.813	0.4049*	0.01%	0.01%	0.4118*
BPSM Nom	47	1999	0.9315	2.7765	-0.01%	0.01%	2.7842	1.445	6.9347*	-0.02%	0.02%	1.9799	2.5843*	11.1856*	-0.02%	0.02%	6.2051*
BPA Nom	48	1999	7.8794*	0.1586	0.02%	0.02%	4.2484	0.5499	0.8393	0.00%	0.00%	2.9176	4.2737*	0.891	0.00%	0.00%	1.0896
BTA Nom	49	1999	0.5172	0.6567	0.03%	0.03%	3.6261	1.0318	0.8572	0.01%	0.01%	4.4742*	2.3076*	1.4652	-0.01%	0.01%	0.9295*
CSMC Nom	50	1999	4.8159	0.0023*	0.39%	0.39%	100.0042*	2.7342	0.0433*	0.18%	0.18%	26.7111*	9.5376*	0.1521*	0.08%	0.08%	14.7104*
CPP Nom	51	1999	0.2038	0.6029	0.02%	0.02%	44.2928*	0.7272	0.8505	0.00%	0.00%	2.5385	5.4592*	1.1791	0.00%	0.00%	5.1325*
Parade, SGPS	52	1999	1.9464	0.1483*	0.02%	0.02%	3.3506	3.1119	0.3756	0.01%	0.01%	0.3927	0.7653	0.3829*	0.02%	0.02%	1.1042
Colep PORT	53	1999	0.0174*	37.5324*	-0.16%	0.16%	0.0424*	0.1902*	1.7608	-0.04%	0.04%	0.852	0.6917	0.9638	0.00%	0.00%	1.7848
EDP	54	1999	20.3867*	0.9792	0.00%	0.00%	0.1842	0.2472*	3.5965*	-0.10%	0.10%	2.603	0.0719*	3.3370*	-0.06%	0.06%	0.7776
Average 1999					0.08%	0.11%				0.04%	0.08%				0.02%	0.05%	
Global Average					0.23%	0.27%				0.19%	0.21%				0.09%	0.11%	

Legend: BB represents Test 2; BA the Test 1 and AA the Test 3. The values below are the statistical tests.
Note: The shadowed cells represent parameters that are statistically significant at a 5% confidence level.