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An Empirical Investigation of Stock market Over/Underreaction

ABSTRACT

The aim of this study was to investigate whether the phenomena of Stock Market Over/Underreaction are present during the time period of 1990 – 1995. Our sample was consisted of 60 socks randomly chosen from the FTSE ALLSHARE. Using the Market Model our results were that we could not find evidence (statistically significant) of the presence of these phenomena.

CHAPTER ONE

1. INTRODUCTION

An extensive body of recent finance literature is the examination of the speed with which information is incorporated in share prices. We usually refer to this as ‘informational efficiency’. A number of researchers though are also concerned with whether prices accurately reflect investors’ expectations about the present value of future cash flows. We will refer to this hypothesis as market rationality to distinguish it from informational efficiency, while recognising that some authors use the word ‘ efficiency; to apply both ideas.

If markets exhibit rationality, there should be no symmetric differences between share prices and the value of the security based on the present value of the cash flow to security holders. Much of the evidence on informational efficiency bears on market rationality. For example if prices can be shown to respond to noneconomic variables such as stock splits, this would be powerful evidence against market rationality.

The existence of excess return as a function of firm characteristics and time patterns in security returns provides evidence against market rationality. Examples of these relationships include the size effect, the market to book effect and the day of the week effect. For informational inefficiency it is necessary to show that a profitable trading strategy can be constructed to exploit the anomaly. However the mere presence of a persistent anomaly calls into question market rationality. The major direct evidence on stock market rationality involves volatility tests, stock market crashes, and tests on market under and overreaction.

A large body of past and recent research has concluded that observed anomalous movements in stock prices, particularly in the long - term reversals of extreme past stock price changes, can be explained by the corrections of initial overreactions to new information. This "stock market overreaction" hypothesis maintains that a given stock decreases (increases) too far in price because of recent bad (good) news associated with the stock, but eventually returns to its fundamental value as investors realise that they had overreacted. Hence, stocks that perform poorly ('losers') relative to the market over a given period of time consistently outperform the market in the subsequent months or years generally known as the portfolio 'test' or 'evaluation period'. Similarly, stocks with high returns ('winners') during the portfolio formation period typically underperform the market during the evaluation period.

The research presented in this paper tests whether or not we can confirm the Over/Underreaction Hypothesis using UK data from 1990 to 1995 drawn from a random sample of 60 stocks and testing it for a period of 12, 24, 36 months in any one year. We find no significant evidence of the Over/Underreaction Hypothesis, which makes conclude that during the period from 1990 to 1995 the London Stock Exchange is (weak – form) efficient.

1.2. THE PAPER'S STRUCTURE

After a brief introduction concerning the issues of stock market over and underreaction, the second chapter presents the results of researches that have been conducted throughout the years, along with their controversial results.

The third chapter introduces the methodology we are going to use, in order to test if these phenomena are present in the London Stock Exchange. Since the model we are going to use in our analysis is the market model these procedures needs further testing for misspecification of the market model, which can be caused by non-linearity, heteroskedasticity, autocorrelation or non-normality.

In chapter four the methodology used in this paper is analysed with details from the first step of data collection, through the econometric estimations and the calculations of the cumulative abnormal returns.

In chapter five an extensive discussion of the empirical results is presented. Comparisons between the results of similar results not only for the London Stock Exchange but also for other exchanges are included.

CHAPTER TWO

1. LITERATURE REVIEW

The issues of stock market under and overreaction are related to various aspects of psychological evidence about individual behaviour. Underreaction is perhaps similar to the phenomenon of conservatism in which individuals are slow to change their beliefs, while overreaction is perhaps related to optimism, in which individuals upward patterns of behaviour where there are none. However, a serious problem with psychological explanations is that they are frequently inconsistent with each other. And more importantly they are ex post.

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Many papers, that try to explain what causes these phenomena, are based on the way that people react to new announcements. There are many studies concerning the empirical examination of whether the phenomena of stock market under and overreaction exist and to what extent. What we will try to do in this section is a presentation of the most important studies

Research in experimental psychology finds that people tend to overreact to unexpected and dramatic events. Applying this result to the stock market DeBondt and Thaler (1985, 1987, and 1991) have written several papers in which they argue that investors overreact. In particular, they find that stocks that are the most extreme losers have abnormally good subsequent performance and that stocks that have been the biggest winners have subsequent poor performance. They attribute this to overreaction on the part of the investors.

In their studies DeBondt and Thaler (1985, 1987) take 35 of the most extreme ‘winners’ and 35 of the most extreme ‘losers’ over the five years from January 1928 to December 1932 (based on monthly return data from the NYSE) and form two distinct portfolios of these companies’ shares. They follow these companies for the next five years (test period). They repeat the exercise 46 times by advancing the start date by one year each time. Finally they calculate the average ‘test period’ performance (in excess of the return on the whole NYSE index) giving equal weight (rather than value weights) to each of the 35 companies. They find that:

1. The five – year price reversals for the ‘loser portfolio’ (at about plus 30%) are more pronounced than for the ‘winner portfolio’ (at minus 10%).
2. The excess returns on the ‘loser portfolio’ occur in January (i.e. appearance of the ‘January effect’)
3. The returns on the portfolios are mean reverting (i.e. a price fall is followed by a price rise and vice versa).
4. The overreaction seems to occur mostly during the second and third year of the test period. DeBondt and Thaler interpreted this evidence as indicative of irrational behaviour by investors, or ‘overreaction’

It is worth emphasising that the so called ‘loser portfolio’ (i.e. one where prices have fallen dramatically in the past) is in fact the one that makes high returns in the future; a somewhat paradoxical definition of ‘loser’. An arbitrage strategy of selling the ‘winner portfolio’ and buying the ‘loser portfolio’ earns profits at an annual rate of around 5% to 8% according to DeBondt and Thaler.

