CONTRARIAN STRATEGIES IN THE ATHENS STOCK EXCHANGE: IS THERE A RATIONAL EXPLANATION?

by

George Christakis

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TABLE OF CONTENTS

TABLE OF TABLES

TABLE OF FIGURES

CHAPTER 1: INTRODUCTION

One of the foundations of modern financial economics is the Efficient Market Hypothesis (EMH, Fama, 1970; Fama, 1991) according to which investors are rational and thus asset prices incorporate all available and relevant information, quickly and accurately. Asset prices are fair, i.e. they equal the discounted future cash flows at the appropriate discount rate; the rate incorporates the asset's risk characteristics to present values. Fama argues that even if market participants are not rational, as long as their trading strategies are unrelated, stock prices will be efficient. Even in the case where irrational trader's strategies are correlated, arbitrageurs will counteract the irrational investment behavior and will correct stocks mispricing.

Fama (1970) categorizes market efficiency into three types each of which is based on the three different types of the stale information. *Weak-form Efficiency* states that it is impossible to earn excess profits based on trading strategies that use historical information (e.g. past prices and returns). *Semi-Strong form efficiency* denotes the same inability of investors to produce excessive risk-adjusted returns by making use any publicly available information (e.g. financial reports, newspaper financial advices or news). Finally the *Strong form efficiency* argues that investors once again can gain no excess profits from trading based on the whole information data set that one can acquire including historical, publicly available or ever private held information. The results of many empirical studies, however, are inconsistent with rational asset-pricing behavior (see Schwert (2003)).

As far as weak-form efficiency is concerned studies showed that stock prices do not strictly follow random walks and securities returns are not identically distributed over time (Fama (1965)). This finding motivated researchers to test for the existence of patterns in returns indicating the possibility of earning superior returns by exploiting past returns and prices of individual stocks or even portfolios of stocks and thus making trading an economically significant action. Patterns like these where actually found for various time-periods (intra-day, weekly and even more monthly patterns) and they were called as Calendar Effects, or Calendar Anomalies. More specifically, important anomalies of this type are the Weekend Effect (French (1980, Keim and Stambaugh (1984)) according to which stock prices, on average, are lower on Mondays and higher on Fridays; the Holiday Effect (Arsad and Coutts (1997, Lakonishok and Smidt (1988)) according to which investors could achieve high abnormal returns on days prior to holidays; or the infamous January Effect according to which stock returns are lower on December and higher on January, on (Rozeff and Kinney (1976); Keim (1983, Reinganum (1983)). Possible explanations of January effect could be attributed to microstructure specificities (such as bid-ask spread especially for low-priced stocks according to Keim (1989)) and the tax-loss selling hypothesis. The concept of this hypothesis postulates that investors take advantage of the tax system and prefer to realize capital losses by selling losing stocks and create tax-loss for them which in order to be profitable it should be greater than the transaction costs. Furthermore the sold stocks rebound after the turn of the year as investors repurchase them in order to reestablish their positions (Branch (1977, Dyl (1977)).

Other studies present anomalies related to firm characteristics such as the Size Effect (Keim (1989)) according to which small-cap stocks have higher average returns than the returns predicted by the CAPM model, or the Value Effect where "Value" stocks seem to outperform, on average, "growth" stocks. Value is measured with metrics such Earnings-to-price (E/P), dividend yield (D/P) or book-to-market (B/M) values, i.e. value stocks are the stocks with high E/P, high D/P or stocks with high B/M values (see also Basu (1977),1983); Fama and French, (1992, 1996, 1998); Davis *et al.* (2000) among others).

A very important study, that initiated a hot debate between supporters of the rational paradigm and supporters of a behavioural point of view for financial markets, is the study by De Bondt and Thaler (1985). Motivated by Kahneman and Tversky's work on cognitive psychology, they were the first who provided explanations over specific observed financial phenomena based on principles of investors' behaviour. De Bondt and Thaler discovered that stock market prices follow specific patterns. They divided stocks into two portfolios, losers and winners, based on their prior performance. Their conclusion was that over the following three to five years horizons losers consistently outperformed the market and winners consistently underperformed the market; investors who went short on prior winners and long on prior losers could earn significant risk-adjusted excess returns. The returns of the zero-cost arbitrage portfolios could reach a 24.6% over a three-year period and this differential in returns between loser and winners could not be explained by the rational pricing model (such as CAPM) in terms of stocks riskiness. The explanation that De Bondt and Thaler offered was that investors undervalue prior looser stocks and overvalue prior winners because of being excessively pessimistic over the loser's poor performance. When new information comes into light (maybe a string of good results for prior losers) then they tend to overreact to recent unexpected information and try to take advantage of this return reversal, helping at the same time to intensify that reversal. This overreaction lasts for long periods of time. Note that stock returns reversal has also been documented for shorter time intervals: empirical studies indicating that short-horizon contrarian strategies consistently make substantial profits where conducted by Jegadeesh (1990) and Lehman (1990). Jegadeesh documented profits of 2% per month from a contrarian strategy that buys and sells stocks based on their prior month returns and holds them for one month.

This result was very hard to reconcile with the EMH and the notion of unpredictability of stock returns. Supporters of the EMH offered an number of possible explanations for the phenomenon such as the time-series properties of stock returns (e.g. data-snooping bias, lead-lag effects), microstructure effects (bid-ask bounce, nonsynchronous trading), firm specific information (trading volume, size), risk based explanations (time-varying risk, bad-model specification), among others (for a detailed review see Chapter 2). On the other hand, behavioural economists point out to *investor overreaction to firm specific information* as the explanation.

Another related anomaly is the Momentum Effect: Jegadeesh (1990) noticed that stocks that have done well over the previous few months continue to have high returns over the next month. In contrast, stocks that have had low returns in recent months tend to continue the poor performance for another month. Jegadeesh and Titman (1993) confirmed this for an intermediate horizon as firms with higher returns over the past 3-12 months subsequently outperform firms with lower returns over the same period.

Therefore by buying stocks with high returns over the previous 3 to 12 months and sell stocks with poor returns over the same time period earn profits of about 1% per month for the following year. Momentum effect gain widespread acceptance as a market irregularity and forced Fama (1991) to admit that moment effect is the most controversial aspects of the debate on market efficiency. As before, behavioural arguments have been put forward as explanation to this effect: investor underreaction to specific information concerning the market or the economy as a whole. Proponents of the EMH point out macroeconomic variables, business cycles, industry effects, combination of the last two, or even bad model specification with omitted risk factors, as explanations.

The results of the empirical literature are inconclusive. The scientific community had been divided into two camps trying to verify or invalidate the EMH. Behavioral finance is far from the phase to be announced as the new economic paradigm; however it has offered a great opportunity to observe capital markets from a more realistic point of view. The human element and investor idiosyncrasy should be taken under consideration on the effort of timing the market. Investor idiosyncrasy is not easily observable and predictable; however people even if they have different levels of experience or expertise usually react similarly to publicly available information concerning stocks.

Motivated by the inconclusive results of the empirical literature this study aims to contribute to the debate by investigating the existence of long-term contrarian profits for stocks listed in the Athens Stock Exchange (ASE) and, in case these profits exist, to investigate the validity of the most prominent rational explanations for the long-run contrarian predictability.

The choice of the sample market is due to a number of reasons. Firstly, there is scarce evidence for the contrarian anomaly for the ASE. More specifically, Antoniou et al. (2005) examine the existence of short-term contrarian profits and focus on the sources of these profits, for the ASE. Their empirical analysis decomposes contrarian profits to sources due to (i) reaction to common factors, (ii) overreaction to firm-specific information, and (iii) profits not related to the previous two terms, as suggested by Jegadeesh and Titman (1995). The results indicate that contrarian strategies are profitable and that overreaction to the firm-specific component appears larger than the underreaction to the common factors. Antoniou et al. (2006) examine whether the profitability of contrarian strategies is affected by time-variation in systematic risk, using a Kalman Filter algorithm to estimate abnormal stock returns. They find that time-variation in systematic risk significantly affects long-term contrarian profits.

Both these studies, however, leave a number of open issues. For instance, Antoniou et al (2005) employ a short-term strategy portfolio strategy that involves shorting every week the previous week's winners, and going long on previous week's losers, i.e. a transaction cost intensive strategy, without incorporating the impact of transactions costs in real-life contrarian profits. In the present study, monthly data are used instead, and a wide range of long-term contrarian strategies are evaluated instead (25 different strategies). In addition, many issues such as, transactions costs, limitations in short-selling, taxes, various robustness tests, etc, are incorporated in the analysis. *As will be discussed later, we arrive at very different conclusions than the previous studies*.

Secondly, the examination of different markets (i.e. other than the USA, UK or other developed markets that are the subject of the majority of earlier studies) may offer important insight and help establish whether there is a cross-country pattern in securities' behavior, as Fama and French (1996) point out.

Thirdly, the ASE institutional framework allows the evaluation of the validity of important issues with regard to contrarian profits. For example, short sales where not allowed in the ASE until after the middle 2000s, which means that it would be impossible for a trader to short past winners and use the cash to long past losers; in other words he/she would have to rely on the long leg of the transaction only, in order to exploit the reversal. This issue is not discussed in previous studies for the ASE. As will be shown later, we find that much of the contrarian strategy profitability in the ASE is due to the winners becoming losers, a result consistent with previous studies for the ASE: Antoniou et al (2006) find (with weekly data) that for a 3-year testing period strategy the return for the winner portfolio is about 30% while the return for the loser portfolio is about 30%, resulting to an overall 60% abnormal return. The results of the present thesis are similar: as will be shown in more detail in Chapter 4, we find (with monthly data) that for a 3-year strategy the profits from "selling" winners are about 40% while the profits from buying losers are about 20%. Overall, the profits are of similar magnitude in both studies and, more importantly, the contribution to the overall profits from the short leg of the transaction (i.e. the winners) ranges from one half (in Antoniou et al.) to one third (in the present study). If short sales are not allowed, however, then a trader will have to rely on the long leg of the transaction only, the portfolio will not be a zero-investment portfolio, and the profits will be much smaller in magnitude. Another important issue related to the institutional framework of the sample market has to do with microstructure biases, (such as bid-ask spreads) that are often suggested as the reason behind the magnitude of the contrarian profits. The trading system in the ASE (continuous trading and no market makers until the 2000s) eliminate bid-ask spreads as a possible explanation for the results.

Fourthly, during the sample period there were no capital gains taxes imposed to investors for stock market transactions in the ASE. This is an important issue since many authors have proposed tax considerations as a rational explanation for contrarian profits. For instance, George and Hwang (2007) argue that "since capital gains are taxed only when realized, investors with locked-in gains have an incentive not to sell winners in order to delay paying capital gain taxes. Consequently, investors' reservation prices for the sale of the winner stocks are elevated by the benefits of capital gains deferral. Stocks with large embedded capital gains will have higher prices, and hence lower expected returns, than otherwise identical stocks with no embedded capital gains" (p. 866). Thus, the ASE offers a natural set up in order to test this hypothesis, in the sense that, if contrarian profits are present they cannot be due to taxes and, thus, an important rational explanation of the anomaly can be ruled out.

Also, this study uses a number of robustness tests, suggested in the literature, in order to evaluate the validity of the empirical results. For instance, we employ both overlapping and non-overlapping periods for the portfolio construction, we leave a month between the formation and testing periods, exclude infrequent trading stocks, compare full sample results with results from a sample where the outliers (2.5% of observations) is "trimmed", incorporate risk as both market risk and risk resulting from the Fama and French three factor model, use size-segments, evaluate the impact of transactions costs, etc. Finally, the relationship of the contrarian profits with business cycle variables is also examined in order to evaluate whether changing economic conditions are a possible source of the profitability of these strategies.

To anticipate the results, our main conclusion is that long-term price reversals exist in the Athens Stock Exchange and lead to long-term abnormal contrarian profits. The economic magnitude of these abnormal profits is significant: a typical three year formation and three year testing period strategy would yield approximately a 60% abnormal return. These profits are robust to the use of overlapping/ non-overlapping formation and testing periods and other robustness tests. Furthermore, these profits cannot be explained by rational arguments such as infrequent trading, bid-ask spreads, taxes, risk, size of the firms, changing economic/business conditions, or methodological drawbacks. Thus, it appears that these profits in the ASE are due to investor overreaction to information.

Contrary to previous studies, though, the main argument of this study is that these contrarian profits are "theoretical", i.e. despite their apparent magnitude they are not exploitable in practice. Thus the market may be informationallly efficient although a price reversal takes place. This argument is based on two findings. Firstly *even if short sales were allowed* the incorporation of transactions costs in the analysis shows that contrarian strategies are marginally profitable only for traders that face a very low transaction cost rate, i.e. below a 0.4% per trade. With the majority of investors in the ASE (institutional and private) facing costs of about 0.5% or above the logical conclusion is that (even if short sales were allowed) contrarian strategies are not exploitable. Secondly, *in the presence of short selling restrictions* a trader could concentrate on the long leg of the transaction only, i.e. simply buy losers, thereby ignoring the short leg. This argument relies on the observation that in most previous studies for international markets the overall profits of contrarian strategies originate from the long leg, i.e. the losers. We, however, find that in the ASE a large portion of the profits is due to the short leg, i.e. the winners. Nevertheless, we perform simulations (with transactions costs) for the case where a trader tries to exploit the anomaly by simply buying losers and the result remains the same: price reversals and contrarian strategies are not exploitable in practice.

Overall, the results of this study are quite interesting: a non-rational price reversal does take place in the ASE, probably due to investor overreaction; however, the market is informationally efficient with respect to this anomaly due to short-sale restrictions and transactions costs.

The rest of the thesis is organized as follows: Chapter 2 reviews the empirical and theoretical literature on behavioral anomalies. An extensive literature review sheds light over the reasons and the procedure in how behavioral finance was created and evolved the last few years. It is important to show how investors form their beliefs and preferences and how different frames influence people when they face investing dilemmas. Chapter 3 presents Athens Stock Exchange, its course through time and specifically through our sample period of 1987-2004, plus few enlightening statistics. Chapter 4 presents the data, the methodology and the empirical results on contrarian profits for overlapping and non-overlapping formation and testing periods. It also presents results for market capitalization sub-samples, the Fama-French risk model, various robustness tests, the effect of transactions costs, the effect of January, etc. Chapter 5 presents the results of several regression models where the time series of contrarian profits are regressed against a set of business cycle variables, in order to evaluate whether price reversals are related to changing economic conditions. Chapter 6 concludes the thesis.

CHAPTER 2: LITERATURE REVIEW

2.1 Efficient Market Hypothesis vs Behavioral Finance

Since the Efficient Market Hypothesis was formulated by Fama (1970) there have been numerous studies which present the so called market anomalies that cast doubts on the validity and the catholic acceptance of Efficient Market Hypothesis (EMH). EMH is one of the four cornerstones of the Neoclassical Finance theory. According to Shefrin (2001) these are: EMH, the Capital Asset Pricing Model, the Black – Scholes theory of pricing financial derivatives and the Mean-Variance Efficient Portfolios Theory. The Efficient Market Hypothesis has its origins from the Neoclassical Economic Theory (Mandelbrot (1971). LeRoy (1989) claims that EMH is the theory of competitive equilibrium applied on Financial Markets. As new observations on various market anomalies came on the surface and as the inexistence of convincing counterarguments continued, more researchers concluded that the traditional models of financial theory were not complete and there must be other factors as well that could affect securities. Investors' psychology, market participants' subjective beliefs and perceptions could play a vital role to the formation of asset prices. A new sector in Economic theory evolved (Behavioural Economics) and inevitably gave birth to a new segment in Financial Theory (Behavioral Finance). Nowadays there is a vivid discussion whether this new financial theory is a new paradigm that will substitute the traditional neoclassical one.

The core disagreement among academics is the way that people make decisions. Advocates of the EMH seem to avoid tackling into depth by setting a number of strict unrealistic rules leaving human factor limited. People's decision process goes through a three stage procedure: observation, data procession and then judgment formation. The spectrum of decisions in finance entail the way people combine portfolios, the number of securities offered, the type of earnings forecasting models they may use, the perception of risk and method by which people price financial products. Important issue for academics is to build a suitable theoretical framework in which observable financial phenomena get a reasonable explanation. In order to achieve this they have to choose specific set of assumptions. The question is whether these assumptions will originate from the neoclassical perspective or the behavioural one.

The former is known as the traditional one and it comes from the neoclassical framework of microeconomics, where Von Neuman and Morgenstern (1944)'s preferences over uncertain wealth distributions and Bayesian techniques (concerning appropriate statistical judgments from a known set of data) dictate humans' financial decisions. However, during the 1970's psychologists who specialized in the area of behavioural decision making provided evidences that people do not behave according to those preferences and often depart from the Baye's rule while forming judgments. Behavioural psychologists suggested alternative theories in their effort to explain the causes and the outcomes of specific humans' behaviour. Behavioral finance researchers driven from psychology theories, made use of methodologies coming from cognitive psychology in their effort to interpret and explain various financial phenomena and the so called market anomalies.

Efficient Market Hypothesis lies on three progressively weakening hypotheses (Shleifer (2000)). The first one claims that investors are rational and therefore valuate financial products in a rational way. Secondly even if investors are not fully rational their actions are random and cancel each other out any influence on the prices of financial assets. The third hypothesis goes one step further and postulates that even if some investors behave irrationally and their actions are on the same direction, then there are rational investors in the market called arbitrageurs who will take advantage the fact that asset prices have departed from their fundamental levels and make riskless profit. In that sense the price levels will revert to their equilibrium levels. An early version of this hypothesis was included on Friedman's work (1953) who claimed that rational negotiators will quickly cover any influence that irrational investors have on the market.

On the antipode of Efficient Market Hypothesis, Behavioral Finance combines empirical observations and psychology theories so as to construct its theoretical foundations. It assumes that investors are systematically not rational and furthermore usually they act on the same way. As far as the arbitrage argument is concerned, Behavioral Finance camp asserts that in reality arbitrage is a costly and risky procedure with limited abilities, extinguishing assets mispricing from their fundamental levels and this holds even for long-term horizons. The following Table 2.1 taken form Du (2004), presents the two theories major differences:

Table 2.1: The EMH &Behavioral Challenges

	Defense of the EMH	Behavioral Challenges
Level 1	Investors are rational in the VNM and Bayesian sense.	Investors are not fully rational as described in neoclassical theory.
Level 2	To the extent that some investors are not rational, their trades are random and therefore cancel each other out without affecting prices	People do not deviate from rationality randomly, but rather most deviate in the same way
Level 3	To the extent that investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices	Real-world arbitrage is risky and therefore limited
Source: Du Kai (2004)		

We can see Behavioral Finance is built on two different pillars. The first one is the science of psychology and particularly investors' psychology and the second is related to the theory of arbitrage limited utility. Both pillars will be presented and analyzed in our effort to understand why many academics believe that Behavioral Finance is a new evolving paradigm.

2.2 Investors Psychology

Investor Psychology refers to the way investors tackle problems as well as the internal and external factors that drive them to those actions. Investors use rules of thumb for their financial dilemmas in order to reach decisions based on time and information restrictions. This drives them to biased beliefs that affect investors or financial advisors predictions on the course of an event. Finally market participants form their beliefs depending on the way a situation is presented to them and how do they perceive information.

The traditional view of decisions making, in the face of uncertain outcomes, is that people seek (or at least should seek) to maximize expected utility (or pleasure, McKenzie (2005)). Neoclassical based paradigm uses normative models, which dictate how an individual should act. Normative models utility is to provide suitable benchmarks against which one can compare human behavior. Kahneman and Tversky (1974) argue that psychological processes underlying judgments bear little or no resemblance to normative models. Psychology researches differ because they focus on how people tackle these tasks.

2.2.1 Heuristics and Biases

There are two key ways in which the behavioural paradigm treats financial decision makers differently from its neoclassical-based counterpart. The first one is the introduction of Heuristics and Biases into research, notably systematic biases that affect predictions and perceptions of risk. The second way concerns Framing effects, the way that decision makers frame their options and make choices. Heuristic is the process people follow in order solve a problem empirically usually by trial and error (Kahneman and Tversky (1974) , Tversky and Kahneman (1982)). Heuristics are rules of thumb for judging probabilities or frequencies. These rules are quite useful when people have to give a quick solution to complex problems or uncertain situations. Unfortunately this process often leads them to limited liability results. A series of serious heuristic-driven biases that affect daily investors' beliefs and predictions concerning a stock's price or market's level are presented.

(a) Representativeness

Representativeness refers to the tendency people have when they interpret random events as a part or as representative of certain situations (Kahneman and Tversky (1974), Tversky and Kahneman (1971)). By using the word representativeness researchers meant that humans tend to suppose that one event is generated by another one if and only if they resemble. This leads them to hypothesize the existence of a series of random events as patterns which, most likely, do not exist. Kahneman and Tversky (1974) propose that this process of reaching a decision lead inevitably to a long list of biases. The consequence of this false belief is that people either (a) tend to give more weight on recent information about a stock (otherwise called base rate neglect, which seems to play important role to long-term stock returns reversals and continuation) (Tversky and Kahneman (1973)) or (b) to assume that a small sample of data is representative of the population (called insensitivity to sample size or else known as sample size neglect) (Kahneman and Tversky (1974), Rabin (2002)).

A real life example, that the human mind is a pattern-seeking device, can be drawn from the Basketball games whereas if one player scores some shots on the raw then he is presumed to be in good shape and that he is most likely to succeed at the next shot. This not statistically confirmed phenomenon is called the ‘hot-hand’ fallacy described by Gilovich *et al.* (1985). In capital markets, however, is a common phenomenon for investors to prefer stocks that in the past had a series of good returns or even paying investment advisors that had been successful for a few years in the row, hoping that this will continue in the future as well (Kahneman and Tversky (1974)). Shleifer (2000) argues that the law of small numbers and representativeness may explain certain anomalies in financial markets.

A more elegant explanation of the sample size neglect effect is that due to the application of the representativeness heuristic, investors attribute the same probability distribution to the empirical mean value for small and large samples; they misinterpret and violate the law of large numbers[1] in probability theory. Kahneman and Tversky (1974) named this habit as the law of small numbers[2] (meaning that people falsely believe that the law of large numbers applies to small samples as well as to large samples). Driven by the law of the small numbers people attribute negative serial correlation to an identical and independently distributed stochastic process.

Tversky and Kahneman (1983) strengthened their research on heuristics and the biases they cause, by showing that Representativeness can also lead people to believe that the joint probability of two events is larger than the probability of one of the constituent events, in contradiction to a fundamental principle of probability (the so called conjunction rule[3]). Another cognitive bias created by representative heuristic is Gambler's Fallacy. Many individuals expect the second draw of a random mechanism to be negatively correlated with the first, even if the draws are statistically independent. If a few early tosses of a fair coin give disproportionately many heads, many individuals

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[1] Law of large numbers is that the probability distribution of the mean from a large sample of independent observations of a random variable is concentrated at the expected value of the random variable, and the variance of the sample mean goes to zero as the sample size increases.

[2] People believe that the mean value from a small sample also has a distribution concentrated at the expected value of the random variable. This leads to ''over-inference'' from short sequences of independent observations.

[3] The conjunction rule states that the probability of the conjunction of two events cannot exceed the probability of either event individually, or $p(A) \geq p(A\&B) \leq p(B)$.

believe that the next flip is more likely to be tails. Equivalently in financial markets believe that the trend in a market will eventually revert. This kind of behaviour is mostly observed from gamblers. In other words there is a prolonged persistence on the statistical modification of time series of reversion to the mean.

(b) Overconfidence

Psychologists show that most people generally are overconfident about their abilities (Frank (1935)) and about the precision of their knowledge (Fischhoff *et al.* (1982), Alpert and Raiffa (1982)). Overconfidence is when people tend to set very narrow confidence bands. They set their high guess too low and their low guess too high (Shefrin (2001)). The reason why people overreact or underreact in certain events could be explained by their tendency to be overconfident about the credibility of their estimations (Oskamp (1962)). Oskamp (1962, 1965) was one of the first who conducted studies concerning overconfidence by taking different groups of psychologists. He denoted that level of confidence is inversely related to the level of experience which is also linearly related to the level of their estimations accuracy. Financial market participants (especially traders) exhibit excessive overconfidence as they usually have to take instant decisions based on random information. Therefore experiments within the population of investors could lead to selection bias problem in favor of overconfidence (Odean (1999)). Overconfidence concerning their ability to time the market usually drives them to biased beliefs. A common biased attitude is when managers attribute successful forecasts to their talents and when possible unsuccessful ones arrive due to bad luck. This is called **self-**

attribution bias (Gervais and Odean (2001)) Moreover after an unfortunate event they usually believe that they have sensed it and predicted that it was going to happen (known as **hindsight bias**).

Overconfidence can lead investors to excess trading (Angelidis and Benos (2009)), (Odean (1998a)). De Bondt and Thaler (1990) state (verifying Slovic (1972) clinical results) that overconfidence is not only a common characteristic of individuals or naïve and less informative investors but it is also appointed to specialized sophisticated financial analysts. Griffin and Tversky (1992) write that when predictability is very low, as in securities markets, experts may even be more prone to overconfidence than novice market players. Institutional investors may also involve in excess trading. The reasons for that may either by overconfidence or agency relationship. Dow and Gorton (1997) argued that money managers might trade so as to signal to their employers that they are earning their fees rather than not doing anything. Excess overconfidence (optimism) which is known as leniency has been documented in many domains of finance such as earnings forecasts Givoly and Lakonishok (1984). A possible explanation for the maintaining of analysts optimism once again, could be due to be agency issues, meaning that analyst who are optimistic over a firm's stock is more likely to get information concerning the future of the company directly from the company's management (Affleck-Graves *et al.* (1990), De Bondt and Thaler (1990)). This especially holds for the presence of unfavorable stock recommendations (Francis and Philbrick (1993)).

(c) Anchoring and Adjustment, Conservatism

Anchoring is when people try to reach an estimate (or assess probabilities) beginning from a possible arbitrary initial estimation (an anchor). In financial markets people regularly face rigidness in revaluating when they think that the price of a stock will move within a particular channel or when they calculate that a firm's profits will move along to its historical average prices. As a result they tend to underreact on the light of new data according to the fundamental value of a stock or to the reversion of the market's trend. This behavior is attributed to people's conservatism (an important factor of humans' mentality, especially towards the unknown, Edwards (1968)). Slovic (1972) claimed that a possible cause for people's conservative attitude is their inability to make an optimum combination and interpretation of different information. Relying on the research of Kahneman and Tversky (1974), Slovic says that people are prone to biased judgments concerning the probability of an event depending on their ability to recall similar events or the misperception of the probabilities of compound events. Slovic also states that investors try to diffuse responsibility in the light of risky decisions by following the norm and the decisions of a group. The cultural value hypothesis declares that professionals also tend to take the same risk as their peers do. Aversion to Ambiguity is the fear of the unknown people face towards dilemmas whose alternative scenarios do not have certain probability distributions. A real life example is the danger US financial system had to face if they had allowed the fall of LTCM or recently the bail out plan for banks and automobile companies as consequences are unknown about the stability of the economy (Shefrin (2001)). Heath and Tversky (1991) believe that aversion to uncertainty is closely related to ones low self-esteem concerning their capabilities. Early remarks on aversion to ambiguity can be found in Knight's work (1921). Knight defines risk as a gamble with known parameters (probability distributions) and uncertainty as a gamble with unknown parameters (probability distributions). He concludes that people avoid uncertainty more than risk. Knights' proposals where later empirically confirmed by Ellsberg (1961).

(d) Availability, Emotion and Cognition

The following three heuristics function as supplementary rules of thumb. **Availability** refers to the ease by which people remember certain events. Individuals judge probabilities by the ease of conjuring up examples. The result is to assign disproportionately high weight to salient or easily remembered information (Kahneman and Tversky (1974)). Familiarity and availability serve as cues for accuracy and relevance. Behavioral Finance makes a special reference to the significant role of media and analyst coverage on information coming form corporate finance. Mere repetition of certain information in the media, regardless of its accuracy, makes it more easily available and therefore falsely perceived as more accurate. Cognitive psychologists consider decision as an interactive process whereas several factors (such as perception, cultural formed beliefs or mental models) interfere in interpreting situations and facts uniquely. Emotions, however, play a special role in shaping the state of mind of the decision maker and especially how people remember events. Attitudes towards people and facts built stable psychological tendencies to relate to a given phenomenon in one's environment. In addition memory of previous decisions and their consequences serve as a critical cognitive function that also has a strong influence on current decision-making.

Emotions and cognition act in unison and affect synchronously in different each time proportions someone's decision. Both involve mental processes and may be psychologically linked as opposed to being separate from each other. Therefore phenomena that involve availability heuristic may reflect both cognitive and emotional elements (Shefrin (2001)).

So far we have reviewed what kind of heuristics people use, alternative known as rules of thumb in order to make quick decisions. We briefly saw how these heuristics are being used and to which kind of mistakes (biases) may lead people to make. In the context of financial theory heuristics had not attracted academics interest until behavioral finance began to form. However, another important unresolved issue in finance is peoples' predictions about the future events concerning economy or even the course of financial products. Financiers' ultimate purpose is to give clear-cut accurate predictions and naturally take advantage of them and profit. Academics of finance are interested how these predictions are formed and why most of them soon or later are rejected or revised. We turn to the way heuristics and biases practically affect investors' predictions in various circumstances.

2.2.2 Predictions

Predictions is the final outcome of a complex procedure which sums up the expectations, hopes, experience and beliefs that people form based on a large set of information. As we denoted heuristics may help people to reach quick decision however they mislead ones approach in the light of new information. Kahneman and Tversky (1974) named the phenomenon of being overconfident on holding error beliefs as the **illusion of validity**. A possible explanation is confirmation bias which is peoples' tendency to seek information that verifies their prior beliefs while at the same time they overlook facts that disconfirm their views. Solt and Statman (1988) argued that technical analysts believe that the sentiment index[4] provides a contrarian indicator of the future direction of the overall market, which can be exploited so as to make a profit. However, Clarke and Statman (1998), show that the views of such financial writers have no predictive power, postulating that their sentiment is highly correlated with past movements of the markets and that financial writers usually extrapolate past trends. De Bondt (1993) found out **naïve trend extrapolation** is a common characteristic of individual investors and financial writers. Investors tend to form skewed prediction confidence intervals whose sign depends on their recent price history. If the stock had a positive trend, then the skewness tends to be negative because market participants may feel that price is more likely to reverse than to increase and vice versa. However, De Bondt denotes that investors' estimate has not been generated by gambler's fallacy, but from the way he presented his subjects the price data (in the form of price levels) which may produce anchored effects on the initial levels of prices of the time series. Similarly Andreassen (1988), had shown that regressiveness of prediction differ whether price levels or recent price changes are more salient. Andreassen (1990) features the influences of three possible elements impose on the procedure of forming predictions. The first one is the way that time series data are presented in terms of levels or in terms of changes. The second one is the importance of information and the third is anchoring and adjustments.

[4] Sentiment index compiles the views of financial newsletter writers about the future direction of the market

Taking into consideration the fact that investors pay more attention to new information and that news mainly concentrate on price changes, this leads us to the conclusion that price changes are even more salient for an investor.

Andreassen makes extensive reference to the two most puzzling aspects of the De Bondt-Thaler winner-loser effect: a) price reversals are mainly observed during January and b) the asymmetric correction pattern where loser effect is three times greater than winners'. Andreassen assumes that price reversals may be more intense at the turn of the year because financial news tends to focus on data with longer-term historical character. Percentage changes create greater attention to base rates at the turn of the year relative to all other months. An additional assumption is the weight that press gives to the firms that has been characterized as winners during the De Bondt- Thaler formation period. Andeassen's assertions are hypothetical and do not take into account two features that De Bondt and Thaler (1987) discuss. First of all earnings reversals are also asymmetric (larger for losers rather than for winners) and second there is a momentum effect in winners' performance during the first January of the formation period. Both features are inconsistent with Andreassen's explanation.

De Bondt (1993) sorts out some of these issues and inconsistencies. For short periods of time, analysts usually predict that earnings will revert to the mean. More precisely in predicting earnings for the current fiscal year and the subsequent fiscal year analysts predict reversals. In fact their short term predictions are overly regressive and consistent with the 'law of small numbers' bias. De Bondt (1993) makes a very interesting discussion concerning the fact that professional economists (from academic and government) are inclined to be overly regressive in short-term predictions of the economy and the stock market. However, in formulating their 5-year earnings growth forecasts analysts extrapolate, excessively as it happens. In making predictions for the long term, analysts overreact as if they underweight base rates.

La Porta (1996) echoes De Bondt (1992) in arguing that expectations of future earnings growth are too extreme. For example he finds that for companies associated with high forecasted earnings growth, subsequent earnings revisions tend to be sharply down. But there is no corresponded revision for companies associated with low forecasted earnings growth. As for returns, La Porta finds that the one-year raw returns of stocks with low expected growth rates are 20% higher on average than the return for stocks with high expected growth rates. For returns around announcement dates he finds that the cumulative one-year returns to high expected growth stocks over a 3-day earnings announcement window are -1.6%. The negative return makes it difficult to use a risk-based argument to justify the return differentials described above. Moreover La Porta find no evidence that low expectation growth stocks carry more risk than stock with high expectations growth. A possible explanation could be that investors have discounted earlier the growth rates of the company and the announcement date comes as a verification of an accurate earlier forecast which at that time has no more profits to give.

The challenging point for behavioral psychologists is to succeed in discerning circumstances where subjects are driven by representativeness or by anchoring and adjustment. Czaczkes and Ganzach (1996) tried to exhibit the interplay between representativeness and anchoring and adjustment by varying the representation of predictor and outcome. In other words the dominant heuristic in prediction varies according to the underlying conditions. They present cases where people rely more on representativeness when the variable, whose value is being predicted, is presented in a compatible way to the value on which the prediction is based. However, a situation that features the possibility of a salient anchor will instead lead to reliance on anchoring and adjustment. They also indicate that deviation representations lead to reliance on anchoring and adjustment while size representations lead to reliance on representativeness. Overall, Czaczkes and Ganzach indicate that intuitive predictions are often influenced by various heuristics that operate concurrently and this was an innovation for behavioral decision theory.

Amir and Ganzach (1998) examined whether combined influence of various heuristics (representativeness, anchoring and adjustment, and leniency) apply to financial analysts earnings predictions. They claim that when they have to predict earnings, analysts are most likely to use a salient value (a previous forecast or previously announced earnings) then proceed in modifying them on the basis of new information. Amir and Ganzach classify modifications in two types, forecast revision[5] and forecast change[6]. Their study examines how the pattern of forecast errors is affected by the type and the sign of the forecast modification. Additionally they trace the dependence to the psychological processes underlying various types of forecast modifications. They showed that leniency leads to overly optimistic prediction and specifically when the forecast modification is negative it also leads to excessively moderate predictions. Representativeness, Anchoring

[5] Forecast revision is the difference between the prediction of future earnings and the previous forecast.
[6] Forecast change is the difference between the prediction of future earnings and the previously announced earnings.

and Adjustment play a significant role only in the extremity of predictions, meaning that the first leads to excessively extreme prediction while the latter leads to excessively moderate prediction. The dominance of one of the last two heuristics depends on the salience of the anchor. The higher the degree of the salience of the anchor the more weight analysts give on anchoring and adjustment. Previous forecasts are more salient than previously announced earnings and moreover in cases of negative modifications the anchor receives greater salience from what it gets in cases of positive ones. Therefore analysts generally overreact to forecast changes and underreact in forecast revisions. This may be happening because in the latter case an analyst has to revise its own past forecasts. He comes up against his own ability of timing the market. He does not want to believe, he has to deviate greatly from what he had suggested or the heuristic of overconfidence about his own predictions does not allow him to do that. This escalates when predictions have to be negatively modified.

These findings are consistent with Staw's (1981) work where he suggests that people tend to have a strong commitment to a course of action once a choice has been made, judgment has been expressed or forecasts communicated. Concerning the case of forecast changes an analyst uses as an anchor objective and beyond doubt data. The impossibility of denying these data makes him available to revise prediction on the direction of the earnings announcements more easily and even more to exaggerate and overreact, especially in the cases of positive modifications. Amir and Ganzach's study claims that the power of the three heuristics increases with forecast horizon. The longer is the prediction horizon, the larger is the prediction bias. Thus the magnitude of the underreaction is linearly related to the time horizon. Amir and Ganzach findings are also in agreement to Weistein's work (1980) that people are prone to be optimistic, previous studies have shown that analysts' forecasts for the subsequent 12 to 18 months are overly optimistic. However, in the case of analysts' forecasts psychological hypothesis may alter. There are many financial strings attached to what they are willing to publish. Many recognize that agency issues exist according to the management relations hypothesis, which states that analysts' optimistic forecasts stem from their interest in currying favor with the firms' managers, on whom they depend for information.

2.2.3 Framing Effects

Frame is the form used to describe a decision problem. Frame independence means that the form is irrelevant to investor's behavior. Traditional finance assumes that framing is transparent, meaning that market participants can see through all the different ways cash flows might be described. However reality, supported by experimental verification, has clearly showed that frames are opaque. People take decisions which may vary according to the frame they use. Ones behavior is defined by his/her decisions and furthermore his/her actions. Framing indicate the way one's behavior depends on the way their dilemmas are framed. Researchers' interest focuses on the application of framing effects on investors' choices, otherwise on the way their preferences or their perception of risk is affected by the existence of different frames. According to Shefrin (2001), frames can be formulated by the aversion of people to Loss or to the feeling of Regret. Frames can change when one has to face Concurrent Decisions and finally Hedonic Editing is the practice of choosing frames that are attractive relative to other frames.

Markowitz (1952) was one the first who tried to explore the notion of the term ‘‘loss’’ in decision making. He focused on how people actually behave through addressing the question posed by Friedman and Savage (1948): Why do people simultaneously purchase insurance and lottery tickets? His results where in agreement to an experiment conducted by Mosteller and Nogee (1951) on how people bet. He introduced for the first time a utility curve with three inflection points. The distance between the inflection points is a nondecreasing function of wealth (wealth people would behave like people with moderate wealth, the inflection points however would slightly move further from the origin). The function is monotonically increasing but bounded. It is first concave, then convex, then concave and finally convex.

He assumes that $\left|U(-X)\right| > U(X),\ X > 0,\ (\textit{where } X = 0 \textit{ is customary wealth})$, meaning that losses loom larger than gains. The second inflection point is what we call present or customary wealth. He signified the difference on present wealth and customary wealth. If no prior gains or losses have occurred these two terms refer to the same inflection point of the utility function, otherwise they are not the same. This partition brought to the surface the use of terms such as gains and losses relative to a reference point. He presented gambles in terms of gains and losses as well as the magnitude of the stakes (small or large). The fact that people play conservatively when they are loosing moderately and more liberally when winning moderately makes the frequency distribution of final outcomes skewed to the right. This implication holds true for every level of wealth.

Markowitz's work (1952) is the cornerstone of behavioral finance where every assumption or insight he made in that text was later extended and further developed by the psychologist who succeeded in merging the basic principles of cognitive psychology with economics (explain phenomena or designed experiments concerning behaviour under risk or uncertainty, Markowitz (1952) p.158).

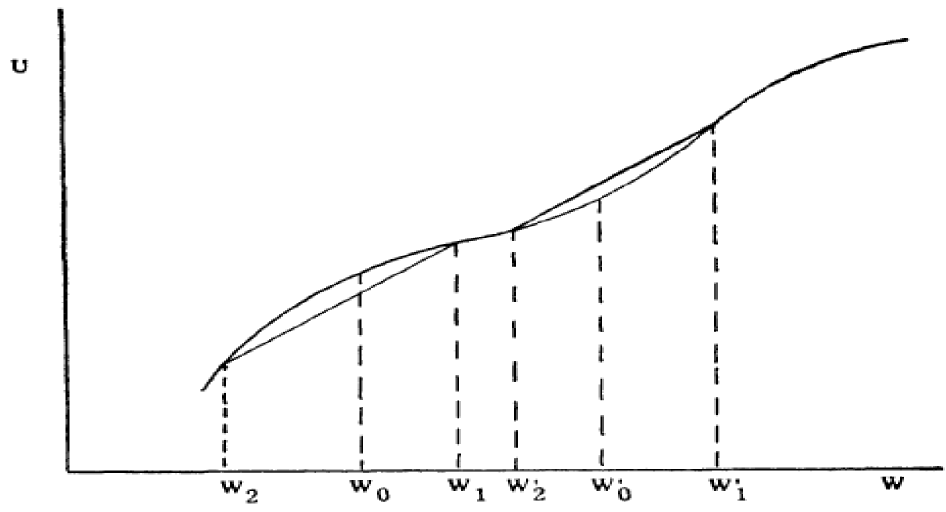

Figure 2.1: Utility Curve of Wealth Markowitz (1952), p. 151

The notion of utility function derived on deviations from a reference point was later used by Kahneman and Tversky (1979) in their well known prospect theory. The fact that people are less willing to bet liberally when they have incurred a prior loss reveals the essence of the term ***loss aversion***.