This tendency for stocks that experience extreme returns to go through subsequent return reversals after portfolios are formed, and for the effect to be observed years after portfolio formation has implications for market efficiency. Specifically, it indicates substantial weak – form inefficiencies, because DeBondt and Thaler are testing whether the overreaction hypothesis is predictive. In other words, according to their research, knowing past stock returns appears to help significantly in predicting future stock returns.

The DeBondt and Thaler articles are an important challenge to market rationality and such has received a fair amount of attention. Other authors have supported or refuted the findings. One area of controversy involves how expected return and thus abnormal return is calculated. Depending on the method of calculating expected return, evidence in support of DeBondt and Thaler or refute is found in the literature during the years. The second issue is how much of this effect is really another effect, such as the small firm effect.

Atkins and Dyl (1990) tried to determine if the stock market overreacts in the short run. One feature that distinguishes this study from previous studies of the overreaction phenomenon is that Atkins and Dyl selected their sample using data and procedures that could actually have been used by market participants in a timely manner. They found that stocks that exhibit a large price decline (losers) subsequently earn significant abnormal returns. Their interpretation was that the initial price change was an overreaction. They also found that stocks that exhibit a large price increase (winners) subsequently earn negative abnormal returns, but the magnitude of the underreaction is much smaller for winners. These findings for both winners and losers are consistent with the findings of many earlier studies.

In support of DeBondt and Thaler (1985, 1987) findings, is a recent study of the overreaction hypothesis, done by Chopra, Lakonishok and Ritter (1992) where they point to investors' tendencies to overreact. They investigate the stock returns of New York Stock Exchange (NYSE) issues from 1926 to 1986 and incorporate size, prior returns, and betas in a multiple regression model. Findings indicate that there is an 'economically important overreaction effect'. More specifically using five - year period to form portfolios, the study revealed the extreme prior losers outperformed extreme prior winners by 5% to 10% per year over the following five years. However, their findings suggest larger arbitrage portfolio returns during January and for smaller firms.

But specific studies question the strong findings of DeBondt and Thaler of stock market overreaction on the grounds of size differences between winner and loser stocks. Fama and French (1988), find that losers outperform winners, but insignificantly, except in January. Furthermore they find asymmetric reversals in favour of the winners, which in contrast to the findings by DeBondt and Thaler. Similarly Zarowin (1990) finds that the three – year return on an arbitrage (loser minus winner) portfolio is not significantly different from zero. Thus, both Fama and French (1988) and Zarowin (1990) indicate that the losing firm effect is subsumed by the size effect

Chan (1988), furthermore, states that the estimation of the abnormal return to the contrarian investment strategy has to do with the model and the estimation methods we use. Using a simple asset pricing model, the CAPM, and an empirical method that is free of the problems caused by risk changes, they find that the contrarian strategy earns a very small abnormal return, which might be economically insignificant. More specifically two features about winners and losers in the stock market make the estimation of abnormal returns sensitive to the procedures used. First, the losers' betas increase after a period of abnormal loss, and the winners' beta decrease after a period of abnormal gain. Betas estimated from the past should not be used. Second, when we evaluate the risk-return relation over an extended period of time that involves that involves updating portfolios, it is incorrect to base the analysis on the relation between the average return and average beta because both the betas and the expected market risk premium might respond to some common state variables, and are thus correlated. The contrarian strategy appears to have an ability to pick riskier losers when the expected market risk premium is high, probably because losers suffer larger losses at economic downturns than at upturns. According to Chan, an investor who follows the contrarian strategy is likely to find that his or her risk exposure varies inversely with the level of economic activity. On average the investor realizes above-market returns, but the excess return is likely to be a normal compensation for the risk in the investment strategy.

Research by Paul. Zarowin (1990), re-examined DeBondt and Thaler's evidence on stock market overreaction showing that the market could not be characterised by the overreaction phenomenon. Their research showed that losers' superior performance over winners during the 3 – year testing period was due, not to investor overreaction, but to size discrepancies between winners and losers since losers tend to be smaller than winners. Without controlling for size, losers significantly outperform winners and neither difference in risk (as measured by beta) nor in January returns can account for this result. When losers and winners of comparable size are matched, there is evidence of differential performance only in January. When 3 – year losers are smaller than winners, losers outperform winners; when 3 – year winners are smaller than loses, winners outperform losers. Thus the winner vs. loser phenomenon found by DeBondt and Thaler appears to be another manifestation of the size phenomenon in finance.

The results of Zarowin's research proposed some interesting questions. While the size phenomenon appears to subsume the 3 – year return reversals documented by DeBondt and Thaler, the anomaly of short-term (i.e., one – day through one – month) overreaction remained. The question that arises from these results had to do with whether these apparent trading rule profits also subsumed by a larger effect. Since losers outperform comparably sized winners in January, this may be due to tax loss selling. An interesting avenue of future research would be to compare the overreaction ranking variable with the tax loss selling measures Reinganum (1983) and Roll (1983)

Andrew Lo and A. Craig MacKinlay (1990) questioned the finding that the profitability of contrarian investment strategies necessarily implies stock market overreaction. More specifically traditional tests of the random walk hypothesis for stock market prices have generally focused on the returns either to individual securities or to portfolios of securities. In their article, they showed that the cross sectional interaction of security returns over time is an important aspect of stock price dynamics. They documented the fact that stock returns are often positively cross – autocorrelated, which reconciles the negative serial dependence in individual security returns with the positive autocorrelation in market indexes. This also implies that stock market overreaction need not be the sole explanation for the profitability in contrarian portfolio strategies. Indeed the empirical evidence suggests that less than 50% of the expected profits from a contrarian investment rule may be attributed to overreaction; the majority of such profits are due to the cross effects among the securities. They had also shown that these cross effects have a very specific pattern for size – sorted portfolios: they displayed a lead – lag relation, with the returns of larger stocks generally leading those of smaller ones. But a tantalising question remained to be investigated. That was, what are the economic sources of positive cross – autocorrelations across securities?