Markowitz also encouraged researchers to find out the consequences of concurrent decisions which were much later expanded by Tversky and Kahneman in (1986). The positively skewed preferences projected in his article could well be announced as the ancestor of the *house money effect* later described by De Bondt and Thaler (1990). One of his last remarks is that the utility level of people, who had won very much, lay beyond the third inflection point of the utility function and therefore they may be willing to play for lower stakes or not to play at all in a gamble. Markowitz commented this behaviour as the tendency of heavy winners to quit while they are winning (p. 156). This suggestion could possibly be a partial explanation of the well known disposition effect hypothesized by Shefrin and Statman (1985) where investor are predispose to sell their winners too early and ride their losers too long.

(a) Loss Aversion

The phenomenon took its name by the Kahneman and Tversky (1974) in the framework of prospect theory. They were inspired by Markowitz insights on framing, gains, losses, reference points and a utility function with concave and convex segments, as well as the propositions postulated by Allais (1979) for its treatment on probabilities. Allais by designing a series of paradoxes demonstrated the fact that people do not behave according to von Neuman and Morgenstern axioms of expected utility. In Kahneman and Tversky's theory, utility of a decision maker is not defined by final value of wealth *per se* that he has in his/her possession, but by the level of gains and losses of an individual relevant to a reference point. This reference point is the decision-maker's current level of wealth. However, reference level could be a desired level of wealth, which includes someone's current level of wealth plus their expectations. According to this theory a decision problem has two stages. The first one is the ''edited'' stage where the reference point is being established. The second stage is the evaluation stage which includes the aftermath of a particular choice where the result is being ''coded'' to gains and losses according to the reference point.

The value function is derived from preferences between changes of wealth and it is S-shaped. It is concave in gain area and convex for losses, exhibiting diminishing sensitivity to changes in both directions. This trait may explain why investors are risk-averse towards gains and risk-loving towards losses. An interesting feature of this curve is that it is steeper for small losses than for gains, meaning that individual investors display greater sensitivity to possible small losses than to possible small gains from a gamble. This explains how loss aversion is expressed by investors. In other words the mental penalty for the probability of incurring losses is larger than the mental reward of the possibility of receiving gains. In their effort to quantify this difference Tversky and Kahneman (1992) concluded to a 2½ times superior impact of the realization of losses than from the realization of gains, contrary to the Markowitz's utility function which is relatively shallow at the same region.

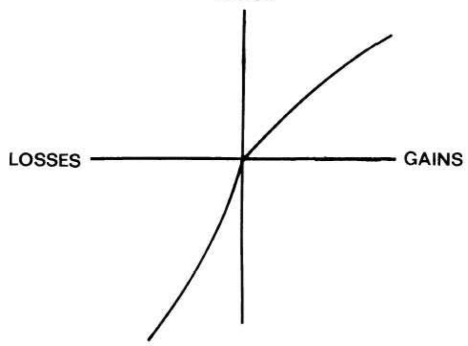

Figure 2.2: Prospect Theory Value Function *Kahneman and Tversky (1979) p.279*

The decision-weight function π is a transformation of objective probabilities p and q. This function is monotonically increasing and it gives systematically overweight to small probabilities and underweight to large probabilities. The last sentence can explain the Allais paradox. A perfect implication of the above feature of the density function has been extensively searched by Kahneman and Tversky. They showed particular interest in the way people behave when they gamble. Although people are thought to be loss averse, in case of gambling where there is a small chance of receiving a great profit, they change attitude against risk. This is happening because people do place greater weight on smaller probabilities. While the convexity of the utility function within the area of losses indicates that people in general are risk-seeking in their effort to avoid possible losses, in case of a small probability of incurring a very large loss investors prefer not to take the particular risk.

Commenting on Loss Aversion, Shefrin (2002) hypothesized that this phenomenon could be minimized if investors panic. The terror of losing a big chunk of their money could lead them to the loading off a great proportion of their portfolio. This was also stated by Rabin (2000), according to him, investors avoid to take great risks when they face gambles that include large amount of money. In prospect theory the authors end up to a series of conclusions related to investors attitude. People usually place greater weight to scenarios which outcome is supposed to be sure than to gambles with unknown parameters. This is called the ***certainty effect***.

(b) Regret Aversion

A possible reason that people engage in frame dependence (especially loss aversion) is the feeling of regret. Kahneman and Tversky in their 1982 article make a reference on the psychological character of regret. Loomes and Sugden (1986) and Bell (1982) based their work on regret and proposed formal choice theories. Regret is worse than the simple realization of the pain (or the material/financial damage) coming from a loss. It is when someone feels responsible for that loss. Regret aversion is considered to be responsible for the fact that people hesitate to sell stocks from their portfolio that show negative returns, in their effort to avoid incurring these losses. People engrave the feeling of regret intensively and their will of avoiding it leads them to exhibit herding behaviour. In other words they prefer to invest in stocks that are considered as good ones since they can function as an alibi towards the feeling of regret.

(c) Concurrent Decisions

Tversky and Kahneman (1986) discussing framing issues relevant to finance they reported the results of an experiment where people had to face a two stage decision problems. In these series of concurrent decisions, people had at the first stage to choose between a sure gain and a possible large gain and in the second stage they had to choose between a sure loss slightly larger than the sure gain of the first stage and a probable large loss. The most intellectual subjects should have picked up a combination that provides them with a minimum loss. However, people failed to recognise how these decisions are interconnected. Half of them chose the sure gain (risk averse) and a possible large loss (loss aversion). This experiment revealed that people separate their choices into mental accounts confirming the existence of frame dependence. A comparable implication of this human failure in finance could be observed when people prefer portfolios that lie below the efficient frontier. Tversky and Kahneman (1986) report that subjects do not prefer dominated gambles. However their choice alters when the decision frame is not transparent. They are prone to choose the dominated gamble when the generating procedure is opaque.

(d) Hedonic Editing

Hedonic editing is the editing rule which is based on the hypothesis that people edit the gambles in a way that would make the prospects appear more pleasant (or at least unpleasant) as Thaler and Johnson (1990) argue. According to Thaler (1985) the hedonic editing hypothesis follow from four principles (segregation or integration of gains are the first two, segregation of small gains from larger losses and finally integration (cancellation) of smaller losses with larger gains). Editing focuses on framing. Some people prefer some frames over others. A key aspect of editing a situation is mental accounting[7]. The reason why people exhibit frame dependence has to do with cognitive as well as emotional explanation. The former has to do with the way they categorize the information they are exposed to and the latter one refers to the emotional situation by the

[7] Mental accounting describes the effort of an individual or a group of people to keep a trace of their money by recording, summarizing, analyzing and reporting the results of transactions and other financial events (Thaler 1999).

time they register the information. Hedonic editing was used as an explanation by many researchers to explain the peculiarities in investors' behaviour. Thaler and Johnson (1990) proposed a theory of hedonic editing for mental accounts. As part of the study they administered a series of choice problems to subjects. The outcome of those problems was that people are not uniform in their tolerance for risk. Some people appear to tolerate risk more readily when they face the prospect of a loss than when they do not.

Thaler (1999) outlined the main elements of mental accounting and their application in finance. He focused on five issues: savings behaviour, cash dividends, the house money effect, myopic loss aversion and finally the 1/n diversification heuristic. We will present briefly three of the characteristic elements of mental accounting. **House Money Effect** exists when a person who has received a recent gain, but has not yet adjusted the reference point; appears to be more tolerant to risk than he was before the last gain he earned, as he may receive gambling as an ongoing procedure which outcome will be counted at the end of it. Up to that point the initial gain allows someone to view the possibility of loss in a future gamble less likely to happen. Barberis *et al.* (1999) suggest that this phenomenon leads investors to be more relevant tolerant of risk in a bull market than a bear market. **Myopic Loss Aversion** is what investors suffer from when they overlook the benefits of time diversification. They have the impression that they face a one-shot deals rather than concurrent gambles, for which they demand higher returns as they perceive them as more risky. Benartzi and Thaler (1995) argue that because investors evaluate their portfolio more than once annually therefore their reference point is always updated and they demand each time an equally large premium. Benartzi and Thaler (1999) postulate that individuals are more willing to hold stocks when they present to them data of 30-year returns rather than when they have available one-year returns of the same data base. Finally the **1/n heuristic** was first mentioned by Tversky and Kahneman (1973) and later discussed by Benartzi and Thaler (1999) and refers to investors inability to form a well-diversified portfolio due to opaque frames. They invest the same amount of money across available assets regardless the return distribution. A characteristic example comes from the 401(k) pension plans where if they provide more bond funds rather than equity funds an investor who strictly rely on the 1/n rule will end up pilling up his investments heavily in bonds and too little on stocks.

According to Shefrin and Thaler (1988) consumers separate their wealth in three mental accounts. These are current income, assets and future income. Saving from current income requires self-control and discipline. Therefore they concluded that it is much easier to save from current income when the desired amount is automatically excluded from their current account, such as in pension account. Retirees are a group of people whose behaviour stimulated psychological research on behavioural finance. The long-standing issue why companies pay dividends may find a reasonable explanation when the retirees' way of thinking is analysed. Shefrin and Statman (1984) argue that people tend to prefer dividends to capital gains despite the tax disadvantage because investors classify dividends as income and not as initial capital. They prefer their life savings to remain untouched. Hence they are keener to invest in portfolio of firms that follow a generous dividend policy.

(e) Disposition effect

Disposition effect refers to the tendency that some investors have to sell the winners stocks of their portfolio too early and hold their losers stocks too long (Shefrin and Statman (1985)). They made two predictions which seem to be valid by the examination of the data. First that up to the eleventh month of a year people tend to sell winners faster than loser stocks and secondly that these pattern reverses in December. They tried to explain this effect by utilizing to main features of prospect theory. First decision-makers frame their choices in term of potential gains and losses and second people behave as if evaluating the decisions consequences on an S-shaped value function, which is concave for gains and convex for losses. This denotes risk aversion in the gain region and risk-seeking in the loss region, the behaviour of shifting risk attitudes for gains and losses was named by Kahneman and Tversky as the 'reflection effect'. Oehler *et al.* (2003) support the view that disposition effect is a product of a reference price (mostly the price at which a stocks was purchased) and the reflection effect presented by Kahneman and Tversky.

Figure 2.3 is the depicting explanation of the above assertion. Gain Area: Suppose Winner stock with Purchase Price (PP) € 65 as reference point. Stock rises to € 70. Gain € 5 valued with v(A). Assume stock i) rises to point A^u = € 73 or ii) false to point A^d = € 67. In the first case the gain would be € 3 and in the second one the loss would be €3. Absolute amount is equal. Because of the concave shape of the curve (value function) in the gain region additional gain is valued in investors mind as a smaller increase ($\nu(A^u)-\nu(A)$) than the equal loss of €3 is valued ($\nu(A)-\nu(A^d)$). Loss Area: Suppose a loser stock. After PP stock falls to point B = €60. Assume equal chances the same stock to bounce back to point B^u =€63 or to fall once more to point B^d €57. Due to the shape of the value function in the loss area the possible loss reduction is valued more severely than the possible increase of the negative value ($\nu(-B)-\nu(-B^u) \succ \nu(-B^d)-\nu(B)$).In the gain area investor decides to sell when the stock reaches € 70, ensuring € 5 gain (risk averse) and in the loss area the same investor is risk seeking and willing to take the second bet in order to avoid the initial € 5 loss (see for details Oehler *et al.* (2003)).

The first conclusion could be explained by a combination of psychological phenomena that dominate the behaviour of an investor. Representativeness may lead someone to believe that the positive returns of his winners stocks will not have the same future course. Otherwise they may predict negative serial correlation to an identical distributed stochastic process. The law of averages may starts playing a greater role in their perception of the financial information extracted by the course of the winner stocks, especially if the profits up to that point have been exceptionally high. Another possible explanation could be that one can easily sacrifice small gains in order to purchase other stocks which according to his prediction they will generate higher gains. However these predictions could be false even if he supports them, possibly lead by his overconfidence.

On the other hand their persistence of holding stocks that have performed badly could be explained by other types of heuristic biases or hedonic editing of the available to them information. Anchored in previous predictions, stock analysts may find it difficult to revise them. Investors feeling regret may prohibit themselves from selling not optimal choices and loss aversion could be a strong motive as not to decide to realize the losses and prefer to characterize them as paper loss.

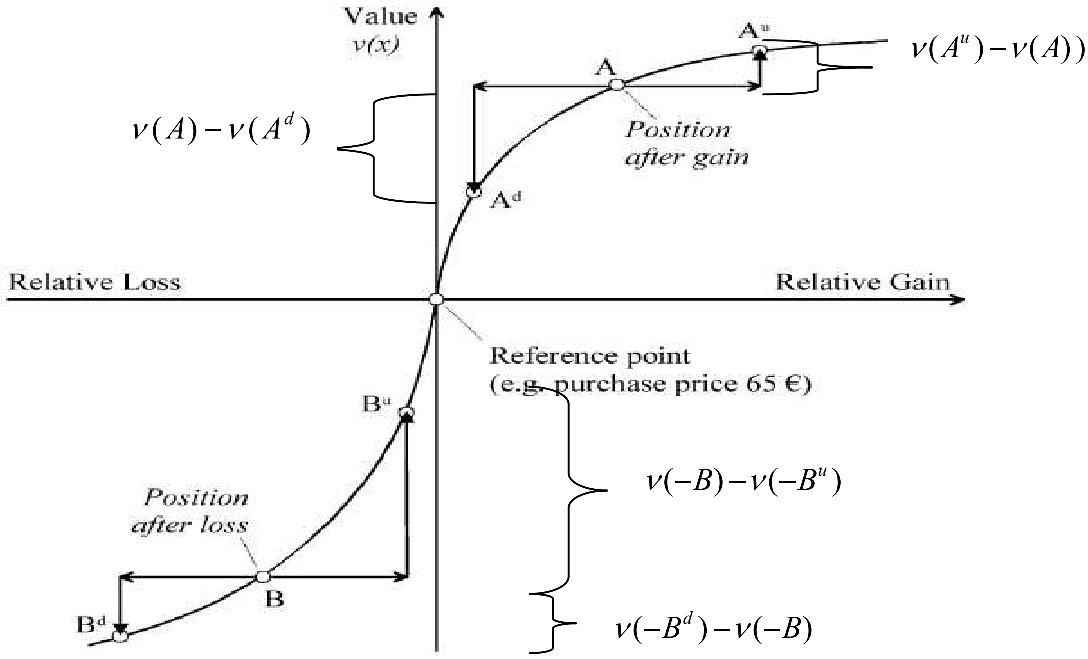

Figure 2.3: Disposition Effect

(A. Oehler et al. / Journal of Int. Fin. Markets, Inst. and Money 13 (2003) 503-524)

A last possible explanation of keeping losing stocks is the tendency many traders have to get-evenitis (LeRoy (1982)). Shefrin (2001) mentions that their dislike of incurring losses makes them to keep losers hopping for a quick reversal of their stock prices. Get-evenitis has been denoted in corporate executives as well, who avoid abandoning a losing project in the hope that small modifications will make it viable.

As far as the second prediction of Shefrin and Statman is concerned, the fact that investor abolish losing stocks more quickly than winners in the last month of the year, can also be explained by tax-loss selling hypothesis. The immediate tax profit that can be achieved from selling the losing stocks seems to be more salient than the aversion of any regret feeling. Odean (1998) who conducted tests on individual traders from 1987 up to 1993 trying to verify the existence of disposition effect confirm both predictions made by Shefrin and Statman. In a later article Odean (1999) added that when investors finally sell their losers they decide to do it at the wrong time.

A few more studies that documented the behaviour of disposition investors under a more behavioural finance view like Shefrin and Statman (1985) was Lakonishok and Smidt (1986) who examined NYSE and AMEX stocks found excess past (for a period of 5, 11, 23 and 35 prior months) trading volume for winners. Odean (1998) (also Barber and Odean (1999)) acquired from a discount broker the transactions of ten thousand individual accounts for which Odean hypothesized that desired and executive trades were not affected by the broker's advice. The result was that investors clearly showed a tendency of realizing paper gains than just compromising with the materialization of paper losses. Shapira and Venezia (2001) and Grinblatt and Keloharju (2001) also proved that disposition effect is commonly found to all classes of market participants either professionals or independent. Disposition effect can also be found in futures trading. Heisler (1994) argues that such traders take position only in case when they feel they have informational advantage. Their rational reaction would be to close these positions when they realize that they lose money or to hold a winning position up the point where the informational advantage will stop, however they held negatively performed positions and involved in non-profitable trading activity.

Weber and Camerer (1998) performed an experiment where individuals had to form a portfolio of six stocks whose price performance was closely related to their learning ability through experience. They find that investors' inertia, reluctance of realizing losses and the presence of the 1/n heuristic rule played a significant role in the appearance of disposition effect even after using two different reference prices such as the purchase price of the stock and the last price of a stock. Investors' attitude in a way resembled gambler's fallacy phenomenon where they tend to buy more stock after losses rather than after gains hoping in a reversion of the market. Finally Weber and Camerer (1998) discovered an investors' behaviour parallel to the one later described to the bubble experiments in Smith *et al.* (1999).

An experiment by Heath *et al.* (1999) included as investors, employees who were entitled of getting stock options. The interesting feature of this group is that they become owners of a substantial number of stocks for which they did not have to pay. This automatically rules out the prospect theoretic reference price that investors have always in mind when they have to decide to sell or to hold a stock in their possession. Employees seem to find another reference point to cling on. This would be the highest price a stock reached in the last eight months. Reaching a price close to that reference point would be a signal for the owners of the stock options to exercise them as quickly as possible. This kind of behaviour is closely related to investor's relation under the disposition effect. Oehler *et al.* (2003) summarize the two driving forces of disposition effect. The first one according to them is the valuation asymmetry between the upside risk and the downside risk of price movements or changes in states of wealth. Investors are more sensitive to losses (wealth worsens) than to gains even more small losses and gains (Shumway (1997)) exhibiting loss aversion (Benartzi and Thaler (2001)). The second has to do with the magnitude of loss aversion investors' experience. Prior gains cushion (House Money Effect) can smooth loss aversion intensiveness whereas prior losses empower this investor's aversion. Furthermore myopic loss aversion described by Benartzi and Thaler (1995) enhances risk-taking behaviour of loss-averse investors as they monitor their portfolio performance infrequent or they have long evaluation periods. Grinblatt and Han (2001), however, argue that disposition effect and loss aversion should not be confused and that it should be considered as something distinct, because in a multiasset multiperiod framework reference prices constantly change so as to force investors to substitute one risky asset with a paper gain or loss for another. The complexity of this scenario is atypical as they say in the modelling of loss aversion. As the reference prices vary then utility assumptions that characterize loss aversion are outdated.

Behavioral finance nowadays extends to the whole spectrum of research that was conducted within traditional finance frames, trying to restate several undisputed till now hypotheses and provide more logical and close to reality explanations for unsolved puzzles of finance. A variety of discrete sciences are combined in an interdisciplinary research conducted the last decade in an effort to finally produce a general equilibrium theory concerning asset pricing from the standpoint of behavioral finance (Figure 2.4, Ricciardi and Simon (2000). This would be the ultimate step to distinguish behavioral finance as a new paradigm completely different and more concrete than neoclassical theory of finance. Up to that point in time behavioral could not be thought as individual theory according to the Kuhnian perspective[8] but only as a supplementary perspective which comes to fulfil and not to capsize the traditional finance suggestion.

[8] The Structure of Scientific Revolutions (Kuhn 1970). He dedicated his work on the evolution of scientific disciplines. His insights can assist someone to understand past and present trends in the finance discipline. Kuhn work focus in two main concepts, paradigm and scientific revolution. Paradigm can be a theory, principle or law or even a normative rule of research. The revolution of a science, follows: the pre-paradigm stage (competing schools of thought examining phenomena), the development of a paradigm consensus or a common body of belief among practising scientists within the field, the stage where paradigm is further articulated to explain the subject body of phenomena called normal science, Crisis stage include anomalies that or observable facts that are unexplained within the existing paradigm, the appearance of a new paradigm re-examining the most fundamental beliefs of the old paradigm about the object of research, the revolution stage where the new paradigm has solved the problems facing the old paradigm and finally the resumption of normal science based upon the new paradigm. According to this we believe that behavioral finance camp is still on the development of a different paradigm.

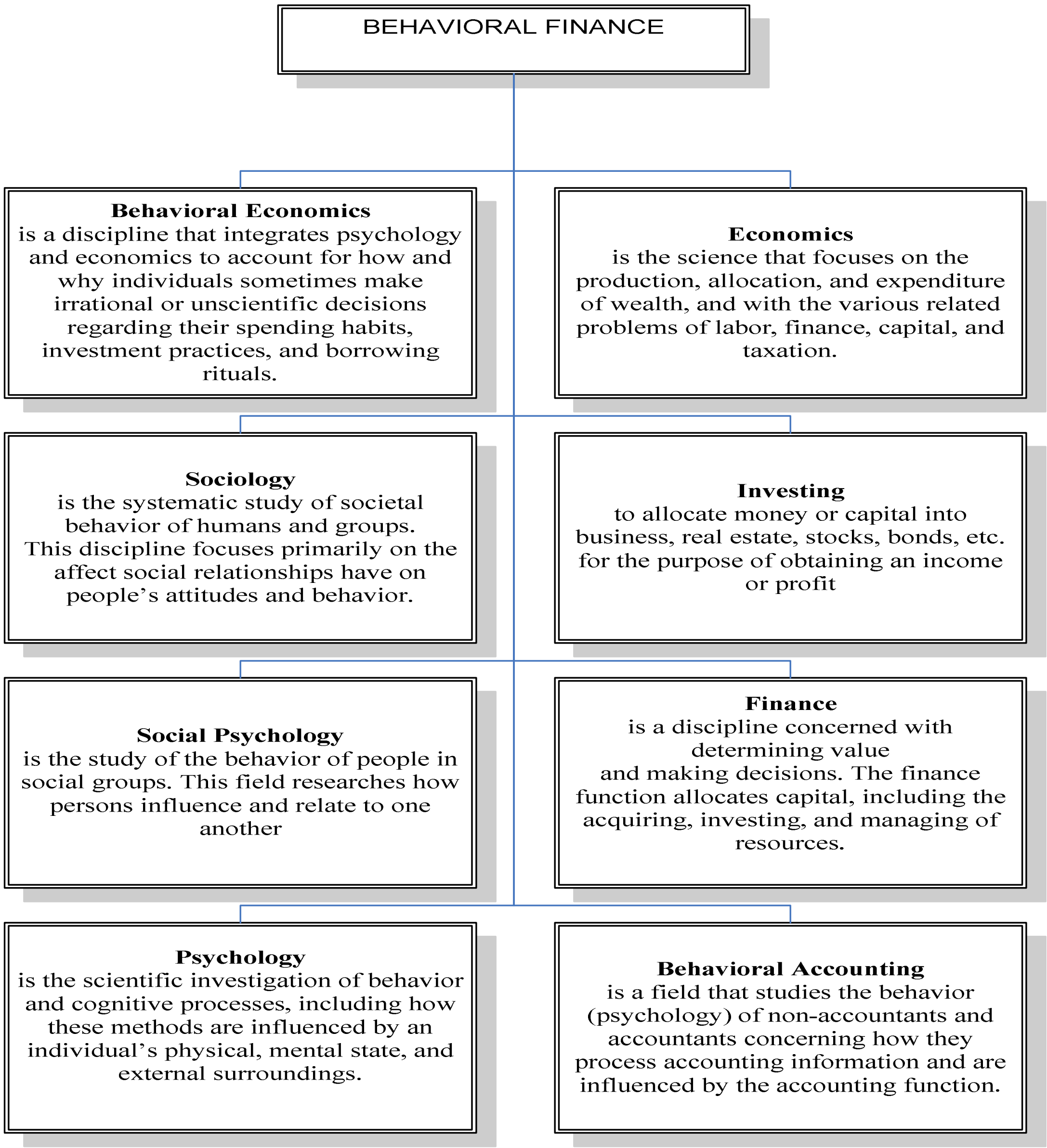

Figure 2.4: An earlier version of this chart appeared in Ricciardi, V and Simon, H. (2000).

2.3 Limited Arbitrage

‘‘Arbitrage is the simultaneous purchase and sale the same or essentially similar security in two different markets for advantageously different prices’’(Sharpe and Alexander (1990)). According to academics when arbitrage works no capital and no risk are involve in this procedure. The function of arbitrage can be summarized in two hypotheses. Firstly investors are able to instantly discern every opportunity actually arises from the departure of the stock’s price from its fundamental value. Secondly rational investors will take advantage of such mispricing leading to the reversion of the price back to its fair value.

Behavioral Finance assumes that there are two reasons why arbitrage can be thought of as a limited tool. Arbitrage in real life is risky and costly. Barberis and Thaler (2003) mention that Fundamental Risk, Noise Trader Risk and Implementation costs are involved in arbitrage. **Implementation Costs** are the material and non-material costs that come up during the implementation of arbitrageur’s strategy. There are trading costs such as commissions, Bid-Ask spread and additionally short sales restrictions, legal restrictions, cost of tracking and exploiting mispricing chances. **Fundamental risk** is related to the fact that there may not be a perfect substitute for the arbitrageur but only a close substitute of a portfolio of stocks. This feature makes arbitrage much more risky as the mispricing could widen and the arbitrageurs incur losses. As far as fundamental risk is concerned, Figlewski (1979) revealed that if arbitrageurs have to bear the particular type of risk it may take even a year until irrational investors lose their money, in other words it may take a long period until arbitrage becomes effective. Shiller (1984) and Campbell and Kyle (1987) focus on the aversion of arbitrageurs to fundamental risk, which can be so strong that it ends up limiting arbitrage greatly, even if arbitrageurs have a long-term strategy.

Shleifer (2000) comments that arbitrage is ineffective even when there is no fundamental risk. He postulates arguments similar to Barberis and Thaler (2003) concerning the costs that follow the implementation of arbitrage. Short- selling restrictions (apart from the fact that short-selling is not allowed in some financial markets by law) make it difficult for arbitrageurs to find stocks that they can borrow and sell. The problem grows bigger when the market is rather illiquid. When the arbitrageur has to close his short position he should be able to find immediately the needed stocks to buy. He may face the danger of the short-squeeze phenomenon which in real life and especially in emerging markets is high. A second argument that Shleifer presents is that there is limited knowledge about the noise (Black (1986) and Summers (1986)) and specifically about the stochastic behaviour of non-informative investors. Even if arbitrageurs are technically capable of proceeding in their counter-investment strategy there are exposed to the investors' sentiment which is difficult (or even impossible) to time and predict. The last argument Shleifer lays is that as transaction costs function as a barrier to irrational investors' expectations of earning excess returns, it may also work the same way for arbitrageurs, especially in less than perfectly liquid markets. Shleifer tried to present a practical proof apart form the presentation of a theoretical model concerning the fact that noise traders increase influence on the stock's price determination. A wide known anomaly is the index inclusion price jump of a security even from the announcement date. He states two possible dangers, noise trader risk and fundamental risk as the main reasons why arbitrage is limited particularly for the S&P index inclusion. Furthermore Roll's (1988) statement that is very difficult to construct a portfolio that share more than 25% of a particular stocks variance based on historical data, indicating that as the co-movement deteriorates, hedging for an arbitrageur (in this case) becomes even more difficult.

De Long *et al.* (1990) argued that the non-predictive behaviour of irrational investors makes arbitrage less lucrative. Investment horizon is also a key factor as the shorter the investment horizon of the arbitrageurs (and therefore the more worried about the liquidity of the positions they have taken in mispriced financial products) the less aggressive their behaviour would be facing the dilemma of exploiting an investment opportunity even if the fundamental risk is limited (even with fundamentally identical stocks). Under these circumstances noise trading may lead to a greater departure of the securities prices from their fundamental values. One could assume that irrational investors may earn the analogous returns for the risk they bear by insisting on trading against rational investors. This approach could be followed in order to explain why non-rational traders succeed excess returns even if they are responsible for the mispricing.

Shleifer and Vishny (1997) extended the argument expressed by De Long *et al.* (1990) and constructed a theoretical model which described how specialized professional arbitrageurs invest funds on behalf of investors who are outside the market. They assume that investors, who provide arbitrageurs with funds, have a limited knowledge of the financial markets and prefer to invest on arbitrageurs based on their historically achieved returns. Shleifer and Vishny believe that the model of specialized arbitrage, where arbitrageurs are evaluated at regular short intervals and paid according to their performance, is not efficient and it can not fulfil its primary purpose of equalize actual securities prices with their fundamental prices, especially under extreme circumstances. They denote that professional rational investors avoid of getting involved in positions even if they offer highly tempting returns but their increased liquidity multiplies the probability of incurring severe losses. Therefore arbitrageurs usually are forced to liquidate their positions even at a loss under the pressure of the funds owners to do so. They reveal an agency problem that exists when the rational trader and the capital owner is not the same person (this agency problem can be created even from inside of an arbitrage association as the director of that firm may force the liquidation of an employee's position). In the latter case the liquidation risk is more intensive when the prices move against the arbitrage procedure and the collaterals falls. Poor performance may have a twofold consequence on arbitrageur such as eroding both the equity base and the borrowing capacity of the arbitrageur. The arbitrageurs' aversion in highly liquid positions could be a possible reason for the excess returns of various stocks for a long period of time. Shleifer believes that arbitrageurs are more cautious on their initial trades and more bullish when the mispricing has taken its toll. He presents a model where he proved theoretically that in panic situations performance based arbitrage can be devastating. Shleifer and Vishny (1997) postulate that imperfect arbitrage is responsible for many of the observed anomalies in financial markets.

There is an alternative point of view in Shleifer and Vishny's theory posed by Brav and Heaton (2002). It states that the key of this theory is the existence of rational structural uncertainty on the part of the investors and explanations involving cognitive biases (presented by the Behavioral Finance camp) have nothing to do with it. This kind of uncertainty causes rational arbitrageurs to have short investment horizons which in turn prevent complete use of the arbitrage element. They believe that the explanation of short horizons may indicate a form of rational structural uncertainty where both arbitrageurs (and the people who finance them) are not certain for the existence of truly exploitable chances of arbitrage and therefore they prefer to minimize their capital commitment in this kind of strategies.

Additionally Brav and Heaton provide a series of second thoughts. The realization of an asset's mispricing as a result of cognitive biases by a large part of market participants may allow arbitrageurs a greater access to the existing pool of arbitrage funds. The number of arbitrageurs who will end up to the same conclusion may be become more aggressive as the mispricing will terminate sooner or may hinder from taking the chance position as the mispricing might not be wide enough so as to involve in such a risky arbitrage position and not receive satisfying expected returns from them, or that the flow of capital to arbitrage activity is positively correlated across arbitrageurs. The additional risk that arbitrageurs face is that naive investors may have learned to identify mispriced assets as arbitrageurs do by observing historical data and make the necessary movements in order to get out of this position acting like arbitrageurs.

Shleifer (2003) mentions three counter-arguments in favour of performance based arbitrage, which in turn he partly rejects them. First of all arbitrageurs' positions may be liquidated with a lag. Most of the arbitrageurs wait until the price of the stocks recovers thanks to contractual restrictions on withdrawals which burden investors' moves. These restrictions may be temporary (in hedge funds one to three years they have no right to withdraw their money) or permanent (in closed-end funds). However this lag may be rather short as these constraints are uncommon and in most of the times hedge funds give investors the choice to withdraw their money with only few weeks notice period. Otherwise the inside agency problem that we mentioned may take effect as the head of the fund may himself order the liquidation of a losing position.

Secondly arbitrageurs do diversify across different assets or various markets. In that sense it is rather difficult to suffer losses at the same time in all of their positions. However Shleifer makes a notice on the severe consequences of extreme situations where panic dominate all market participants, insiders and outsiders (fund managers, money owners, creditors and even more arbitrageurs themselves). Creditors' (in other words financial institutions) reaction is the most prevailing of all as they are the most cautious players in the market. Arbitrageurs who are scarce of money in defending their strategy they end up to banks lending sums of money using as collaterals stocks they have in their possession. Bankers follow closely the market and if the collaterals value falls then they proceed in ruthless liquidation of the collaterals in order to safeguard their credit risk. Sometimes even moral hazard problems may arise known as front running. This kind of danger has not been measured or quantified but experience from the market reveal evidences of these actions. Front running means that creditors who are aware of the arbitrageurs' portfolio and do not trust the arbitrageurs ability, may proceed in excessive short-selling of the particular set of stocks forcing these stocks prices downwards and decreasing eventually the value of the collaterals. The second drawback that Shleifer presents in havoc times is that when liquidation of the position is demanded, there are spillover effects across multiple markets as arbitrageurs prefer to liquidate stocks from a market different from their native one or from markets where restrictions are looser.

The last strong argument in favour of performance based arbitrage is that some arbitrageurs especially the most experienced ones with long and successful track from the one hand have access to funds irrelevantly of their prior performance and from the other hand they have gain investors' trust over the years. Even so, in order arbitrage by experience professionals to be successful the needed capital is huge and most arbitrageurs specialize in specific markets and lack experience from multiple markets. This is particularly important when the liquidation phenomenon takes a widespread twist.

Shleifer concludes that arbitrage may be a correction mechanism that is theoretically able to lead financial market to efficiency but not solely under the assumptions of lag counter-reaction by capital owners, arbitrageurs diversification or unlimited access to fund raising by arbitrageurs. Governmental authorities' interventions are necessary particularly in crisis times, where central banks or other institutions become the lender of the last resort as he characteristically mentions. They step in, when situations are out of control and succeed in stopping the chain of liquidations. Similar studies on this topic have been conducted by Bagehot (1872) and Kindleberger (1978). This is consistent with the long-standing issue that was raised from the United States Big Crash, where uncontrolled capitalism without the proper official authoritative involvement, the crisis was enhanced and unavoidable. Markets' efficiency is not a chimera but a result of an artificial and multiple, counter-active process. The question is whether it is a long-standing one or instantly achieved equilibrium.

2.4 Behavioral Based Theories

Researchers in their effort to model and interpret investors' behaviour and the irrationalities that appear in capital markets, they developed theories based on cognitive psychology; Cognitive psychology describes the way people understand and interpret various events. All these theories try to model the interaction of two contradicting groups in financial markets, sophisticated investors and the so called naïve investors. Investor's sentiment (and how it leads investors to biased judgements, exhibiting some times overreaction and other times underreaction) is the centre of attention in these behavioral theories and what separates them from the rational based ones. Study of those models reveals overall that investors place their resorts based on funds' past performance.

2.4.1 Barberis, Shleifer and Vishny (1998)

The first one presented as belongs to Barberis *et al.* (1998) (hereafter as BSV). They constructed a model concerning the way investors form their beliefs based on conservatism, representativeness and how the importance or not of an event, affect decision makers. Moreover they use elements of accounting in their effort to explain the stocks' trend after corporate earnings announcements.

They assumed that:

1. There is only one security that pays all earnings as dividends. The earnings of a company follow a random walk. Equilibrium price is the net present value of the future earnings that an investor forecast.

2. There is only one representative risk-neutral non-rational investor with a constant discount rate. An investor who does not realize that earnings follow a random walk.
3. There are two regimes in investors' mind concerning the future course of the company's earnings. These two states of mind succeed one another. The first regime supposes mean-reverting earnings and the second one assumes trending earnings.

Analysts and Investors find difficulty in interpreting properly all the provided information. They are ambivalent between the two earning regimes. According to the first one they think investors are more conservative (Edwards (1968)) and it is more likely to follow the anchoring and adjustment heuristic. Therefore they more prejudice to adjust their forecasts in the light of new information, especially if they contradict to their prior beliefs. Finally they will do it but in a smaller magnitude than the true normative rational Bayesian value. Market participants tend to overweigh base rate information and consequently stock prices underreact to earnings announcements.

First Regime

	$y_{t+1} = y^1$	$y_{t+1} = -y$
$y_t = y$	π_L	$1-\pi_L$
$y_t = -y$	$1-\pi_L$	π_L

y_t is the earnings shock at time t which can take two values +y and -y

Where $0< \pi_L<0.5$. The former table denotes that a positive earnings shock in investors' mind is more likely to reverse despite the equal probability a positive and a negative consecutive shock has.

In the second regime (continuation mind set) investors believe that earnings will continue their upward trend and presumably with more intense growth rhythms. This part of the theory has its foundations on the experimental work of Tversky and Kahneman (1974) who observed that people are usually carried away from the beliefs of their peers. They feel more secure when they act in a representative way and underreacting or overreacting in a similar way to new information. When a company has a string of positive earnings returns, investors attribute to that firm special features and believe that this growth will continue, overweighing information about past growth rates.

Second Regime

	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_H	$1-\pi_H$
$y_t = -y$	$1-\pi_H$	π_H

Where $0.5 < \pi_H < 1$, meaning that a positive earnings-shock, in investors mindset, is more likely to be followed by subsequent positive shock.

According to BSV theory analysts assume that the Markov switching regime is valid and therefore they behave likewise. When S_t takes value 1 then they assume that earnings shock is perceived to be generated by the first regime. When S_t takes value 2 then they assume that earnings shock is perceived to be generated by the second regime. λ_1 and λ_2 are the transition probabilities from one state of investors mind to the other which are small and $\lambda_1 < \lambda_2$ (indicating regime 1 more likely than regime 2).

Regime Switching Model

	$s_{t+1} = 1$	$s_{t+1} = 2$
$s_t = 1$	$1-\lambda_1$	λ_1
$s_t = 2$	λ_2	$1-\lambda_2$

Market participants have to decide which regime rules the current earnings pattern. They base their estimation on past series of earnings and use the transition probabilities to forecast next period's earnings. λ_1 and λ_2 remain constant.

The price of the security in this regime-switching model is

$$P_t = \frac{N_t}{\delta} + y_t(p_1 - p_2 q_t)$$

p_1 and p_2 are the constants that depend on π_H, π_L, λ_1 and λ_2 . The first term in the equation is the stock's fundamental value (the price when investor uses random walk process to forecast earnings changes). The second term is the sentiment indicator which affects the actual price level from the fundamental value of the security. If the representative investor underreacts to positive earnings shock, because this information is contradicting to his mind set, then the price of the security will lay below its fundamental value (depending on the sign of the earnings shock), which means that the investor sentiment factor is negative $p_1 < p_2 q_t$. If now investor overreacts to a positive shock then security price will be higher of its fundamental value. $p_1 > p_2 q_t$. The aim of this model would be to present the learning process of the time-series course after earnings shocks. This means that the majority of the investors fail to identify the permanent nature of this price changes and hence they react with a lag. Only after a series of contradicting to their beliefs new information, analysts and investors alter their views and forecasts. The feeling of regret for not having reacted otherwise makes investors to exaggerate on the other way in order to make things up, leading them inevitable in overreacting practices. Barberis *et al.* (1998) calculate the difference in returns of two portfolios on positive and negative earnings changes for a performance period of one year. The results of their simulation reveal the pattern that we just described a post-announcement drift and long-term reversals.

Brav and Heaton (2002) make argue that BSV model does succeed in capturing both representativeness heuristic and conservatism but they also make a very striking note which has not been denied by the authors of the model that BSV model is fully Bayesian and its mathematical structure is, in formal sense, consistent with rational information processing. An input of a random pattern of earnings changes leads to the generation of non-random pattern of stock return. The BSV model has also been examined by Nyarko much earlier in 1991. He examined the monopolist's problem of learning a demand curve when the true parameters of the demand curve lie outside the support of his prior distribution. He shows that monopolist would cycle indefinitely between two erroneous models that come closest to the true model, which by assumption he can never learn. However, Nyarko (1991) adopts a completely rational interpretation of his model. BSV and Nyarko approaches the structural uncertainty that both models indirectly include and how these common features could be used in order to find out whether actually there are normative difference between the two competing theories.

2.4.2 Daniel, Hirshleifer and Subrahmanyam (1998)

The second theory that has been developed on psychological factors was issued by Daniel *et al.* (1998) (henceforth DHS). They tried to embody in a theoretical model the pattern of the short-term trend of stocks returns and of long-term returns reversal. DHS focus on investors' reaction towards public and private information, driven by overconfidence on their abilities and the fluctuations of their confidence level which are determined by self-attribution. The main characteristic of an overconfident investor or analyst is that he attributes high significance to the precision of the unpublished estimation he possess (especially if he has personally contributed in the derivation of it) and at the same time underestimates information coming from public sources and which are widely then known. This is happening because they think of themselves more adequate and capable in evaluating the true value of a stock (Greenwald (1980), Cooper et al (1988), Taylor and Brown (1988)).

As long as the incoming information verifies their privately produced forecasts he becomes even more confident about them. The successfulness of these predictions leads him to self-attribution bias. A consequence of this bias is to promote boldly his estimations to their clients and encourage the overinvestment on the particular stock, leading to a temporary increase for the stocks' price. However when the news from the market (public information) start dominates their initial speculations (private information) then analysts is forced to revaluate their views and a correction phase is underway. According to DHS this is why stocks do present an upward trend after the publication of their earnings which then reverses when the fact disapprove their primary estimates. DHS differs from BSV in the fact that overreaction happens first and this is what leads to mispricing (especially momentum) and underreaction shows up in the correction phase.

2.4.3 Hong and Stein (1999)

The last theory was postulated by Hong and Stein (1999). Contrary to the previous researchers they haven't relied to theories coming from psychology but they focus on the behaviour and the interaction of two heterogeneous groups of investors, who they assume to be partly rational. Starting from these hypotheses they provide a plausible explanation of the short-term stocks' overreaction and the long-term returns reversal, stocks present on the way back to their fundamental value. Both groups have a partial knowledge of the available bulk of information concerning a stock. The first one has access to the publicly available information; they formulate their own conclusions and personal projections relative to a stock's fundamental value. They name them as Newswatchers. The second group that participates into the market they are solely based on historical data of the stocks' price and they try through technical analysis and the use of charts to make an accurate forecast about the stocks' future course. Therefore Newstraders trade based on information that slowly diffuses in the market and consequently to them, while momentum traders make their deals by using simple overreaction rules of the existing stocks' trend. As a result Newswatchers delay in taking advantage of information relative to the stocks fundamental value and this is something that technical analysts take up by watching the stocks' trend. The strategy that the later group uses leads to securities price overreaction even for medium time intervals. This anomaly is later inverted when fundamentalists come into the game.

Hong and Stein hypothesize that the diffusion speed of the information into the market, concerning a stock, is linearly related to the number of analyst who cover the particular company and the degree of publicity that company's news has attracted. According to their estimation momentum effect is much more intense for small capitalization stocks. The importance of journalists' coverage of a firm is also denoted by Shefrin in his book *Beyond Greed and Fear*, where he reaches the same conclusion as Hong and Stein.

2.5 Empirical Studies on Return Reversals

Up to this point we have presented the theoretical framework on which Behavioral Finance was constructed and expanded for the last 15 years. According to the Kuhnian approach an established theory is under revision when new empirical findings come into light contrasting the proposition of the official perspective. Studies that were indicating results departing form the originally postulated Efficient Market Hypothesis existed since the appearance of the latter theory. However they were only speculating about the causes of the non-rational behaviour of the market. Boudoukh *et al.* (1994) supports the view that the two main important pieces of evidence which provide strong support that stock returns are predictable (especially short-horizon ones) are that portfolio returns exhibit significant autocorrelation and secondly the fact that returns are highly cross-serially correlated. The vast literature over the last twenty years has been evolved trying to attribute these correlations as phenomena that could be endorsed in a broader sense of market efficiency or as indications doubting the monopoly of the EMH validity and pointing towards the creation of a new economic paradigm. Studies supporting the later tried to induce elements of other sciences (such as psychology) into the obsolete since then hypothetical and numerical based financial theory, advocates of which had deliberately excluded human factor for the underlying process of asset pricing.

We will outline the main researches that have tried to explain the verified indications of asset returns reversals through typical repetitive human behaviours that have been characterized as non-rational by the traditional financial theories. By using the word human we mean the markets participants such as analysts or/and investors whose irrational behaviour could be summarized as overreaction or underreaction to certain information or situations. The first study that made a step further and tried to trace and establish a connection between observed financial phenomena and psychology came from De Bondt and Thaler in 1985 which for the first time introduced the term of Overreaction Hypothesis.

2.5.1 Overreaction Effect

(a) Long-term overreaction

Empirical evidence of predictability of aggregate index returns over long horizons was conducted by Fama and French (1988), Poterba and Summers (1988) and Cutler *et al.* (1991) for a variety of markets. The majority of the evidence revealed that over three to five years as investment horizons, stock returns exhibit slight negative autocorrelation. The most convincing evidence comes from the cross-sectional examination of stock returns. Particularly De Bondt and Thaler (1985) explored the profitability a simple investment strategy on stocks traded from the New York Stock Exchange between 1926 and 1982. Their effort was motivated by the paper of Kahneman and Tversky (1974) in the field of cognitive psychology and focused on intuitive forecasts according to the course of the stock prices. This strategy was inspired by the belief that investor do not interpret Bay's law in the proper way when they have to make a decision. In problems of reviewing probabilities in the light of new information people tend to overreact or underreact to them. When they overreact, they do so because they overestimate recent unexpected information and underestimate data they used as a reference point for their future forecasts (such as historical data or else base rate). The opposite happens when they underreact.

Their research focuses on the fact that investors' behaviour could affect stocks' prices. De Bondt and Thaler assumed that investors tend to be overconfident for the stocks that had a recent good record (named as winners) and at the same time they are overly pessimistic towards stocks that had negative past returns for a time interval of 3 to 5 years. The study of these two different portfolios showed that the extreme 'losers' portfolio received over the following years systematically excess returns in contrast to the opposite extreme 'winners' portfolio. They proved that forming zero money arbitrage portfolios by selling short past winners and taking a long position in past losers, investors could earn within the next three years returns up to 24,6%. If this phenomenon is valid then the investors' overreaction lasts for long periods of time and the efficient market hypothesis especially in its weak form is rejected in the sense that we can use historical data (here past performance) in order to achieve excess returns. However stock prices overreaction or stocks returns reversal was not only documented for long-term periods but for shorter time intervals as well.

(b) Short-term Overreaction

Evidence that individual stock returns exhibit negative serial correlation has been well known for almost 30 years (Fama (1965), Cootner (1964), Lo and MacKinlay (1988) however without making further suggestion of exploiting these patterns by using contrarian strategies). Rosenberg and Rudd (1982), Rosenberg *et al.* (1985), Lehman (1990) and Bremer and Sweeney (1987) found evidence of overreaction in short-term price movements (one day for Bremer and Sweeny, one week for Lehman, and one month in Rosenberg and Rudd, and Rosenberg *et al*). But only recently these short-term return reversals have been considered as economically important. Empirical studies indicating that short-horizon contrarian strategies consistently make substantial profits where conducted by Jegadeesh (1990) and Lehman (1990). Jegadeesh documented profits of 2% per month from a contrarian strategy that buys and sells stocks based on their prior month returns and a holding period of one month. Lehman (1990) followed similar strategy but for shorter time intervals. He used weekly portfolio formation and holding periods generating profits in every six month period in his sample.

2.5.2 Explanations for Return Reversals

The autocorrelation and cross-serial correlations are large and statistically significant. The debatable issue among financial researchers is the economic interpretation of these correlations and the exact causality of their existence. Throughout the years there have been established three schools of thought: Loyalists, Revisionists and Heretics

(Boudoukh *et al.* (1994)). Loyalists accept stock markets efficiency and attribute large autocorrelations and stock returns predictability to data mis-measurement (non-synchronous trading Cohen *et al.* (1986), Lo and MacKinlay (1990b)), price discreteness or bid-ask spread (Conrad *et al.* (1997)) or market imperfections (thin trading, Bessembinder and Hertzel (1993), or transaction costs Keim (1989)). Revisionists believe that markets are efficient (they are similar to loyalists). However they believe that even in frictionless markets, short-horizon stock returns can be autocorrelated. Specifically their view is that correlation patterns are consistent with time-varying economic risk premiums. Changing risk premiums can be explained by intertemporal asset pricing models, such as conditional versions of the arbitrage pricing theory or the consumption based asset pricing model. That is, variation in risk factors, such as past market returns, past size returns, or interest rate spreads, can induce variation in short-horizon risk premium (Keim and Stambaugh (1986) and Lo and MacKinlay (1997) for monthly returns using linear factor models; see Conrad and Kaul (1989) for weekly returns in univariate settings; and for an analysis of weekly returns in a multivariate framework, see (Conrad *et al.* (1991) and Hameed (1997)). Heretics argue that markets are not rational, that profitable trading strategies do exist (even on a risk-adjusted basis) and that psychological factors are important for pricing securities. According to their view, time series patterns in returns occur because investors either overreact or only partially adjust to information arriving to the market. Thus, for "astute" investors, excess profits can exist even if financial markets are well functioning.

We are going to present the various sources of return reversals individually, without following the pattern of schools of thought segmentation. The reason is that the following sources have been examined and contemporaneously have been used as possible partial explanation of the reversal phenomenon by more than one school of thought and the meaning they attributed on them may, each time, be slightly different.

(a) Data-Snooping Bias

First, empirical patterns in stock returns might be a simple consequence of data-snooping bias. In fact, the ability to process an enormous amount of financial data might reveal just by chance some significant patterns among the large number of possible trading strategies tested. Detection of this bias can be done by testing whether in-sample returns predictability persists in out-of-sample experiments. However, there have been voluminous findings in favour of this winner-loser effect across all financial markets, developed or emerging and for various sample periods. Confirmation of the contrarian effect can be found in the United Kingdom (among others; Campbell and Limmack (1997); Nagel (2001)), France (Mai (1995)), and Spain (Alonso and Rubio (1990)). Also Chang *et al.* (1995) for Japan; Hameed and Ting (2000) for Malaysia; Kang *et al.* (2002) for China; Bowman and Iverson (1998) for New Zealand, Schiereck *et al.* (1999) for Germany, Mun *et al.* (2000) for US versus Canada, Antoniou et al. (2005) for Greece.

Moreover Poterba and Summers (1988) in a study of 15 markets, they find long-term negative serial correlation consistent with contrarian strategies for the UK. Baytas and Cakici (1999) find abnormal profits of long-term contrarian strategies in the stock markets of seven non-US industrialized countries. Stock (1990) found evidence of long-term overreaction in Germany and Dissanaike (1997) in UK; and Kato (1990), using De Bondt and Thaler methodology, showed that in Japan most of the overreaction occurs in the winner portfolio. Dissanaike (1997) employs long-term contrarian strategies adjusted for risk and finds that not only past losers outperform past winners, but that they are also less risky. Brouwer *et al.* (1997) test value strategies in connection to the overreaction hypothesis for the UK, France and Germany and find that past losers (based on several accounting ratios) outperform past winners form longer-run strategies. Richards (1997) unveils long-run overreaction profits that are not due to risk or anomalies using data on 16 markets. Balvers *et al.* (2000) tested for long-term contrarian strategies in 18 markets with results that are positive for mean reversion and consistent with the overreaction hypothesis.

All these studies reveal the undeniable existence of the phenomenon of either short-term or long-term return reversals phenomenon not as a result of pure luck bias or intentionally transformed available data (data-mining) but because something had not been taken under consideration even if this could be time-series properties, investors' sentiments, risk-based factors, financial markets' structure and/or frictions.

(b) Lead-Lag Effect

Many researchers have been puzzled over the lead-lag effect on cross-autocorrelations as an important component of stock return dynamics Another important study concerning short-term contrarian profits that took place at the same time period as to Jegadeesh's and

Lehman's articles was carried out by Lo and Mackinlay (1990). They examined US weekly stock prices. According to them contrarian profits could be achieved by both overreaction and underreaction (or else described as delayed reaction) of prices to information. In order to support this theoretical statement and to analyse the importance of various sources of contrarian profits they examined the returns of a portfolio with weights inversely proportional to each stock's past returns less the return on the equally weighted index. This portfolio had the property that its expected profits could be easily decomposed into three components (the dispersion of the expected returns, serial covariance of returns and cross-serial covariance of returns). By using the last one they measured the contribution of the lead-lag structure to contrarian profits. The lead-lag effect exists when some stocks react more quickly to information (leading stocks) than others (lagging stocks). The pattern of cross-serial covariance documented by Lo and Mackinlay implied a size-dependent lead-lag structure. They found large positive covariance between the returns of small stocks and lagged large stocks returns, but virtually no correlation between returns of large stocks and lagged small stock returns. Based on those evidences Lo and Mackinlay concluded that ''a systematic lead-lag relationship among returns of size-sorted portfolios is an important source of contrarian profits''. They further argued that ''less than 50% of the profit from a contrarian investment rule may be attributed to overreaction''. In other words Lo and MacKinlay supported that contrarian profits come mainly from some stocks that react quicker to information than others. A number of empirical studies have established that lead/lag relationships can occur across portfolios, particularly when formed on a size-related basis. That is, portfolios comprising large market capitalization stocks tend to lead the corresponding small market capitalization portfolios (Campbell *et al.* (1997)). The statistical size and significance of this effect seems that it has been accepted by the majority of the authors.

Treating nonsynchronous data as if they are observed at the same time can create false autocorrelation. As a result apparent lead–lag effects may exist among securities even though this is purely an artefact of the manner in which returns are measured. If we consider that we have two stocks (A and B for example), where the returns of each one will be given by the following linear relationship: $r_{it} = \mu_i + \beta_i f_t + \varepsilon_{it}$ where f_t is the common market news component and ε_{it} is the firm-specific component, then if we assume that ε_{At} and ε_{Bt} are independent and stock A trades more frequently than stock B, the implication will be under these two assumptions that common news will generally influence r_{At} prior to r_{Bt}, meaning that r_{At} will lead r_{Bt}.

Jegadeesh and Titman (1995b) however, argue that the lead–lag structure arises from investors' delayed reaction to common factors. They show that the main source of contrarian profits is not the lead–lag structure but the overreaction to firm-specific information. Campbell *et al.* (1997) conclude that ". . . the recent empirical evidence provides little support for non-trading as an important source of spurious correlation in the returns of common stock over daily and long frequencies" (p. 134). Furthermore Lo and MacKinlay (1990) also show that attributing all of the observed cross-autocorrelations to nonsynchronous trading would require unrealistically thin markets even after allowing for extreme heterogeneity in nontrading probability and beta. Furthermore, Mech (1993) and McQueen *et al.* (1996) test the nonsynchronous trading hypothesis using return series that have been adjusted for non-trading, and conclude that only a small portion of the observed cross-autocorrelations can be attributed to nonsynchronous trading. Kadlec and Patterson (1999) study the nontrading problem by sampling stock returns from transaction data where the actual trade times can be obtained. They estimate that the proportion of autocorrelation (and cross-autocorrelation) due to nonsynchronous trading is roughly 25 percent.

Poshakwale and Theobald (2004) address this issue by modelling the extend to which prices under or over-react relative to their intrinsic values using a partial-adjustment with noise model (Amihud and Mendelson (1987)). By modelling both the thin trading and the partial adjustment processes they are able to establish the extent to which cross-correlations derive from partial adjustments and the extent to which they derive from thin trading. Since the speed of adjustment and thin trading effects are distinct phenomena with differing implications it is important to be able to distinguish between them. Using a number of Indian equity index series that differ in their market capitalization characteristics, they found out that large cap indices lead small cap indices and to have higher speeds of adjustment towards intrinsic values. More precisely thin trading effects alone contribute significantly to the lead/lag effects; however, a mixed adjustment/thin trading effect contributes between 34% and 55% of this lead/lag effect, depending upon the index series and estimates used. Thus, the thin trading effect is a strong contributory factor to the large cap/small cap lead-lag relationship in the Indian market in contrast to the situation in the US as summarised in Campbell *et al*. (1997).

Other potential sources that can give rise to lead-lag patterns across stocks are the differences in the level of time variation of expected returns. (Conrad and Kaul (1988,1989), Conrad *et al.* (1991), Boudoukh *et al.* (1994) and Hameed (1997)). It has been argued that asymmetric cross-autocorrelations can be better explained by portfolio autocorrelations coupled with high contemporaneous correlations across portfolios. Hou (2007) found that lagged returns on big firms can reliably predict current returns on small firms above and beyond the predictive power of lagged returns on small firms. To his concern it seems unlikely that time-varying expected returns can fully explain the lead-lag effect but one could argue that he examined the effect for stocks within however the same industry.

A third reason responsible for the creation of the lead-lag effect is the slow diffusion of information (Lo and MacKinlay (1990) and Chordia and Swaminathan (2000)). The economic forces of the slow information diffusion in the equity market could be information costs, noise traders, transactions costs, asymmetric information, short-sales restrictions and other market frictions and institutional constraints. Merton (1987) is among the first to recognize the importance of information costs and institutional restrictions in the information acquisition and dissemination process. Extending the work of Kyle (1985), Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) demonstrate that the presence of more informed investors leads to faster stock price adjustment to new information. This is directly related to the number of analysts following the specific firm (Brennan *et al.* (1993)).

Diamond and Verrecchia (1987) argue that short sale constraints can slow down the response of stock prices to new information, especially when the information is negative. Mech (1993) shows that stock prices respond to new information more rapidly when price changes are large relative to the bid-ask spread. Chan (1993) presents an incomplete information model in which cross-sectional differences in the signal quality can give rise to asymmetric cross-autocorrelations. Badrinath *et al.* (1995) develop a multi-period model in which the information set-up cost and/or prudence restrictions (as postulated by Merton (1987)) lead to a lead-lag relation between institutionally "favored" firms and "unfavored" firms. Finally, Peng and Xiong (2002) constructs a learning model in which incomplete information, in the form of an information capacity constraint faced by the representative investor, causes a delay in the price adjustment process.

(c) Market Microstructure Effects

The term market microstructure effect incorporates three phenomena widely examined in the financial literature. These are Bid-Ask bounce, non-synchronous trading and illiquidity or non-trading. Ball *et al.* (1995) argue that a large part of the contrarian strategies' profitability is driven by microstructure-induced biases. One of the first counterarguments of the efficient market advocate's camp is that most of the observed contrarian profits coming from price return reversals are not due to the market's overreaction to new information (negative auto-covariance of the individual securities of the contrarian portfolio) but coming from the positive auto-covariance of the equal-weighted return of all the securities in the contrarian portfolio. Moreover measurement errors such as bid-ask bounce play a significant role in the generation of abnormal contrarian profits. Accounting for this bounce by using bid prices instead of documented transaction prices eliminates all profits from price reversals.

Kaul and Nimalendran (1990) provided evidence for a NASDAQ sample that suggests that bid-ask errors account for a large proportion of daily return variances and may be the most important source of price reversals in daily data. On the other hand, Park (1995) used an "event study" methodology and found that short-run abnormal returns to NASDAQ stocks after large positive/negative price changes cannot be completely explained by the bid-ask effect. Conrad *et al.* (1997) applied contrarian strategies to weekly transaction returns of both NASDAQ from 1985-1989 and NYSE/AMEX stocks from 1990-1991) excluding all small and infrequently traded securities from the NASDAQ index. They yield positive expected profits. However, they postulate that all transaction prices used in all previous studies contained measurement errors. The consequence of the measurement errors is that calculated returns will be negatively autocorrelated at least at lag 1, even if true returns are serially uncorrelated. One important source of measurement errors in transaction prices and therefore transaction returns is the bid-ask spread. They then directly demonstrate the importance of market microstructure effects, especially Bid-Ask bounce, for the profitability of contrarian portfolios by computing the profits using bid returns that do not contain bid-ask errors. Although the sample was rather narrow due to availability constraints, they managed to show that all the documented profitability due to price return reversals for NASDAQ firms indeed emanated from the bid-ask bounce. They denote that the price reversals in the transaction-returns sample are the largest in magnitude for the smallest in size firms of the sample. The specific profits fell to about 25% of their magnitude when bid returns are used. The connection between Bid-Ask bounce effect and the abnormal portfolio returns was also partially true for the NYSE/AMEX sample. Finally low levels of stock transaction costs (less than 0.20%) eliminated all profits from the discussed stock return pattern even for large institutional investors. Conrad *et al.* (1994) and Jegadeesh and Titman (1995a) have shown that by using returns based on either bid or ask quotes (or any combination of the two), their sample would be free of measurement errors due to bid-ask bounce. Lo and Coggins (2006) in an attempt to minimize the effect of bid-ask bounce, they decide to use the mid-spread price between bid and ask for their analysis.

Another important source of measurement error could be infrequent trading. According to Miller *et al.* (1994) there are two forms of infrequent trading: non-synchronous trading and nontrading. Lo and Mackinlay (1990) support the view that nonsynchronous trading could be generated when stock prices are incorrectly assumed to be sampled simultaneously. The notion of the nonsynchronous trading or thin trading is that although prices are often recorded at regular intervals, actually they do not trade at the same time. The implications are the appearance of cross-correlations between stock returns or serial correlation in portfolio returns and possible negative serial correlation in individual returns. In contrast, non-trading occurs when stocks do not trade in every consecutive interval. Ferson *et al.* (1993) document that incidents of non-trading may upwardly bias contrarian profits. For short trading intervals such as daily and hourly, the problem of non-synchronous trading is minimal. However, as the trading interval shrinks non-synchronous trading gives way to the problem of non-trading. In many papers the problem of non-trading and non-synchronous trading can be substantially minimized by concentrating the analysis on the large-capitalization and most traded securities, a methodology which in turn can be heavily question for excluding a large number of the markets' stocks.

(d) Trading Volume

Numerous studies have examined whether incorporating other information such as trading volume can help improve the profitability of purely returns-based contrarian strategies. Their aim is mainly to investigate whether liquidity pressure can help explain the reversal and overreaction effects and whether it can be used as a contrarian trading signal. Blume *et al.* (1994) present a model where traders can profit from using volume information in addition to historical price information in making projections about future price changes, suggesting an information signalling role of volume in return predictability. Conrad *et al.* (1994) find price reversals for heavily traded securities and price continuation for low volume securities, suggesting a significant relationship between lagged volume and the current returns of securities. However, there is an objection concerning Conrad *et al*'s methodology. They do not distinguish between high- and low- volume securities, but they classify a security into the high-volume or low volume group if the security's trading volume is higher or lower than its historical average respectively. Therefore it is highly probable that a security can be falsely classified into a thinly or heavily traded group relative to other securities in the market.

Campbell *et al.* (1993) argue that volume information may help to distinguish between price movements that are due to public information and those that reflect changes in expected returns. In their model risk-averse utility maximizers might act as market makers who must be compensated for offsetting the fluctuation demands of liquidity or non-informational trades and price changes accompanied by high volume will tend to be reversed, this will be less true of price changes on days with low volume (Campbell *et al* 1993 p. 906). The notion of this statement is that investors, who take offsetting positions in order to counteract the selling pressure induced by contra-traders in the event of a price decline, require compensation and therefore higher expected returns. This leads to a price reversal after a price decline (consistent results where provided by Hammed and Ting (2000) for emerging markets). Jegadeesh and Titman (1995a) assumed that return reversals may be caused by price pressure generated by liquidity motivated trades. They also expect that the profitability of contrarian strategies could decline over time as the liquidity in a market gradually improves. Henceforth as a possible rationalization was that the markets in which this phenomenon took place lack sufficient liquidity which could offset short-term price swings caused by unexpected buying and selling pressure (Grossman and Miller (1988)).

Both Blume *et al* (1994) and Campbell *et al* (1993) conjecture that the relation between past volume and concurrent prices is more pronounced for smaller and less widely followed firms. Tkac (1999) provides a theoretical rebalancing of the portfolios' benchmark for trading volume that connects trading activity of individual stocks to that of the market. Based on the two-fund theorem, she shows that volume measures that distinguish between normal and abnormal volume provide good proxies for information trading. Hameed and Ting (2000) uncover a distinctive positive relationship between contrarian profits and the level of trading activity in the securities. Particularly they postulate that contrarian strategy generated significantly higher profits for the heavily and frequently traded securities rather than that generated from the low trading activity securities. This is consistent with Conrad *et al* (1994) findings. Lee *et al.* (2003), however, provided a totally contradicting outcome for the Australian Stocks Market. By using three volume sorted portfolios (low, medium and high) they present for the combined equal-weighted price portfolios significant positive short-term contrarian profits. Particularly low and medium volume portfolios provide significantly higher (at the 5% level) short-term contrarian profits when compared to the high volume portfolio. The possible explanation that different stock markets were each time analysed in these studies (New Zealand for Hameed and Ting (2000), US for Conrad *et al* (1994) and Australian for Lee *et al* (2003)) is not very persuasive as they are not that dissimilar. Lee's *et al* explanation is that although small firms achieve higher returns (small firm effect) they may face lower trading volume levels when compared with larger firms, because small firms tend to be researched, monitored and traded to a far less extent than larger firms. This concept is consistent to Brennan *et al.* (1993) study, where they argue that the size of a firm increases as the number of analysts researching a firm does also and as a final consequence would be the increased speed with which prices adjust to new information. Lee *et al* (2003) therefore provide support to this volume/small firm hypothesis.

In most papers that try to unveil a relationship between trading activity and stock returns, trading activity is usually measured as volume. However there are other ways of measuring trading activity. Wang (1994) relates volume to the degree of information asymmetry as formalized in the framework of an informed/uninformed traders' model. An alternative measure of net liquidity demand or imbalance would be the net order flow. One measure of net order flow is the difference between buyer and seller initiated volumes. Order flow conveys information beyond trading volume Chordia *et al.* (2002) suggest that order flow imbalance (otherwise a change in demand or supply) may sometimes reveal private information. Lo and Coggins (2006) also argue a degree of return reversal is positively related to order flow imbalance. Their findings result that market overreaction can be caused by temporal liquidity imbalance. Moreover lack of liquidity may force prices to overshoot as it generates a type of limited arbitrage. That seems to disappear as liquidity imbalance gradually dissipates. Their research reveals some sort of linear connection between profitability of contrarian strategies and the level of order flow imbalance of individual securities. However we have to emphasize that the denoted contrarian profits were easily wiped out by merely levels of transaction costs.

Later articles attempted to study large price changes accompanied by news announcements. Larson and Madura (2003) found no overreaction in response to informed events such as news announcements cited in the Wall Street Journal, but there is overreaction in response to uninformed events that are not explained in the newspaper. Pritamani and Singal (2001) also stated large price changes on both trading volume and public announcement.

In an article quite different from the line of the previous, Cooper (1999) tried to explore predictability of stock returns and principally stock returns reversals for the large-capitalization NYSE and AMEX securities by using filter rules on lagged returns and lagged volume information for his portfolio formation method. He managed to uncover the existence of weekly large statistically significant overreaction profits during the 1962-1993 period. He found that decreasing-volume stocks experience greater reversals, whereas high-growth-in-volume stocks exhibit weaker reversals and positive autocorrelation, supporting Wang's (1994) model, where he stated that when informed investors condition their trades on private information, then high future returns (indicating price continuations) are expected when high returns are accompanied by high trading volume. Furthermore he conducted out-of-sample forecasting experiments by using real-time simulation of the filter rules. His finding are in consistence with the in-sample showing that an active investor with relatively low transaction costs would strongly outperform an investor who follows a passive buy and hold strategy.

(e) Transaction Costs

Trading costs have a dual role in explaining the appearance of excess returns on contrarian and momentum strategies. First of all transaction costs may prohibit arbitrageurs or otherwise called informed investors to trade against those who overshoot stock prices and bring stock prices back to their fundamental levels by proceeding in the appropriate short-selling of the mis-valued stocks. Secondly in most studies transaction costs are not included concerning the evaluation of the actual returns taken from a strategy, because sometimes they have not been recorded or even if they are available they may be cumbersome to use and expensive to purchase as investors do not always face the same costs depending on the broker company or the privileges an investor (institutional or individual one) might have. Therefore the reduction or the inclusion of transaction costs in a research is of utmost importance issue for the validity of all the studies concerning market efficiency or the domination of irrational market participants.

There are several components of trading costs that differ dramatically in size and ease of measurement. Trading costs of commissions and bid/ask spreads are components that can be measured with the least error. When an institutional investor trades proportional costs of commission and bid/ask spread can be swamped away by the additional non-proportional costs of price impact of an institution trading over a stock's price and by the other hidden costs of post-trade adverse price movement (Treynor (1994)). Transaction costs as it was expected increase as the size of an order increase. Schultz (1983) and Stoll and Whaley (1983) investigate the effect of commissions and spreads on size-based trading strategies. Ball, Kothari and Shanken (1995) showed that trading costs component such as bid-ask spreads significantly reduce the profitability of contrarian strategy. Mitchell and Pulvino (2001) incorporate commissions and price impact into a merger arbitrage portfolio strategy. They found that trading costs reduce the profits of the strategy by 300 basis points per year. Kato and Loewenstein (1995) argued about the scarcity of transaction costs estimates outside the United States. Karpoff and Walkling (1988) and Bhushan (1991) denote the difficulty in obtaining transaction costs for market efficiency tests that extend to long time periods before transaction cost data were collected. Both these studies used proxy variables of price, trading volume, firm size and the number of shares outstanding under the assumption that these variables are negatively related to transaction costs.

Lee *et al* (2003) state that when they employ a practical contrarian strategy that allows for short-selling and the inclusion of transaction costs, they find that the contrarian strategy does not, for any portfolio, record statistically significant profits. An interesting finding is that the most profitable small stock portfolio strategies (for all the pricing schemes) required lower levels of transaction costs to erode all profits. This is happening because the most profitable small portfolios would have experienced larger return reversals, which leads to larger expected profits and greater assigned stock weights and finally larger the number of stocks required to be bought or sold. Therefore the higher the levels of stocks bought or sold for the small stock portfolio strategies these portfolios would be more sensitive to transaction costs. However they postulate that contrarian approach has only limited value as a stand-alone strategy they underline that it may have important uses and benefits when employed as an overlay strategy to an existing portfolio strategy. Comerton-Forde *et al.* (2005) measure execution costs as the sum of temporary and permanent measures. Temporary measures the return between the post execution benchmark and the average traded price of the trade package, while permanent measures the return between the post and the pre-execution benchmark. Bikker *et al.* (2007) have also found average execution costs equal 27 basis points for buys and 38 basis points for sells, using data from worldwide trades. Bikker *et al*. (2004) define execution costs as the sum of price impact costs and commission. Lo and Coggins (2006) find that after taken into consideration transaction cost (given by Comerton-Forde *et al* (2005)) the small statistically significant contrarian profits, using daily and hourly returns, can not be exploited by economically even by institutions.

Lesmond *et al.* (1999) present a new model of estimating transaction costs which at first seems rather simple as it requires only the time series of daily security returns. It actually endogenously estimates the effective transaction costs no matter firm, exchange or time period. The feature of the data that is just necessary for the approximation of the transaction costs is the incidence of zero returns. Transaction cost-based model of security returns uses an LDV specification (Limited Depended Variable model of Tobin (1958)), incorporating zero returns in the return-generating process the model provides continuous estimates of average round-trip transaction costs from 1963 to 1990 that are 1.2% and 10.3% for large and small size companies, respectively. These estimates have an 85% correlation coefficient with the most commonly used estimate of transaction costs, spread plus commissions. The LDV estimates tend to be smaller, indicating that studies that use the spread plus commissions as estimates for transaction costs will overstate the effective trading costs by at least 15% for small firms and by as much 50% for large firms. Lesmond *et al.* (2004) research seems to be inconsistence to Petersen and Fialkowski (1994) who find the effective spread is a smaller spread that the quoted one.

The meaning of trading or execution costs analysis in both contrarian and momentum strategies (which are mainly trading intensive strategies especially for short time intervals) is vital for a very simple reason. If trading costs appear to eliminate any excess return profits in contrarian or momentum strategy then weak type of market efficiency holds and behavioural finance's up to now main empirical argument against EMH seems useless. This particularly important for momentum strategies where risk-premia based theories have not presented a plausible explanation for the asset's returns continuation effects.

(f) Investors' Overreaction to Firm Specific Information

Apart from the transaction costs rationalization, various explanations were presented in the effort to justify the existence of the short-term return reversals. Following the De Bondt and Thaler article in 1985 were the overreaction hypothesis were first stated, the most reasonable interpretation was that short-term contrarian profits were initially regarded as evidence that market prices tend to overreact to information, which would have important policy implications. Stiglitz (1989) and Summers and Summers (1989) supported the view that overreaction was caused by speculative trading and recommended methods by which the state can intervene and discourage short-term speculation. Mun *et al* (1999), as well as Bacmann and Dubois (1998) persisted on the fact that investor's overreaction on firm specific information is the primary reason behind the abnormal profits of short-term strategies. De Bondt and Thaler (1985, 1987) attribute overreaction to the psychological phenomenon of recency[9]. When processing information people tend to overweight recent information compared to their prior belief. Thus traders who are not sure of the intrinsic value of a stock will be optimistic about its value when the firm is winning and too pessimistic when the firm is loosing. Therefore recency may be considered responsible for at least a temporary wedge between stock prices and fair values. Similar results as to De Bondt and Thaler's were verified by Chopra *et al.* (1992).

Subsequently, academics drew their attention from the course of past returns to other measures of valuations, for which early studies have revealed evidence of return

[9] The recency effect, in psychology, is a cognitive bias that results from disproportionate salience of recent stimuli or observations. People tend to recall items that were at the end on a list rather than items that were in the middle on a list (http://en.wikipedia.org/wiki/Recency_effect).

predictability (mostly return continuation rather than reversal). These measures of valuations could be characterized as price scaled variables, such earnings-to-price, dividend-to-price, cash-flow-to-price, the book-to-market ratio and market capitalization. All these could be used to forecast future returns. For evidence on E/P, see Basu (1983), Jaffe *et al.* (1989). For B/M, see Statman (1980), Rosenberg *et al.* (1985), De Bondt and Thaler (1987), and Fama and French (1992). For C/P see Lakonishok *et al.* (1994) and Chan *et al.* (1991) provide evidence on C/P and other price-scaled variables in the US and Japan, respectively. The vast majority of the empirical work has drawn book-to-market ratio and firm size. Stocks with high book-to-market ratios have historically generated higher returns than stocks with low book-to-market ratios.

Lakonishok *et al* (1994) examined US stocks dated from 1968 up to 1990 and argued that stocks with very high valuations relative to their assets or earnings (growth or glamour stocks), which tend to be stocks of companies with extremely high earnings growth over the previous several years, earn relatively low risk-adjusted returns in the future, whereas stocks with low valuations (value stocks) earn relatively high returns. They argue that this is happening because markets are not efficient. Investors in their effort to forecast future earnings extrapolate firms' past earnings growths and as a result stock prices of firms with poor past earnings (will tend to have high B/M ratios) get pushed down. In other words investors fall for naïve trend extrapolation. Once the actual earnings are realized, investors reconcile their forecasts; prices recover, leading high B/M firms to higher returns. Lakonishok *et al* (1994) provide support for this extrapolation hypothesis by showing that a two-way sort on cash-flow/price and five-year sales growth produces more dispersion in average returns than other variables such as B/M. The sort on five-year sales growth classifies firms according to past performance and the sort on cash flow/price separates firms according to expected future performance. The extrapolation hypothesis poses that firms with low sales growth and high cash flow/price should have the highest returns, since the poor historical performance (measured by sales growth) is projected into the future (reflected by cash-flow/price). Henceforth, Lakonishok *et al* (1994) present evidence indicating an investors' systematic pattern of expectational errors, which seems suitable in explaining the differential stock returns across glamour and value stocks.

It may be tempting to think that overreaction is created by the misguided behaviour of a small group of noise traders. However, De Bondt and Thaler (1990), Bulkley and Harris (1997) and Amir and Ganzach (1998) present evidence that even the judgement of professional security analysts reflect systematic biases. De Bondt and Thaler were once again the first to observe that while most economists recognize that not everyone is fully rational, the existence of irrational agents in the stock market is often dismissed as irrelevant. They investigate security analysts as one possible source of irrationality in financial markets, and find that security analysts have a tendency to make forecasts that are too extreme, given the predictive value of the information available to the forecaster. In fact, forecasted changes are simply too extreme to be considered rational. They suggest the behavior of the security analyst community as one possible source of long-term overreaction in the equity markets.

La Porta (1996) used professional analysts' long-term earnings growth forecasts in order to sort a large number of US stocks. He concluded that analysts' forecasts were exceptionally bullish concerning stocks that were optimistic about and not the other hand they forecasted lowest growth rates for the stocks they were pessimist about. However future course of stocks' prices proved them wrong, indicating the element of overreaction not only from analysts but in price levels equally. These evidences clearly seemed to violate the Efficient Market Hypothesis in the semi-strong form. La Porta *et al.* (1997) proceeded in confirming overreaction indications in glamour and value stocks, after having used accounting variables in order to define stocks classification. The results revealed negative returns for glamour stocks on the day of earnings announcements and positive returns for value stocks. Hence announcement days expose valuations extremities by the market which later investors' try to minimize. The essence of this research is that earnings announcements seemed to be faced as unexpected surprises, something that should not be happening within the framework of a rational efficient capital market.

De Bondt and Thaler's research gave a rise to a broadening stream of academic inquiry that gives strong support to the premise of long-term overreaction in the stocks market to specific information events. Dreman and Berry (1995) examine the importance of earnings surprises within the context of contrarian investment strategies. They report that positive and negative earnings surprises affect "best" and "worst" stocks in an asymmetric manner that favours worst stocks. They demonstrate that stocks are not immediately priced at an appropriate level after an earnings surprise. Rather, over a prolonged period of time (at least five years), stock prices revert to the mean, with low-P/E stocks outperforming and the high-P/E stocks underperforming the market. This evidence is consistent with the overreaction hypotheses that investors misprice best and worst stocks because their expectations are too one-sided. An explanation to this finding could be that companies with low P/E tend to be undervalued because investors become excessively pessimist after a series of bad earnings reports or other relevant bad news. Once future earnings proved to move on the other side the investors' confidence is restored and the price adjust upwards. Companies with high P/E are considered to be overvalued before their prices adjust to lower levels. In other words prices once again systematically overshoot and their reversals should be predictable from their past return data alone.

Jegadeesh and Titman (1995b), opposed to Lo and Mackinlay's perspective, declared that return reversals are economically significant and deserve further attention. They examined separately the nature of price reactions to common factors and firm-specific information of NYSE and AMEX stocks. They found that stock prices react with a delay to common factors but overreact to firm-specific information. Theoretically these delayed reactions to common factors could give rise to the lead-lag effect in stock returns. Even if overreaction and underreaction could lead to the profitability of contrarian strategies, however their findings revealed that delayed reactions cannot be exploited by contrarian trading strategies. Moreover they recognized as the primary source of the observed contrarian profits, the reversal of the firm-specific component or returns. This reversal of the firm-specific component has generally been interpreted as corrections of prior overreactions. Mun *et al* (1999) and Kang *et al.* (2002) also concluded that the more distinct contrarian profits are due to the dominance of stock prices' overreactions to firm specific information. Lee *et al* (2003) using the Jegadeesh and Titman (1995b) methodology found that most of the contrarian profits are on average attributable to an overreaction to firm specific information. They postulate that actually lead-lag effect, on average, detracts rather than adds to contrarian profits.

(g) Firm Size Effect and Seasonality Effect

Some authors argue that the possibility of overreaction or return reversals is a manifestation of some other familiar anomalies. One of the explanations that were initially proposed by the supporters of the Efficient Market Hypothesis in order to belittle the validity and importance of the overreaction effect was the size effect of the companies included in the looser and winner portfolios. De Bondt and Thaler (1987) hypothesized that the reason for the overreaction is earnings information, by presenting that the subsequent earnings changes of extreme prior period stock returns, show a reversal pattern. Zarowin (1989), however, argues that their findings are consistent with, but not evidence of, an efficient markets anomaly due to earnings myopia. His findings do not provide support to earnings hypothesis. Although poorest earnings performers outperform the earnings performers by a statistically significant 16.6% over the 36 moths subsequent to the extreme earnings year, this result is due primarily to differences in size between two groups. Poor earners tend to be smaller firms than good earners. When poor earners are matched with good earners of equal size then there is little difference in return behaviour. When poor (or good) earners of different sizes are compared, small firms outperform large firms and smaller winners outperform larger losers. The statistical significant differences between the returns of extreme prior period performers appear to be the result of investor overreaction not to earnings but of the size effect.

Zarowin (1990) re-examines the De Bondt and Thaler's evidence on stock market overreaction, controlling for size differences between winners and losers. He finds that losers are usually smaller than winners in 13 of the 17 non-overlapping 3-year sample periods studied. By matching subgroups of winners and losers of equal size, he finds that all returns discrepancies, except those in January are eliminated, suggesting that other kind of effects might be responsible such as the tax-loss selling hypothesis postulated by Chan (1986) and Jones *et al.* (1987). His results reveal that differential size and not investors' overreaction is driving the winner-loser phenomenon and that a widely regarded efficient markets anomaly is subsumed by the size and seasonal phenomena.