The examination of whether stock markets under or overreacts continued throughout the years. The results are continuing to be controversial depending on the assumptions and the starting point from which each researcher begins. For example a recent paper in the area of cognitive psychology by Griffin and Tversky (1992) in which the authors try to link together the ideas of conservatism and optimism motivates another approach of Barberis et al. (1998). According to Griffin and Tversky a signal has both strength and weight. Strength relates to the size of the signal, whereas weight relates to how much importance should be placed on it. Griffin and Tversky use a recommendation letter to explain the concepts; strength relates to how favourable is the referee's report, whereas weight relates to the reputation of the referee and how much importance should be placed on the referees recommendation.

Barberis et. al. tried to translate these ideas in terms of financial earnings; the strength of an earnings signal is probably its size, while the weight of an earnings signal is probably its implications for forecasting next period's earnings.

The driver of both under and overreaction is that investors focus too much on strength and too little on the weight of a signal. Therefore:

- Underreaction will tend to occur in signals of low strength and high weight, while
- Overreaction will tend to occur in signals of high strength and low weight.

Hirshleifer and Subrahmanyam (1998), attempt to integrate underreaction and overreaction using psychological evidence about individual behaviour. Their work is based on two ideas:

- Firstly, the robust finding in psychology that individuals are overconfident and
- Secondly, on the idea of biased self-attribution.

Overconfidence is said to be more severe for diffuse tasks (those requiring judgement) and for those with delayed feedback. Also experts tend to be more overconfident than the inexperienced. Biased self-attribution concerns how investors adjust their beliefs when public information is disclosed. When the public information is an agreement with their prior private beliefs then their confidence grows. However it does not fall commensurately when the public information contradicts private prior beliefs. When public information does not confirm their private information, they tend to interpret the results to bad luck rather to their ability.

Clare and Thomas (1995) conducted a very interesting research on the UK stock market. They tried to test the overreaction hypothesis using disaggregated UK stock price data. Their results showed that previous losers have tended to subsequently outperform previous winners over the period 1955 to 1990, although the difference in performance is probably economically insignificant. When they tested for asymmetric differences in post portfolio formation performance between small and large firms, they found that losers tended to be small and that the limited overreaction effects documented were probably due to the size effect. Further more when the Ball and Kothari (1989) findings (that when annual return rather than monthly return data is used, support of the overreaction hypothesis becomes weaker) are taken under consideration, their results for the UK using monthly return data should be viewed with some caution

So by resuming what we mentioned earlier above, we can say that the confirmation or not of the Over/Underreaction Hypothesis is not something that can be taken for granted. The different models and methods employed during the years prove that the results are rather controversial and that every research has its criticism.

CHAPTER THREE

3.1. DATA AND METHODOLOGY

As with all methods of analysing and gathering conclusions, the first stage is the sample collection. For our study we are going to use monthly data from London Stock Exchange. More specifically we are going to use a data base consisted of the end month closing prices of 60 stock prices (randomly chosen) along with the end month closing prices of FTSE - ALLSHARE, which will be used as a proxy for the market index, for the period between January 1990 and December 1995.

We order stocks into portfolios according to their performance relative to the performance of the market over the formation period of twelve months. We calculate the market adjusted return for any month as:

$$U_{jt} = R_{jt} - R_{Mt} \qquad [1]$$

where *Ujt* is the difference between the return on the stock j at period t, R_{jt} and the return on the market at period t, R_{Mt}. More formally

$R_{jt} = \log [P_{it} / P_{i\,(t-1)}]$ i.e. the return on the j 'th firm's security in period t and

$R_{Mt} = \log [P_{Mt} / P_{M\,(t-1)}]$ i.e. the return on the market in period t.

although it can be proved that:

$$R = [P_{(t)} - P_{(t-1)}] / P_{(t-1)}$$

tends to produce similar results. But for statistical reasons we tend to use the logarithmic form (since it produces a more symmetrical distribution). Then the Average Return AVR_j for every stock j is computed and is the mean of the U_j over the formation period.

On the basis of the AVR_j we assign that stock to one of 12 portfolios: ordering stocks by their average returns from high to low, where the first five stocks are grouped together to form an equally weighted portfolio of winners while those stocks in the final quintile are grouped together to form an equally weighted portfolio of losers. Having formed portfolios of winners and losers we can calculate the average return of the portfolio AVR_p over the post portfolio formation period of 12, 24, 36 months. Here we have to make clear that the 'winner' and 'loser' portfolios are formed conditional upon past excess returns, rather than some firm-generated informational variable such as earnings. In other words our analysis is similar to an event study analysis but it is not like that.

The test we perform on the average portfolio is based upon forming an average 'difference' portfolio, $AVR_{D,\ t}$ where the average return of the winner portfolio, $AVR_{W,\ p}$, is subtracted from the average return of the loser portfolio $AVR_{L,\ p.}$ If the return on the 'difference' portfolio, $AVR_{D,\ t}$ is insignificantly different from zero then we can reject the simple Over/Underreaction Hypothesis (assuming that differences in the transactions costs between winners and losers do not influence $AVR_{D,\ t}$). In order to test the above we employed the market model which is expressed as:

$$AVR_{D,\ t} = \alpha_j + \beta_j\ R_{Mt} + \varepsilon_{jt} \qquad [2]$$

where:

a_j = is the component of security j 's return that is independent of the market's performance (a random variable in other words)

β_j = is a constant that measures the expected change in R_j given a change in R_M (the slope coefficient)

ε_{jt} = the error term.

The reason we employ the market model in order to estimate the abnormal returns (instead of the mean adjusted returns approach that the DeBondt and Thaler follow), is that the market model provides a measure of abnormal returns that considers both differences in risk among fluctuations during the period being studied.