Conrad and Kaul (1993) argue that the abnormal performance in De Bondt and Thaler's model is mainly due to a combination of both biased performance measure and the January effect that is not related to prior performance. In fact, they show that in non-January months the arbitrage portfolio of losers and winners earns negative returns. Baytas and Cakici (1999) postulate that long-term investment strategies based on size and especially price produce returns higher than those based on past performance, and since losers (winners) tend to be low (high) price and low (high) market value firms, price and size effects might explain some of the long-term price reversals observed in winner and loser stocks. However, Chopra *et al*. (1992) find that the overreaction persists after controlling for size as do Albert and Henderson (1995) after correcting potential biases in Zarowin's methodology.

Clare and Thomas (1995) used 1000 randomly selected stocks all traded on London Stock Exchange from January 1955 to 1990 (36 years) and find long-term evidence consistent with the overreaction hypothesis, not explained by risk or the January effect. Clare and Thomas gave two possible explanations for the phenomenon. One of the possible explanations that Clare and Thomas gave was that overreaction effect is just another manifestation of the size effect as most of the outperforming firms are smaller ones. Lee *et al.* (2003) argue that when testing for firm size, they found the magnitude of the contrarian profits is strongly related to the size/small stock portfolios experienced larger return reversals, and thus profits, when compared to large stock portfolios. This is further supported by the lower profits experienced when using the value-weighted methodology, which places a larger weighting towards larger stocks

Pettengill and Jordan (1990) find that the strict reversal of gains and losses suggested by the Contrarian/Overreaction Hypothesis only occurs with large firms and that most of the effects leading to this observed return pattern are accounted for in the month of January. Dissanaike's (2002) evidence of size effect within the FTSE 500 companies seems to be in agreement with Pettngill and Jordan's findings. He poses that for the UK stock market size effect and winner-loser effect are not completely independent of each other but there is no evidence to suggest that size effect subsumes the winner-loser effect. In order to reinforce his statement he recalls the study of Levis (1989) who states that for a period of 1961-1985 size is not the sole anomaly, not even the most dominant. Dimson and Marsh (1999) state that size effect in the UK the last few years seemed to operate in the reverse direction, meaning that large firms yield higher stock returns than small firms. Dissanaike (2002) denotes the fact that size portfolios are typically formed using market values rather assets, therefore small-sized firms may be a losing firm effect not vice versa. As far as his findings are concerned, Dissanaike admitted that FTSE 500 is biases towards larger firms so the conclusion that the size effect does not subsume the winner-loser effect might not hold for more broad-based samples.

As far as seasonality is concerned Ritter (1988) uses a buy/sell index of Merrill Lynch focusing on the time period of December – January and he realized that before the turn of the year investors present an undoubted tendency of selling stocks. This tendency was changing direction the following year. This behaviour alteration of the specific index is closely related to the turn of the year effect or else known January effect. According to this phenomenon small capitalization stocks have unusually high returns during January, which fades away as we approach the end of the month. A possible cause is that investors sell losing stocks for tax loss reasons, but they do not proceed in immediate placement of their money right after the turn of the year but they wait until January to do so to a wider range of cheaper and more feasible to buy stocks. This reversed tendency within January is enforced by the bonuses that employee get from their jobs or from the rebalancing of the portfolio held by funds which proceed in liquidation of the long-term gains from blocks of large capitalization stocks. Both may choose to place their money on smaller stocks. This kind of return predictability is against the notion of the Efficient Market Hypothesis. Chan (1988) explains the winner-loser effect as an artefact of beta nonstationarity since the standard form of the overreaction hypothesis assumes risk to be time invariant. Fama and French (1986) also find that the size effect may largely subsume the return reversal effect. Thus Zarowin's results are consistent with Chan's and Fama and French's proving additional evidence against the overreaction hypothesis.

(h) Time-Varying risk

A long-running debate centres on whether the contrarian profitability is a "free lunch" to astute investors or compensation for the greater risk inherent in contrarian portfolios. Fama and French (1988), Chan (1988), Ball and Kothari (1989), Glosten *et al.* (1993), and Ball *et al.* (1995), among others, maintain that the risk-price disparity and the asymmetric reverting pattern, reflect the pricing of stocks by investors who react rationally to the changing volatility. In their view, contrarian returns do not survive risk adjustment. For them a possible explanation for the appearance of abnormal excess return from contrarian strategies is the just the use of bad model by the analyst which does not take under includes all the necessary factors that encounter risk of a portfolio or a stock.

More specifically Fama and French (1988) suggest that time-varying rational expectations on the part of investors are responsible for predictable price volatilities. Chan (1988), finding that only small abnormal returns exist between winners and losers during the test period, offers only weak support for the Contrarian/Overreaction Hypothesis. He also criticizes earlier Contrarian/Overreaction research, citing the reliance on an assumption of constant risk for both the winner and loser stocks overtime. Thus, the estimation of betas or risk coefficients is different in the formation versus the test period, implying that the same beta cannot be used in estimating the abnormal returns. In other words Chan states that contrarian excess profits could be attributed to firms' changing systematic risks induced by imputed rising shifts in the firm financial leverage, which are driven by changing market values in the winner and loser stocks that in turn are merely projections of changing expected returns. Kothari and Shanken (1992) reinforced Chan's findings with risk estimates based on conditional multi-factor beta values. Ball *et al.* (1995), citing extensive measurement problems with previous capital asset pricing model-based studies, find no evidence of contrarian profitability.

Jones (1993) replicated De Bondt and Thaler's strategy. He concurs with Chan's analysis after correcting a bias in the latter's beta calculations by modifying the cross-sectional beta adjustment technique of Kothari and Shanken. He shows that the selection criterion of the Contrarian/ Overreaction Strategy implies that its betas are conditional on the index returns of the formation period and that Contrarian returns would then seem to be attributable to differences in risk. He believes that the profitability of contrarian portfolios is a pre-WW II phenomenon that has since largely disappeared.

On the other side there has been a variety of article rejecting the time-varying risk explanation for overreaction phenomenon and encourage further research for a more plausible causality. In 1987 De Bondt and Thaler made a further research on the overreaction phenomenon by testing the effect of time-varying factors that contained systematic risk (time varying betas), the presence of the January effect, the momentum effect, the role of the stocks capitalization of a company, the ratio of book value to market value of a firm, the firm specific announcements concerning their earnings and finally the asymmetry that has been denoted between the returns of winners and losers. The article originally tried to investigate two plausible explanations of the winner-loser phenomenon based on risk factors and the size. However later on they presented new elements, in line with the behavioural finance theory, whereas investors underreact to short term announcements of firms' profitability.

Chopra *et al.* (1992), Balvers *et al.* (2000), and Nam *et al.* (2001) support De Bondt and Thaler's (1985, 1987) overreaction hypothesis, affirming systematic mispricing and attendant risk adjusted excess returns that can be exploited by contrarian strategists. Chopra *et al.* (1992) argue that Ball and Kothari have underestimated excess returns by adopting CAPM, which assumes that the compensation per unit of beta risk is equal to the excess returns on the market portfolio. By estimating empirical security market line through risk return relations of portfolios formed on the basis of prior return, they report economically significant return reversals that are consistent with the overreaction hypothesis. Chopra *et al* (1992) extended their research in order to include other possible sources for overreaction. They found that overreaction persists even after controlling for size as do Albert and Henderson (1995) after correcting potential biases in Zarowin's methodology.

Furthermore Dissanaike (1994) finds that estimates of portfolio performance are highly sensitive to the methods used to compute both the formation and test period returns. Potential problems include model specification and faulty estimation of the underlying beta or risk coefficient. Dissanaike (1997) found evidence of winner-loser anomaly among the FTSE 500 companies in the UK and found evidence consisted with stock price reversals even after controlling for time-varying risk (in a separate paper Dissanaike (1999) found that test-period betas do not explain stock price reversals) and addressing concerns about bid-ask biases, metric related issues and look-ahead and survivorship biases. He dismissed the possibility that the winner-loser effect could be subsumed by the size effect (as Zarowin (1990), p.124 argued). But his study was restricted to large FTSE 500 companies, with which one would not usually associate the small firm anomaly.

Conrad and Kaul (1998) argue that even in frictionless markets, short-term stock returns can be negatively auto-correlated and negatively cross-correlated and that these negative serial correlations are consistent with time-varying common factors. Mun *et al* (2000) argued that corresponding risk coefficient changes are insignificant for each significant contrarian portfolio in their research. They believe that this indicates that some other factors must be attributed to the change in returns, apart from risk. An explanation proposed is that there exists some investor overreaction. Of course, in some cases the contrarian strategy has been shown to earn insignificant abnormal returns after the time-varying beta risk for the winner and loser stocks are adjusted for. For countries other than the US, the differential risk does not always seem to be a possible explanation for higher returns to losers. Clare and Thomas (1995) for the UK market although they recognized within their findings overreaction effects, they argued that the reversals fortune reflect changes in equilibrium required returns. The losers argued to be likely to have considerably higher CAPM betas, reflecting investors' perceptions that they are more risky. Of course, betas can change over time and a substantial fall in the firms' share price (for the losers) would lead to rise in their leverage ratios, leading in all likelihood to an increase in their perceived riskiness. Therefore, the required rate of return on the losers will be larger and their ex post performance better.

(i) Risk-Based Explanations and Inefficiency

Supporters of the efficient market hypothesis tried to create new models to substitute the inability of the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner

(1965) and Black (1972) to include other risk factors in their model such as B/M apart from the beta. The necessity for adoption of new models concerned not only time-series analysis but it was also a matter of cross-sectional regressions. Fama and French (1992) test the CAPM and find that a single factor, beta, does not sufficiently explain stock returns. Their first results where controversial. At first they showed that previously documented positive relation between beta and average returns was an artefact of the negative correlation between firm size and the beta, which once it is accounted for and the beta was allowed to vary in a manner unrelated to size, the documented beta-return relation disappears. In their search to find a variable that could have a stronger explanatory power they compared size, leverage, E/P, B/M and beta in cross-sectional regressions that spanned from 1963-1990 period. Their empirical research finds support for the inclusion of both size (measured using market value of equity) and leverage variables. The two leverage variables found to be significant were the book-to-market ratio and the price-to-earnings ratio. However, when used together, the book-to-market ratio and size variable absorb the effects of the price-to-earnings ratio. With empirical support that beta alone is insufficient to capture risk; their model relies on the addition of the natural logarithm of both the book-to-market ratio and the size of the firm's market equity so as to describe the cross-section of average stock returns:

$$E\left[R_{i,t}\right]-R_{f,t}=\beta_{i,t}\left(E\left[R_{m,t}\right]-R_{f,t}\right)+\delta_{i,t}\ln\left(B/M_{i,t}\right)+\gamma_{i,t}\ln\left(ME_{i,t}\right)$$

where $R_{i,t}$, $R_{m,t}$, and $R_{f,t}$ are the individual stock return for firm i, the market return, and the risk-free rate of return at time t, respectively. $B/M_{i,t}$ and $ME_{i,t}$ are the book-to-market ratio and the size of the market value of equity value for firm i at time t, respectively.

Black (1993) suggested that Fama-French results were likely to be due to data-mining. He believes that some of the statistical tests in Fama and French study were not properly specified, suggesting that since the relation between returns, size and B/M would disappear if another time period or market's data were examined. MacKinlay (1995) posed data mining as a possible explanation for the success of the Fama/French model.

Banz and Breen (1986), Breen and Korajczyk (1995) and Kothari *et al.* (1995) argue that Compustat database which was widely used in previous studies suffers from survivorship bias. An explanation to this problem is that firms added to the database during a given year were firms that existed at that time; therefore the backfilling of historical data for the previous several years biases the database toward firms that survived through those years. Other firms that terminated during those years and that were not already in the database, were never included. The so called ex-post selection bias can have a significant effect on cross-sectional studies of stock returns. Kothari *et al* (1995) claimed that the observed explanatory power of B/M is probably due to the described survivorship bias. It is likely that many of the firms excluded had high B/M ratio and low returns. Therefore by adding those firms on the database the alleged Fama French conclusion concerning the explanatory power of B/M factor is under consideration. Furthermore Kothari *et al.* (1995) continued their criticism on Fama and French focusing on the estimation of beta. Driven by the Levhari and Levy (1977) finding that beta coefficients estimated with monthly returns are not the same as beta estimated with annual returns, Kothari et al. (1995) argued that annual betas are more appropriate monthly betas since the investment horizon of a typical investor is closer to a year than a month, revealing a stronger relation between beta and returns when annually estimated beta are used.

On the other side of the fence there has been a series of articles that tried to restore credibility of Fama and French (1992) methodology and findings. Davis (1994) constructed a database of book values from large US industrial firms for the 1940-1963 period. It is important to mention that this time period is poorly or not-covered by the Compustat database. This database is free of survivorship bias and it examined a period prior to the period that Fama-French examined. The beta coefficients were estimated using annual returns in order to face one of Kotharis's *et al.* main criticisms. His results verified Fama/French results proving the existence of B/M's explanatory power even if the magnitude of the return dispersion was smaller probably due to the fact that only large firms were included in that sample. The relation of beta and average returns was flat, indicating the fact that betas estimated on annual returns could not improve CAPM's performance. Chan *et al* (1995) after examining the 1968-1991 period by combining CRSP and Compustat databases, they concluded that Fama/French results were unaffected by survivorship bias as few firms where missing from the tape. Furthermore they discovered a reliable B/M effect for a sample of large firms. Continuing on the researches supporting Fama/French results validity, Barber and Lyon (1997) tackled the data mining problem by examining and founding for the 1973-1994 period the B/M effect among the sample of financial firms. They idea of their research was that empirical results that are caused by data mining should appear to other independent samples. We know from the Fama/French study that financial firms were excluded, thus Barber and Lyon's results provided independent evidence of the explanatory power of B/M factor. Articles that added to the defensive line of the Fama and French results came from Capaul *et al.* (1993) who found evidence of a B/M effect in the US and five other developed countries for the 1981-1992 period. Fama and French (1998) also found a significant B/M effect in several developed countries for the 1975-1995 period. Researchers reached the conclusion that size and B/M effects are real over different time spans and different stock markets. The question was why size and B/M were able to produce cross-sectional dispersion in average returns. The two main explanations were risk and inefficiency.

Chan and Chen (1991) and Fama and French (1993) proposed that B/M could play the role of a distress factor that could explain variation in stock returns. Poorly performing or distressed firms which have high B/M due to their low Market Value of equity are rather sensitive to broader economic conditions and their returns might be driven by the variation of the similar macroeconomic factors (bankruptcy costs and accessibility of credit market). Ball (1978) and Berk (1995) tried to link B/M to risk, through the inverse relation of Market Value to discount rates. Once again by holding B/M constant, a firm's B/M ratio increases as expected return and therefore risk increases.

Fama and French (1993) examined a multifactor model from 1963 to 1991 on the CRSP database consisted of beta, size and book-to-market factors, where the last two are stock portfolios constructed in order to mimic underlying risk factors in returns. The three-factor regressions tend to produce significant coefficients on all three factors and regressions R-squared values are close to one for most portfolios. This indicates that the three factors are capturing much of the common variation in portfolio returns. If this model is adequate to explain the cross-sectional variation in average returns, the intercepts will be zero when excess returns are regressed on the three factors. Consistent to the risk-based efficient market looking explanation Fama and French find that the model explains average returns for portfolios sorted by size, B/M, Earning-price ratios and other characteristics. Furthermore they reveal a strong relation between a stock's B/M ratio and its loadings on the B/M factor. Therefore SMB and HML factors seem to capture independent sources of systematic risk. They behave like risk factors in APT and ICAPM models. The time series of SMB and HML can be interpreted as the average risk premiums for these risk factors. According to three factor model small capitalization stocks and value stocks have high average returns because they are risky meaning that they have high sensitivity to the risk factors that are being measured by SMB and HML. Many empirical papers test the hypothesis that Fama-French factors merely reflect distress risk, which when it is taken under consideration then observed abnormal returns are eliminated (Dichev (1998), Griffin and Lemmon (2002), Vassalou and Xing (2004) and Ferguson and Shockley (2003)).

Fama and French (1996) claimed that many of these anomalies concerning the average return calculated from the Capital Asset Pricing Model are interrelated and included in the three factor model they initiated in 1993 and which can be categorized within the general framework of efficient market hypothesis. According to this model the risk premium of a portfolio $E\left[R_{i,t}\right]-R_{f,t}$ can be explained by the following three factors: the market risk premium $R_M - R_f$, the difference in returns of a portfolio which is consisted by small market capitalizations stocks and a portfolio consisted by big market capitalization stocks (otherwise called SMB, small minus big) and finally by a factor that describes the difference of a portfolio that includes stocks with high book-to-market value and low book-to-market stocks (henceforth HML, High minus Low).

To be more precise the expected extreme returns of a portfolio are given by the following equation:

$$E\left[R_i\right]-R_f=b_i\left(E\left[R_m\right]-R_f\right)+s_iE\left(SMB\right)+h_iE\left(HML\right) \qquad (1)$$

Whereas, b_i, s_i and h_i are the slopes of the following time series regression:

$$R_i-R_f=a_i+b_i\left(R_M-R_f\right)+s_iSMB+h_i\left(HML\right)+\varepsilon_i \qquad (2)$$

Fama and French argue that since past performance is likely to be negatively associated with changes in systematic risk, high B/M firms are likely to be riskier, and hence require higher expected returns. Moreover they postulate that poor past performance of high book-to-market firms means that they are more likely to be distressed and consequently more exposed to a priced systematic risk factor. They managed to measure this risk as the covariance between the stock returns and the returns of their HML portfolio, a zero investment portfolio that consists of long positions in high B/M stocks and short positions in low B/M stocks.

The three factor risk model from Fama and French 1996 study, seems to capture the stocks long-term returns reversal that was initially observed by De Bondt and Thaler (1985) and moreover explains the dominant portfolio return patterns which are formed by indices like Earnings to Price, Cash Flows to Price and finally variables like increasing sales growth suggested by Lakonishok *et al.* (1994). Nevertheless Fama and French admit that the particular risk-return model fails to explain the short-term price continuation phenomenon known as momentum effect that was firstly observed by Jegadeesh and

Titman (1993). They describe the existence of this effect as the greatest embarrassment of the three factor model.

Despite the criticism of the three factor approach, it has become one of the major methods in the finance field for controlling for risk in event studies ((Brennan *et al.* (1998), Boehme and Sorescu (2002), Mitchell and Stafford (2000) and Naranjo *et al.* (1998)), in portfolio trading strategies and in distinguishing the effects of risk from market inefficiencies. Griffin (2002) used the method in order to discover whether or not factors are global or country specific. Vassalou (2003), and Liew and Vassalou (2000) tried to ascertain whether the SMB and HML factors are able to predict fundamental macroeconomic variables such as GDP growth in some countries and term spread. However, the relation between these variables and GDP growth in some countries is weak and especially for US does not exist for the 1957-1998 period. According to the framework of the rational asset pricing theories the ability of the Fama-French factor loadings to predict returns derives from a combination of investor risk aversion and covariance of returns with the marginal utility of consumption.

In contrast to the risk-based explanation comes the naïve extrapolation hypothesis given by Lakonishok *et al.* (1994) which we have already mentioned. In few words the high returns to value stocks (and the low returns to growth stocks) are due to investors being systematically wrong about the future. The implication of this theory is that investors can increase returns without increasing the riskiness of their portfolio by simply buying value stocks and selling, or at least not buying growth, stocks. However this explanation has been captured by Fama and French (1996) three factor model.

The main argument that has been expressed by many researchers concerning the suitability of the three-factor model given by Fama and French is that factors are extracted from security prices, not from fundamental macroeconomic news about cash flows (Chen *et al.* (1986) study include factors based upon news about fundamentals like inflation surprises). The question that many researchers has raised is that whether Fama-French factor loadings represent rational priced risks or is there another reason why these loading on return-predicting portfolios would themselves predict returns.

Daniel and Titman (1997) argue that Fama and French model appears to explain average returns only because the factor loadings are correlated with firms' characteristics (size and B/M). In order to separate the explanatory power of the factor loading for that of firms characteristics they constructed portfolios by sorting stocks first on B/M and then on factor loadings. They discovered a stronger relation between expected returns and B/M than between expected returns and factor loadings. In other words firm characteristics and not covariance determine expected stock returns, findings that are consistent with mispricing-based models. Daniel and Titman argue that high B/M stocks have high returns due to some other reason (possibly overreaction) so that the achievement of high returns has nothing to do with systematic risk. The cross-sectional correlation between B/M and HML sensitivity is quite high and therefore is difficult to discern which of these variables is the most powerful to explain the return dispersion. Daniel and Titman believe that characteristic-based explanation is the most plausible one for the 1973-1993 period. However Davis *et al.* (1999) show that Daniel and Titman findings have been restored due to the small sample they examined. Davis *et al.* applied the same methodology from 1927 up to 1997 and realized covariances as the main reason for the abnormal returns.

Both behavioural and risk-based explanations, although very different, they follow the same hypothesis that high returns earned by high B/M firms are associated with the deterioration of a firm's economic fundamentals. Overall in De Bondt and Thaler and Lakonishok, Shleifer and Vishny's articles, investors tend to overreact to the information contained in accounting growth rates and in the FF story the increased risk and return of high BM firms is a result of the distress created by poor past performance.

2.6 Stocks' Delayed Reaction

2.6.1 Assets Returns Continuation

Within the financial markets framework people's tendency to underreact to specific information concerning the market or the economy as a whole is reflected on stocks price as the continuation of their tendency to move in the same direction for several months after an initial impulse. This phenomenon is commonly known as Momentum effect and according to various researches throughout many countries reveal that this stock market anomaly usually appears for mid-term investment horizons such as from three to twelve months after portfolio formation. Many practitioners but also academics of the financial markets assume that this effect could easily be exploited for the achievement of excess returns.

First evidence comes from Jegadeesh in (1990). He found that stock returns tends to exhibit short-term momentum; stocks that have done well over the previous few months continue to have high returns over the next month. In contrast, stocks that have had low returns continued the poor performance for a short period of time. Jegadeesh and Titman (1993) confirmed the above results. They found a new twist to the literature of short-term return reversals by documenting that over an intermediate horizon of three to twelve months, past winners on average continue to outperform past losers. Firms with higher returns over the past 3-12 months subsequently outperform firms with lower returns over the same period. Therefore by buying stocks with high returns over the previous 3 to 12 months and selling stocks with poor returns over the same time period earn profits of about 1% per month for the following year. Using data from the NYSE and stocks listed on the American Stock Exchange (AMEX) from 1965 – 1989, they rank stocks in ascending order based on their past 3-12 months returns and form ten equally weighted deciles of portfolios. Top decile is classified as the 'loser' decile and the bottom decile as the 'winner' decile. In each overlapping period, the strategy is then to buy the winner decile and sell the loser decile with holding periods of 3-12 months. They argue that momentum is stronger for firms that have had poor performance. The tendency of recent good performance to continue is weaker. The pattern here is the opposite of that found in the long-term overreaction papers. Investment strategies that exploit such momentum (buying past winners, selling past losers) were followed by many professional investors. They argue that the profitability of this strategy is not related to the systematic risk and it can only partially attributed by the delayed reaction of the stocks' price to other factors. However a substantial portion of the excess profits of the first year after the portfolio formation is lost within the next two years (the attenuation of momentum strategy abnormal profits after the first 12 months were also verified by Grinblatt and Titman (1989)). The popularity of this approach has grown to the extent that momentum investing constitutes a distinct, well-recognized style of investment in the United States and other equity markets. The evidence of return predictability is as Fama (1991) notes, among the most controversial aspects of the debate on market efficiency. This strategy, which was called relative strength rule by technicians, has been popularized by the name of momentum strategies in academic research.

The first study to examine the existence of momentum effect within a multinational environment was conducted by Rouwenhorst (1998) and focused on medium-term international return continuation within markets and across markets at the individual stock level using a sample of 2190 stocks from 12 European countries from 1978 to 1995. The main finding of Rouwenhorst was that an internationally diversified relative strength portfolio which invested in medium-term winners and sold past medium-term losers earns approximately 1% per month. Momentum effects exist in all 12 markets. and hold across size deciles, although return continuation is stronger for small stocks rather than large stocks. The outperformance lasts for about a year and cannot be attributed to conventional measures of risk. Rouwenhorst (1999) showed significant profits of momentum strategies for a sample of 20 emerging markets. However Bekaert *et al.* (1997) find that momentum strategies are not consistently profitable for emerging markets, although they perform better when the investable indexes are examined.

Richards (1997), using monthly returns from stock indices of 16 countries for the period of 1970-1995 he found that the momentum effect is stronger at the 6-month horizon with an annual excess return of 3.4%. For horizon longer than 1 year, ranking period losers began to outperform winners with an average annualized excess return of more than 5.8%. Similar results were obtained by Chan *et al.* (2000) for stock indices of 23 countries over the period 1980-1995. Momentum profits are still present although they are slightly less significant when applied to country indices.

Clare and Thomas (1995) and Dissanaike (1997) both find some evidence of momentum in the UK, though the focus of their work is on long-run over-reaction, rather than short-term momentum effects. Both studies use a sample of returns from securities on the LSPD database. Clare and Thomas (1995) use a random sample of stocks on the LSPD over the period 1955-1990, find weak evidence of momentum at the 12 month horizon, in that although winners outperform losers, the average return difference is insignificant different from zero. They find that at the 24-month (and also at the 36 month) horizon there is significant evidence of over-reaction. Dissanaike (1997) used a sample of large stocks that are constituents of FT500 index, over the period 1975-1991 find that there is some evidence of momentum (rather than reversals) up to the 24-month horizon. Hence the results at the 24-month horizon from the Clare and Thomas (1995) and Dissanaike (1997) are contradictory.

There have been conducted other similar studies for the Canadian market with encouraging results over the profitability of the momentum strategies (Korkie and Plas (1995)). Foerster *et al.* (1994) after performing a similar strategy to Jegadeesh and Titman's (1993) for a time period of 1978 up to 1993, they documented stronger evidence of momentum in stock returns. Sean and Inglis (1998) found evidence of receiving abnormal returns from momentum strategies on Canadian Stocks. However they postulate that these profits merely represent the compensation for risk and risk premium that vary through time. They argue also that this momentum strategy might not be exploitable by the average retail investors facing higher levels of transactions costs. For the Asian markets except for Japan and Korea, Chui *et al.* (2000) found significant profits coming from momentum trading strategies.

Momentum effect has been denoted not only for individual stocks but also for indices as well. There has been recently a number of studies that present momentum profitable strategies by using not only sector indices within the same stock market but also studies which reveal analogous portfolio return patterns across stock markets at country level index (Asness *et al.* (1997) and Richards (1997)). Momentum effect do not confine its existence into stock markets but also in other kind of financial markets such as the currency market where Okunev and White (2003) reveal profitable momentum strategies throughout 1980s and 1990s.

Campbell summarized the momentum effect into three different types. The main form is price momentum where an initial impulse is simply a change in the price itself. Price momentum was denoted by Poterba and Summers (1988) in aggregate US stock prices at the end of the 1980's decade. The same effect was revealed by Jegadeesh and Titman (1993) for individual US stock prices in the early 1990s. International evidences of the same observable fact were presented by Rouwenhorst (1998, 1999). The Momentum effect has been observed after the announcement of non-anticipated earnings by the firms. This is called Post-Earnings and has been widely mentioned by Ball and Brown (1968) and Bernard and Thomas ((1989), (1990)). The last type of momentum effect is closely related to the second one but it is caused by another segment of market participants. It is known as earnings momentum and it refers to the stock prices' continuation following a revision in analysts' earnings forecasts (Chan *et al.* (1996)).

2.6.2 Explanations for Momentum effect

Momentum effect explanations can be divided into two different camps, which naturally have been provided by two opposing theories in finance. Within the traditional asset pricing model framework one could pose the argument that the returns associated with momentum strategies are attributable to risk that may not have been detected with traditional measures such as the capital asset pricing model (CAPM) or the Fama and French (1993) three-factor model. Therefore the achievement of higher returns from momentum strategies is just the reward of investor's boldness to take higher risks which could be captured by a more adequate asset pricing model. This explanation was taken under serious consideration by Jegadeesh and Titman (1993) especially for their momentum strategy as winner and loser portfolios are classified based on past returns. According to them to the extent that high past returns may be partly due to high expected returns, the winner portfolios could potentially contain high-risk stocks that would continue to earn higher expected returns in the future. For that reason, Jegadeesh and Titman calculates momentum profits within subsamples with lower dispersion in expected returns (e.g., size-based and beta-based subsamples). They find that momentum profits are not necessarily smaller within samples with lower dispersion in expected returns. Based on this evidence, Jegadeesh and Titman concludes that the dispersion in expected returns is not the source of momentum profits.

Furthermore many counter-arguments have been developed throughout the years that demolish the neoclassical finance effort to explain what has been called as the bigger shame of the Efficient Market Hypothesis: the momentum effect. Grundy and Martin (2001), as well as Griffin *et al.* (2003) argued that stocks, whose returns have risen recently or have had positive earnings surprises, typically they seem to have lower risk and not higher risk as it would be required to explain momentum effect. Moreover the equity of a leveraged company becomes safer when good news increases the market value of the company relative to the burden of its debt. The idea that cross-sectional variation in expected returns can generate momentum has attracted renewed attention in the theoretical as well as the empirical literature. In particular, Chordia and Swaminathan (2000) address this issue empirically and Berk *et al.* (1999) develop a theoretical model where the cross-sectional dispersion in risk and expected returns generate momentum profits. In contrast to Berk *et al.* (1999) and Chordia and Shivakumar (2000), who consider cases where momentum is generated by time-varying expected returns, Conrad and Kaul claim that it is the cross-sectional dispersion in unconditional expected returns that generate momentum profits.

Conrad and Kaul (1998) postulate that profits on trading strategies based on securities' past performance contain two components: one that results from time-series predictability in security returns and another that arises due to cross-sectional variation in the mean returns of the securities comprising the portfolio. They suggested that cross-sectional variation in the mean returns of individual securities play nontrivial role in determining the profitability of momentum strategies. Their additional bootstrap experiments suggest that the magnitude of momentum profits found in the actual data can be obtained with randomly generated data constructed to have no time-series dependence. Ahn *et al.* (2003) show that their nonparametric risk adjustment can account for roughly half momentum profits. Jegadeesh and Titman (2002) presented their opposition on Conrad and Kaul’s view. They proved empirically that cross-section variation in expected returns have a small explanatory power for the observed momentum profits because the cross-sectional variation in unconditional expected returns is small relative to the variation in realized returns and a stock's realized return over any six-month period provides very little information about the stock's unconditional expected return. Hence the unconditional expected return of past winners is unlikely to be significantly different from that of past losers. They reveal that Conrad and Kaul’s empirical tests contain a small sample bias that is identical to the bias in bootstrap experiment and simulations. By applying an unbiased variation of Conrad and Kaul’s bootstrap they find that momentum profits are zero, confirming their intuition that the primary reason of Conrad and Kaul’s results was the small sample bias.

On a theoretical approach of the question Conrad and Kaul rose whether momentum profits can be generated by the cross-sectional dispersion in risk and expected returns Berk *et al.* (1999) present a theoretical model in which the value of a firm is the sum of the value of its existing assets and the value of growth options. In their model, the expected returns of stocks are determined jointly by the current interest rates, the average systematic risk of the firm's existing assets, and the number of active projects. Their model predicts that changes in interest rates will affect the expected stock returns differently for various firms, depending on the number of active projects. These theoretical arguments provide a direct link between cross-sectional dispersion of expected returns and the macroeconomic variables, particularly interest rates. Consistent with these theories, Perez-Quiros and Timmermann (2000) document larger variation in risk characteristics across business cycles for small firms than for large firms. In other words Berk *et al. (1999)* developed a dynamic model that relates a firm's conditional expected return to the movements of its systematic risk. Their analysis suggests that variables such as size and book-to-market can summarize changes in firms' risk well. Their model implies that the momentum effect is related to the predictability of the movements in firms' risk and hence their expected returns.

(a) Momentum Profits, Macroeconomic Variables and Market States

Chordia and Shivakumar (2002) provided an empirical verification of the Berk *et al.* (1999) theoretical model. They analyzed the relative importance of common factors versus firm-specific information as sources of momentum profit. They showed that profits from momentum strategies payoffs are captured by a parsimonious set of standard macroeconomic variables (such as dividend yield, default spread, yield on three-month T-bills, and term structure spread) that are related to the business cycle and which are known to predict market returns. Their analysis uncovers interesting time variation in payoffs from a momentum strategy. Returns to momentum strategies are strong in economic expansions but are nonexistent in recessions. Using a set of lagged macroeconomic variables to predict one-month ahead returns, they showed that the predicted part of returns is the primary cause of the observed momentum phenomenon. These evidences are consistent with recent work by Bernanke and Gertler (1989), Gertler and Gilchrist (1994), and Kiyotaki and Moore (1997) predict that changing credit market conditions can have very different effects on small and large firms' risks and expected returns. Such theories also predict time variation in expected returns that is dependent on the state of the economy. Chordia and Shivakumar (2002) admit that although they interpret their result as consistent with the role of time-varying expected returns in explaining momentum payoffs, most of their findings could easily be interpreted to be consistent with theoretical models of investor irrationality.

Conrad *et al.* (1999) showed that the momentum strategy is significantly influenced by the market condition: the profits of momentum strategies are substantially higher when the market is bullish. These strategies are not profitable over the whole 1926-1994 period but that they are profitable since 1950; see Chordia and Shivakumar (2000). These authors were the first to highlight that momentum strategies are predominantly profitable in expansionary cycles of the US economy. The link between macroeconomic variables and momentum profits is important from a theoretical standpoint. In fact, asset pricing model like APT and ICAPM are mute concerning the factors driving stocks returns. Fama and French (1993) suggested that Book-to-Market and size are two candidates and Carhart (1997) added a third factor designed to capture the momentum effect. While Liew and Vassalou (2000) showed that the first two factors anticipate economic growth, they were unable to find such a relation for the momentum factor.

Cooper *et al.* (2004) also found that there is a relation between different states of the stock market and the profitability of momentum strategies. They categorize the US stock market (stocks included in AMEX and NYSE) in UP (when the lagged three-year market return is non-negative) and DOWN (when the three-year lagged market return is negative) states for the period of January 1926-December 1995. A six-month momentum portfolio is profitable only after following periods of market gains (UP market states), consistent with the overreaction models of Daniel *et al*. (1998) and Hong and Stein (1999). They find that that momentum profits increase as the lagged market return increases. However, at high levels of lagged market returns, the profits diminish but do not eliminate. Additionally, they reconfirm the findings of Lee and Swaminathan (2000), Jegadeesh and Titman (2001) and Griffin *et al.* (2003) that momentum profits are reversed in the long-run, as predicted by the overreaction theories, a pattern that seems inconsistent with the existing risk-based explanations (Conrad and Kaul (1998), Berk *et al.* (1999) and Johnson (2002)). Significant long-run reversals are pointed out in the DOWN states, although these reversal are not solely due to the corrections of prior momentum. Furthermore they postulate that multifactor macroeconomic models of returns presented by Chordia and Shivakumar (2002) are not robust in explaining momentum profits when market friction controls (such as a price screen and skip-month returns) are involved.

(b) Momentum Profits and Industry Momentum

Grinblatt and Moskowitz (1999) used portfolios consisted of industries instead of portfolios of stocks. They identify industry momentum as the source of much of the momentum trading profits at short (at the one-month horizon) and intermediate horizons. They claim that industry momentum strategies are more profitable than individual stock momentum strategies, even among the largest and most liquid stocks, but also more robust. Industry momentum strategies exhibit significant momentum, even after controlling for size, book to market equity (BE/ME), individual stock momentum, the cross-sectional dispersion in mean returns and potential microstructure influences. Once returns are adjusted for industry effects, momentum profits from individual equities are significantly weaker and for the most part are statistically insignificant (industry momentum drives much individual stock momentum). Industry momentum effect is asymmetric (buy-side profits diminish faster than short-side ones) and tend to dissipate after 12 months and eventually reversing at long horizons (after 2 or 3 years). A possible explanation could be the difficulty for investors to short assets and therefore to arbitrage away momentum on the downside or the fact that analysts withhold bad information (Hong *et al.* (2000))

Moskowitz and Grinblatt's result concerning the profitability superiority of industry momentum strategy was challenged by Grundy and Martin (2001) who claim that although the returns to an industry based momentum strategy are consistent with an intra-industry lead-lag effect, industry momentum alone does not explain the profitability of momentum strategies profitability. In their study, the profitability of a momentum strategy is not fully explained by the cross-sectional variability of expected returns or the risk exposure to a specific industry. Findings opposing to Moskowtiz and Griblatt's study come from Asness *et al.* (2000) as well as from Lee and Swaminathan (2000). Similar results to Moskowitz and Grinblatt came from Chen and Hong (2002) in their short discussion where buying past industry winning portfolios and selling past losing portfolios generate positive returns for horizons up to one year after the formation period.

Bacmann *et al.* (2001) motivated by the previous studies, examined the evidence of momentum strategies by analyzing stock markets of the countries member of the G-7 countries (USA, Canada, Japan, UK, France, Germany, Italy). They searched for the source of the profitability of these strategies on indices that represent the various industrial sectors over the period 1973- 2000. They investigate the link with industries and the evolution of the business cycle in each of these countries. They divide indices into two categories, the ones that represent more cyclical industries and the others that are considered to encounter more defensive industries. The average monthly returns of cyclical industries are higher than the monthly returns of defensive industries for all the G-7 countries. Moreover the difference of returns (long in cyclical industries and short in defensive industries) is positive and significant (one sided t-test) with the notable exception of the Germany. As far as the business cycles[10] are concerned there are various sources that determine the phases and more specifically the peaks and troughs of them. Their results are similar to Grinblatt and Moskowitz (1999), referring to positive profits of standard and normalized strategies for 6 months up to 24 months for the US and to

10 They used the cycle dating provided by the Organisation for Economic Cooperation and Development (OECD).

Rouwenhorst (1998) study over 12 European countries. The profits are not that sensitive to the way by which the weights are computed. For all the G-7 countries, the 6 months normalized strategy is positive and significant (at 5%), the 9 months normalized strategy is also positive in six countries, Japan being an exception. The US is the only country for which the profits persist over 24 months. Reconfirming Cyclical and Defensive industries to perform differently over the Business Cycle, the Cyclical Portfolio outperforms the Defensive Portfolio during the expansion periods (Japan, France, UK Italy and Canada) while the reverse is expected during the recession periods. However, the monthly average return of the zero-cost portfolio long in the Cyclical Portfolio and short in the Defensive Portfolio is positive but not significant at 5% (the p-value is 6%)..

Lewellen (2002) conducted a research where size and book-to-market portfolios also exhibit momentum, similar in magnitude (in some cases even stronger) but distinct from momentum in individuals stocks and industry. However they believe that momentum cannot be attributed simply by firm-specific returns. Size and B/M portfolios are quite well diversified, so their returns reflect systematic factors. Macroeconomic factors, not firm-specific returns, must be responsible for size and B/M momentum. Lewellen by using raw returns, calculates (separately) for industry, size and book-to-market portfolios auto- and cross-serial covariances among the portfolios. For each of the three sets of portfolios, the average of the auto-covariances is slightly negative but not statistically significant (contrary to Barberis *et al.* (1998) and Hong and Stein (1999)). The corresponding average of cross-serial covariances tend to be more negative but also not generally statistically significant, meaning that momentum in these portfolios is due to future stock returns being negatively correlated with the lagged return of other stocks consistent with an overreaction hypothesis in which certain stocks overreact to a common factor and others do not. Chen and Hong (2002) verified the existence of the momentum effect of the size and B/M portfolios; however they postulate that Lewellen's findings on negative average auto- and cross-serial covariances among the portfolios can be consistent with the underreaction-based explanations these findings are driven by the in-sample serial correlation of the market factor

The momentum effect seems to find a more suitable explanation within the framework of Behavioral Asset Pricing Model. This kind of a model approaches momentum as the interaction of imperfectly rational investors (many of whom are individuals lacking professional investment expertise) with rational arbitrageurs. There are two main categories of Behavioral explanations for momentum.

(c) Underreaction

Due to the gradual adjustment to new information, stock prices initially underreact to news and they adjust over time so that the long-term response is the most appropriate and rational one. Underreaction is most likely to occur when complicated fundamental news arrives that has important implications for the future cash flows of a stock. The limited ability of most investors to access and process information, escorted by overconfidence, leads investors to cling to their original views even in the face of relevant new information. According to Daniel *et al.* (1998), these are the most two common reasons for the delayed estimation of the real value of the incoming information. Rational arbitrageurs on the other hand, do respond to fundamental news, but they do not trade aggressively enough to drive prices all the way to the level that would be justified by fundamentals. Instead, on good news they drive the price up to a level at which it is still profitable to hold the stock, while on bad news they drive the price down to a level at which it is still profitable to short the stock. Over time, the price adjusts fully to the news and this allows arbitrageurs to unwind their positions profitably. This story is consistent with the strong evidence for momentum in response to fundamental impulses such as earnings announcements or analysts' forecast revisions.