In terms of hypothesis testing the null and the alternative hypothesis are:

$$H_0: a_j = 0$$

$$H_1: a_j \neq 0$$

whereas in the case we want to control for risk the null and the alternative are:

$$H_0: \beta_j \neq 0$$

$$H_1: \beta_j = 0$$

A significantly positive value of a_j can be seen as confirmation of the Over/Underreaction Hypothesis. If β_j is significantly different from zero then differences in systematic risk explain some of the differences in returns. A significantly positive value for β_j means that losers may embody more systematic risk than winners.

However we should be very careful with the interpretation of the results. Some of them might give misleading impression due to problems that may arise from the specification of our model. Therefore it is essential to make a thorough examination of the factors that may cause misspecification problems.

3.2. MISSPECIFICATION OF THE MARKET MODEL

Although much empirical work has been based to the single index market model, not many tests have been made for the statistical assumptions. For instance, misspecification of the model used can result to erroneous conclusions, according to (Coutts et al, 1994b) about the impact of a popular event on security returns. This implication can be caused by incorrect estimates of the market model parameters and this will lead to incorrect estimation of the abnormal returns and consequently the cumulative abnormal returns. Another reason that may cause misspecification of the market model is the incorrect estimates leading again to invalid conclusions.

The specification tests should show the statistical adequacy of the model estimated. Therefore, tests for non-linearity, autocorrelation, heteroskedasticity and for non – normality of the residuals are important, in order to support that the ordinary least squares (OLS) estimation is valid. If this is the case, then the errors are BLUE (best linear unbiased estimation) and IID (identically and independently distributed with zero mean and standard deviation σ), or in other words, white noise. More over, the variance σ^2 should be unbiased and consistent otherwise new methods have to be established.

Heteroskedasticity is the first test to be made. In this study *White's Heteroskedasticity Test* will be used. It is applicable only to the residuals from a least square regression. This test is indicated for model misspecification, since the null hypothesis underlying the test assumes that the errors are both homoskedastic and independent of the regressors and that the linear specification of the model is correct. Failure of any one or more of these conditions could lead to a significant test statistic.

The next step to be followed is testing for autocorrelated disturbances. The *Breuch-Godfrey Serial Correlation LM Test* will be used. Among other, it is applicable to illustrate whether or not lagged values of the dependent variable appear among the regressors. The null hypothesis tested is that there is no higher – order autocorrelation.

Normality can be tested by *Jarque-Bera* statistic test. This test of normality is an asymptotic, or large-sample test, which shows whether the residuals are normally distributed and indicates the existence or not of skewness and kurtosis. The skewness of a symmetrical distribution, such as the normal distribution, is zero. If the upper tail of the distribution is thicker than the lower tail, skewness will be positive. The kurtosis of a normal distribution is 3. If the distribution has thicker tails than the normal distribution, its kurtosis will exceed three. The greater the kurtosis is the greater the difference in the slope coefficients between Least Squares (LS) and the robust estimation will be according to Coutts et al (1997a). Unfortunately Coutts et al. (1994a) found that the residuals are often not normal and have fat tails. In excess kurtosis, the LS estimator is inefficient and extremely sensitive to outliners. When omitting these outliners, the results are significantly improved. In order to omit the outliners, dummy variables can be used. It has been concluded that a robust approach is better than omitting the outliners, according to Huber (1981).

Also the OLS regression can lead to inappropriate parameters estimates and variances, as well as to incorrect CARs. According to Coutts et al (1995), when the OLS regression is not applicable, other methods can be used. There are methods that are based upon the regression quantile technique according to Koenker and Baste (1978). This technique minimises the weighted sum of the absolute values of the residuals, and the outliners have less importance. Ruppert and Carroll, named as Trimmed Least Squares, introduced a similar method in 1980. They used a trimmed regression quantile estimator and they applied OLS to observations into a specific interval, which they first define.

To examine misspecification in the model the *Ramsey's RESET Test* will be used. The postulated model is $y = X\beta + \varepsilon$, where the disturbance vector is presumed to have the multivariate normal distribution $N(0, \sigma^2 I)$. According to that model serially correlated, heteroskedastic or non-normal disturbances all violate the assumption that the disturbances are distributed $N(0, \sigma^2 I)$. A misspecified model has:

- Omitted variables (X does not include all relevant variables)
- Incorrect functional form (some or all of the variables in y and X should be transformed to logs, powers, reciprocals, or in some other way)
- Correlation between X and ε (which may be caused by such things as measurement error in X, simultaneous equation considerations, combination of lagged y values and serially correlated disturbances).

In cases of misspecified models, Least Squares estimators will be biased and inconsistent, and conventional inference procedures will be invalidated. In 1969

Ramsey, showed that any or all of these specification errors produce a non-zero mean vector for ε. Thus the null and alternative hypothesis are:

$$H_0: \varepsilon \sim N\,(0, \sigma^2 I)$$

$$H_1: \varepsilon \sim N\,(\mu, \sigma^2 I),\ \mu \neq 0$$

The *ARCH* test (Autoregressive Conditional Heteroskedasticity), which was originally introduced by Engle (1982), has become widely used in various branches of economics. ARCH shows whether the variance is stable over the whole period estimated. The null hypothesis tested is that there is no ARCH effect, otherwise, the residuals are non-normal. Misspecification of the model is a serious problem which must be first identified and then confronted.

In this section the analysis of misspecification and how this can be detected was presented. From all the tests analyzed and the possible problems that lead to model misspecification the most serious is the non-normality case according to Coutt et al (1994a), which is the effect of the existence of excess kurtosis. The outlying observations have a large impact on estimates of the market model and hence, on the estimation of abnormal returns. These signs need further discussion and require econometric tests.

3.3. TESTS FOR STATIONARITY

Testing for stationarity is considered to be an important step before proceeding to the estimation of the econometric model. If a time series is not stationary, then either the series have to be made stationary or the OLS test is invalid and is giving misleading results. 'A stochastic process is said to be stationary if its mean and variance are constant over time and the value of covariance between two time periods depends only on the distance or lag between the two periods and not on the actual time at which the covariance is computed.' According to Gujarati, (1995).