Hong *et al.* (2000) drew their attention to a behavioural approach. They searched whether momentum reflects the gradual diffusion of firm-specific information not made publicly available to all investors simultaneously. They predicted that stocks with slower information diffusion will exhibit more pronounced momentum. By using a sample of stocks from 1980 up to 1996 taken from NYSE, AMEX and NASDAQ along with data from analyst coverage, they separated stocks into different classes according to their speed of information diffusion. Firstly they segregated stocks by size and indicated that momentum strategy profitability declines sharply with market capitalization (except for the participation on tiny stocks were thin trading may be responsible for more pronounces supply-stock-induced reversals). Their plausible explanation was that information about smaller firms seeps out more slowly than information about big firms and this due to the fact that people are more willing to consume time and money in order to acquire information for stocks on which they invest larger amounts of money. In a second type of tests Hong *et al.* (2000) use analyst coverage as an alternative proxy for information flow on the hypothesis that with less analyst coverage, information gets out more slowly to the investing public. By keeping size constant evidences verify that stocks with slower information diffusion exhibit more pronounced momentum. Finally the authors showed the existing asymmetric impact that analyst coverage has for good and bad news. The effect of analyst coverage is far more pronounced for stocks that are past losers than for past winners. This is consistent with the hypothesis that firm-specific information, particularly bad news, diffuses only gradually across the investing public as managers seek to publicize only good news when they have it.

Post-earnings announcement drift is a special segment of the research literature on momentum effect This is the general phenomenon where analysts' forecasts tend to underreact to earnings information and the market prices underreact to analysts' forecasts (Bernard (1993), also Mendenhall (1991) and Abarbanell and Bernard (1992). Bernard reports that post announcement stock prices for firms that have reported "good news" tend to drift up, whereas the prices for firms that have reported "bad news" tend to drift down. The categorization of news event to good or bad was accomplished by using a criterion called Standarized Unexpected Earnings (SUE[11]). Then he divided all companies into ten groups according to their SUE values and took two extreme portfolios, the one with the highest SUE value (stocks with extreme good earnings) and the other with the lowest SUE values stocks with extreme bad earnings). A trading strategy being long on highest SUE firms and short on lowest SUE firms, would pay out a total abnormal return of 4.2% and size seems to play a significant role as for small and medium-size firms the benefits could overcome a 10% profit.

[11] SUE is computed by taking the quarterly earnings surprise and scaling by the standard deviation of earnings for that quarter.

Bernard and Thomas ((1989), (1990)) and Wiggins (1991) find it pays to hold stocks that have experienced recent large positive earnings surprises as the market has not fully adjusted to the good news even after 3 quarters. The abnormal returns all tend to concentrate in the first three trading days. They are not spread out evenly throughout the quarter. Possible explanation could be that investors and analysts overconfidently remain anchored to their prior view of company's prospects. So they underweight evidence that disconfirms their prior view. They interpret a permanent change as temporary leading to slow adjustment of the price. Adding to the behavioural based explanations of the phenomenon first stated by Bernard in 1993, Andreassen (1990) and Andreassen and Kraus (1990) denoted the importance of salience for financial predictions (also Amir and Ganzach (1998)). They documented the investors' tendency to place little weight on changes to a series, unless the recent changes are salient and attributable to a stable underlying cause. Later several behavioural based theories by Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong *et al.* (2000) tried to capture Post-earnings-announcement drift as a part of a more general phenomenon involving momentum in the intermediate term and overreaction in the long term. However Shefrin in his book (2001) do not share the same enthusiasm according to the out-of-the-sample explanatory ability of these theories.

(d) Overreaction

Irrational investors may overreact to information of uncertain relevance. According to Daniel and Titman (2006) overreaction is more likely to be associated with soft or qualitative information which may also generate momentum in the short run as irrational investors respond gradually to them. This may happen if they copy each others' trades or if they tend to buy stocks that have performed well recently. These behaviour patterns are known as herding hypothesis (individual investors are attracted to funds, fund categories, and fund families that have performed well recently (Sirri and Tufano (1998)). Grinblatt *et al.* (1995) identified among 155 mutual funds over the 1975-1984 period, a statistical significant relationship of herding[12] and momentum strategies, which is also highly correlated to the funds performance. . However the link between funds tendency to ''go with the crowd'' and their excess performance was largely vanished after controlling for the fund's tendency to buy past winners. Similar results came from Brunnermeier and Nagel (2004) study where they showed that the evidence for momentum generated by overreaction (herding) is weaker than the evidence for momentum generated by underreaction to fundamentals.

Another perspective in the role of the overreaction phenomena as a plausible reason for momentum effects was provided by Xiang *et al.* (2002). They postulate that continuous overreaction causes the intermediate momentum effects and as well as later stock prices reversals. Xiang *et al.* (2002) also investigate the influence of insider trading and explanatory power of these trading activities on the momentum effects, motivated by the fact that investors overreact on the stocks when they observe insiders are involved in buying (or selling) a stock. If the public information confirms their findings then investors will overreact continuously. This continuous overreaction is the cause of momentum effects. In consistence to the findings of Seyhun (1992) and Lakonishok and

[12] All agents are buying or selling of the same stocks at the same time.

Lee (2001) they find that the aggregate insiders trading activities contain valuable information in predicting cross-sectional stock returns during the period from 1985 up to 1997 for the US stock market. Xiang *et al.* (2002) went one step further and tried to relate this discovery with two behavioural based theories. For example within the framework of Barberis *et al.* (1998) they claimed that stocks performed good (bad) and bought (sold) by insiders in the past, falls into the trend regime and stocks performed good (bad) and sold (bought) by insiders in the past, falls into mean-reverting regime, implying that conservatism bias of investors is the main cause for the appearance of momentum effects. On the other hand slow information diffusion and bounded rationality of newswatchers and momentum traders in Hong and Stein's theory (1999) can lead to the appearance of similar momentum effects. Another explanation can be ascribed to the Daniel *et al.* (1998) theory, where both short-term momentum effects and long-run reversals are caused by overconfidence and self-attribution bias, which means that people will be slow to change their initial beliefs and only react modestly, leading to continuous overreaction and the intermediate-horizon momentum effects.

Following closely the latest literature relative to the sources of momentum profits it seems that a growing dispute has arose. Papers like Jegadeesh and Titman (2001) and Lee and Swaminathan (2000) examine long-horizon payoffs of momentum strategies in event time. The notion behind this approach is that if delayed overreaction is driving momentum, then strategies that buy winners and sell losers will be profitable in the short-run as good (bad) news in the pre-formation period pushes post-formation prices above (below) fundamental value. However, these deviations from fundamental values are only temporary. Cumulative momentum profits will therefore disappear or even turn negative in the long-run. On the other hand, if momentum profits are driven by underreaction (as Chan *et al.* (1996) and Hong et al (2000) verify with their findings), then the good (bad) performance of winners (losers) continues in the post-formation period until all the pre-formation news is incorporated in prices. In this case momentum profits persist in the long-run.

(e) Momentum Profits and Trading Volume

Lee and Swaminathan (2000), by using a sample of NYSE and AMEX stocks from January 1965 up to December 1995, assume that stock returns and trading volume are jointly determined by the same market dynamics and are inextricably linked in theory (e.g. Blume *et al.* (1994)). They investigate the usefulness of trading volume in predicting cross-sectional returns for various price momentum portfolios. They assert that intermediate-horizon momentum is followed by long-horizon overreaction indicating them as two elements of the same continuous process and supporting the view that initial momentum gains are partially a result of overreacting behaviour of investors as postulated by De Long *et al.* (1990). A second contribution of their work has to do with the trading volume as a separate volume effect which is robust to various risk adjustments. They show that most of the excess returns to volume-based strategies are attributable to changes in trading volume. They find that low (high) volume stocks display many characteristics commonly associated with value (glamour) investing. Specifically, lower (higher) trading volume is associated with worse (better) current operating performance, larger (smaller) declines in past operating performance, higher (lower) book-to-market ratios, lower (higher) analyst followings, lower (higher) long-term earnings growth estimates, higher (lower) factor loadings on the Fama–French HML factor, and lower (higher) stock returns over the previous five years. Further analyses show that the higher (lower) future returns experienced by low (high) volume stocks are related to investor misperceptions about future earnings. Analysts provide lower (higher) long-term earnings growth forecasts for low (high) volume stocks. However, low (high) volume firms experience significantly better (worse) future operating performance. Moreover, they find that short-window earnings announcement returns are significantly more positive (negative) for low (high) volume firms over each of the next eight quarters. The same pattern is observed for both past winners and past losers. Evidently the market is “surprised” by the systematically higher (lower) future earnings of low (high) volume firms.

(f) Momentum Profits and Disposition Effect

Grinblatt and Han (2001) believe than within the same market there are investors with different behavioural patterns, rational and keen to disposition, investors. Disposition investors hold higher future return expectations for stocks with past aggregate capital losses and lower return expectations for stocks with past aggregate capital gains. This distorted belief makes investors to underreact to public information concerning these stocks. Disposition effect makes investors more reluctant to sell past losing stocks than past winner stocks. This is how fundamental to actual price spread is created.. According to them momentum effect can be documented only if there is a subsequent price reversal.

This can be realized due to a variety of factors such as different press releases or even just by the trading activity exhibited by disposition investors which can cause mean reversion of the misevaluation. Therefore the stochastic process of a stock's price is actually the stochastic process of the fundamental value minus the spread. Stocks with positive (negative) spreads imply the risk-adjusted returns above (below) the risk-free rate and it reflects the expected returns of the stock. This capital gain overhang as the authors call it can be used as a proxy for aggregate unrealized capital gains. Cross-sectional empirical tests of the model find that stocks with large aggregate unrealized capital gains tend to have higher expected returns than stocks with large aggregate unrealized capital losses and that this capital gains ''overhang" appears to be the key variable that generates the probability of a momentum strategy. When this capital gains variable is used as a regressor along with past returns and volume to predict future returns, the momentum effect disappears. Conclusively Grinblatt and Han argue that the spread between the fundamental value (the true price) and the price biased by the disposition effect generated the profitability of a momentum strategy.

Oehler *et al.* (2003) demonstrated a market where two momentum and disposition investors coexist. The crucial question in their research was whether individual-level disposition effects attenuate or survive in a dynamic market setting. They showed that disposition bias affect the majority of the market participants, thus disposition survive but it does not affect the whole market or its liquidity. The reason for this is the existence and interaction of these two different groups of investors. Disposition investors act like contrarians investors who sell winning stocks and buy loser stocks and momentum investors act on a totally diverse way. They also denote the vital role of the reference price someone uses in their experiment. Disposition effect appears to be even more intense when as reference point they use the purchase price of a stock. On the other hand when the last quoted price is used then disposition effect seems to be reduced. Prior performance activity seems to play a significant role on the future trading activity. Prior gains make investors less loss-averse but this is not the case when it has happened more than ones. A latest article by Frazzini (2006) indicates that mutual funds are reluctance to sell stocks with high purchasing price (in other words exhibiting disposition effect) and this behaviour has a result to intensify the observed post-earnings announcement drift.

(g) Momentum Profits and Positive-Feedback Trading

De Long *et al.* (1990) developed a theoretical model where they argued that positive feedback trading can be one of the driving forces of stock return momentum. In their model three types of investors dominate the market: positive-feedback traders, passive traders and rational speculators. Passive traders and rational traders can be thought of as informed traders who decide based on firm specific information or on superior information. Positive Feedback Traders buy stocks when prices rise and sell stocks when prices fell. Another research conducted by Hong and Stein (1999) refers to the existence of momentum investors who are responsible for the creation of momentum effect. Nofsinger and Sias (1999) indicate a positive relation between institutional positive-feedback trading and return momentum which can be attributed at trend chasing on behalf of institutions.

Shu (2007) takes a new approach by measuring the positive-feedback trading by institutions at individual stock level. He creates a momentum trading measure that evaluates the amount of institutional positive-feedback trading on a stock during a certain period of time. A high level of this measure signifies the increased likelihood that institutions will buy a stock and vice versa. Moreover by initiating a 6months/6months holding momentum strategy he managed to verify an economically significant relationship of return momentum and the MT (Momentum Trading) measure. The monthly momentum profit of the top MT quintile is 0.47% higher than the bottom MT quintile. This statistically significant outcome compounded annually gives a 6.57% difference. Furthermore Shu (2007) finds the effect of institutional positive-feedback trading on return momentum to be robust after controlling for size, B/M and turnover. This would signify the independence of the above phenomena as explanatory proxies of momentum effect. Shu's paper suggests that institutional positive feedback trading drives stock prices further away from the fundamental values of the firms thus destabilizing stock prices and hampering market efficiency.

(h) Long-Term Momentum Hypothesis

Kim (2002) developed a simple model based on the experimental evidence of Andreassen and Kraus (1990). Andreassen and Kraus (1990) believed that in the market there are two groups of investors: momentum and rational ones. They argued that when stock prices exhibit a trend, momentum traders tend to chase the trend (buy more when prices rise and sell when prices fall). The stronger the trend the bigger the momentum trading as new momentum traders come into the market. Thus, price momentum driven by long-term (short-term) good or poor performance is described as "long-term (short-term) momentum". This model is distinct from the other overreaction models since it claims that long-term momentum is stronger than short-term momentum. In order to test the long-term momentum hypothesis they had to implement new contrarian and momentum strategies designed by using past returns. Namely these tests were: 1) double-extreme contrarian strategy. 2) The trend-bucking contrarian strategy and 3) The high momentum strategy is supposed to yield higher returns than the original momentum strategy.

Several conclusions came out from his research. First of all financial distress premium hypothesis can not explain any of the above patterns. Kim's empirical results oppose or find difficulty to reconcile with other behavioural based theories. Third the robustness of price reversals and momentum phenomena signifies that these anomalies are not entirely due to data snooping biases. Kim's findings relate to other parts of momentum effect's sources literature, such as Lee and Swaminathan's (2000) late strategies where they long high volume stocks and short low volume stocks. Kim assumes that long-term momentum hypothesis may be able to explain patterns of Lee and Swaminathan's strategies as it does for the doubly-extreme contrarians' strategy. Finally Kim mentions possible caveats concerning long-term momentum hypothesis being mostly favoured by size effect.

Finally there is a recent article by Lesmond *et al.* (2004) who postulate that the returns produced by relative strength investing strategies (buying past winners and selling past losers) do not exceed trading costs. They believe that Berkowitz *et al.* (1988) measure understates the full trading costs facing investors as it excludes a number of important costs of such as bid-ask spread, taxes, short-sales and holding period risk. They find that the majority of relative strength returns are generated by return continuation among the poor performing stocks. Since profiting from the ongoing poor performance of these stocks requires maintaining short positions, ignoring short-sale costs for these strategies is particularly concerning. Hence the magnitude of the trading costs associated with these momentum strategies is much larger than previously appreciated, since the composition of standard relative strength portfolios is heavily weighted toward trading of particularly high transaction cost stocks. Moreover, large cross-sectional variation in relative strength returns is increasing in trading-cost proxies, suggesting that trading costs are binding to arbitrage. The existence of performance persistence patterns in returns does not appear to conflict with information efficiency or suggest the existence of arbitrage opportunity. The evidence is consistent with sluggishness in the updating of equity prices. Nagel (2002) argues that relative strength portfolio returns are best characterized by information underreaction.

CHAPTER 3: THE ATHENS STOCK EXCHANGE

3.1 Review and Statistics

Studying the history of the Greek capital market one can easily understand that the way stock exchanges function is crucially affected by the political status of the country they operate, the openness of the country's economy as well as by the international economic environment. The Greek Stock Market was established in 1876 and it was based on the French Commercial Code. However a newly founded state with vague border line and extended percent of population living in poverty had other priorities than establishing a functional capital market. Only upper class echelon citizens had the luxury of showing an amateurs' interest. For more than half of the 20th century, Athens's stock market could not penetrate to the masses of individual investors as international and domestic political and economic circumstances were not favourable. World War I and II, Balkan Wars, Smyrna Catastrophe, Refugee arrival, collapse of the major international stock market crisis in 1929, Greek Civil were was some of the milestone events that prohibited the expansion of the Hellenic stock market. Furthermore, throughout the century, the lack of investors' education, incomplete regulating framework and few unfortunate speculating games prohibited stock market's popularity.

There were few periods when Athens Stock Exchange had the chance to play its primary financial role: to provide a source of funds to finance the growth in enterprise and the economy. The period at the end of 1960's, happened to be a very fruitful for ASE period.

Three factors allowed this incident to happen: the state's will to provide the right legislation framework for capital markets, international positive capital markets momentum and activation of the private sector. Contingency law 148/1967 made mandatory dividend payments from all listed firms, tax exemption of dividend up to a certain amount and reduction of the top companies' taxation percent from 38% to 30% and finally declared the right of listed firms to issue preferred stocks. It was the same law that initiated Securities Committee which gained its crucial role many years later.

Another event that contributed to spread the investment mentality to the masses of individual investors was the institution of Mutual Fund and Portfolio Investment Companies. These institutions were common in developed economies decades earlier. Moreover firms that were completely owned by the founding families took the chance of raising capital by issuing new stocks for extremely high prices due to increasing demand for stock ownership by individuals who had no prior experience of investing. Undeniable evidence of this frenzy is the number of the listed firms in 1974 which totalled 124 companies whereas eight years earlier only 76 of them existed. The years that followed could be characterised as a period of stagflation (low GDP growth and high inflation), which in Greece's case was sparkled by political and financial turmoil (International oil crisis, Cyprus invasion and occupation).

This image of an extremely active stock market was about to be revitalised almost 15 years later in 1989-1990 (which is included in the sample period of this study). 1989 was an intense political year as it was a pre-election year, however the GPI[13] rose by 42.5% and the annual turnover value reached 89.1 billion drachmas (261.5 million Euros). In February 1990 central security depository was introduced and within three months (April to July) the General Price Index rose by nearly 150% (from 671.99 to 1,684.31 points) and the value of transactions at the end of the year had racketeered to 609 billion drachmas (€1.78 billion). The end of this bull period came with Iraqi invasion of Kuwait, the following Gulf War I and the existing turmoil in the rest Balkan countries. At the end of 1992 the GPI had dived to 672 points, although the new electronic trading system was initiated in August 1992 and the signing of the Maastricht Treaty in September 1992 opened the way to significant budgetary and monetary policy changes.

Apart from 1993's temporary stock market rally, driven by the construction company sector, the 1990-1996 period did not offer much excitement to market participants. In March 1994 stocks and fixed income securities were dematerialized and together with the abolition of capital controls in May 1994 helped significantly to the rise of transactions' value year by year, reaching from 637 billion drachmas (Euros 1.89 billion) in 1993 up to 1,990 billion drachmas (Euros 5.8 billions) in 1996. That was the last year of a prolonged stagflation recession and a downward phase of a major cycle in the Greece. Early results from the financial support that was decided by the initiation of Maastricht Treaty in December 1992, began to realize plus there was the political determination of fulfilling the criteria in order to become the 12th member of the Economic and Monetary Union.

[13] The ASE GPI is a value-weighted portfolio that is composed mainly of the most heavily traded stocks that represent approximately 70% of total market capitalisation and approximately 80% of total transaction volume.

In 1997 international markets were experiencing the greatest bull markets in history, while the international stock crisis in autumn 1998 halted ASE only temporarily. From 1997 up to 1999 ASE went through the greatest phase as individual investors reached 1.5 million, average daily turnover exceeded 220 billion drachmas (€586,9 millions) and market capitalization as percent of Gross Domestic Product since mid September 1999 120%. The capital that was raised within three years 1997-2000 reached 10.8 trillion drachmas (approximately 31 billions, see table 3.2). Foreign investors' participation started to be mentioned by financial press as an important evidence of Athens Stock Exchange's quality.

By 17th of September 1999 the ASE General Price Index reached its all time historical peak of 6,335 points; even nearly nine years later the General Price Index is more than 2,000 points lower than its historical peak. However, similar stock rallies had been noticed in the history of ASE before. In 1986 the index had risen 46.38% and turnover catapulted to 59.6 billion drachmas (174 million euros). That was thought to be the outcome of combined events such as the announcement of a programme for economic stability by the Greek government aiming to improvement of balance of payment and to stem the double-digit inflation. Moreover the rise of dollar made Greek exports more lucrative especially for textile and cement companies, the reduction of labour costs contribute in increasing companies' profits and finally implementation of the first European Directives regarding stock market function into to Greek Law system encouraging foreign funds to enter our stock market. But what happened during the first ten and a half months of 1987 was unexpected as the index rose 399.32% from 103.86 points to 518.89 and then as the bubble burst after Black Monday (19/10/1987) the index dived by more than 47% within one month still gaining though 162.4% since the beginning of the year. Market capitalization on that year ended up to 566 billion drachmas (€1.66 billion) and annual values of trades reached just Dr 60 billion (a mere €176 millions).

But in 1999 fundamentals were totally different as participation of the masses had driven daily trading volumes in 1999 (especially the week from 14th to 20th of September) steadily to more than 400 million euros nearly one quarter of the annual trading volume of 1995. On the 17th of September this amount reached 522.3 million euros. Market Capitalization escalated to more than 197 billion euros as the result of market openness, foreign capital inflow and newly automated trading system. The geographical spread of the investment crowd was not confined to Athens or at least major cities, but stock market frenzy had reached every part of Greek territory. Four years earlier market capitalization could barely reach 11.8 billion euros (see table 3.4).

Investor irrational exuberance ended with the introduction of the new millennium. Expectations concerning Dot-com industry dynamic were moving faster than technology growth itself and therefore the tech-bubble retreated taking downwards both emerging and developed market. Internationally institutional investors started retrieving their money from peripheral illiquid stock exchanges in order to minimize losses. Value of shares traded began to fall rapidly by March 2000 under €200 millions per day and since June 2000 and by the end of the year value of trades were halved. It is impressive the fact that during 2000, 105 out of 252 trading days in total, did not exceed €100 million value of trades (and 19 of them below €50m.). People initially were driven by house money effect as they had achieved substantial capital gains the previous years and as months went by they were trapped by disposition effect. Lower value of trades indicated their reluctance to sell and realize paper loss. Market capitalization at the end of 2000 fell by 66.9% (€118 billions) compared to last year.

A paradox to the usual international practice of a falling stock is that the number of newly listed firms increased by 43% marking an all time record (in 2000 we had 53 new companies whereas in 1999 only 37 firms entered ASE, see Table 3.1). Possible explanations of this peculiarity are that entrepreneurs were hoping that this downturn would be temporary or they were just following the momentum from last year). The period of 2000-2001 was rather crucial for the banking sector in Greece and the creation of large banking institutions apart from the state-owned ones began to show up. Alpha bank was created from the acquisition of Ioniki Bank from Pisteos Bank, Piraeus Bank acquired Chios Bank and Bank of Macedonia-Thrace. Interbank proceeded in buying Creta Bank and Ergasias bank. These three institutions today represent the 2nd, 3rd and 4th largest private banks in Greece and some of the largest banks in the Eastern and New Europe countries. During the 1999-2000 period the capital that companies managed to raise either from Initial Public Offerings or from Rights Issue was enormous, as the data in Table 3.2. indicate. Companies found access to more than 13 billion euros the first year and almost 10 billion euros in 2000. The difference is huge and indicates the influx of investors' masses into the Athens Stock Exchange. IPO's offered tremendous extra values as limit up barrier of 8%, 10% and much later 12%, kept securities prices increasing for many trading days.

Table 3.1: Number of Firms on ASE

Year	Number of Firms listed	New Listed Firms	Delisted
1990	121	28	0
1991	135	14	0
1992	140	5	0
1993	150	10	0
1994	196	46	0
1995	215	20	1
1996	235	20	0
1997	237	12	10
1998	258	23	2
1999	294	37	1
2000	342	53	5
2001	349	21	14
2002	349	21	21
2003	355	15	9

* sources ASE Fact book, Helex Annual Reports, Bloomberg, Datastream

Table 3.2: Capital Raised in ASE

Capital raised in the Athens Stock Exchange (in millions Euros)			
Year	**Listed Companies**	**New Listings**	**Total**
1991	283	159	443
1992	90	1	92
1993	235	61	296
1994	482	290	772
1995	189	70	259
1996	200	640	840
1997	2.180	70	2.250
1998	3.980	1.420	5.400
1999	12.180	970	13.150
2000	8.220	1.710	9.930
2001	330	1.500	1.830
2002	1.810	100	1.910
2003	1.770	120	1.890

* sources Factbook ASE, Helex Annual Reports, Bloomberg, Datastream

The General Price Index remained falling throughout 2000 (a drop of 38.77%) and 2001 (a drop of 23.53%). In other words in two years time the GPI fall by 53.17%. Nearly nine years later the General Price Index is more than 2,000 points lower (see Table 3.3).

Capital funding through the stock market in 2001 retreated to levels prior to 1997. 79.8% of the trading days in 2001 had value of trades lower than €200 million. Twin towers hit on 11/9 of the same year worsened investors' pessimism and pushed markets even further. By the end of 2002 GPI fell to 1748 points (-32.53% in a year and more than 72% drop since September 1999. Daily values of trades fell bellow € 100 millions for 161 days (65.2% of the total trading days) in 2002. The situation began to alter slightly in 2003 and companies from other sectors apart from banking and financial services, entered ASE. Volume of trading increased and few significant deals raised value of trades to more than €500 millions for six days of the 246 trading days. Annual turnover was increased by €10 billions (€34.9 billions) since the previous year and the General Index closed 2003 with an increase of 29.46%.

Table 3.3: General Price Index

YEAR	GPI	% CHANGE
1986	103,86	46.38%
1987	272,47	162.34%
1988	279,65	2.64%
1989	459,43	64,29%
1990	932	102,86%
1991	809,71	-13,12%
1992	672,31	-16,97%
1993	958,66	42,59%
1994	868,91	-9,36%
1995	914,15	5,21%
1996	933,48	2,11%
1997	1479,63	58,51%
1998	2737,55	85,02%
1999	5535,09	102,19%
2000	3388,86	-38,77%
2001	2591,56	-23,53%
2002	1748,42	-32,53%
2003	2263,58	29,46%

An interesting feature of the stock market activity of that period is that for the first time a substantial number of companies were delisted. In 2000 we had only 5, in 2001 14 and in 2002 the number reached 21 and then drop to 9 in 2003. The reason why this happened is not only due to economic downturn. Some companies were bought by conglomerates that were listed in other exchanges so there was no reason of keeping the stock on ASE. On the other hand banking sector began to transform and contracted, and this had a direct effect to their subsidiaries involved in insurance or asset management. Especially the last category suffered a lot from the international stock market crisis by writing down great portfolio losses and losing the trust of the investors. Therefore banks proceeded in absorbing these companies in order to protect them.

Some other companies with core business in computer technology followed the same path of merging as their financial results were becoming worse. Textile companies suffered from the great import of much cheaper products from Asia or other countries of Eastern Europe and Middle East where wages are much lower. Moreover traditional retail traders of consumer goods who were not ready to face the entrance of multinational retail companies, who had capital advantage, better managerial structure and lower functional cost, inevitably they were forced to shut down.

Table 3.4: Market Capitalization (closing price - in million Euros)

Year	Main Market	Paraller Market	New Market	Total
1990	6.685,77			6.685,77
1991	6.856,81	54,91		6.911,72
1992	5.946,35	53,24		5.999,59
1993	9.119,39	28,29		9.147,68
1994	10.402,55	246,69		10.649,24
1995	11.371,56	450,95		11.822,51
1996	16.883,21	563,06		17.446,27
1997	27.830,43	962,86		28.793,29
1998	64.156,98	2.867,85		67.024,83
1999	177.890,54	19.646,66		197.537,20
2000	107.283,93	10.672,34		117.956,27
2001	89.178,46	7.720,80	50,24	96.949,50
2002	60.439,55	5.188,29	122,07	65.749,91
2003	78.170,00	6.110,00		84.280,00

3.2 Market Categories and Indices

Market categories and indices for the period under study (1990-2003) were slightly different that the current ones. Listed companies were classified in separate ATHEX markets according mainly to the size of the companies using the traded securities (the level of their capitalization). There were three markets. The Main Market, the Parallel Market and the New Market (see Table 3.4). In the Main Market shares of large and middle capitalization firms were traded. The requirements were set forth in 1985 (following the European Council Directive) and obliged the company to employ minimum of owned funds of €11.74 millions in the year of its listing application, legal, audit and financial compliance to markets standards for three years prior to the listing. Fast track procedures were not excluded for quick enlisting but additional information was needed and it was on board of directors' discretion. Free float percentage to broad investing public of at least 25% was necessary and dispersion of them must me wide, meaning to at least 2000 individuals with no more than 2% of the total number of shares. The number of prerequisites increased for companies belonging to sectors such as construction, insurance, shipping, automobile and trading.

The Parallel Market was created in 1988 in order to encourage small and medium size companies to raise money for their expansion. A company needed to have own funds of €2.9 million at least, to comply in terms of legal, audit and financial requirements for at least two years and to have sufficient dispersion of no less than 20%. These shares must have been distributed to more than 1000 individuals while each one can not hold more than 2%. At least 80% of the total number of shares being distributed should have originated from a share capital increase. Fast track procedures were allowed but underwriter was obliged to absorb any shares left by the public. Parallel's market stocks could be transferred to the main market after two years of unproblematic presence, if they satisfy main market's requirements and have made proper use of the capital raised as had been originally stated in the relevant prospectuses.

The new market ''NEHA'' is the last market segment that was created (legal framework was set in 1999 and 2000 and the actual listing began in 2001 with just one company) and allowed companies to enlist with minimum needed paid-up capital of €0.586 million for the fiscal years prior to the submission of the listing application (otherwise include shares of companies characterized as dynamic and innovative). Legal, audit and financial compliance is the same as the parallel's market. Moreover any shareholder with shares valued equal or more than 5% of company's share capital prior to the listing were obliged for a year not to transfer more than 20% of their stake and for a three years period the percentage increase to 50%. In any case before a company is listed on NEHA, 80% of the company shares must have been blocked.

For the period under study there were seven significant indices: Composite index for the main market, Total return composite index for the main market, Composite index for the Parallel Market, Total return composite index for the Parallel Market, Sector Indices, Index of newly listed companies, and the All-share Index. The composition of the indices was reviewed every six months. The main market composite index included the first 60 shares of all sectors of the main market according to market capitalization and value of transactions. The parallel market composite index included the first 40 shares in aspect of market capitalization and value of transactions. The total return composite index of the two markets showed the total return of each market general index assuming reinvestment of shares dividends. Sector indices to be created must have included at least five companies for which the average market value of shares was greater than or equal to 1% of the market value of the ASE-listed shares. A sector could be established by just three shares if their market shares exceeded 3% of the market value of all ASE-listed shares. Finally the number of shares constituting the sector index must correspond to at least 65% of the sector's average market value. Since 2/1/2006 Athex BoD put into effect as far as sectors are concerned the FTSE Dow Jones Industry Classification Benchmark (ICB). Stocks are currently classified into various sectors of economic activity according to which activity is the major source of profits for the company. Some of the main FTSE indexes created during the sample period are:

FTSE/ATHEX 20 INDEX	Is the large cap index, capturing the 20 largest blue chip companies within the Big Cap segment of Athens Market. First calculates in Sept 1997
FTSE/ATHEX MID 40 INDEX	Is the mid cap index and captures the performance of the next 40 companies within the Big Cap segment of the Athens Market. Initiated in December 1999.
FTSE/ATHEX Small Cap 80 INDEX	Is the small cap index and captures the performance of the largest 80 companies within the Mid/Small Cap segment of the Athens Market. Launched in May 2001.
FTSE/ATHEX 140 INDEX	Is the benchmark index and captures the performance of all eligible companies within the Big Cap segment of the Athens Market plus the constituents of FTSE/ATHEX Small Cap 80 Indices. It started in January 2002 with a starting value of 2,000 points. At the end of 2003 the index reached 2,669 (increase +33.45%).

This sector classification was approved by the Capital Market Commission (published in Gov. Gaz 1884 B/20.12.2004). The same Decision forced the new integrated Securities Market, which is divided into five categories: Big Capitalization, Medium and Small Capitalization, Special Stock Exchange Characteristics, Under Supervision and Under Suspension. In order for one firm to be listed into Big Capitalization Category it must have an average capitalization over € 100 millions, their stock must have a liquidity of 15% or a liquidity of more than 10% but dispersion of stocks per owner less than 2%. The company must keep a free float of at least 20%. Mid & Small Capitalization category includes listed companies which have a capitalization less than 100 million and do not belong to the rest of the following categories. Special Stock Exchange Characteristics category is consisted of companies that have liquidity of less than 5% or spread of ownership more than 6% or free float less than 10%. Furthermore the price of the stock must be lower than € 0.30 or the turnover of the company must be below € 3 millions.

Under supervision stocks are those who accumulate losses higher than their own equity or when their own equity becomes in value less than the 50% of the share capital. When the company i) accumulated losses greater than own funds, ii) concentration of own funds smaller than 50% of share capital, iii)achieves a negative Earnings Before Interest Taxies Depreciation and Amortization or it has significant overdue debt, iv) has significant delinquent debts, v) has been classified in articles 44, 45 &46 of Law 1892/1990 (refers to firms that fulfill bankruptcy law's criteria in order to make special arrangements with their debtors), vi) receives vague or negative comments by the Chartered Accountants, vii) announcements or events that creates uncertainty concerning the continuation of the company's business. If these companies can not recover then the chairman of ATHEX board of Directors has the right to suspend the company's shares from trading.

3.3 Short Selling in Athens Stock Exchange

An important issue that we have to mention is the existence and the feasibility of short selling in ASE. Short selling in Hellenic Capital Market was not allowed for most of our testing period and even after the initial legal formulations it was rather limited and unknown to most investors. Trades used to be cleared in three days after the day of transaction. The first law for short selling was put into power in 1995. Law 2324[14] allowed short selling under specific circumstances (it could be performed only through Over The Counter transactions and only if the total value of the sold stocks represented 10% of the total value of the company). The second law regarding further provisions for short selling and securities lending was voted in 1997[15] that was when also the legal framework for the privatisation of Athens Stock Exchange was empowered. That was the

[14] Gov. Gaz. A 146/17-7-1995
[15] Law 2533/1997, Gov. Gaz. A 228/11-11-1997

year when Athens Derivatives Exchange (ADEX) and Athens Derivatives (ADECH) were legally established and one could officially trade derivatives on commodities, stocks and indices. However borrowing and lending of stocks was only allowed under strict conditions and only if the board of directors of ASE issued a relevant decision.

It was not until 2001 when with the Regulation 2/216/17-5-2001[16] of the Capital Market Commission short sales in the Main and the Parallel Markets of the Athens Stock Exchanges were realized. ASE members either on their own account or for their customers could proceed in short selling if there was a lending of equivalent securities by the Athens Derivatives Exchanges Clearing House (ADECH). This means that an investor in order to finalize a short selling, must previously or the same day at the latest have acquired the shares he short sales by ADECH. The acquisition of these shares is achieved through a stock lending contract at the ADEX through an ADEX Member. The acquisition of the shares from the ADECH was necessary so that the short selling is cleared either by the ASE member or a Custodian. The product which are connected to the short selling are stock repos (stock lending) and stock reverse repos (stock borrowing) and they are traded on the ADEX.

In the frame of the Greek Capital Market development, the Athens Stock Exchange, in cooperation with the ADEX, ADECH and Central Securities Depository, provided the investment tool of short selling for shares listed on the ASE, with a simultaneous or previous stock lending from the ADECH. The stock lending from the ADECH is made through the realization of an agreement of purchase of shares with a Stock Reverse Repo

[16] Gov. Gaz. 667B/31-5-2001

through trading of the corresponding product. Short selling tool was thought to enhance liquidity and therefore reliability of the market. The maximum short selling open position per investor and per share is the 1% of the free float rate of the share. Also at that time the up-tick rule applied. Specifically the short selling order was always executed at higher price than the last transaction and therefore these orders could not cause a fall of the share price (there was no market order).

In order for someone to cover a short sale on a stock, there has to be another counterparty who lends the particular stock. Stock lending became feasible after the imposition of the aforementioned law. The lenders offered their shares to ADECH receiving as a fee their participation to the profits from the interest that the ADECH receives from the further lending of shares. The return is not known in advance. Finally ADECH created a shares pool which may be used for the lending of the shares to investors who need them either to cover short selling or to cover obligations of shares delivery.

There is a limit that ADECH can lend. Specifically, ADECH ceased to lend shares when the non-disposed shares were below the 25% of the total volume that ADECH has borrowed. Lenders may ask to get back the total number or part of the shares they have lent. Maximum daily limit for shares repurchase by the lender was 0.03% of the existing shares of the issuer, in order the short squeeze to be avoided. ADECH had the ability to borrow in total no more than 5% of the existing shares of the issuer. Stock borrowers (through stock reverse repos) were the investors, whereas lender could be only ADECH. ADECH lends the shares to the investors who needed to cover the short selling. The buyer paid ADECH a daily interest that corresponded to the borrowing of the shares. The borrower was able to give back the total number or a part of the shares he has borrowed at any time. The shares borrowing interest rate was never less than 3-month Euribor interest rate and it was formed according to the demand. The commission of the transaction for borrowing was doubled (from 0.015% to 0.03% on the value of the transaction). ADECH required a margin of up to 150%.

These institutional changes accompanied by fiscal and monetary policy changes allowed the Greek capital market to be upgraded by Morgan Stanley Capital International (MSCI) on 31st May of 2001 from an emerging market to the developed status.

The framework that was structured in 2001, continued to be reformed with the following laws of the Greek Parliament and decisions by the Capital Market Commission in their effort to adjust to the rapid changes that took place internationally after the 11/9/2001 and especially after the credit crunch in late 2008. We will briefly refer to them even if these laws lay beyond the chronological horizon of our sample data. Under the Regulation 5/403/8-11-2006 of the Capital Market Commission specified the perquisites when short-selling of a stock is actually allowed, the foundation of an on-line system where short-sales could be registered, the more specific clearing directions, the obligation of the commission to inform investors concerning the short-sales daily orders.

In 2008 a series of reforms by the Hellenic Capital Market Commission altered the framework of short selling in the ASE. This has happened because of the turbulence in the international capital markets and the precaution measurements that the American and later on the European supervisory committees imposed. Following the coordinative action of the Committee of European Securities Regulators, Regulation 1/485/23-09-2008 of the Hellenic Capital Market Commission decided that every member of the ASE should declare if any order for sale was a short-sale one (flagging) and the same holds for every order that closed up a short sale position. In the case when there are technical problems the orders for opening or closing a position is valid until the end of the session. Any information relative to short-selling positions (such as volumes, number of stocks that had been lent per firm, negative net short position on every stock that exceeds the 0,10% of the issued number of stocks and every change of this position) should be publicly available every day.

Regulation 1/486/6-10-2008 of the Hellenic Capital Market Commission declared that short-selling orders would be introduced into the trading system of ASE with a price higher than the last price of a non-prearranged trade of a particular stock (uptick rule). There were strict rules of whom and when could be excluded by this regulation. Finally just few days later according to the Regulation 1/488/10-10-2008 any kind of short-selling was forbidden initially until the end of October 2008, then until the end of the year 2008 (Regulation 1/490/31-10-2008) and finally until 31-5-2009[17].

[17] According the decision of the Board of Directors 493/11-12-2008.

CHAPTER 4: CONTRARIAN STRATEGIES IN THE ASE

In this chapter we test for the existence of contrarian profits in the Athens Stock Exchange. The methodology employed in this chapter is the De Bondt and Thaler (1985) methodology and is thoroughly outlined below.

4.1 Data

In order to conduct our empirical analysis we use monthly closing prices of all stocks listed in the Athens Stock Exchange (source: DataStream). We have 14 calendar consecutive years of data from December 1989 until January 2004. We use both overlapping formation periods and non-overlapping formation periods. The fact that we use monthly data instead of daily or weekly reduces the transaction costs, which in general they have been presented as the final frontier of safeguarding market efficiency as many trading strategies fail to produce positive outcomes after considering transaction costs. An additional advantage of using monthly data is the success of avoiding microstructure biases such as bid-ask bounce effect or non-synchronous trading. (See following chapters for a discussion on microstructure biases). By using overlapping formation periods we are able to capture all the different combinations of formation periods coming from a single sample. The following tables show how the available dataset is used to create several overlapping formation periods (Table 4.1) and non-overlapping formation periods (Table 4.2) of various lengths and the potential performance periods we can take in order to evaluate the returns of the arbitrage portfolios. For instance, in Table 4.1 we can see that the number of the overlapping formation periods is inversely related on the length of the formation period. For our overlapping methodology we tried formation periods of one, two and up to five years (12, 24, 36, 48 and 60 months). For a one year formation strategy we have 13 overlapping formation periods. For two years we get 12 overlapping formation periods. Equally we had for a 36 month time interval as formation periods with 11 different overlapping formation periods, a 48 month gave us 10 periods and finally a five year period segmentation left us with just 9 available testing periods. Furthermore, in Table 4.2 we can see that the choice of non-overlapping formation periods significantly reduces the number of periods especially as the time span increases. For 24 months we can form six different time intervals. Three years formation non-overlapping period gives us only four different testing periods, a four years non-overlapping periods end up with three formation periods, and the five years time interval offers just two formation periods.