The first test to be employed is the *Augmented Dickey Fuller* (ADF) test which investigates the existence or not of unit roots. If the coefficient of the test is significantly different from zero then the hypothesis that the independent variable contains a unit root is rejected and the hypothesis accepted is that this variable is stationary rather than integrated.

A large negative t-statistic rejects the hypothesis of a unit root and suggests that the series is stationary. If the *Dickey Fuller t*-statistic is smaller (in absolute value) than the reported critical values, then the series may not be stationary. A test can indicate whether the series is I (1) (integrated of order one) or integrated of higher order. A series is I (1) if its first difference does not contain a unit root.

Phillips and Perron developed an alternative test for unit a root. Unlike the ADF test, there are no lagged difference terms. Instead, the equation is estimated by ordinary least squares and then the t-statistic of the coefficient is corrected for serial correlation in it.

The above-mentioned tests are primarily made for every time series model. OLS estimation can be invalid if stationarity does not exist in the time series.

CHAPTER FOUR

4.1. PRESENTATION OF THE EMPIRICAL RESULTS

4.1.1. TESTING FOR STATIONARITY

In this section our purpose is to present the empirical results from the analysis of our data. But before we move on to the analysis of the data let us remind the main aim of this paper. Our purpose is to test the existence or not of the phenomena of stock market over and underreaction at the London Stock Exchange. Our sample is consisted of 60 stock prices, obtained by Datastream (randomly chosen) without any missing values and observed values at least five years before our first formation period (which is 1990).

Having gathered the data that we are going to use and having specified the model we are going to use for our analysis is to proceed with the import of the data in our statistical package (which in this case is MICROFIT v. 4).

First we test for stationarity using the correlogram of each variable. The calculation of the autocorrelation function along with the correlogram of each variable are presented to the appendix. What we can observe is that almost all of the time series based on monthly share prices (variables X, S1, S2, …, S60) were found to be non – stationary (Appendix 1). However, the time series based on the returns were all found to be stationary (Appendix 2). We must not forget that for a variable to be stationary, the convergence of the autocorrelation coefficient towards zero should be rather rapid, something that we cannot observe from the correlograms. What we observe instead, is a rather slow convergence of the autocorrelation coefficient towards zero. Thus we can conclude that our variables based on daily share prices are non – stationary. The same results can be exported by using the DF and ADF test in order to confirm that our variables are non – stationary. More specifically if we compare the critical values of ADF shown at the tables with that of the DF test we observe that the critical value of ADF is more negative than that of the DF, which implies that our variables are non – stationary.

For the time series based on the returns, on the other hand, what we observe is a rather rapid convergence of the autocorrelation coefficient, something which drives us to the conclusion that these variables are stationary.

4.1.2. INFORMATION COMING FROM THE MICROFIT RESULT SCREEN

At this point it would be useful to give a description of what measures MICROFIT gives us before we proceed to the analysis of the statistical results. First we get the specification results and then the misspecification results or the diagnostic tests. In order to see whether our model is good we need to see examine both of them. A quick way to decide whether our variables are significant or not is by checking the p – values (the values in the square brackets). We want this probability to be small (generally less than 5%) thus we are looking for values less than 0.05. In the case we see a value grater than 0.05 we should disregard the variable as statistically insignificant.

One kind of information we use from the Ordinary Least Squares Estimation table is the *R – square* and *R –bar – square figures, which show us how well the model,* fits the data. They vary between one and minus one, where one indicates a perfect fit, zero means no fit and minus one suggests a perfect negative fit. Generally the higher the value of these statistics the better. The two estimates are approximately the same with the exception that the second takes account of the existence of many regressors, where the first is upwardly biased the greater the number of the regressors is. Using the *R – square* we can make comparisons between models provided that the models have the sama functional form (i.e. are linear) and have the same number of regressors. If the numbers of regressors is different, the *R – bar – square* should be used. These estimators however, are not always very reliable and we certainly cannot accept or reject a model simple by looking at them. If we have differenced series for example we cannot expect these estimates to be high, but this does not mean that a model is worthless.

The *F* – statistic examines whether the *R – square* is zero (all the coefficients are jointly zero) and thus the model meaningless. The *F* – statistic is calculated as:

$$F=\frac{\frac{R^2}{k-1}}{\frac{1-R^2}{n-k}}$$

where *n* is the sample size and *k* is the number of variables. Again here we compare the statistic with appropriate *F* critical values, but we can use the *p* – values, where the same principles apply as before.

The *Durbin – Watchon* (DW) statistic is a useful indicator of serial correlation. Further more a DW statistic which is smaller than the *R – square* of the model is a serious indication (but not 100% accurate, due to cointegration) indication of spuriousness in the model.

The *Akaike Information Criterion* and the *Schwarz Baysian Criterion* are normally used with VAR econometrics and in these cases the higher they are the betters. In the case of linear regression, however estimation of these numbers depend on the estimated variance and standard errors of the regression. In that case, and if other things are equal, we choose the model, which has the smallest values of these two criteria.

The Diagnostic Tests table (see Appendix 3) provided by MICROFIT examines how well the model is specified on the basis of whether it satisfies the Gauss – Markov conditions of normality of residuals, that is whether the residuals are normally distributed, of homoscedasticity, and of no serial correlation. All these assumptions make the OLS the Best Linear Unbiased Estimator (BLUE).

Another test is a test of whether the model has the correct functional form, for example is the model linear as we may thing or is it something else. Finally, if we make any predictions, we can see a predictive failure *chi – square* test based on the adequacy of the predictions our model can make, and a *Chow Chi – square* test on the stability of the regression coefficient, i.e. whether the coefficients we estimated are stable over time.

We can come to conclusions of whether the model is misspecified or not using tables and critical values or examining the *p* – values as before. However, the *p* – values should be the opposite of the ones used previously. Hence in order to reject the hypothesis of serial correlation, of wrong functional form, of non – normality of the residuals, of heteroskedasticity, of predictive failure and of instability of the coefficients, we are looking for *p* – values grater than 0.05.

4.2. ANALYSIS OF THE RESULTS

The results of the tests developed in the previous section will be presented here. The presentation of our results will be done according to each formation period. As we can observe from Table 1, our findings suggest that there are no price reversals of the stock prices that were included to the winner and loser portfolios. What we can observe that the intercept term a_j is negative in every testing period (of N=12, 24, 36 months) not only for the formation period of 1990 but also for the formation period of 1991, something which is giving us the impression that there exists return reversal in the UK stock market, where losers do outperform winners. But these results are statistically insignificant, (when we check *t* – ratios), which make us conclude that the analysis of data as presented in Table 1 is not consistent with the Over/Underreaction Hypothesis.

Another interesting point to be made is that if we observe the β_j coefficient of the difference portfolio 36 months after its formation we find a significantly different from zero value, which means that difference in systematic risk explain some of the differences in the returns

Table 1

Estimates of a Regression Relating the Average Return of the Difference Portfolio to the Average Return of the Market

Data is monthly returns over the period 1990 to 1995. The equation estimated in every formation period of 12 months (1990, 1991) is:

$$AVR_{D,t} = \alpha_j + \beta_j R_{Mt} + \varepsilon_{jt}$$

where $AVR_{D,t}$ is the difference portfolio and R_{Mt} is the average return on the market for every testing period of N = 12, 24, 36 months

	1990						1991					
	N = 12		N = 24		N = 36		N = 12		N = 24		N = 36	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
α_j	-0.0233 (-0.352)	0.0663	-0.04827 (-1.3175)	0.0366	-0.01286 (-0.502)	0.02559	-0.77431 (-0.9953)	0.07792	-0.02333 (0.42389)	0.055045	-0.022199 (-0.60965)	0.036414
β_j	-0.4565 (-0.2807)	1.6264	-0.82195 (-1.2371)	0.6644	-1.0619 (-2.063)	0.51450	1.6567 (1.4155)	1.1704	0.77769 (0.75837)	1.0255	0.77874 (1.1062)	0.70399
R^2	0.0078192		0.065043		0.11133		0.16692		0.025476		0.034739	
Serial Correlation	2.8890 [0.089]		2.7223 [0.099		3.2834 [0.070]		2.4748 [0.116]		2.0260 [0.155]		2.8486 [0.091]	
Functional Form	1.6693 [0.196]		0.14276 [0.706		0.0046976 [0.945]		0.11134 [0.739]		0.14342 [0.705]		0.34255 [0.558]	
Normality	1.1953 [0.550]		5.8340 [0.054]		22.1154 [0.0000]		0.20567 [0.902]		0.50526 [0.975]		1.9593 [0.375]	
Heterosced	1.1028 [0.294]		1.5601 [0.212]		1.0777 [0.2999]		0.075623 [0.783]		0.94209 [0.332]		0.43582 [0.509]	

The same arguments apply during the formation period of 1992 as we can observe from table 2. But an interesting point can be made after a closer look of the results during the formation period of 1993. What we observe is that when as a testing period periods for our portfolio of winners and losers we use the period of 24 and 36 months, we find evidence or return reversal in the UK stock market, where losers seems to outperform winners. But by checking the *t* – ratios (or the *p* – values) we come to the conclusion that the difference between winners and losers is insignificantly different from zero and for that reason we state that we cannot confirm the Under/Overreaction Hypothesis..

Testing on whether differences on systematic risk can explain the difference on returns we find that something like that cannot be justified.

Table 2

Estimates of a Regression Relating the Average Return of the Difference Portfolio to the Average Return of the Market

Data is monthly returns over the period 1990 to 1995. The equation estimated in every formation period of 12 months (1992, 1993) is:

$$AVR_{D,t} = \alpha_j + \beta_j R_{Mt} + \varepsilon_{jt}$$

where $AVR_{D,t}$ is the difference portfolio and R_{Mt} is the average return on the market for every testing period of N = 12, 24, 36 months

	1992						1993					
	N = 12		N = 24		N = 36		N = 12		N = 24		N = 36	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
α_j	-0.017289 (-0.304887)	0.56707	-0.014341 (-0.36845)	0.038922	-0.0062108 (-0.18910)	0.032845	-0.004681 (-0.11321)	0.041234	0.0023787 (0.10301)	0.023091	0.0025459 (0.887)	0.017848
β_j	-1.5289 (-0.98874)	1.5463	-0.8418 (-0.91836)	0.91629	-1.4022 (-1.5974)	0.87776	0.50299 (0.5841)	0.86662	0.47302 (0.77406)	0.61110	0.53281 (0.98879)	0.53886
R^2	0.089055		0.036920		0.069812		0.032589		0.025613		0.027952	
Serial Correlation	0.22789 [0.633]		0.14611 [0.702]		2.1234 [0.145]		0.62815 [0.980]		0.032844 [0.856]		0.65862 [0.417]	
Functional Form	3.8950 [0.048]		2.2269 [0.136]		3.6382 [0.056]		0.74596 [0.388]		1.1782 [0.278]		0.91791 [0.338]	
Normality	1.3264 [0.515]		4.3714 [0.112]		9.1910 [0.010]		0.68806 [0.703]		0.56646 [0.753]		0.8004 [0.670]	
Heterosced	0.78325 [0.376]		0.33662 [0.562]		0.35099 [0.554]		0.025364 [0.873]		0.95088 [0.329]		0.68805 [0.407]	

On the other hand when as a formation period we use 1994 (table 3), then for all the three testing periods; that is N = 12, N = 24, N = 36, we observe a difference between winners and losers which again is insignificantly different from zero, and for that reason we cannot confirm the Over/Underreaction Hypothesis. These results seem to confirm DeBondt and Thaler’s (1985) original findings that losers remain as losers for short periods of time. This result also accords with the general conclusion of Kryzanowski and Zhang (1992) who find ‘continuation’ to be a feature of the Canadian equity market rather than overreaction.