According to Jegadeesh and Titman (1993) the use of overlapping time periods increases the significance of the tests and their empirical results. Hon and Tonks (2002) argue that by conducting non-overlapping tests for long-horizons is inevitable to loose crucial information, plus that there is a chance that the economy cycle may be a major of component in determining the outcome of contrarian and momentum strategies due to limited data range. This is issue is further investigated in chapter 5. Attributing in favour of overlapping use of data Boudoukh *et al.* (1994) claim that, apart from the risk of heteroskedasticity, the results of the Richardson and Smith (1991) study imply that the variances of the autocorrelation estimators using nonoverlapping data will be (asymptotically) 47 percent higher, which can be interpreted as the percentage number of additional observations needed to achieve the same power as the overlapping method. However, Smith and Yadav (1996) conclude that for explanatory variables with serial correlation, GMM estimators perform worse than non-overlapping regressions in a matter of producing low standard errors (i.e. generating empirical size probabilities above that of their respective theoretical values). Moreover Hon and Tonks (2003) made a comment on the use of overlapping data periods that they are particularly transaction intensive as each month a huge number of transactions may take place for rebalancing portfolios. This counterargument will be presented thoroughly in the following chapter. De Bondt and Thaler (1985) originally used non-overlapping periods in their study. Their data set extended from few years before the big crash, up to the beginning of the 1980's. A database like this, gave them the ability to make a sustainable number of non-overlapping formation periods so as to examine their hypothesis.

The rest of the dataset used in this research includes three-month Treasury bill rates as a proxy for risk-free returns and as a proxy for the market portfolio we use monthly returns of the Athens Stock Exchange General Price Index (source: DataStream), which is a value-weighted index that is composed by the most heavily traded stocks that represent approximately 70% of total market capitalization and approximately 80% of total volume transactions volume. Galariotis (2004) shows that the selection of a value weighted or an equally weighted index does not alter the main findings. Furthermore the empirical analysis requires an accounting data such as annual market capitalization and book value of equity. Stock returns are continuously compounded, defined as the first-difference of the natural logarithmic price levels adjusted for stock dividends, stock splits and dividend yields.

We excluded from our sample for each formation period that we apply, stocks which had for three consecutive months the same price or their prices were non-available. Our intention was to eliminate stocks that could have been either under Stock Exchange Committees' supervision or they had low volume or even they had been terminated from the trading activity. We tried to stay close to the methodology and the assumptions of De Bondt and Thaler (1985,1987) and we excluded the possibility of observing an underreaction effect due to the low volatility of a stock. The total number of the firms included in each formation period depends on the length of that formation period.

Table 4.3 presents a detailed description of the available firms. It is obvious that the number of the firms examined, increases as we move towards the end of the decade and the beginning of the new century. The enthusiasm of Greece adopting Euro as the common currency and abolishing the fear of the existing, up to that moment, danger of currency instability, the lack of strict financial and regulatory constraints for the inclusion of new firms into the Athens Stock Market, created the illusion to companies managers that they found a relatively cheaper way of raising capital for their firms. Specifically for the five-year formation period scheme (1990-1994) we find the fewest stocks included, only 34. On the other side the formation period with the largest sample of stocks is the 12 month formation period of 2002. It is important to say that for the first few years of our sample the number of companies that were excluded from the analysis due to the constraints of consequent identical monthly return or due to the exodus from the index reached almost the increment of 30%. At the end of our sample over 85% of the stocks traded on ASE participated in the contrarian trading strategies.

Table 4.1: Overlapping Formation & Testing Periods

OVERLAPPING

FORMATION PERIOD	PERFORMANCE PERIOD				
1Y	**1Y**	**2Y**	**3Y**	**4Y**	**5y**
90	91	91-92	91-93	91-94	91-95
91	92	92-93	92-94	92-95	92-96
92	93	93-94	93-95	93-96	93-97
93	94	94-95	94-96	94-97	94-98
94	95	95-96	95-97	95-98	95-99
95	96	96-97	96-98	96-99	96-00
96	97	97-98	97-99	97-00	97-01
97	98	98-99	98-00	98-01	98-02
98	99	99-00	99-01	99-02	99-03
99	00	00-01	00-02	00-03	
00	01	01-02	01-03		
01	02	02-03			
02	03				

FORMATION PERIOD	PERFORMANCE PERIOD				
2Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-91	92	92-93	92-94	92-95	92-96
91-92	93	93-94	93-95	93-96	93-97
92-93	94	94-95	94-96	94-97	94-98
93-94	95	95-96	95-97	95-98	95-99
94-95	96	96-97	96-98	96-99	96-00
95-96	97	97-98	97-99	97-00	97-01
96-97	98	98-99	98-00	98-01	98-02
97-98	99	99-00	99-01	99-02	99-03
98-99	00	00-01	00-02	00-03	
99-00	01	01-02	01-03		
00-01	02	02-03			
01-02	03				

FORMATION PERIOD	PERFORMANCE PERIOD				
3Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-92	93	93-94	93-95	93-96	93-97
91-93	94	94-95	94-96	94-97	94-98
92-94	95	95-96	95-97	95-98	95-99
93-95	96	96-97	96-98	96-99	96-00
94-96	97	97-98	97-99	97-00	97-01
95-97	98	98-99	98-00	98-01	98-02
96-98	99	99-00	99-01	99-02	99-03
97-99	00	00-01	00-02	00-03	
98-00	01	01-02	01-03		
99-01	02	02-03			
00-02	03				

FORMATION PERIOD	PERFORMANCE PERIOD				
4Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-93	94	94-95	94-96	94-97	94-98
91-94	95	95-96	95-97	95-98	95-99
92-95	96	96-97	96-98	96-99	96-00
93-96	97	97-98	97-99	97-00	97-01
94-97	98	98-99	98-00	98-01	98-02
95-98	99	99-00	99-01	99-02	99-03
96-99	00	00-01	00-02	00-03	
97-00	01	01-02	01-03		
98-01	02	02-03			
99-02	03				

FORMATION PERIOD	PERFORMANCE PERIOD				
5Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-94	95	95-96	95-97	95-98	95-99
91-95	96	96-97	96-98	96-99	96-00
92-96	97	97-98	97-99	97-00	97-01
93-97	98	98-99	98-00	98-01	98-02
94-98	99	99-00	99-01	99-02	99-03
95-99	00	00-01	00-02	00-03	
96-00	01	01-02	01-03		
97-01	02	02-03			
98-02	03				

Table 4.2: Non-Overlapping Formation & Testing Periods

NON-OVERLAPPING

FORMATION PERIOD	PERFORMANCE PERIOD				
1Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90	91	91-92	91-93	91-94	91-95
91	92	92-93	92-94	92-95	92-96
92	93	93-94	93-95	93-96	93-97
93	94	94-95	94-96	94-97	94-98
94	95	95-96	95-97	95-98	95-99
95	96	96-97	96-98	96-99	96-00
96	97	97-98	97-99	97-00	97-01
97	98	98-99	98-00	98-01	98-02
98	99	99-00	99-01	99-02	99-03
99	00	00-01	00-02	00-03	
00	01	01-02	01-03		
01	02	02-03			
02	03				

FORMATION PERIOD	PERFORMANCE PERIOD				
2Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-91	92	92-93	92-94	92-95	92-96
92-93	94	94-95	94-96	94-97	94-98
94-95	96	96-97	96-98	96-99	96-00
96-97	98	98-99	98-00	98-01	98-02
98-99	00	00-01	00-02	00-03	
00-01	02	02-03			

FORMATION PERIOD	PERFORMANCE PERIOD				
4Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-93	94	94-95	94-96	94-97	94-98
94-97	98	98-99	98-00	98-01	98-02
98-01	02	02-03			

FORMATION PERIOD	PERFORMANCE PERIOD				
3Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-92	93	93-94	93-95	93-96	93-97
93-95	96	96-97	96-98	96-99	96-00
96-98	99	99-00	99-01	99-02	99-03
99-01	02	02-03			

FORMATION PERIOD	PERFORMANCE PERIOD				
5Y	**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
90-94	95	95-96	95-97	95-98	95-99
95-99	00	00-01	00-02	00-03	

Table 4.3: Number Of Firms Available For The Strategies

FORMATION PERIOD	1Y	Number of Firms	2Y	Number of Firms	3Y	Number of Firms	4Y	Number of Firms	5Y	Number of Firms
	1990	44	1990-1991	41	1990-1992	64	1990-1993	36	1990-1994	34
	1991	66	1991-1992	62	1991-1993	87	1991-1994	53	1991-1995	50
	1992	80	1992-1993	78	1992-1994	100	1992-1995	66	1992-1996	62
	1993	92	1993-1994	89	1993-1995	105	1993-1996	75	1993-1997	72
	1994	103	1994-1995	96	1994-1996	114	1994-1997	83	1994-1998	80
	1995	135	1995-1996	123	1995-1997	150	1995-1998	114	1995-1999	111
	1996	149	1996-1997	142	1996-1998	166	1996-1999	135	1996-2000	134
	1997	165	1997-1998	157	1997-1999	182	1997-2000	155	1997-2001	152
	1998	179	1998-1999	176	1998-2000	192	1998-2001	176	1998-2002	173
	1999	205	1999-2000	205	1999-2001	204	1999-2002	202		
	2000	240	2000-2001	238	2000-2002	248				
	2001	290	2001-2002	285						
	2002	308								

4.2 Methodology

Stock returns are computed as the logarithmic return of each stock:

$$r_{j,t} = \ln(\frac{P_{j,t}}{P_{j,t-1}}) \qquad (3)$$

Following De Bondt and Thaler (1985), for each month starting from January 1990 and for each stock j on the ASE we estimate each monthly market-adjusted excess returns AR_{it} as follows:

$$AR_{jt} = R_{jt} - R_{mt} \qquad (4)$$

where R_{it} is the return of each stock j for every month t and R_{mt} is the return of the value-weighted market index. As discussed by Doukas and Petmezas (2007), Fuller *et al.* (2002) and Dong *et al.* (2006), who employ a similar definition of abnormal returns, equation (4) can be shown to be a special case of the market model. This approach amounts to assuming that α=0 and β=1 for the firms in our sample. Note that later in the study we also employ the Fama and French (1996) three factor model to obtain abnormal returns.

After calculating the excess returns or abnormal returns (ARs) we proceed in estimating the cumulative abnormal returns of each stock for the desired time interval (CARs). This consists the formation period for each stock:

$$CAR_j = \sum_{t-n}^{0} AR_{jt} \qquad (5)$$

We then categorize stocks according to their cumulative abnormal returns and the top ten in performance consist the winners' portfolio for that formation period. On the other hand, the ten stocks with the lowest cumulative abnormal returns form the losers' portfolio. Both portfolios consist of equally-weighted stocks. We repeat this procedure for the next formation period (i.e. the next 12, 24, 36, 48 or 60 months) by starting from the second consecutive year of our sample and we repeat until the end of the sample. This is how the overlapping formation periods are created. On the other side when we decide to divide our dataset to non-overlapping formation periods the procedure starts all over again for the next separate time interval.

After completing constructing winners and losers portfolios within the formation periods then we proceed in the evaluation (or else called holding or testing) periods of these extreme portfolios. We evaluate once more the Abnormal Returns of each stock of the extreme portfolio and then the Cumulative Abnormal Returns (CARs) for the sum of the testing periods that are created after deciding which length period we will choose for our strategy. Note that if either winner or loser stocks, which are constituents of any arbitrage portfolio, happen to become delisted from the Athens Stock Market during performance period then we drop them from our portfolio and the money invested on that are spread equally over the remaining stocks. Cumulative Abnormal Returns can be calculated as follows:

$$CAR_{W,j,t} = \sum_{t-1}^{t} AR_{W,j,t} \qquad (6)$$

$$CAR_{L,j,t} = \sum_{t-1}^{t} AR_{L,j,t} \qquad (7)$$

Where $CAR_{W,j,t}$ is the Cumulative Abnormal Returns of the Winner Portfolio and $CAR_{L,j,t}$ are the Cumulative Abnormal Returns of the Loser Portfolio. The final step is to estimate the Average Cumulative Abnormal Returns (ACARs) for every portfolio from each testing period:

$$ACAR_{W,j,t} = \frac{1}{N}\sum_{t-1}^{N} CAR_{W,j,t} \qquad (8)$$

$$ACAR_{L,j,t} = \frac{1}{N}\sum_{t-1}^{N} CAR_{L,j,t} \qquad (9)$$

where N represents the number of all testing periods. For t>0 (t = 1,2,…,12) if the market overreact to new information then we expect according to De Bondt and Thaler (1985):

$$ACAR_{L,t} > 0$$

$$ACAR_{W,t} < 0 \qquad (10)$$

$$ACAR_{AP,t} = ACAR_{L,t} - ACAR_{W,t} > 0$$

Where $ACAR_{AP}$ stands for the Average Cumulative Abnormal Return of the arbitrage portfolio. If the market, however, underreacts to new information then we would expect the above relationships to change direction:

$$ACAR_{L,t} < 0$$

$$ACAR_{W,t} > 0 \qquad (11)$$

$$ACAR_{AP,t} = ACAR_{L,t} - ACAR_{W,t} < 0$$

According to the weakly efficient market the inequalities should not appear. In order our results to be consistent with Efficient Market Hypothesis and especially the weak type of it the above relationship should become:

$$ACAR_{AP} = ACAR_{L,t} - ACAR_{W,t} = 0 \qquad (12)$$

In order to evaluate whether ACARs are statistically significant at any time we have to use the t-statistic suggested by De Bondt and Thaler (1985). In order to achieve that we need the pooled estimate of the population variance in CAR_t:

$$S_t^2 = \frac{\left[\sum_{n=1}^{N} \left(CAR_{W,n,t} - ACAR_{W,t} \right)^2 + \sum_{n=1}^{N} \left(CAR_{L,n,t} - ACAR_{L,t} \right)^2 \right]}{2(N-1)} \tag{13}$$

With two samples of equal size N, the variance of the difference of sample means equals $2\frac{S_t^2}{N}$ and the t-statistic is therefore:

$$T_t = \frac{\left[ACAR_{L,t} - ACAR_{W,t} \right]}{\sqrt{\frac{2S_t^2}{N}}} \tag{14}$$

Relevant t-statistic can be found for each of the 12, 24, 36, 48 and 60 post-formation months. The number of the performance periods once more varies according to the time interval we are willing to use. Each formation period can be followed by a 12, 24, 36, 48 or even 60 months of testing period where the performance of the arbitrage portfolio will be evaluated for their magnitude and significance.

4.3 Results

In this sub-section we are going to present the results that we exported from applying the DeBondt and Thaler methodology to the available database for the Athens Stock Exchange.

4.3.1 Overlapping Data

As far as the overlapping formation periods results are concerned (Table 4.4), the overreaction hypothesis seems to hold for all trading strategies we employed. Overall we achieved a maximum number of 25 contrarian trading strategies from a combination of 55 formation periods and 225 different performance periods. More specifically, the 1Y formation period (1YF henceforth) contrarian strategy achieves highly (for 1% level of significance) statistical significant profits for testing periods of two or more years of performing period: the 3-year performing period profits amount to 36,5%, the 4-years performing period profits equal 34%. The shorter term 1Y formation period and 1Y testing period strategy yields a moderate 10% profit significant at 10% level of significance. For the 2YF periods the generated contrarian profits are statistically significant at 1% for all holding periods and maximum profitability is achieved for the 2x2 strategy (i.e. the 2 year formation period – 2 year testing period).

Overall, the maximum profits result from the 3x3 strategy (i.e. the 3 year formation period – 3 year testing period) and are about 66% and are statistically significant at the 1% level of significance. These profits seem to also be statistically significant. Note that this is also the combination of formation-performance period for which De Bondt and Thaler present as the most profitable in their original article. The choice of the particular 36 months portfolio formation period is consistent with the opinion expressed by Graham (1959), whereas the required interval for a substantial underevaluation to correct itself averages approximately 1½ to 2½ years and therefore a 3YF-3YP strategy compromises between statistical and economic considerations.

One extremely important feature of the results we have just presented is that the overreaction effect of the arbitrage portfolios is strongly asymmetric as it has been widely reported to the international relevant literature (De Bondt and Thaler (1989), Dissanaike (1996), Chopra *et al.* (1992)). The impressive and unique characteristic of the contrarian profits in the Athens Stock Market, however, is that this asymmetry comes from the exact opposite side of the portfolio, than the one that has been suggested in the previous academic literature for international markets. That is, contrarian profits for the majority of the trading schemes originate from the winner side of the portfolio (i.e. the short position) and *not* from the loser side of the portfolio (i.e. the long position). In other words the overreaction phenomenon is attributed mainly to previous winner stocks that lose great percentage of their price during the performance period and which contrarians short them at the end of formation period. This conclusion for the ASE contradicts most authors' view that the overreaction effect is mainly due to profits generated by the excess performance of the loser-side of the portfolio.

Findings similar to ours came from Kato (1990) who initially documented a long-term return reversal in the stock market of Japan in which losers outperform winners. However, he showed that winners do not perform badly in the subsequent period, unlike US firms (see also Baytas and Cakici (1999)). These results suggest that price reversal for winners is much larger in Japan than it is for losers. Specifically, over three years winner portfolios earn 68.7% less than the market, whereas loser portfolios of 35 stocks earn, on average, 25.9%. In our case, the highest reversal for the top ten winners stocks is met for the 4YF-3YP period where winners achieve 50.4% less than the market and at the same time the bottom loser portfolio losses a mere 4.9% comparing to the market.

This asymmetric reaction is less pronounced in countries like US (Zarowin (1990)), UK (Clare and Thomas (1995)), Germany and France (Mun *et al.* (1999), Bacmann and Dubois (1998)), where losers outperform the market to a somewhat greater extent than winners underperform it. A few explanations have been advanced for the apparent asymmetry found in other studies as well. Initially, De Bondt and Thaler (1985), who indicated larger overreaction effect for losers in the US, had argued that differences in systematic risk could explain the asymmetry. Later, Conrad and Kaul (1993) tried to explain it in terms of bid-ask biases and infrequent trading. Finally, Dissanaike (1996) maintained that the observed asymmetry might be entirely "illusory" and may be explained by the peculiar properties of returns, saying that "the test-period returns on a contrarian portfolio are not always a reliable measure of the strength of price reversals".

Baytas and Cakici (1999) believe that for the Japan stock market's asymmetry responsible is the frenzy market run-up that Japan's market faced during the 1980's, whereas European markets were relatively less bullish that period. Their argument is based on that in boom markets investors tend to overreact more on the upside than on the downside. For example they argue that if good news is received by the market as great news while bad news is received by the market as not so bad news, then winners may be reasonably strayed far away from their fundamental values, while losers are not bid too far down. We could assume that this mis-pricing story holds for the Greek Capital Market as well. Investors' intention to overreact to any given positive information concerning the future price of a stock especially at the end of the past decade has exceeded any plausible explanation. Rumours and fake news regarding new allies or mergers and acquisitions concerning firms listed on the ASE, used to swing the decisions of investors.

A peculiar feature of our findings is that for many of the tested strategies the long side of the investors' arbitrage portfolios produces marginally positive or even more negative results, indicating that the observed contrarian profits are entirely coming from winner short-side. For the traditional, according to De Bondt and Thaler's methodology, portfolio intervals (3 and 5 years) the long side of the portfolios produced positive returns which are still two to three times smaller than winners' side price reversal. We may assume that although loser stocks have not been undervalued that much, investors find difficulty in confining themselves to buying stocks that had poorly performed for the past few years. This may be caused by investors' conservatism or due to the slow diffusion of the markets good news for the prior loser stocks.

4.3.2 Non-Overlapping Data

De Bondt and Thaler (1985) tested their methodology on non-overlapping periods due to their extensive sample period. Even though our sample period extends to just 14 years by using non-overlapping formation periods we managed to apply 24 contrarian trading strategies from a combination of 29 formation periods and 119 different performance periods. *This is an important step in the analysis since it serves as a reliable robustness test for the aforementioned results*. The non-overlapping period results are presented in Table 4.5.

As can be seen from Table 4.5, non-overlapping formation period results are similar to overlapping period results as regards to one-year overlapping formation periods (1YF) regardless of the time span of the performance period, both in economic significance and in statistical significance. Concerning other available combinations derived by non-overlapping formation data we highlight that after the 48months formation period contrarians' strategies, especially with performance periods more than a year do not provide statistically significant profits, with the exemption of the 3x3 strategy (profits 96% with a t-statistic of 3.41). Generally the acceptance of the overreaction effect is seriously in doubt as the length of the formation period extends to more than three years.

One plausible explanation for this would be the small duration of the data sample that we possess. By the use of non-overlapping formation periods the examined performance periods lessens greatly as the time interval widens. It is obvious that for a two-year formation periods we get six only different periods for which we have to examine the viability of the contrarian strategies. This number doubles when overlapping data are being used. When the time span grows like for 3-year period or for 4-year formation period the various performance portfolios reduce to four and three equivalently. We have to mention that the methodology of calculating abnormal returns, cumulative abnormal returns and average cumulative abnormal returns is exactly the same.

The magnitude of the profits for a one-year formation period extends form a 19.8% of the two-year's performance period up to the maximum 36.5% of the 3YP strategy. For the 2YF strategy profits are impressive, offering minimum 35.1% on the 5YP and maximum 60.7% for the 3YP strategy. Following a 3YF strategy profits are not feasible or significant for the first and the last two different performance periods. However for the 3YF-3YP strategy we get maximization of profitability among all strategies achieving a

96.6% significant for 5% level of significance. The last profitable strategy concerns the 4YF-1YP indicating the existence of a momentum effect rather that an overreaction phenomenon. Figures 4-7 present the profits of 4 indicative strategies graphically with overlapping and non-overlapping data.

Overall it is obvious that the use of non-overlapping periods *reduces but in no way eliminates contrarian profits*. Especially for the 3x3 strategy by De Bondt and Thaler, profits seem to be really high and statistically significant. Summing up contrarian long-term strategies constructed by the well known De Bondt and Thaler (1985) methodology are profitable in the Athens Stock Exchange. The results indicate that one may benefit from shorting prior winner stocks and going long to prior loser stocks, i.e. contrarian strategies are profitable in the ASE, irrespective of methodological issues (overlapping & non-overlapping periods).

De Bondt and Thaler (1985), among others, argue that this is due to investor overreaction to information and subsequent miss-pricing; furthermore, the higher the miss-pricing the higher the forthcoming price reversal. Many authors, however, have argued that these profits may be explained within a rational pricing framework. For instance Fama & French in a series of articles (1992, 1993, and 1996) present a multi-factor pricing model and show that the anomalous returns of contrarian strategies are explained within the model.

The following sub-sections aim to investigate this argument. In other words, are contrarian profits in the ASE explained with rational arguments? If not, then the obvious explanation may be behavioural biases on investor behaviour.

Table 4.4: Contrarian Profits for Overlapping Formation Periods

		PERFORMANCE PERIOD				
FORMATION PERIOD		**1Y**	**2Y**	**3Y**	**4Y**	**5Y**
1Y	Winners	-15,5%	-25,5%	-36,6%	-38,4%	-31%
	Losers	-5,3%	-5,8%	-0,1%	-4,4%	-5,6%
	ACARap	10,2%	19,8%	36,5%	34%	25,4%
	t-statistic[18]	1,92*	2,89***	4,61***	3,92***	4,13***
2Y	Winners	-13,8%	-36,4%	-45,8%	-45%	-34%
	Losers	6,1%	10,9%	17,5%	15,5%	12,2%
	ACARap	19,9%	47,3%	63,3%	61%	45,8%
	t-statistic	3,32***	6,47***	7,25***	7,38***	6,54***
3Y	Winners	-14,6%	-36%	-46,3%	-47,0%	-30%
	Losers	7,7%	11,3%	19,7%	3,3%	5,7%
	ACARap	22,3%	63,3%	66,0%	50,3%	35,6%
	t-statistic	3,20***	7,25***	6,37***	4,34***	4,12***
4Y	Winners	-23,9%	-44,5%	-50,4%	-43,9%	-24%
	Losers	3,6%	-0,9%	-4,9%	-9,7%	7,8%
	ACARap	27,5%	43,5%	45,5%	34%	32,2%
	t-statistic	3,70***	5,31***	4,09***	2,68***	3,33***
5Y	Winners	-20,3%	-37,7%	-40,2%	-32%	-12%
	Losers	10,1%	6,7%	6,8%	13,5%	32,6%
	ACARap	30,4%	44,5%	47,0%	45%	45,0%
	t-statistic	3,61***	4,06***	3,19***	2,65**	3,77***

Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level.

[18] All t-statistics not adjusted for heteroscedasticity because we have checked for ARCH effects in the Cumulative Abnormal Returns series and find no evidence of AutoRegressive Conditional Heteroscedasticity effects. For indicative purposes, Appendix III presents some illustrative results for various portfolios and strategies".

Table 4.5: Contrarian Profits for Non-Overlapping Formation Periods

	PERFORMANCE PERIOD									
FORMATION PERIOD	**1Y**		**2Y**		**3Y**		**4Y**		**5Y**	
1Y	Winners	-15,5%	Winners	-25,5%	Winners	-36,6%	Winners	-38,4%	Winners	-31%
	Losers	-5,3%	Losers	-5,8%	Losers	-0,1%	Losers	-4,4%	Losers	-5,6%
	ACARap	10,2%	ACARap	19,8%	ACARap	36,5%	ACARap	34%	ACARap	25,4%
	t-statistic	1,92*	t-statistic	2,89***	t-statistic	4,61***	t-statistic	3,92***	t-statistic	4,13***
2Y	Winners	-26,2%	Winners	-34,5%	Winners	-63,7%	Winners	-45,4%	Winners	-34,1%
	Losers	-15,1%	Losers	8,1%	Losers	3,0%	Losers	7,9%	Losers	10,0%
	ACARap	11,1%	ACARap	42,6%	ACARap	60,7%	ACARap	53%	ACARap	35,1%
	t-statistic	1,34	t-statistic	2,49**	t-statistic	3,39***	t-statistic	2,90***	t-statistic	2,89**
3Y	Winners	7,8%	Winners	-24%	Winners	-41,7%	Winners	-6,9%	Winners	-36%
	Losers	40,7%	Losers	15,6%	Losers	54,9%	Losers	36,0%	Losers	4,6%
	ACARap	32,9%	ACARap	39,9%	ACARap	96,6%	ACARap	42,9%	ACARap	40,7%
	t-statistic	1,17	t-statistic	1,92	t-statistic	3,41***	t-statistic	1,97	t-statistic	1,80
4Y	Winners	18,5%	Winners	-16,8%	Winners	-14,9%	Winners	-25,5%	Winners	-39%
	Losers	-3,4%	Losers	34,2%	Losers	15,8%	Losers	3,7%	Losers	6,4%
	ACARap	15,0%	ACARap	50,9%	ACARap	30,7%	ACARap	29%	ACARap	32,3%
	t-statistic	2,53*	t-statistic	1,96	t-statistic	0,94	t-statistic	0,63	t-statistic	0,83
5Y	Winners	-51,6%	Winners	-62,9%	Winners	-86,7%	Winners	-83%		
	Losers	-25,2%	Losers	-45,4%	Losers	-67,6%	Losers	-66,7%		
	ACARap	26,4%	ACARap	17,6%	ACARap	19,2%	ACARap	16%		
	t-statistic	0,59	t-statistic	0,38	t-statistic	0,33	t-statistic	0,42		

Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level.

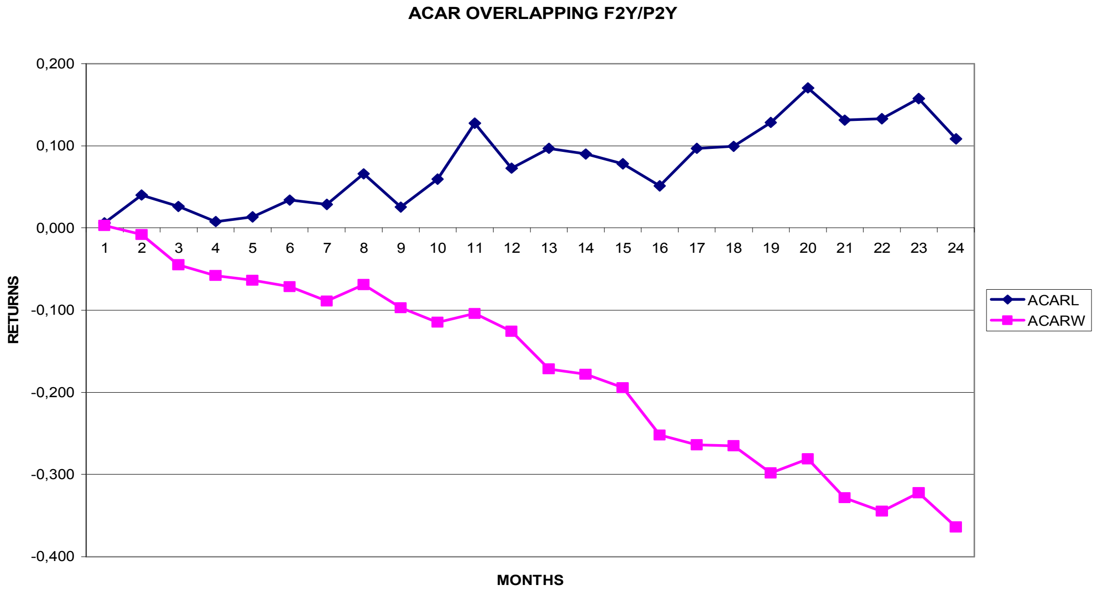

Figure 4.1: Plots of profits for overlapping periods: strategy 2x2

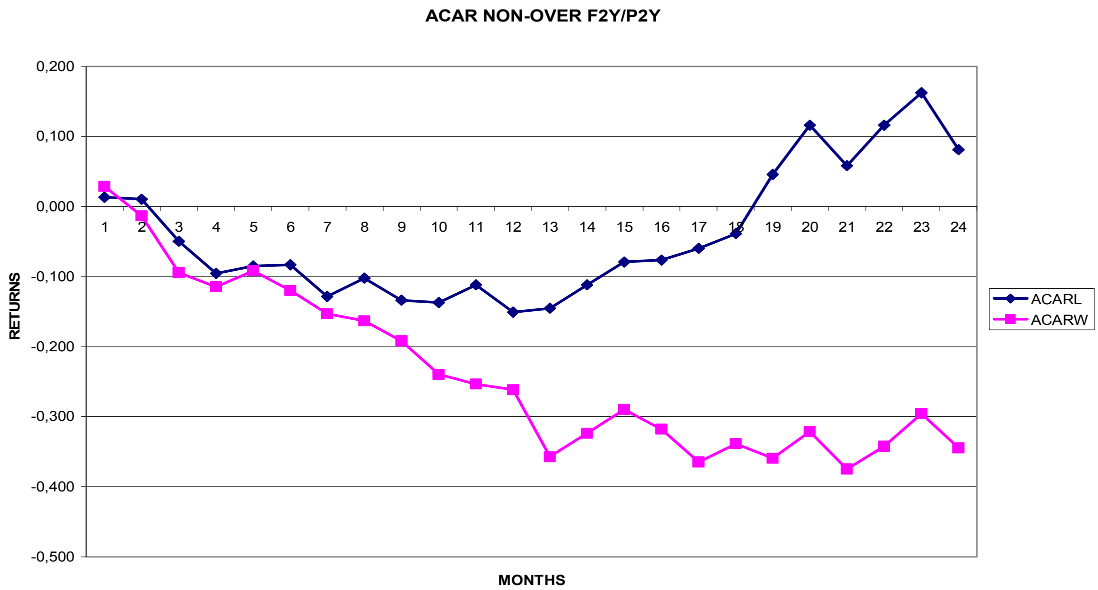

Figure 4.2: Plots of profits for non-overlapping periods: strategy 2x2

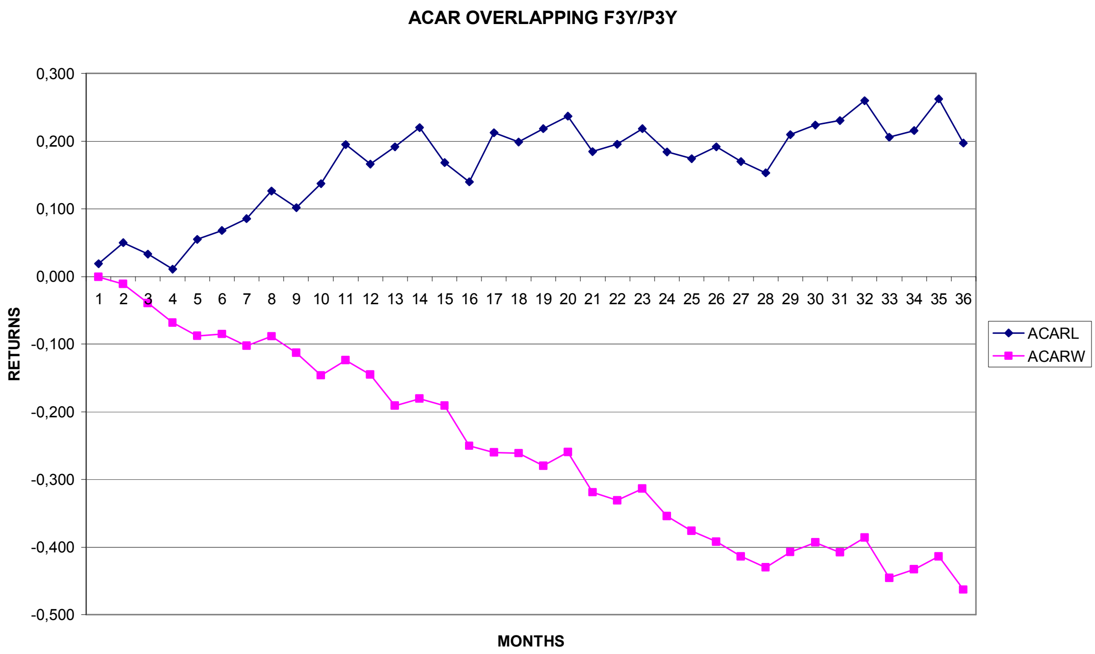

Figure 4.3: Plots of profits for overlapping periods: strategy 3x3

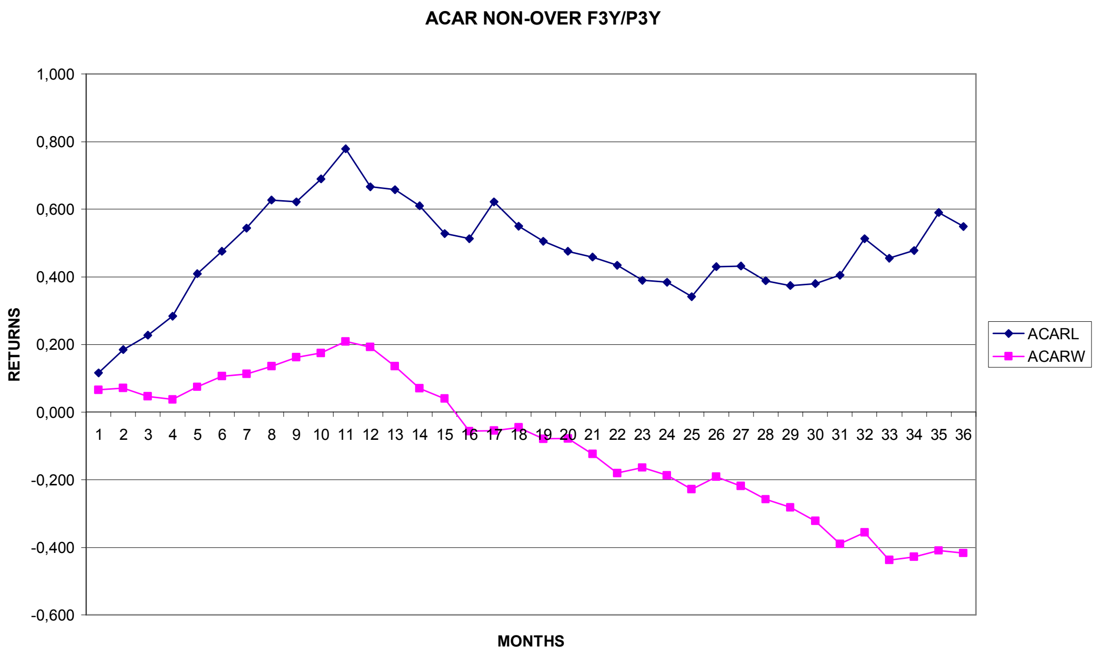

Figure 4.4: Plots of profits for non-overlapping periods: strategy 3x3

4.4 Robustness Tests

In our effort to examine the robustness of the contrarian strategies' profitability we apply two robustness tests at the same number of trading strategies for both overlapping and non-overlapping data (25 and 24 contrarian strategies respectively). The first one is to leave one month gap between the formation and the performance period and the second one to exclude from the winner and losers portfolio the extreme 2.5% observation from the formation as well as from the performance period. Skipping one month between formation and performance period is intended to reduce potential biases induced by non synchronous trading, the price pressure and the lagged reaction documented by Jegadeesh (1990) and Lehman (1990). Jegadeesh and Titman (1993) implemented this time lag to their contrarian strategies. Their results apart from one of the 32 strategies they followed have not weakened statistical significance of their results. In our case considering the fact that we structure our winner-loser portfolios at the end of the formation period irregardless of their duration (one year up to five years), the month that we leave as a gap between formation and performance period is January. Regarding holding periods we take stock price from February and then calculate returns and abnormal returns as we did in the previous section. Holding periods last for an equal time period as formation periods.

Trimming an arbitrarily 2.5% of the extreme observation of our winner-loser portfolio will help us realize if outliers are the main drivers of our zero-cost arbitrage contrarian portfolio profits. As we denoted above our portfolios are consisted of 10 winner and 10 loser stocks. The purpose of taking so small number of stocks was to make our strategy less trading-cost intensive. As we will discuss later in the study transaction costs play a significant role in any potential profitability. Therefore when we take out 2.5% of our portfolios we actually exclude 2 stocks per portfolio (the best performing stocks for the winner and two most underperforming stocks from the losers at the end of the formation period). These stocks are excluded from the holding periods as well. However in most of the cases in the loser portfolios it is common phenomenon, especially after year 2000, some of the stocks that had been chosen during the formation period to have been already excluded due to their delisting. In that case we followed De Bondt and Thaler's method of investing the equally weighted to the rest of the stocks. Therefore by trimming two of the most high performance losers stocks, to have actually minimize our portfolio to more than 2.5%. Moreover Knez and Ready (1997) document that the risk premium on size documented by Fama and French (1992) completely disappears when 1% of extreme observations is trimmed.

4.4.1 Results for Robustness Tests for Overlapping Periods

As we can see from Table 4.6, where the robustness test results are presented, for the one-year formation period (1YF) winner portfolios seem to achieve lower negative returns when we skip one month between formation and performance period in all different performance periods. The same result holds for all previous winners' portfolios in the case of trimming 2.5% of the extreme observations. While winner stocks seems to reverse, losers appear to experience a momentum effect at a smaller magnitude for the one month lag robustness check but at a greater degree for the outliers trimming effect.

By the time that losers continue to achieve negative returns by subtracting the most underperforming stocks leads the whole portfolio to a worse performance. As a result the zero cost portfolios, that consists of taking short position on prior winners and long position on prior losers, overall offers lower returns after the robustness checks. The statistical significance of these profits seems to hold strong when we skip one month but weakens after excluding the outliers. However the 1x3 strategy offers the highest profitability which is statistically significant at the 1% level of significance.

As regards to the two-year formation period (2YF), robustness tests do not seem to lower winners performance at least up to three year of holding period. This is only happening for the 48month of holding period. Moreover for the lengthiest performance skipping one month leads to higher returns. On the loser side portfolios, robustness tests seem to result in even higher returns for the first three performance periods. On the last four and five years holding periods losers performance seem lower but to not a significant level. Overall contrarian portfolios for 12, 24 and 36 months of performance period achieve equally high (for trimming 2,5%) or even higher returns for four out five cases than our initial calculations (1YP: 21.4%, 2YP: 50.5%, 3YP: 63.8% and 4YP: 46.2%). Statistical significance in the first two holding periods has increased after leaving one month gap and for the rest of the periods has worsen but still remained significant at the 1% level.