At this point it is important to mention that when we control for risk during the formation period of 1994, we find significant differences between the β_S of winners and losers for both the testing periods of 24 and 36 months. In that case we can conclude that differences in systematic risk (as measured by beta) explain some of the difference in returns.

Table 3

Estimates of a Regression Relating the Average Return of the Difference Portfolio to the Average Return of the Market

Data is monthly returns over the period 1990 to 1995. The equation estimated in every formation period of 12 months (1994, 1995) is:

$$AVR_{D,\,t} = \alpha_j + \beta_j R_{Mt} + \varepsilon_{jt}$$

where $AVR_{D,\,t}$ is the difference portfolio and R_{Mt} is the average return on the market for every testing period of N = 12, 24, 36 months

	1994						1995					
	N = 12		N = 24		N = 36		N = 12		N = 24		N = 36	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
α_j	0.064118 (2.4233)	0.026460	0.054951 (2.0719)	0.026522	0.025737 (1.2626)	0.020383	-0.053488 (-0.91870)	0.058221)	-0.011278 (-0.35591)	0.031688	-0.007139 (-0.32904)	0.021697
β_j	-1.8500 (-1.7008)	1.0877	-3.4362 (-2.9365)	1.1702	-1.6437 (-2.3477)	0.70015	3.9502 (1.4162)	2.7893	0.49692 (0.48977)	1.0146	-0.20450 (-0.35801)	0.57120
R^2	0.22437		0.28159		0.13950		0.16706		0.010786		0.0037556	
Serial Correlation	0.057772 [0.810]		0.84488 [0.358]		3.6279 [0.057]		2.2187 [0.136]		4.3012 [0.038]		6.7674 [0.009]	
Functional Form	0.40968 [0.5220		0.71507 [0.398]		0.020023 [0.887]		0.015686 [0.900]		0.31632 [0.999]		0.23813 [0.626]	
Normality	0.065566 [0.968]		6.3827 [0.041]		15.2903 [0.000		0.26953 [0.874]		14.8690 [0.001]		53.0803 [0.000]	
Heterosced	0.13429 [0.714]		0.99853 [0.318]		0.0022208 [0.962]		5.7605 [0.016		0.05210 [0.819]		0.050507 [0.822]	

CHAPTER FIVE

5.1. CONCLUSIONS

In an efficient market all players have access to the same information, they process the information in the same ‘rational way’ and all have equal opportunities for borrowing and lending. In the real world these conditions are unlikely to be met. For example, different investors may form different probability assessments about future outcomes or use different economic models in determining expected returns. They may also face differences in transactions costs (e.g. insurance companies versus individuals when purchasing shares), or face different tax rates and of cource they will devote a different amount of resources (i.e. time and money) in collecting and processing information. Of course, if these heterogenous elements play a rather minor role then asset prices and rates of return will be determined mainly by economic fundamentals and rational behavior. But if not, prices may deviate substantially and persistently from their fundamental values.

In this study we tried to see whether the phenomena of stock market over/underreaction take place at the London Stock Exchange. We must have in mind that the price behaviour of a national stock market is important for several reasons. First increasing global integration can cause individual stock markets to ba affected by developments in other stock markets, especially since many trade and capital restrictions between countries have been eliminated. Furthermore, valuations of European stock markets have become more transparent in response to the introduction of a single currency (the ‘Euro’).

What we found was that the overreaction hypothesis couldn't be confirmed. Although there were price reversals in some cases, their importance proved to be not statistically significant. In that point we will have to mention the fact that our research was quite restricted. What we mean by that is that we tried to examine the confirmation or not of the overreaction hypothesis, by using only one testing period (12 months). We might have come up with some different results if we also used and other formation periods consisting of different durations (weakly data, intra – daily data etc.).

As compared to the plenitude of studies addressing the stock market overreaction in the United States, the literature on overreaction in foreign markets is quite sparse. In general, the international overreaction literature tends to either investigate one country by itself or individual countries in a multiple-country context.

Studies investigating the overreaction hypothesis for individual stocks in a single foreign country focus primarily on the UK, but include studies investigating less well – developed stock markets such as Brazil and Spain. Overall, the evidence indicates that foreign stock markets overreact, similar to individual stocks in the U.S.

As we mentioned in the first chapter, Clare and Thomas (1995) investigated the overreaction hypothesis in the United Kingdom. They found that previous losers tend to subsequently outperform previous winners over the 1955 to 1990 period, although the difference in performance is economically insignificant. Furthermore, losers tend to be small and the overreaction effect appears to be primarily a size effect.

The UK stock market is more recently investigated by Cambell and Limmack (1997), who test for long – term reversals in the abnormal returns of UK companies classified as winners and losers over the period from January 1979 to December 1990 using the LSPD tapes. The findings indicate that, in the 12 months following portfolio formation, loser companies generated positive abnormal returns. Furthermore, the smallest loser companies experienced a reversal in their abnormal returns over the following 12 months, but no such reversal existed for the smallest winner companies.

Yet another study focusing on the UK stock market is that by Dissanaike (1997), who investigates nearly 1000 larger UK companies, thereby mitigating the confounding size, bid – ask, and liquidity effects that may drive over/underreaction. He finds evidence supporting the overreaction hypothesis. Furthermore, differential risk does not seem to be driving the results.

DaCosta (1994) investigates the overreaction hypothesis for the Brazilian stock market over the period 1970 – 1989 using both market – adjusted returns and the standard Sharpe – Litner CAPM adjusted returns. Price reversals two-year returns are detected, and the results contrast with the US evidence in that the magnitude of the effect is more pronounced than in the US. Furthermore, differences in risk, as measured by CAPM betas, cannot account for the overreaction effect.