Three-year formation periods seemed to offer similar results as the two-year ones after applying robustness checks. Losers experience for the third year of holding period the greatest reversals both after skipping one month (+19.9%) or trimming extreme observations (+24.3%). Winners apart from the first 12 months of performing they reverse to negative results but not in the same magnitude as the initial calculations. These mixed portfolio movements leads to zero-cost portfolios equally high as before the robustness checks and in three out of five cases (1YP, 3YP and 5YP) to higher returns after testing for robustness. The most impressing profitability comes from the 3x3 strategy with 70.4% for the contrarian portfolio after the exclusion 2.5% of the outliers. Statistical significance of the results is moreover equally high across the performance periods reaching 1% level of significance. *Overall, the 3x3 year strategy yields contrarian profits between 60%-70% irrespective of robustness tests.*

Four years of formation period shows that winners still perform better after skipping one month between formation and performance and after trimming 2.5% of the extreme portfolio (i.e. lower negative returns) and prior loser portfolios again realize better returns. Therefore zero cost portfolios after the first twelve months accomplice better returns after robustness checks while being statistically significant at the 1% level. Taking 60 months as our last formation period we observed that after robustness checks prior winner portfolios still make negative returns but to a much lower degree. The differences from our first calculations especially after skipping one month could reach from 2% up to 30% as the performance period lengthens. Loser portfolios returns, on the other side, reverse but to a greater extend especially after skipping one month for the four year performance period (+36.8%). Zero-cost arbitrage portfolios for the one and for two year performance periods seem to achieve almost identical outcomes after robustness checks and only for the three and five year performance periods after leaving one month gap they manage to achieve even higher returns (50.4% and 51.4% respectfully). Statistical significance of the contrarian profits remain at the 1% level of significance.

Table 4.6: Comparison of Contrarian Profitability after Robustness Checks for Overlapping Periods

OVERLAPPING FORMATION PERIODS						
FORMATION PERIOD/ PERFORMANCE PERIOD		1Y	2Y	3Y	4Y	5Y
1Y	Winners	-15,5%	-25,5%	-36,6%	-38,4%	-31,0%
	Winners 1M lag	-13,1%	-21,3%	-32,1%	-22,0%	-28,4%
	Winners trim 2,5%	-13,3%	-19,6%	-30,3%	-32,1%	-24,2%
	Losers	-5,3%	-5,8%	-0,1%	-4,4%	-5,6%
	Losers 1M lag	-3,3%	-3,0%	6,0%	-5,1%	-7,7%
	Losers trim2,5%	-5,7%	-7,1%	-7,0%	-15,8%	-16,6%
	ACARap	10,2%	19,8%	36,5%	34,0%	25,4%
	ACARap1M lag	9,8%	18,3%	38,1%	16,9%	20,7%
	ACARap trim2,5%	7,6%	12,5%	23,3%	16,2%	7,6%
	t-statistic	1,92*	2,89***	4,61***	3,92***	4,13***
	t-statistic 1M lag	2,17**	2,88***	4,61***	2,07*	2,84***
	t-statistic trim 2,5%	1,46	2,03*	3,04***	1,98*	1,14
2Y	Winners	-13,8%	-36,4%	-45,8%	-45,0%	-33,6%
	Winners 1M lag	-15,6%	-34,1%	-42,9%	-31,0%	-37,8%
	Winners trim 2,5%	-11,5%	-32,9%	-41,6%	-36,8%	-26,1%
	Losers	6,1%	10,9%	17,5%	15,5%	12,2%
	Losers 1M lag	5,8%	16,3%	20,9%	12,3%	8,4%
	Losers trim2,5%	7,2%	10,3%	16,8%	12,4%	10,0%
	ACARap	19,9%	47,3%	63,3%	60,5%	45,8%
	ACARap1M lag	21,4%	50,5%	63,8%	43,3%	46,2%
	ACARap trim2,5%	18,7%	43,2%	58,5%	49,3%	36,1%
	t-statistic	3,32***	6,47***	7,25***	7,38***	6,54***
	t-statistic 1M lag	4,14***	6,60***	6,21***	4,90***	4,90***
	t-statistic trim 2,5%	3,05***	5,95***	6,63***	5,53***	4,56***
3Y	Winners	-14,6%	-36,0%	-46,3%	-47,0%	-29,9%
	Winners 1M lag	-18,1%	-34,3%	-39,7%	-21,1%	-25,2%
	Winners trim 2,5%	-11,1%	-32,4%	-46,1%	-38,7%	-19,0%
	Losers	7,7%	11,3%	19,7%	3,3%	5,7%
	Losers 1M lag	6,5%	17,3%	19,9%	13,0%	11,8%
	Losers trim2,5%	6,6%	12,8%	24,3%	9,6%	14,0%
	ACARap	22,3%	63,3%	66,0%	50,3%	35,6%
	ACARap1M lag	24,6%	51,7%	59,6%	34,1%	37,0%
	ACARap trim2,5%	17,8%	45,2%	70,4%	48,3%	33,0%
	t-statistic	3,20***	7,25***	6,37***	4,34***	4,12***
	t-statistic 1M lag	4,23***	6,60***	5,02***	3,27***	3,29***
	t-statistic trim 2,5%	2,56***	5,70***	6,31***	3,88***	3,64***
4Y	Winners	-23,9%	-44,5%	-50,4%	-43,9%	-24,3%
	Winners 1M lag	-24,7%	-37,6%	-39,6%	-16,7%	-18,8%
	Winners trim 2,5%	-20,8%	-43,9%	-47,8%	-40,5%	-13,5%
	Losers	3,6%	-0,9%	-4,9%	-9,7%	7,8%
	Losers 1M lag	1,0%	2,4%	2,6%	12,9%	21,0%
	Losers trim2,5%	4,6%	-0,1%	-1,4%	-2,8%	16,4%
	ACARap	27,5%	43,5%	45,5%	34,2%	32,2%
	ACARap1M lag	25,7%	40,0%	42,2%	29,6%	39,8%
	ACARap trim2,5%	25,4%	43,8%	46,4%	37,7%	29,9%
	t-statistic	3,70***	5,31***	4,09***	2,68***	3,33
	t-statistic 1M lag	4,26***	4,42***	3,13***	2,43**	2,92***
	t-statistic trim 2,5%	3,45***	5,46***	4,28***	3,16***	2,52**
5Y	Winners	-20,3%	-37,7%	-40,2%	-32,0%	-12,4%
	Winners 1M lag	-19,7%	-31,4%	-30,0%	-2,5%	-5,5%
	Winners trim 2,5%	-19,7%	-34,3%	-35,2%	-25,7%	-0,6%
	Losers	10,1%	6,7%	6,8%	13,5%	32,6%
	Losers 1M lag	10,8%	11,3%	20,5%	36,8%	45,9%
	Losers trim2,5%	11,6%	9,6%	7,6%	19,7%	28,3%
	ACARap	30,4%	44,5%	47,0%	45,4%	45,0%
	ACARap1M lag	30,4%	42,7%	50,4%	39,3%	51,4%
	ACARap trim2,5%	31,3%	43,9%	42,8%	45,4%	28,9%
	t-statistic	3,61***	4,06***	3,19***	2,65**	3,77***
	t-statistic 1M lag	3,74***	3,52***	3,08***	3,20***	4,34***
	t-statistic trim 2,5%	3,81***	3,72***	2,96***	2,60**	2,23*

Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level.

4.4.2 Robustness Checks for Nonoverlapping Periods

Non-overlapping formation periods results (see Table 4.7) are similar with overlapping periods for the first 12-month duration. Therefore we will not repeat our previous analysis for these strategies. Furthermore holding periods of 48 and 60-months do not offer statistically significant results for any of the alternative contrarian strategies before and after the robustness checks as the number of observations minimize greatly. We suppose that for a lengthier sample period the considerable contrarian profits, which come mainly from the short side for the 5Y Performance and from the long side for the 4Y Performance, could become statistically significant.

Zero cost arbitrage portfolios for three-years holding periods realize the highest profitability for the 3x3 strategy even after both robustness checks (1 month gap 72.5% and trimming 2.5% 109.9%). These profits are statistical significant at 5% level of significance and furthermore its primary source comes from the long side (losers portfolio). For the 3x2 strategy following robustness checks contrarian portfolio profitability of 35.8% and 47.4% (skip one month and trimming outliers respectively) reach statistical significance of 5% and 10% level. The rest of the portfolio combinations do not make statistically significant profits.

Finally the two year formation period for all the possible performance periods do not present important variations after the robustness checks for the winners side portfolios (except the 2x4 strategy). On the long side of the strategy for the 12month performance losers seem to face momentum at the same magnitude as before the tests however statistical significance is rather low. Losers seem to reverse greatly for 2x2 and 2x4 strategies returning more than 20%. For the 2x3 and 2x5 losers do reverse at a lower percentage than the rest alterations. Average cumulative abnormal returns of the contrarian portfolios perform higher after the one month gap robustness than initial calculations for the four out of five (12, 24, 36 and 60 months) different performance periods. T-statistics after the robustness checks remain significant at 1% level for the two and three year performance periods and slightly weaken on the four year performance periods.

Overall robustness checks do not significantly alter our initial results especially for the contrarian strategies that are statistically significant. Minor differences were expected as we exclude information from our sample. The exclusion of January as a one month gap, at the beginning of the performance periods could have affected substantially the portfolios performance (bearing in mind the possibility of January effect) especially for the shorter holding periods. However this has not been verified. Similar results after robustness checks have been documented for the Japanese Capital Market from Chou *et al.* (2007)

On the other hand by trimming 2.5% of the extreme observations of our sample for each variation of contrarian strategies following De Bondt and Thaler's methodology (a methodology that is founded on the reversibility of the portfolio components' returns), one could have anticipated an important weakening of the zero-cost arbitrage portfolios. Negative returns are generally lower for the winners' side after the exclusion of the outliers however for the long side of the strategy losers (especially the De Bondt and Thaler's 3x3 strategy) experience the greatest reversal. Subsequently contrarian profitability escalates to almost 110%.

4.5 Rational Explanations & Contrarian Profits

The empirical literature on investor overreaction and contrarian strategies focuses on several "rational" explanations for these profits. [19] For instance, Zarowin (1990) indicates that contrarian profits are due to a size-effect. Lo and MacKinlay (1990) argue that a lead-lag effect may contribute to contrarian profits, however, Jegadeesh and Titman (1995a) show that delayed reactions cannot lead to contrarian profits. Chan (1988), Ball and Kothari (1989) argue that abnormal profits could be explained by changes in the equilibrium required returns, while Fama and French (1996) argue that their 3-risk factor model explains long-term return reversals such as the ones documented in the previous chapter. In other words, supporters of the efficient market hypothesis argue that contrarian profits are compensation for bearing excess risk that is not accounted for properly; i.e. profits will disappear if risk is properly accounted for.

[19] On the other side, several studies explain the anomaly with behavioral models (Daniel, Hirshleifer and Subrahmanyam (1998); Hong and Stein (1999); Barberis, Shleifer, and Vishny (1998)). See the Literature Review for a detailed discussion of both points of view.

Table 4.7: Comparison of Contrarian Profitability after Robustness Checks for Non-Overlapping Periods

NONOVERLAPPING FORMATION PERIODS						
FORMATION PERIOD/ PERFORMANCE PERIOD		1Y	2Y	3Y	4Y	5Y
1Y	Winners	-15,5%	-25,5%	-36,6%	-38,4%	-31,0%
	Winners 1M lag	-13,1%	-21,3%	-32,1%	-22,0%	-28,4%
	Winners trim 2,5%	-13,3%	-19,6%	-30,3%	-32,1%	-24,2%
	Losers	-5,3%	-5,8%	-0,1%	-4,4%	-5,6%
	Losers 1M lag	-3,3%	-3,0%	6,0%	-5,1%	-7,7%
	Losers trim 2,5%	-5,7%	-7,1%	-7,0%	-15,8%	-16,6%
	ACARap	10,2%	19,8%	36,5%	34,0%	25,4%
	ACARap1M lag	9,8%	18,3%	38,1%	16,9%	20,7%
	ACARap trim 2,5%	7,6%	12,5%	23,3%	16,2%	7,6%
	t-statistic	1,92*	2,89***	4,61***	3,92***	4,13***
	t-statistic 1M lag	2,17**	2,88***	4,61***	2,07*	2,84***
	t-statistic trim 2,5%	1,46	2,03*	3,04***	1,98*	1,14
2Y	Winners	-26,2%	-34,5%	-63,7%	-45,4%	-34,1%
	Winners 1M lag	-31,0%	-28,6%	-66,1%	-11,7%	-34,0%
	Winners trim 2,5%	-26,5%	-35,1%	-59,5%	-35,6%	-20,8%
	Losers	-15,1%	8,1%	3,0%	7,9%	10,0%
	Losers 1M lag	-12,2%	20,2%	2,0%	20,7%	9,5%
	Losers trim 2,5%	-16,8%	7,0%	-4,6%	4,6%	0,6%
	ACARap	11,1%	42,6%	60,7%	53,3%	35,1%
	ACARap1M lag	18,8%	48,8%	68,1%	32,3%	43,4%
	ACARap trim 2,5%	9,7%	42,1%	54,9%	40,1%	21,4%
	t-statistic	1,34	2,49**	3,39***	2,90***	2,89**
	t-statistic 1M lag	2,02*	2,81***	3,01***	2,03*	2,09*
	t-statistic trim 2,5%	1,15	2,48*	3,05***	1,99*	1,61
3Y	Winners	-7,8%	-24,3%	-41,7%	-6,9%	-36,1%
	Winners 1M lag	-11,6%	-19,6%	-40,1%	-24,9%	-38,8%
	Winners trim 2,5%	8,6%	-28,3%	-47,1%	-1,1%	-30,8%
	Losers	-40,7%	15,6%	54,9%	36,0%	4,6%
	Losers 1M lag	11,6%	16,1%	32,4%	-9,8%	-19,9%
	Losers trim 2,5%	36,0%	19,0%	62,8%	47,2%	6,5%
	ACARap	32,9%	39,9%	96,6%	42,9%	40,7%
	ACARap1M lag	23,2%	35,8%	72,5%	15,1%	18,8%
	ACARap trim 2,5%	27,5%	47,4%	109,9%	48,3%	37,3%
	t-statistic	1,17	1,92	3,41***	1,97	1,80
	t-statistic 1M lag	0,95	2,62**	3,61**	0,61	0,94
	t-statistic trim 2,5%	0,97	2,14*	3,40**	1,98	1,68
4Y	Winners	18,5%	-16,8%	-14,9%	-25,5%	-38,7%
	Winners 1M lag	-24,9%	0,1%	-19,5%	-28,6%	-39,5%
	Winners trim 2,5%	-15,2%	-16,0%	-8,3%	-14,7%	-16,3%
	Losers	-3,4%	34,2%	15,8%	3,7%	6,4%
	Losers 1M lag	-2,5%	51,0%	37,5%	44,8%	32,3%
	Losers trim 2,5%	-12,9%	30,2%	13,0%	7,2%	3,0%
	ACARap	15,0%	50,9%	30,7%	29,2%	32,3%
	ACARap1M lag	22,4%	50,8%	57,1%	73,4%	71,8%
	ACARap trim 2,5%	2,3%	46,3%	21,3%	21,9%	19,2%
	t-statistic	2,53*	1,96	0,94	0,63	0,83
	t-statistic 1M lag	1,23	1,68	0,80	0,93	1,01
	t-statistic trim 2,5%	0,44	1,83	0,66	0,54	0,52
5Y	Winners	-51,6%	-62,9%	-86,7%	-82,9%	
	Winners 1M lag	-45,6%	-56,8%	-102,2%	0,1%	
	Winners trim 2,5%	-48,2%	-63,6%	-84,9%	-74,2%	
	Losers	-25,2%	-45,4%	-67,6%	-66,7%	
	Losers 1M lag	10,8%	11,3%	20,5%	36,8%	
	Losers trim 2,5%	-24,4%	-38,6%	-60,8%	-54,9%	
	ACARap	26,4%	17,6%	19,2%	16,2%	
	ACARap1M lag	56,4%	68,1%	122,7%	36,8%	
	ACARap trim 2,5%	23,8%	25,0%	24,1%	19,3%	
	t-statistic	0,59	0,38	0,33	0,42	
	t-statistic 1M lag	0,58	0,56	1,01	0,62	
	t-statistic trim 2,5%	0,64	0,53	0,39	0,30	

Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level

Conrad and Kaul (1993) point out that bid-ask biases may explain this anomaly. In addition, Kaul and Nimalendran (1990) provided evidence for a NASDAQ sample that suggests that bid-ask errors account for a large proportion of daily return variances and may be the most important source of price reversals in daily data. Conrad *et al.* (1997) directly demonstrate the importance of market microstructure effects, especially Bid-Ask bounce, for the profitability of contrarian portfolios by computing the profits using bid returns that do not contain bid-ask errors. They show that all the documented profitability due to price return reversals for NASDAQ firms emanates from the bid-ask bounce.

Another important source of measurement error could be infrequent trading. According to Miller *et al.* (1994) there are two forms of infrequent trading: non-synchronous trading and nontrading. Lo and Mackinlay (1990b) support the view that nonsynchronous trading could be generated when stock prices are incorrectly assumed to be sampled simultaneously. The notion of the nonsynchronous trading or thin trading is that although prices are often recorded at regular intervals, actually they do not trade at the same time. The implications are the appearance of cross-correlations between stock returns or serial correlation in portfolio returns and possible negative serial correlation in individual returns. In contrast, non-trading occurs when stocks do not trade in every consecutive interval. Schultz (1983) and Stoll and Whaley (1983) investigate the effect of transactions costs, i.e. the effect of commissions and spreads on size-based trading strategies. Ball *et al.* (1995) showed that trading costs component such as bid-ask spreads significantly reduce the profitability of contrarian strategy. Mitchell and Pulvino (2001) incorporate commissions and price impact into a merger arbitrage portfolio strategy. They found that trading costs reduce the profits of the strategy by 300 basis points per year.

The results so far indicate that contrarian strategies are profitable in the ASE, irrespective of methodological issues (overlapping and non-overlapping periods, robustness tests). The aim of the following sub-section is to investigate the possibility that these profits are explained within a "rational" point of view. Thus, in what follows, the explanations that are discussed above will be investigated for the sample of firms employed in the study.

4.6 Size Effects

It is rather interesting to search why the contrarian strategies appear to be so intense in the Greek capital market. One of the first plausible sources of risk premium of stocks returns that authors look for is size effect and how this effect plays a significant role for the success of the contrarian strategies achieving extreme abnormal returns. Zarowin (1989, 1990) was one of the first to show the contrarian profits were driven by the market capitalization of the stocks traded. His results were either supported (Clare and Thomas (1995), Lee *et al.* (2003)), partially supported (Baytas and Cakici, 1999) or even doubted (Chopra *et al.* (1992), Albert and Henderson (1995)) by later studies. As for the Greek Capital Market, Leledakis *et al.* (2003) have indicated the dominance of size effect over other cross-sectional variables such as B/M ratio even after controlling for January effect.

The size effect in financial literature is thought of being responsible for anomalies in stock prices movement. We control for the size effect by separating for every formation period stocks into three deciles. The deciles would be Top-size 25%, Medium-size 50% and Bottom-size 25% based on market capitalization. The percentage division taken for categorizing size capitalization of all stocks listed on the ASE is arbitrary. The notion of this methodology is to find out whether contrarian profits hold in each of the different size segments and if this is true whether we can generate profits from the implementation of contrarian strategies.

We measure the profitability of the zero-cost arbitrage contrarian strategies[20] for 12month, 24month and 36month performance periods. The testing methodology (ranking of loser and winner stocks, portfolio construction, measures of profitability, statistical significance) is identical to the one in the previous sub-sections. We constructed 324 different portfolios which will be synoptically presented in 27 concentrated contrarian strategies varying the formation and performance duration of them (Tables 4.8, 4.9, 4.10 and 4.11 present the formation-testing periods available for the empirical analysis).

Before we proceed in analyzing the results of our strategies we have to mention few things about the course of size capitalization all the stocks included in Athens Stocks Exchange and as well as the three different size related categories. First of all the number of available stocks for each formation period escalated impressively the last decade as more firms discovered stock exchange as a source of receiving cheaper capital. The highest number of initial public offerings took place in 1998 and 1999. More than 50 firms had already entered the market at the beginning of 1999, a number that reach the 21% of all the listed stocks.

[20] Since the results of the previous section suggest that contrarian profits are present irrespective of the use of overlapping or non-overlapping periods we present here results for overlapping periods.

Top size segment of the market increases its total capitalization impressively on the verge of 1990s decade achieving a percentage of 121%. The next two years when Golf War began and oil prices went up for stock markets faced a small recession period by losing 2% and 8% respectively. We can discern a small but consistent pattern of highest percentage increase for the top size stocks in every three years (1993: 44%, 1996: 95% and 1999: 135%). This pattern is not constant for medium and small size stocks. Both of them increase their total capitalization but in 1996 the medium size segment face a small decrease of 3,77% and bottom size segment reach a negative rate of increase of 4,6%. However after three years (1999) the market value increase of those two was multiple times greater than that of the top size one. That was the year when Athens Stock Exchange really took off and reached its historically highest level. Interesting results can be extracted from observing the behavior of the medium and bottom size deciles during the periods of bear markets such as the period of 2000-2003, whereas the fall in size of the bottom segment (-55%) was double the market's fall (-28.08%) as well as the top-size fall in 2000 (-20.33%). To sum up, small size stocks tend to increase or decrease in value disproportionately to the markets increase. A possible explanation to this reaction could have been the argument that small size stocks tend to be preferred by individual investors rather than institutional ones, therefore their behavior reflects the spontaneity of naïve investors. Furthermore small size stocks are not that closely monitor by the Capital Market Commission leaving open space for possible stock price manipulation.

The number of stocks included in extreme deciles is the same and this makes it easy to figure out the great differences among the biggest and the smallest stocks. For example throughout the examined period the total value of small size stocks segments rarely exceeded 2% of the total value of the Top size slice of the market. The only noticeable increase in this comparison is that in 1999 when the market faced its highest level small size market value reached 4.3% of the biggest firms in size. The second close up to that number happened in 1995 where the above percentage reached 3%. Extending this comparison between medium size firms and small size firms we realize that the value of small size stocks increases on behalf of the value of the mid-size sector in more consistent way. In 1990 bottom-size segment value equalled 5% of the value of the mid-size sector. The same percentage gradually reached in 2002, 12.5% with its highest price recorded in 1999 of 14.2%. Finally comparing the value of medium size firms to the top size firms' value, we conclude that the percentage starts from 19% increases up to 31% and then after falling to 10% reached again its highest value ending up to a 14% in 2002.

The results for the contrarian strategies for the size sub-samples are presented in Table 4.12. For the Bottom 25% size segment contrarian strategies produce no statistically significant profits apart from the strategies following one-year formation periods (1x2 and 1x3 strategies produce returns of 24.6% and 30.3% respectively with statistical significance at 1%). These results directly contradict Zarowin's conclusions according to which small-sized stocks should offer greater abnormal profits following contrarian strategy, as smaller-sized stocks are thought to be financially less solvent, more risky to invest in and therefore investors reasonably would demand greater risk premium. Interestingly profitability for the smaller size stocks comes from the prior Losers stocks (or else from the long-side of zero-cost arbitrage portfolio) for all possible combinations of contrarian strategies. This could mean that loser stocks were downgraded by the investors who turned to reverse their opinion as firms could achieve greater than anticipated financial results. Results confirm Rastogi *et al.* (2009) results concerning the Indian capital market that profitability of contrarian strategies comes mostly from the medium sized stocks.

Contrarian strategies for medium-size segment of stocks follow a completely different pattern as far as the profitability is concerned. Abnormal excess returns come mainly from the short-side or prior winner side of the arbitrage portfolio. Moreover for the medium size segment profitability seems to escalate as performance period exceeds 24 months. Following a strategy with 12-months formation period for all three different performance periods 1-year, 2-years and 3-years we get statistical significant profits of 15%, 25.5% and 36.6% respectively at 1% level of significance. Similar results we get for the lengthier formation periods of 24 and 36 months.

For the Top-size 25% percentile of the Greek stock market statistical significant profits are produced for the 2x3 strategy (13.1% significant at 5%) and for all three combinations of the 3-years formation periods: 8.8% (t-statistic: 2.63), 16.6% (t-statistic: 3.71), 23.4% (t-statistic: 3.97), respectively. Profits mainly come from short-side of the portfolios indicating that investors could have pushed prior winners stock price beyond their fair value and this reverses as investors realize their mistake or news coming from the market force them to restate their expectations. For the one year of formation period top 25% stocks experience a mixed momentum effect as zero-cost arbitrage portfolio achieved negative return which for the 12 and 24 months of performance these returns are strongly statistically significant (as prior loser stocks continue to perform negatively and prior winner stocks' performance reverse).

Overall, the results suggest that the market segment where contrarian strategies consistently produce economically and statistically significant profits (i) the medium size firms, and (ii) the large size firms for long term strategies (3 years). These results suggest that size cannot account for the “anomaly” as suggested by Zarowin (1990). Note that our results are consistent with Dissanaike (2002) who reports no evidence that the winner-loser effect in the UK can be subsumed by the size effect.

Table 4.8: Size Effects & Contrarian Profits Formation & Performance Periods: 1-Year

ONE YEAR FORMATION PERIOD				
PORTFOLIO SELECTION ACCORDING TO MARKET VALUE	FINDING WINNER-LOSER FROM EACH DECILE	PERFORMANCE OF EACH WINNER-LOSER PORTFOLIOS		
90	90	**91**	**91-92**	**91-93**
91	91	**92**	**92-93**	**92-94**
92	92	**93**	**93-94**	**93-95**
93	93	**94**	**94-95**	**94-96**
94	94	**95**	**95-96**	**95-97**
95	95	**96**	**96-97**	**96-98**
96	96	**97**	**97-98**	**97-99**
97	97	**98**	**98-99**	**98-00**
98	98	**99**	**99-00**	**99-01**
99	99	**00**	**00-01**	**00-02**
00	00	**01**	**01-02**	**01-03**
01	01	**02**	**02-03**	
02	02	**03**		

Table 4.9: Size Effects & Contrarian Profits Formation & Performance Periods: 2-Year

TWO YEAR FORMATION PERIOD				
PORTFOLIO SELECTION ACCORDING TO MARKET VALUE	FINDING WINNER-LOSER FROM EACH DECILE	PERFORMANCE OF EACH WINNER-LOSER PORTFOLIOS		
91	90-91	**92**	**92-93**	**92-94**
92	91-92	**93**	**93-94**	**93-95**
93	92-93	**94**	**94-95**	**94-96**
94	93-94	**95**	**95-96**	**95-97**
95	94-95	**96**	**96-97**	**96-98**
96	95-96	**97**	**97-98**	**97-99**
97	96-97	**98**	**98-99**	**98-00**
98	97-98	**99**	**99-00**	**99-01**
99	98-99	**00**	**00-01**	**00-02**
00	99-00	**01**	**01-02**	**01-03**
01	00-01	**02**	**02-03**	
02	01-02	**03**		

Table 4.10: Size Effects & Contrarian Profits Formation & Performance Periods: 3-Year

THREE YEAR FORMATION PERIOD				
PORTFOLIO SELECTION ACCORDING TO MARKET VALUE	FINDING WINNER-LOSER FROM EACH DECILE	PERFORMANCE OF EACH WINNER-LOSER PORTFOLIOS		
92	90-92	**93**	**93-94**	**93-95**
93	91-93	**94**	**94-95**	**94-96**
94	92-94	**95**	**95-96**	**95-97**
95	93-95	**96**	**96-97**	**96-98**
96	94-96	**97**	**97-98**	**97-99**
97	95-97	**98**	**98-99**	**98-00**
98	96-98	**99**	**99-00**	**99-01**
99	97-99	**2000**	**00-01**	**00-02**
2000	98-00	**2001**	**01-03**	
2001	99-01	**2002**	**02-03**	
2002	00-02	**2003**		

Table 4.11: Size Effects & Strategies

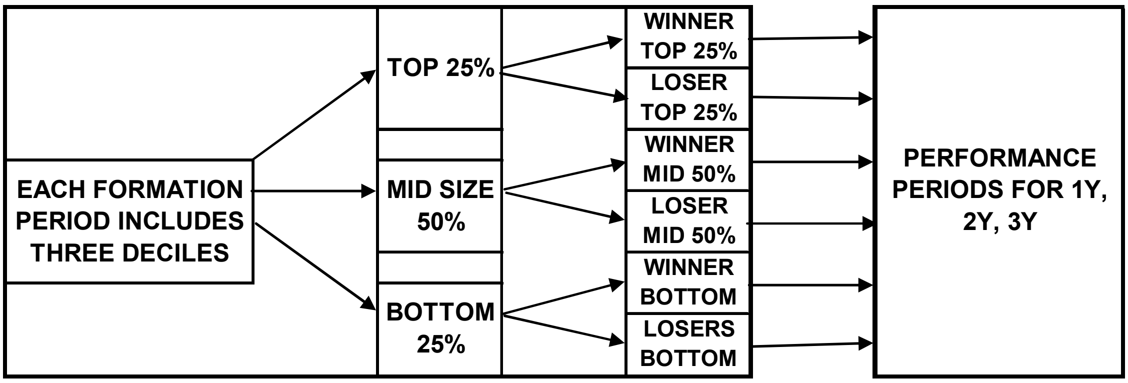

Table 4.12: Size Effects & Contrarian Profits

SIZE EFFECT												
RANK BY SIZE	**TOP 25%**				**MID 50%**				**BOTTOM 25%**			
Formation Period / Performance Period		**1**	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	Winners	-2,4%	-7,7%	-16,0%	Winners	-22,7%	-34,7%	-48,5%	Winners	-2,0%	-3,9%	-5,6%
	Losers	-10,7%	-20,2%	-17,4%	Losers	-7,7%	-9,2%	-11,9%	Losers	10,8%	20,7%	24,7%
	ACARap	-8,3%	-12,5%	-1,4%	ACARap	15,0%	25,5%	36,6%	ACARap	12,8%	24,6%	30,3%
	t-statistic	-3***	-2,84***	0,30	t-statistic	2,90***	4,09***	4,30***	t-statistic	1,81*	2,73***	2,85***
2	Winners	-2,6%	-13,1%	-22,6%	Winners	-8,3%	-28,8%	-37,9%	Winners	11,3%	7,1%	7,5%
	Losers	-4,7%	-10,5%	-9,6%	Losers	-5,7%	-12,1%	-15,6%	Losers	10,7%	20,8%	13,4%
	ACARap	-2,0%	2,6%	13,1%	ACARap	2,6%	16,7%	22,3%	ACARap	-0,6%	13,7%	6,0%
	t-statistic	-0,45	0,55	2,50**	t-statistic	0,34	2,19**	2,54***	t-statistic	-0,06	1,29	0,51
3	Winners	-12,0%	-18,7%	-26,5%	Winners	-17,7%	-31,3%	-31,9%	Winners	-3,5%	-1,7%	-0,2%
	Losers	-3,2%	-2,0%	-3,1%	Losers	-5,9%	-4,8%	-3,2%	Losers	12,0%	15,9%	22,6%
	ACARap	8,8%	16,6%	23,4%	ACARap	11,9%	26,5%	28,7%	ACARap	15,5%	17,6%	22,8%
	t-statistic	2,63***	3,71***	3,97***	t-statistic	1,65	3,06***	2,67***	t-statistic	1,74	1,55	1,64

Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level

4.7 Fama and French Factors

An obvious next step in the analysis would be to investigate whether the contrarian profits evidence so far are due to risk mis-measurement (Chan (1988), Ball and Kothari, (1989)). Recent studies (Antoniou *et al.* (2005)) investigate whether contrarian strategies are still profitable after exposure to more than one risk factor (market factor, taking residuals from the market model). More specifically, they study whether expected return on a portfolio in excess of the risk-free rate may be explained by the sensitivity of its return to the Fama-French three factor model (Fama and French (1993, 1996)):

$$\mathrm{E}(r_i) - r_f = b_{mkt,i}[E(r_m) - r_f] + b_{smb,i}E(SMB) + b_{hml,i}E(HML) \quad (15)$$

Where the factor sensitivities are the slopes in the time-series regression:

$$r_i - r_f = a_i + \beta_{mkt,i}\left[r_m - r_f\right] + \beta_{smb,i}SMB + \beta_{hml,i}HML + \varepsilon_i \qquad (16)$$

Fama and French advocate a multifactor model which relates the expected return on a portfolio in excess of the risk-free rate to the excess return on a market portfolio $\left[r_m - r_f\right]$ plus two other common risk factors: the return premium coming from of Small Minus Big stocks (SMB) and the return premium we get from high Book/Market minus low Book/Market stocks (HML). Unlike the Roll-Ross model these factors have no obvious interpretation as risk factors. Fama and French presumed that if variables are associated with movements in the return to diversified portfolios, then they must proxy for some underlying risk factor. The SMB factor is designed to measure the additional return investors have received by investing in stock of companies with relatively small market capitalization The additional return is often referred to as the ‘‘size premium’’. The HML factor measures the “value premium” provided to investors for investing in companies with high book-to-market values (essentially the value placed on the company by accountants as a ratio relative to the value the public markets placed on the company commonly expressed as B/M).

Fama and French have shown that extending the Capital Asset Pricing Model (CAPM) to include additional factors explains the contrarian profits in the US. According to them, this occurs because past losers are relatively distressed firms, and past winners are stronger firms. That is why past losers have higher expected returns compared to past winners, and their model is able to capture these two qualities. In order to examine whether the three factor model captures the profitability of the contrarian strategies, we regress stock returns of each firm in the sample to this three factors and employ the adjusted returns (the residuals from the above regression) to compute the contrarian profits (profits as described in previous sub-chapter) from the size segmented arbitrage portfolios.

Regarding the construction of the Fama French factors for the ASE to be included in a portfolio, we use firms with common equity and those with available data at least two years. Size (ME) is measured as the stock’s price times the number of shares at the end of the previous year. We define book equity (BE) as the book value of common shareholder's equity. All relevant data are obtained from DataStream.

SMB is constructed as follows: every year stocks are ranked according to the previous year's market capitalisation. The top and bottom 20% of stocks are then selected to form two equally weighted portfolios of high and low capitalization stocks respectively. The factor is constructed as the difference of the returns of the two portfolios. A similar procedure is followed for the construction of the HML factor. Every year stocks are ranked according to the previous year's book-to-market ratio. The top and bottom 20% of stocks are then selected to form two equally weighted portfolios of high and low book-to-market stocks respectively. The factor is constructed as the difference of the returns of the two portfolios.

The proxy of the Market Factor in the FF three-factor model is the excess market return, $\left[r_m - r_f \right]$, r_m is the return on the value-weighted portfolio and as a proxy of the risk free rate r_f is the three month Treasury Bill.

Once the factors are constructed we then regress each stock's raw return on the three factors and obtain the time series of the residuals for each stock. This series is denoted as the abnormal return of each stock, i.e. the return adjusted for risk factors. Then we perform the same analysis as in sub-section 4.6, i.e. for different market capitalization segments of the market. The results are presented in Table 4.13. As a general conclusion, interestingly the adjustment for the Fama-French risk factors results higher contrarian profits in all three size segments (Top 25%, Medium 50% and Bottom 25%) and higher t-statistics (only two of three out of the 27 different strategies received insignificant statistical returns and eighteen of them are statistically significant at 1% level of significance). Moreover contrarian portfolios returns increase as the length of the performance period extends.

Referring to the top 25% size segment we have to comment that momentum effect that had been noticed in

Table 4.13 (controlling for size effect) for the one-year testing period seems now to have been reduced due to the better performance of the short-side of the portfolio (prior winners stocks reverse to a greater extent). Looser stocks keep their negative sign but to a smaller degree. The 3x3 strategy for the top 25% segment achieves a 36.6% profitability with the highest t-statistic (8,21).

Medium size stocks, after controlling for the three Fama-French factors, also achieve higher and more statistically significant contrarian returns. Prior Looser stocks achieve profits especially for the lengthiest formation and performance periods. For the 3x3 strategy the profitability driver is mostly the long side of the portfolio (prior looser stocks, with Fama French methodology profits sums up to 27.2% comparing to the loses that the same strategy had after controlling just for size). Prior Winner stocks on the other side accomplish now less negative returns meaning that long side of the strategy serves to a smaller percent to the total contrarian profitability. Overall contrarian strategies applied for mid-size stocks after controlling for Fama French factors offer highly statistically significant profits.

The Bottom 25% size segmented side of the Hellenic stock market offers the highest contrarian profits for the 3x3 and 2x2 strategies (45.9% with t-statistic 3.38 and 26.2% with t-statistic 2.26). The impressive element is that long side of the portfolio is highly profitable in both cases (53.8% and 66.1% respectively) meaning that when we induce all three factors to our analysis contrarian strategies become meaningfully exploitable in the Athens stocks exchange as short-selling was either prohibited or merely used in ASE.

A reasonable explanation for the out-performance of the prior Looser stocks would be that prior Losers are relatively distressed firms and past winners are stronger firms (Fama and French (1993,1996). Therefore prior loser stocks have higher expected returns compared to the short-side stocks of the zero-cost arbitrage contrarian portfolio. However after extending our market model with the two extra factors (provided that they are appropriate measures of risk) proposed by Fama and French, the abnormal returns of the contrarian strategies (taken as the compensation for risk buying loser stocks) should have been diminished. Not only this was not the case, but contrarian portfolios returns where ascended and became even more important statistically. The increase in profits could be due to the fact that, when we adjust for risk, there is a large increase (more than 10%) on the number of stocks that are negatively serially correlated and this could lead to higher profits (Chordia and Shivakumar (2002)).

4.8 Taxed-based rational explanations of contrarian profits

De Bondt and Thaler (1987) show that significant long-term reversals for losers in the USA tend to occur during the month of January. This finding may suggest that the effect in the USA may be related to a January seasonal. George and Hwang (2007) argue that a rational explanation of the anomaly could be taxes. More specifically as they point out "since capital gains are taxed only when realized, investors with locked-in gains have an incentive not to sell winners in order to delay paying capital gain taxes. Consequently, investors' reservation prices for the sale of the winner stocks are elevated by the benefits of capital gains deferral. Stocks with large embedded capital gains will have higher prices, and hence lower expected returns, than otherwise identical stocks with no embedded capital gains" (p. 866). Their results indicate that the long-term reversals in the USA may not be caused by investor overreaction to information but reflect a rational response of investors to tax considerations.

The use of the ASE as a sample market for the study offers a natural set up in order to test this hypothesis, in the sense that during the sample period there were no capital gains taxes imposed to investors for stock market transactions in the ASE. In other words, tax-based explanations cannot be the cause for the contrarian profits in the ASE. Furthermore, recall that the above mentioned results indicate that there is no January seasonal in contrarian profits for Greek stocks (January is excluded in the robustness test where a month is skipped); a finding that further supports the claim of no relationship between taxes and contrarian profits.

Table 4.13: Contrarian Profits Adjusted for Fama-French Risk Factors

FAMA FRENCH FACTORS ANALYSIS										
RANK BY SIZE		**TOP 25%**			**MID 50%**			**BOTTOM 25%**		
Formation Period / Performance Period		**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	Winners	-6,6%	-13,6%	-23,3%	-20,1%	-25,8%	-36,2%	2,8%	7,6%	11,3%
	Losers	-3,8%	-10,9%	-9,1%	-2,0%	0,7%	7,3%	18,2%	35,9%	50,6%
	ACARap	2,8%	2,7%	14,3%	18,1%	26,6%	43,4%	15,4%	28,3%	39,3%
	t-statistic	1,25	0,88	4,49***	3,94***	4,67***	5,99***	2,44**	3,54***	4,20***
2	Winners	-12,6%	-19,4%	-27,1%	-10,3%	-19,2%	-18,4%	9,2%	18,1%	27,6%
	Losers	-7,3%	-8,9%	-3,0%	-3,5%	-0,6%	7,7%	15,9%	41,8%	53,8%
	ACARap	5,3%	10,5%	24,1%	6,7%	18,6%	26,1%	6,7%	23,7%	26,2%
	t-statistic	2,03*	2,56***	5,90***	1,04	3,07***	3,54***	0,84	2,45**	2,26**
3	Winners	-12,4%	-21,3%	-29,2%	-10,3%	-15,0%	-10,4%	0,4%	12,7%	20,2%
	Losers	-0,3%	4,4%	7,4%	2,0%	12,8%	27,2%	24,3%	46,1%	66,1%
	ACARap	12,1%	25,7%	36,6%	12,2%	27,8%	37,6%	23,9%	33,4%	45,9%
	t-statistic	4,34***	7,38***	8,21***	2,09**	4,08***	3,87***	2,88***	3,11***	3,38***

Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level

4.9 Bid-Ask Spreads

Supporters of the efficient market hypothesis also point out that bid-ask bias could give the false impression of negative autocorrelation that leads to contrarian profits (Conrad and Kaul (1993), Kaul and Nimalendran (1990)). However, this explanation cannot stand for the ASE, since the ASE does not employ a market-maker trading system but an electronic order-driven system, where trading is computerized (orders that are initiated from security firms via computer terminals). For example, during the sample period of the study, closing prices are determined by a standard algorithm of the average of the last 10 minutes' transaction prices (or a variant of this approach)[21].