In summary studies investigating individual foreign equity markets find overreaction evidence comparable to that reported for US stocks. The evidence appears to be strongest, however, for less developed equity markets such as Spain and

Brazil. These findings could easily trigger a vast amount of research on the way that stock markets of less developed countries over/underreact to economic news. Another interesting area of research could be the way that mature and emerged markets over/underreact to the same economic news and the way that phenomena of over/underreaction in mature markets affect other stock exchanges.

REFERENCES

- Allen B. Atkins, Edward A. Dyl (1990): "Price Reversals, Bid – Ask Spreads, and Market Efficiency", Journal of Financial and Quantitative Analysis, Vol.25, Issue 4, pp. 535-547
- Andrew Clare and Stephen Thomas (1995): "The Overreaction Hypothesis and the UK Stock Market", Journal of Business Finance and Accounting, Vol. 22, Issue 2, pp. 961-973
- Andrew W. Lo., A. Craig MacKinlay (1990): "When are Contrarian Profits Due to Stock Market Overreaction?", Review of Financial Studies, Vol. 3, Issue 2, pp. 175-205
- Anthony J. Richards (1997): "Winner – Loser Reversals in National Stock Market Indices: Can They be Explained?", Journal of Finance, Vol. 52, Issue 5, pp 2129-2144
- Cambell, K., R.J. Limmack (1997): "Long – Term Overreaction in the UK Stock Market and Size Adjustments", Applied Financial Economics, Vol. 7, pp 537 – 548
- Coutts J.A., Mills T. (1994a): "Misspecification Testing and Robust Estimation of the Market Model and Their Implications for Event Studies", University of Sheffield Management School, Working Paper (March)
- Coutts J.A., Mills T. (1994b): "Misspecification of the Market Model: Their Implications for Event Studies", University of Sheffield Management School, Working Paper (August)

- Coutts J.A., Mills T. (1995): "Misspecification Testing and Robust Estimation of The Market Model: Estimating Betas for the FTSE Industry Baskets", University of Sheffield Management School, Working Paper (September)
- Coutts J.A., Mills T. (1997a): "Parameter Stability in the Market Model: Tests and Time Varying Parameter Estimation with UK Data", Journal of the Royal Statistical Society, Series D, no 57
- DaCosta, N. (1994): "Overreaction in the Brazilian Stock Market", Journal of Banking and Finance, Vol. 18, pp 633 – 642
- Elton E., Gruber M. (1995): "Modern Portfolio Theory and Investment Analysis", Wiley, 5th edition
- Eugene F. Fama, Kenneth R. French (1988): "Permanent and Temporary Components of Stock Prices", The Journal of Political Economy, Vol.96, Issue 2, pp. 246-273
- James M. Poterba, Lawrence H. Summers (1986): "The Persistence of Volatility and Stock Market Fluctuations", The American Economic Review, Vol. 26, Issue 5, pp. 1142-1151
- Jeffry S. Abarbanell, Victor L. Bernard (1992): "Tests of Analysts' Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior", Journal of Finance, Vol. 47, Issue 3, pp. 1181-1207
- Jennifer Conrad, Gautman Kaul (1993): "Long Term Market Overreaction or Biases in Computed Returns?", Journal of Finance, Vol. 48, Issue 1, pp. 39-63
- Josef Lakonishok, Andrei Shleifer, Robert Vishny (1994): "Contrarian Investment, Extrapolation, and Risk", Journal of Finance, Vol. 49, Issue 5, pp. 1541-1578

- K. C. Chan (1988): “On the Contrarian Investment Strategy”, Journal of Business, Vol. 61, Issue 2, pp. 147-163
- Kent L, Womack (1996): “Do Brokerage Analysts’ Recommendations Have Investment Value?”, Journal of Finance, Vol. 51, Issue 1, pp. 137-167
- Lawrence Kryzanowski, Hao Zhang (1992): “The Contrarian Investment Strategy does not work In Canadian Markets”, Journal of Financial and Quantitative Analysis, Vol. 27, Issue 3, pp. 383-395
- Louis K. C. Chan, Narasimhan Jegadeesh, Joseph Lakonishok (1996): “Momentum Strategies”, Journal of Finance, Vol. 51, Issue 5, pp 1681-1713
- M. Rozeff, M. Zaman (1998): “Overreaction and Insider Trading: Evidence from Growth and Value Portfolios”, Journal of Finance, Vol. 53, Issue 2 pp 701 – 810
- Narasimhan Jegadeesh, Sheridan Titman (1993): “Returns in Buying Winners and Selling Losers: Implications for Stock Market Efficiency”, Journal of Finance, Vol. 48, Issue 1, pp. 65-91
- Paul Zarowin (1989): “Does the Stock Market Overreact to Corporate Earnings Information?”, Journal of Finance, Vol. 44, Issue 5, pp. 1385-1399
- Paul Zarowin (1990): “Size, Seasonality, and Stock Market Overreaction”, Journal of Financial and Quantitative Analysis, Vol. 25, Issue 1, pp. 113-125
- Peter L. Bernstein (1985): “Does the Stock Market Overreact?: Discussion”, Journal of Finance, Vol. 40, Issue 3, pp. 806-808
- Phillip A, Braun, Daniel B. Nelson, Alain M. Sunier (1995): “Good News, Bad News, Volatility, and Betas”, Journal of Finance, Vol. 50, Issue 5, pp. 1575-1603
- Tim Loughman, Jay R. Ritter (1996): “Long – Term Market Overreaction: The Effect of Low – Priced Stocks”, Journal of Finance, Vol. 51, Issue 5, pp 1959-1970

- Werner F. M. De Bondt, Richard Thaler (1985): "Does the Stock Market Overreact?", Journal of Finance, Vol. 40, Issue 3, pp. 793-805
- Werner F. M. De Bondt, Richard Thaler (1987): "Further Evidence on Investor Overreaction and Stock Market Seasonality", Vol. 42, Issue 3, pp. 557-581