Also in case no transactions are recorded during that time the last 20 minutes are used; in case no transactions are recorded during the last 20 minutes the last 30 minutes are employed; in case no transactions are recorded during the last 30 minutes the trading day’s average transaction prices are used. This point is also argued in Milonas and Travlos (2001) and Antoniou *et al.* (2005). In other words, closing prices cannot be defined as either bid or ask prices; in addition, even in the case there is a bid-ask bias this bias is reduced by the averaging procedure and the use of monthly data.

[21] The ASE changes from time to time the method of recording the closing price in order to avoid manipulation of closing prices by market participants. The methods employed are variation of the one we discuss here.

4.10 Infrequent Trading

As discussed in the introduction, supporters of the efficient market hypothesis also point out that infrequent and thin trading can give the false impression of contrarian or momentum profits (Clare *et al.* (2002)) especially in thinly trading markets like the Greek one (Bartholdy and Riding (1994)). Our methodology, however, not only employs monthly data (which minimizes the thin trading problem), but has excluded from the sample stocks which had for three consecutive months the same price or had non-available prices.

This was done for two reasons: on one hand in order to eliminate stocks that could have been under Stock Exchange Committees' supervision and/or terminated trading activity (delisting), and on the other hand to eliminate stocks that had thin and infrequent trading activity. Furthermore, this bias is mostly evidenced in small stocks. We have seen though that small stock portfolios in the ASE do not lead to contrarian profits. Thus, this bias is not present in the study and cannot be an explanation of the results.

4.11 Transaction Costs

The final frontier of every supporter of the efficient market camp is the argument of trading costs. This is what makes a strategy from a hypothetical experiment to a practical profit-making procedure. Commissions in the ASE were deregulated in 1995 and since then they were set freely by the trading parties. In general terms, commission fees vary significantly (1% for trading values up to € 2.934,70, 0,75% for trading values between €2.934,71- €8.804,11 and finally 0.50% for trading values above € 8.804,75). The Athens Stocks Exchange even today holds one of the most expensive transaction fees systems. According to their costing services analysis that was reviewed on 20-09-2007 for the last time, members have to pay for each trade (buy or sell) a minimum fee of 0.04% plus a tax in favor of the Greek State 0.15% of the total value. As far as the 0.04% is concerned, it includes a member's fee in favor of the Stock Exchange 0.015% and 0.025% as for rights on the Hellenic Exchanges Group.

According to Milonas and Travlos (2001) as well as from direct interviews with some of the largest Greek stockbrokers companies average transaction costs for stocks with high floating rate and sophisticated institutional investors could be assumed as close as up to or less than 0,5% for each trade. For individual investors transaction costs may even reach 0.8%-1%. The difference between the final level of transaction fees and the standard cost of 0.21% per trade may include brokerage or else execution fees (orders to buy or sell stocks), consulting and information or else reporting fees (fee for stocks analyses by local analysts who have an in depth view of the market), fees for managing client portfolios as well as the functional cost of the brokerage firms.

Motivate by the different costs that brokerage firms impose to investors; in this sub-section we examine the profitability of the contrarian strategies with different levels of commission fees. We start from zero and gradually raise the fee level by 0.1% each time (up to 0.6%) in order to examine whether contrarian profits exist for both overlapping and non-overlapping formation periods strategies after the imposition of transaction costs.

A drawback of contrarian strategies, as opponents argue, is that they are highly trading intensive strategies, meaning that final cumulative trading costs become significantly high. Particularly if we assume that an investor buys and sells one just stock of the constituents of his contrarian portfolios on every time he restructures them, then total transaction costs overcome any possible statistically significant profits. This is true especially when we use overlapping formation periods as the same strategy is executed multiple times over the same period of time. However a counterargument is that in overlapping formation periods it happens that a significant number of stocks remain on the same side (either long or short) portfolios so that investors do not need to replace them and pay extra commission. Non-overlapping periods offer fewer portfolio reshufflings and therefore lower commission fees.

We examine different levels of commission fees starting from zero and raising the level 0.1% each time up to 0.6% in order to realize to what extent contrarian profits no longer exist for both overlapping and non-overlapping formation periods strategies. Figure 4.5 presents graphically the five different levels of transaction costs calculated for each contrarian strategy separately and Table 4.14 presents the same costs numerically for each strategy. As we can see from Figure 4.5 and Table 4.14, assuming a 0.6% cost per trade, the 1x1 strategy reaches at total (i.e. full period) trading cost of approximately 141% which falls to approximately 37% for the 5x5 strategy. Similarly, with a 0.4% cost per trade the 1x1 strategy requires almost 91% trading cost which falls to about 25% for the 5x5 strategy. Thus, transaction costs are high and may play an important role in the profitability of the contrarian strategies.

The procedure of calculating commission costs is the same for every strategy. We take any level of commission per trade and we multiply it with the number of stocks included in each portfolio (maximum number 10 times 2 portfolios – winners and losers) on each rebalancing of our strategy. As one can observe from Table 4.14 transaction costs are extremely high for the short-horizon strategies, such as F1Y-P1Y, of the original amount invested and henceforth it is easily understood that statistically significant abnormal profits are eliminated. As investment horizon lengthens commission fees become smaller.

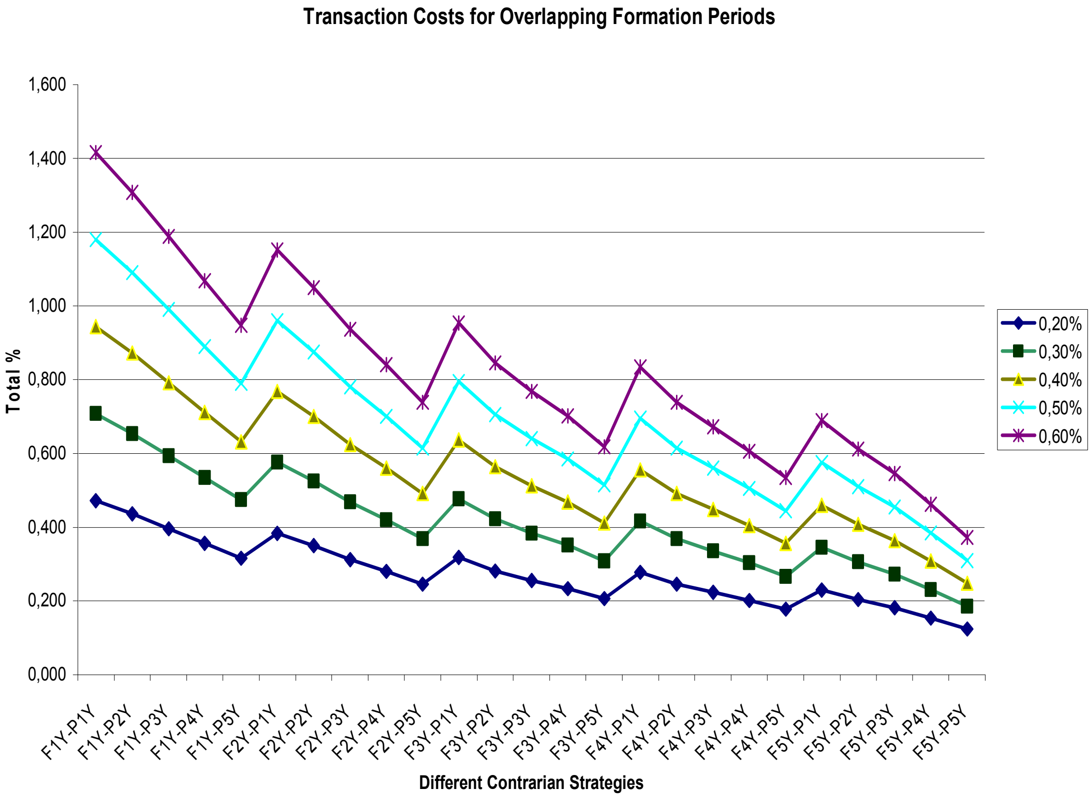

Figure 4.5: Various Levels Of Transaction Cost For Contrarian Strategies Using Overlapping Formation Periods

Table 4.14 shows, in more detail that the level of transaction cost for each strategy seems to be inversely related to the length of formation periods. Maximum fees are paid when contrarian strategy F1Y-F5Y is preferred reaching costs of 146% of the original amount invested. Lowest commission is paid when F5Y-P5Y strategy is implemented, accomplishing a minimum of 6.2%. The result of comparing these costs against contrarian profits are presented in Table 4.15, where net contrarian returns are presented for strategies utilizing overlapping formation periods. We have to mention that apart from the F1Y-P1Y strategy all other combinations offer statistically significant profits before commissions. Table 4.15 reproduces the profits as in Table 4.4 and present the frequency of rebalances for each strategy for overlapping time periods.

At the level of 0.50% cost per trade contrarian net profits are generated only in four strategies (F3Y-P3Y, i.e. the same as De Bondt and Thaler, and F5Y with holding periods more than three years). The highest of these abnormal risk-adjusted net profits reach a decent 14% for F5Y-P5Y and the smallest net returns are achieved when F5Y-F3Y is followed with just 1,5%. For the highest hypothesized commission of 0.60% we get only one profitable strategy with 7.8% (F5Y-P5Y). But as we further reduced the commission amount the documented profitable strategies after costs increase offering significant profits. Specifically for a 0.40% fee we get 9 profitable strategies, for 0.30% we get 15, for 0.20% 17 out of 25 strategies in total. Figure 4.6 presents graphically contrarian profits for various levels of transaction costs.

As far as non-overlapping performance periods is concerned contrarian profits for the same variety of transaction costs are impressively high at least for the strategies that had initially offered statistically significant profits as shown in Table 4.16 . In the same table cells that do not include a number indicate that the strategy was not profitable even before we impose transaction costs. The other cells colored red point that these profits were statistically significant at the level of 1% or 5%. The rest of the strategies colored grey represent the net trading profits. For two contrarian strategies F2Y-P3Y and F3Y-P3Y we get net profits for all levels of costs.

Table 4.14: Trading Costs For Overlapping Periods

Transaction Costs per trade	0,10%	0,20%	0,30%	0,40%	0,50%	0,60%
F1Y-P1Y	0,236	0,472	0,708	0,944	1,180	1,416
F1Y-P2Y	0,218	0,436	0,654	0,872	1,090	1,308
F1Y-P3Y	0,198	0,396	0,594	0,792	0,990	1,188
F1Y-P4Y	0,178	0,356	0,534	0,712	0,890	1,068
F1Y-P5Y	0,158	0,316	0,474	0,632	0,790	0,948
F2Y-P1Y	0,223	0,384	0,576	0,768	0,960	1,152
F2Y-P2Y	0,206	0,350	0,525	0,700	0,875	1,050
F2Y-P3Y	0,187	0,312	0,468	0,624	0,780	0,936
F2Y-P4Y	0,171	0,280	0,420	0,560	0,700	0,840
F2Y-P5Y	0,154	0,246	0,369	0,492	0,615	0,738
F3Y-P1Y	0,159	0,318	0,477	0,636	0,795	0,954
F3Y-P2Y	0,141	0,282	0,423	0,564	0,705	0,846
F3Y-P3Y	0,128	0,256	0,384	0,512	0,640	0,768
F3Y-P4Y	0,117	0,234	0,351	0,468	0,585	0,702
F3Y-P5Y	0,103	0,206	0,309	0,412	0,515	0,618
F4Y-P1Y	0,139	0,278	0,417	0,556	0,695	0,834
F4Y-P2Y	0,123	0,246	0,369	0,492	0,615	0,738
F4Y-P3Y	0,112	0,224	0,336	0,448	0,560	0,672
F4Y-P4Y	0,101	0,202	0,303	0,404	0,505	0,606
F4Y-P5Y	0,089	0,178	0,267	0,356	0,445	0,534
F5Y-P1Y	0,115	0,230	0,345	0,460	0,575	0,690
F5Y-P2Y	0,102	0,204	0,306	0,408	0,510	0,612
F5Y-P3Y	0,091	0,182	0,273	0,364	0,455	0,546
F5Y-P4Y	0,077	0,154	0,231	0,308	0,385	0,462
F5Y-P5Y	0,062	0,124	0,186	0,248	0,310	0,372

Table 4.15: Contrarian Profitability for Overlapping Periods After Transaction Costs

Contrarian Strategies	Different level of Transaction Costs per Trade 0%	0,10%	0,20%	0,30%	0,40%	0,50%	0,60%	
F1Y-P1Y	0,102	-0,134	-0,370	-0,606	-0,842	-1,078	-1,314	Net Contrarian Returns
F1Y-P2Y	0,198	-0,020	-0,238	-0,456	-0,674	-0,892	-1,110	
F1Y-P3Y	0,365	0,167	-0,031	-0,229	-0,427	-0,625	-0,823	
F1Y-P4Y	0,34	0,162	-0,016	-0,194	-0,372	-0,550	-0,728	
F1Y-P5Y	0,254	0,096	-0,062	-0,220	-0,378	-0,536	-0,694	
F2Y-P1Y	0,199	-0,024	-0,185	-0,377	-0,569	-0,761	-0,953	
F2Y-P2Y	0,473	0,267	0,123	-0,052	-0,227	-0,402	-0,577	
F2Y-P3Y	0,633	0,446	0,321	0,165	0,009	-0,147	-0,303	
F2Y-P4Y	0,605	0,434	0,325	0,185	0,045	-0,095	-0,235	
F2Y-P5Y	0,458	0,304	0,212	0,089	-0,034	-0,157	-0,280	
F3Y-P1Y	0,223	0,064	-0,095	-0,254	-0,413	-0,572	-0,731	
F3Y-P2Y	0,473	0,332	0,191	0,050	-0,091	-0,232	-0,373	
F3Y-P3Y	0,66	0,532	0,404	0,276	0,148	0,020	-0,108	
F3Y-P4Y	0,503	0,386	0,269	0,152	0,035	-0,082	-0,199	
F3Y-P5Y	0,356	0,253	0,150	0,047	-0,056	-0,159	-0,262	
F4Y-P1Y	0,275	0,136	-0,003	-0,142	-0,281	-0,420	-0,559	
F4Y-P2Y	0,435	0,312	0,189	0,066	-0,057	-0,180	-0,303	
F4Y-P3Y	0,455	0,343	0,231	0,119	0,007	-0,105	-0,217	
F4Y-P4Y	0,342	0,241	0,140	0,039	-0,062	-0,163	-0,264	
F4Y-P5Y	0,322	0,233	0,144	0,055	-0,034	-0,123	-0,212	
F5Y-P1Y	0,304	0,189	0,074	-0,041	-0,156	-0,271	-0,386	
F5Y-P2Y	0,445	0,343	0,241	0,139	0,037	-0,065	-0,167	
F5Y-P3Y	0,47	0,379	0,288	0,197	0,106	0,015	-0,076	
F5Y-P4Y	0,454	0,377	0,300	0,223	0,146	0,069	-0,008	
F5Y-P5Y	0,45	0,388	0,326	0,264	0,202	0,140	0,078	

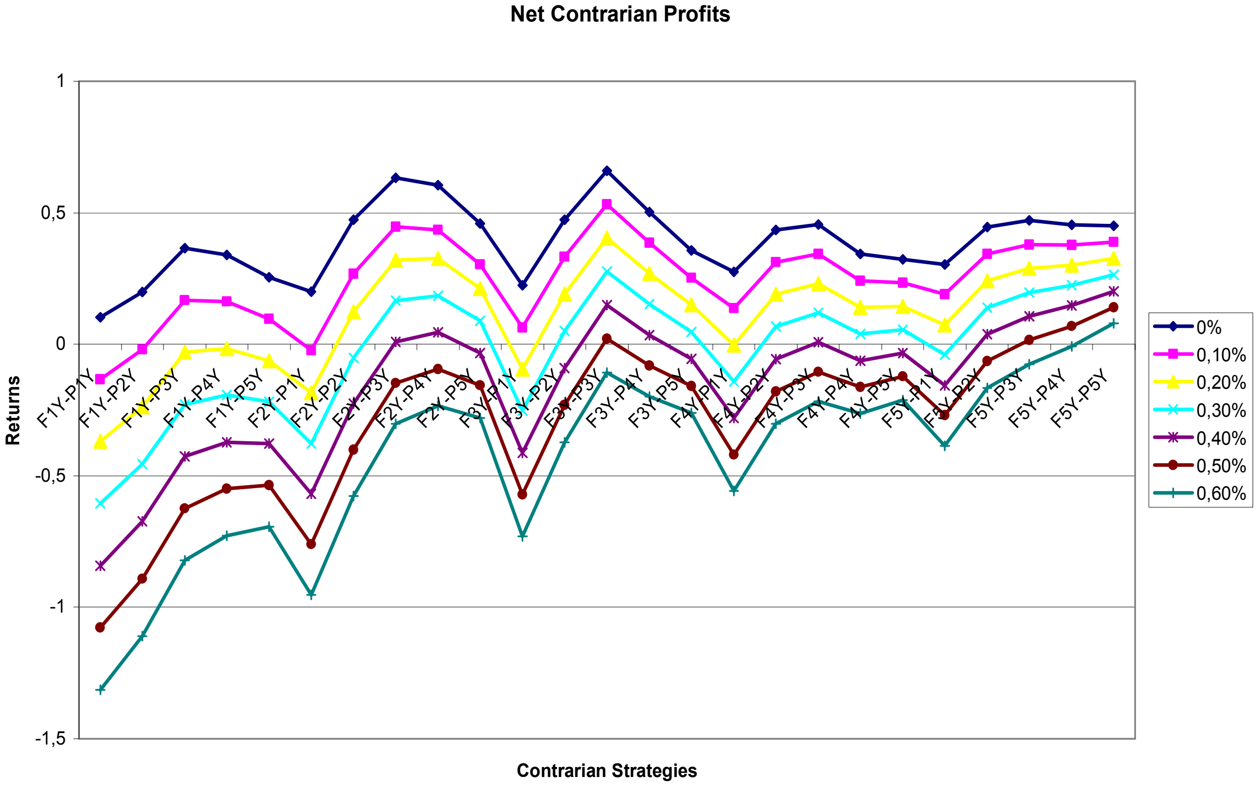

Figure 4.6: Various Levels Of Profitability After Costs For Contrarian Strategies Using Overlapping Formation Periods

Table 4.16: Contrarian Profitability for Non-overlapping Periods after Transaction Costs

	Different level of Transaction Costs per Trade							
Contrarian Strategies	**0%**	**0,10%**	**0,20%**	**0,30%**	**0,40%**	**0,50%**	**0,60%**	
F1Y-P1Y	0,102	-0,134	-0,370	-0,606	-0,842	-1,078	-1,314	**Net Contrarian Profits**
F1Y-P2Y	0,198	-0,020	-0,238	-0,456	-0,674	-0,892	-1,110	
F1Y-P3Y	0,365	0,167	-0,031	-0,229	-0,427	-0,625	-0,823	
F1Y-P4Y	0,340	0,162	-0,016	-0,194	-0,372	-0,550	-0,728	
F1Y-P5Y	0,254	0,096	-0,062	-0,220	-0,378	-0,536	-0,694	
F2Y-P1Y	0,151	0,034	-0,083	-0,200	-0,317	-0,434	-0,551	
F2Y-P2Y	0,426	0,309	0,192	0,075	-0,042	-0,159	-0,276	
F2Y-P3Y	0,607	0,510	0,413	0,316	0,219	0,122	0,025	
F2Y-P4Y	0,533	0,436	0,339	0,242	0,145	0,048	-0,049	
F2Y-P5Y	0,351	0,274	0,197	0,120	0,043	-0,034	-0,111	
F3Y-P1Y	0,329	0,249	0,169	0,089	0,009	-0,071	-0,151	
F3Y-P2Y	0,399	0,319	0,239	0,159	0,079	-0,001	-0,081	
F3Y-P3Y	0,966	0,906	0,846	0,786	0,726	0,666	0,606	
F3Y-P4Y	0,429	0,369	0,309	0,249	0,189	0,129	0,069	
F3Y-P5Y	0,407	0,347	0,287	0,227	0,167	0,107	0,047	
F4Y-P1Y	0,150	0,093	0,036	-0,021	-0,078	-0,135	-0,192	
F4Y-P2Y	0,509	0,452	0,395	0,338	0,281	0,224	0,167	
F4Y-P3Y	0,307	0,270	0,233	0,196	0,159	0,122	0,085	
F4Y-P4Y	0,292	0,255	0,218	0,181	0,144	0,107	0,070	
F4Y-P5Y	0,322	0,285	0,248	0,211	0,174	0,137	0,100	
F5Y-P1Y	0,264	0,224	0,184	0,144	0,104	0,064	0,024	
F5Y-P2Y	0,176	0,136	0,096	0,056	0,016	-0,024	-0,064	
F5Y-P3Y	0,192	0,152	0,112	0,072	0,032	-0,008	-0,048	
F5Y-P4Y	0,162	0,122	0,082	0,042	0,002	-0,038	-0,078	
F5Y-P5Y	-	-	-	-	-	-	-	

Specifically for the 3x3 strategy profits escalate up to 60.6% for the trading cost of 0.6%. If we follow Milonas and Travlos (2001) suggestion to assume 0.50% for trading costs per trade then we get just three profitable contrarian strategies with highest profits reaching 66.6% of the initial invested amount.

In the future trading costs will reduce as the Markets in Financial Instruments Directive (Law 3606/2007) is forcing brokerage companies to provide full information of the costs they impose on their clients and, thus, investors may be able to negotiate fees. Similar regulation acts in United States (Securities and Exchange Commission's Regulation NMS) lead to ratcheting up a price war among execution venues vying for order flow.[22] Furthermore seven bulge-bracket firms[23] are ready to enforce Project Turquoise, a pan-European platform that would compete against the exchanges by slashing trading fees in half. The combination of a new regulatory regime and an electronic trading market will mean more choices for investors. National exchanges that split European volatility in different trading centers will face difficult times as fees will be rock-bottomed.

4.12 Short-selling restrictions in Athens Stock Exchange

Another important issue regarding the implementation of contrarian strategies in the Greek Stock Market is that short positions where not allowed in ASE for the period under study. Only lately the ASE allows short-selling for a minimum period of three months

[22] www.pionline.com/apps/pbcs.dll/article?AID=/20071029/PRINTSUB/71026056/1031/TOC
[23] Citigroup Inc., Credit Suisse Group, Deutsche Bank AG, Goldman Sachs Group Inc., Merrill Lynch & Co. Inc, Morgan Stanley and UBS AG.

(this can also be done through futures market for selected only stocks but the volume is also rather low). As has been demonstrated above contrarian profits in the ASE come from short positions (contrary to the literature). That is, winners become losers and not losers become winners. As a result, the profits are theoretical and could not have been achieved in practice; verifying that market is efficient with respect to this anomaly.

In order to explore this issue further in this sub-section we investigate whether contrarian strategies in the ASE are profitable even in the absence of the short selling position. In other words, could an investor exploit the "anomaly" if he/she assumes the long position only? Or, alternatively, do the zero-cost portfolios produce economically significant profits (after transaction costs) with the long position only? We examine this issue for both for overlapping and non-overlapping formation periods.

Tables 4.17 and 4.19 present the cumulative transaction costs for the various strategies for the long-side of the contrarian portfolios only, for overlapping formation periods and long non-overlapping formation periods respectively. As we can be seen transaction costs are inversely linearly related to the length of the formation and performance periods of contrarian strategies. Those who have shorter-time intervals and therefore more rebalances have substantially higher trading costs. The one year formation strategy costs are more than 15% from the two year formation strategy and this difference escalates when we compare it with lengthiest strategies according to the formation period (the highest difference in total transaction costs is between the five year formation and one year formation strategy costing 91.3%). Transaction costs vary not only due to the length of the formation period but also due to the duration of the performance periods. For example 1YF-5YP strategy costs 34.5% lower than 1YF-1YP. Table 4.19 shows the cumulative transaction costs of the long side of the contrarian portfolios for non-overlapping formation periods, and the conclusion is similar to the one that was drown from Table 4.17. Due to the fact that we use non-overlapping periods, less formation periods are involved and therefore fewer rebalances for strategies with more than 12 months testing period, leading to cheaper trading strategies.

Tables 4.18 and 4.20 present the profitability of the long side of the transaction for these strategies once we have incorporated the transactions costs, for overlapping formation periods and long non-overlapping formation periods respectively. For instance, as we can see from Table 4.18 profits are considerably diminished. Most of the tested strategies are not profitable even for the lowest transaction cost levels. For the one year formation period strategies the prior losers continue to lose exhibiting a momentum effect. The only strategy that survives and manage to offer significant profits is the 5YF-5YP one. Even for the 0,60% cost per trade profits reach up to 13.4%.

As we can see from Table 4.20 the long side of the contrarian portfolio achieves a maximum profitability for 36-months and 48-months of formation periods. The 3x3 strategy offers profits of 54.9% with no transaction costs, however, with costs between 0,50% to 0,60% this falls to about 36%. As expected the fact that transaction costs are, in this case lower, at least seven out of 25 strategies (even for the 0.6% cost per trade) offer significant profits from 9.6% the lowest (4YF-5YP) up to 36.9% for the 3YF-3YP. The important issue for the non-overlapping data is that, apart from the 3YF-3YP strategy, the rest of the strategies that seems to offer profits are not statistically significant.

Overall, profitability coming from the long side of the initial zero cost arbitrage portfolios vanishes when we incorporate transaction costs into our study. Adjusting contrarian strategies to the Greek capital market's restrictions for the specific sample period (1990-2003) we realize that the Efficient Market Hypothesis could not be rejected after all. Transaction costs pose a barrier to trading techniques that has proven their effectiveness to other stock markets with more liberalized frame of rules (short-selling). However, neither transaction costs nor other market friction place a theoretical argument against behavioural finance and moreover strategies that seems to capture investors' actual reactions and decisions.

4.13 Conclusion

This chapter examines whether contrarian profits are present in the ASE with a methodology similar to De Bondt and Thaler (1985, 1987). Both overlapping and non-overlapping periods are considered for a large number (25) of possible contrarian strategies. The results show that these strategies are profitable, with the 3x3 year contrarian strategy being the most prominent; a result consistent with previous studies for international markets. We, however, find that the profits arrive mainly from the short leg of the transaction, i.e. the winners are becoming losers.

Table 4.17: Transaction Costs of Long Side of Contrarian Portfolio for Overlapping Formation Periods.

Transaction Costs per trade	0.10%	0.20%	0.30%	0.40%	0.50%	0.60%
F1Y-P1Y	0.113	0.226	0.339	0.452	0.565	0.678
F1Y-P2Y	0.104	0.208	0.312	0.416	0.520	0.624
F1Y-P3Y	0.094	0.188	0.282	0.376	0.470	0.564
F1Y-P4Y	0.084	0.168	0.252	0.336	0.420	0.504
F1Y-P5Y	0.074	0.148	0.222	0.296	0.370	0.444
F2Y-P1Y	0.095	0.190	0.285	0.380	0.475	0.570
F2Y-P2Y	0.087	0.174	0.261	0.348	0.435	0.522
F2Y-P3Y	0.078	0.156	0.234	0.312	0.390	0.468
F2Y-P4Y	0.070	0.140	0.210	0.280	0.350	0.420
F2Y-P5Y	0.061	0.122	0.183	0.244	0.305	0.366
F3Y-P1Y	0.082	0.164	0.246	0.328	0.410	0.492
F3Y-P2Y	0.073	0.146	0.219	0.292	0.365	0.438
F3Y-P3Y	0.065	0.130	0.195	0.260	0.325	0.390
F3Y-P4Y	0.060	0.120	0.180	0.240	0.300	0.360
F3Y-P5Y	0.052	0.104	0.156	0.208	0.260	0.312
F4Y-P1Y	0.064	0.128	0.192	0.256	0.320	0.384
F4Y-P2Y	0.054	0.108	0.162	0.216	0.270	0.324
F4Y-P3Y	0.049	0.098	0.147	0.196	0.245	0.294
F4Y-P4Y	0.044	0.088	0.132	0.176	0.220	0.264
F4Y-P5Y	0.040	0.080	0.120	0.160	0.200	0.240
F5Y-P1Y	0.354	0.295	0.236	0.177	0.118	0.059
F5Y-P2Y	0.306	0.255	0.204	0.153	0.102	0.051
F5Y-P3Y	0.276	0.230	0.184	0.138	0.092	0.046
F5Y-P4Y	0.234	0.195	0.156	0.117	0.078	0.039
F5Y-P5Y	0.192	0.160	0.128	0.096	0.064	0.032

Table 4.18: Contrarian Profitability of Prior Losers for Overlapping Periods After Transaction Costs

	Different level of Transaction Costs per Trade						
	0%	0.10%	0.20%	0.30%	0.40%	0.50%	0.60%
F1Y-P1Y	-0.053	-0.166	-0.279	-0.392	-0.505	-0.618	-0.731
F1Y-P2Y	-0.058	-0.162	-0.266	-0.370	-0.474	-0.578	-0.682
F1Y-P3Y	-0.001	-0.095	-0.189	-0.283	-0.377	-0.471	-0.565
F1Y-P4Y	-0.044	-0.128	-0.212	-0.296	-0.380	-0.464	-0.548
F1Y-P5Y	-0.056	-0.130	-0.204	-0.278	-0.352	-0.426	-0.500
F2Y-P1Y	0.061	-0.034	-0.129	-0.224	-0.319	-0.414	-0.509
F2Y-P2Y	0.109	0.022	-0.065	-0.152	-0.239	-0.326	-0.413
F2Y-P3Y	0.175	0.097	0.019	-0.059	-0.137	-0.215	-0.293
F2Y-P4Y	0.155	0.085	0.015	-0.055	-0.125	-0.195	-0.265
F2Y-P5Y	0.122	0.061	0.000	-0.061	-0.122	-0.183	-0.244
F3Y-P1Y	0.077	-0.005	-0.087	-0.169	-0.251	-0.333	-0.415
F3Y-P2Y	0.113	0.040	-0.033	-0.106	-0.179	-0.252	-0.325
F3Y-P3Y	0.197	0.132	0.067	0.002	-0.063	-0.128	-0.193
F3Y-P4Y	0.033	-0.027	-0.087	-0.147	-0.207	-0.267	-0.327
F3Y-P5Y	0.057	0.005	-0.047	-0.099	-0.151	-0.203	-0.255
F4Y-P1Y	0.036	-0.028	-0.092	-0.156	-0.220	-0.284	-0.348
F4Y-P2Y	-0.009	-0.063	-0.117	-0.171	-0.225	-0.279	-0.333
F4Y-P3Y	-0.049	-0.098	-0.147	-0.196	-0.245	-0.294	-0.343
F4Y-P4Y	-0.097	-0.141	-0.185	-0.229	-0.273	-0.317	-0.361
F4Y-P5Y	0.078	0.038	-0.002	-0.042	-0.082	-0.122	-0.162
F5Y-P1Y	0.101	0.042	-0.017	-0.076	-0.135	-0.194	-0.253
F5Y-P2Y	0.067	0.016	-0.035	-0.086	-0.137	-0.188	-0.239
F5Y-P3Y	0.068	0.022	-0.024	-0.070	-0.116	-0.162	-0.208
F5Y-P4Y	0.135	0.096	0.057	0.018	-0.021	-0.060	-0.099
F5Y-P5Y	0.326	0.294	0.262	0.230	0.198	0.166	0.134

Net Long Side Returns

Table 4.19: Transaction Costs of Long Side of Contrarian Portfolio for Overlapping Formation Periods

Transaction Costs per trade	0.10%	0.20%	0.30%	0.40%	0.50%	0.60%
F1Y-P1Y	0.113	0.226	0.339	0.452	0.565	0.678
F1Y-P2Y	0.104	0.208	0.312	0.416	0.520	0.624
F1Y-P3Y	0.094	0.188	0.282	0.376	0.470	0.564
F1Y-P4Y	0.084	0.168	0.252	0.336	0.420	0.504
F1Y-P5Y	0.074	0.148	0.222	0.296	0.370	0.444
F2Y-P1Y	0.057	0.114	0.171	0.228	0.285	0.342
F2Y-P2Y	0.057	0.114	0.171	0.228	0.285	0.342
F2Y-P3Y	0.047	0.094	0.141	0.188	0.235	0.282
F2Y-P4Y	0.047	0.094	0.141	0.188	0.235	0.282
F2Y-P5Y	0.111	0.185	0.259	0.333	0.407	0.222
F3Y-P1Y	0.040	0.080	0.120	0.160	0.200	0.240
F3Y-P2Y	0.040	0.080	0.120	0.160	0.200	0.240
F3Y-P3Y	0.030	0.060	0.090	0.120	0.150	0.180
F3Y-P4Y	0.030	0.060	0.090	0.120	0.150	0.180
F3Y-P5Y	0.030	0.060	0.090	0.120	0.150	0.180
F4Y-P1Y	0.029	0.058	0.087	0.116	0.145	0.174
F4Y-P2Y	0.029	0.058	0.087	0.116	0.145	0.174
F4Y-P3Y	0.019	0.038	0.057	0.076	0.095	0.114
F4Y-P4Y	0.019	0.038	0.057	0.076	0.095	0.114
F4Y-P5Y	0.019	0.038	0.057	0.076	0.095	0.114
F5Y-P1Y	0.020	0.040	0.060	0.080	0.100	0.120
F5Y-P2Y	0.020	0.040	0.060	0.080	0.100	0.120
F5Y-P3Y	0.020	0.040	0.060	0.080	0.100	0.120
F5Y-P4Y	0.020	0.040	0.060	0.080	0.100	0.120
F5Y-P5Y	0.010	0.020	0.030	0.040	0.050	0.060

Table 4.20: Contrarian Profitability of Prior Losers for Non-overlapping Periods After Transaction Costs

	Different level of Transaction Costs per Trade							
	0%	0.10%	0.20%	0.30%	0.40%	0.50%	0.60%	
F1Y-P1Y	-0.053	-0.166	-0.279	-0.392	-0.505	-0.618	-0.731	Net Long Side Returns
F1Y-P2Y	-0.058	-0.162	-0.266	-0.370	-0.474	-0.578	-0.682	
F1Y-P3Y	-0.001	-0.095	-0.189	-0.283	-0.377	-0.471	-0.565	
F1Y-P4Y	-0.044	-0.128	-0.212	-0.296	-0.380	-0.464	-0.548	
F1Y-P5Y	-0.056	-0.130	-0.204	-0.278	-0.352	-0.426	-0.500	
F2Y-P1Y	-0.151	-0.208	-0.265	-0.322	-0.379	-0.436	-0.493	
F2Y-P2Y	0.081	0.024	-0.033	-0.090	-0.147	-0.204	-0.261	
F2Y-P3Y	-0.030	-0.077	-0.124	-0.171	-0.218	-0.265	-0.312	
F2Y-P4Y	0.079	0.032	-0.015	-0.062	-0.109	-0.156	-0.203	
F2Y-P5Y	0.010	-0.101	-0.175	-0.249	-0.323	-0.397	-0.212	
F3Y-P1Y	0.407	0.367	0.327	0.287	0.247	0.207	0.167	
F3Y-P2Y	0.156	0.116	0.076	0.036	-0.004	-0.044	-0.084	
F3Y-P3Y	0.549	0.519	0.489	0.459	0.429	0.399	0.369	
F3Y-P4Y	0.360	0.330	0.300	0.270	0.240	0.210	0.180	
F3Y-P5Y	0.046	0.016	-0.014	-0.044	-0.074	-0.104	-0.134	
F4Y-P1Y	-0.034	-0.063	-0.092	-0.121	-0.150	-0.179	-0.208	
F4Y-P2Y	0.407	0.378	0.349	0.320	0.291	0.262	0.233	
F4Y-P3Y	0.158	0.139	0.120	0.101	0.082	0.063	0.044	
F4Y-P4Y	0.252	0.233	0.214	0.195	0.176	0.157	0.138	
F4Y-P5Y	0.210	0.191	0.172	0.153	0.134	0.115	0.096	
F5Y-P1Y	-0.252	-0.272	-0.292	-0.312	-0.332	-0.352	-0.372	
F5Y-P2Y	-0.454	-0.474	-0.494	-0.514	-0.534	-0.554	-0.574	
F5Y-P3Y	-0.676	-0.696	-0.716	-0.736	-0.756	-0.776	-0.796	
F5Y-P4Y	-0.667	-0.687	-0.707	-0.727	-0.747	-0.767	-0.787	
F5Y-P5Y	-	-	-	-	-	-	-	

For instance, for the 3x3 year strategy the profits from "selling" winners are about 40% while the profits from buying losers are about 20%. The profits are also statistically significant and there is no jump in returns during January. We do not detect any medium term momentum profits. Finally, we find that for very long periods (4x4, 5x5) the contrarian profits tend to decrease. Also, a number of robustness tests are performed; for instance, a month is skipped between the formations and testing periods, outliers are "trimmed", January is excluded from the sample. The results are essentially similar. The discussion in the chapter also suggests that microstructure biases, such as bid-ask spreads and infrequent trading, are not responsible for contrarian profits, nor is taxes and risk (as measured by the market and the Fama-French factors). Further, contrarian profits are more prominent for middle and large capitalisation stocks (in the latter case for the long term).

We argue, however, that these contrarian profits are "theoretical" i.e., despite their apparent magnitude, they are not exploitable in practice. Thus, the market may be informationally efficient although a price reversal does takes place. We argue that based on two findings. Firstly, *even if short sales were allowed* the incorporation of transactions costs in the analysis shows that contrarian strategies are marginally profitable only for traders that face a very low transaction cost rate, i.e. below a 0.4% per trade. With the majority of investors in the ASE (institutional and private) facing costs of about 0.5% or above the logical conclusion is that (even if short sales *were* allowed) contrarian strategies are not exploitable in practice. Secondly, it could be argued that, *in the presence of short selling restrictions* a trader could concentrate on the long leg of the transaction only, i.e. simply buy losers, thereby ignoring the short leg. This argument relies on the observation that in most previous studies for international markets the overall profits of contrarian strategies originate from the long leg, i.e. the losers. We, however, find that in the ASE a large portion of the profits is due to the short leg, i.e. the winners. Nevertheless, we perform simulations (with transactions costs) for the case where a trader tries to exploit the anomaly by simply buying losers and the result remains the same: price reversals and contrarian strategies are not exploitable in practice.

Overall, the results of this chapter are quite interesting: a seemingly non-rational price reversal does take place in the ASE, probably due to investor overreaction; however, the market is informationally efficient with respect to this anomaly due to short-sale restrictions and transactions costs.

CHAPTER 5: RELATION OF CONTRARIAN PROFITS TO BUSINESS CYCLE FACTORS

5.1 Introduction

So far we have seen that price reversals do take place in the ASE, although they do not lead to economically significant contrarian profits. We have also seen that these price reversals are not due to a number of "rational" reasons, such as risk among others. An interesting issue is whether the reversals are related to business cycle variables, i.e. factors that are undetected so far. Many previous studies focused in identifying a possible relationship between business cycles and the momentum effect, because reversals and contrarian profitability has been considered as captured by asset pricing models like the Fama-French three factor model. However in our study contrarian profitability is still present even after employing Fama-French factors and it completely vanishes only for transaction costs greater than average. We will briefly refer to business cycle variables and the momentum phenomenon and then we will try to employ a model where business cycle factors function as independent variables with contrarian profits used as the dependent one.

Grundy and Martin (2001) employed Fama French three-factor model in order to adjust cross-sectional differences in risk while trying to identify the connection of momentum effect to risk-based explanations. They concluded that neither industry effects nor cross-sectional differences in expected returns are the primary cause of the momentum phenomenon. Chordia and Shivakumar (2002) showed that business cycle variables can explain momentum profits in the US stock market. They applied a predictive regression framework and identified that the profitability of momentum strategies is due to cross-sectional differences in expected returns and that momentum profits are only a compensation for bearing business cycle risk. Antoniou *et al.* (2007) applied Chordia and Shivakumar's model to three major European stock markets in their effort to investigate whether momentum profits are also explained in Europe by the following variables: (i) three-month Treasury bill yield (YLD), (ii) the value weighted market dividend yield (DIV), (iii) the default risk premium (DEF) and (iv) the term spread (TERM). All these variables are included in the business cycle model:

$$R_{i,t} = \phi_{i,0} + \sum_{j=1}^{4} \phi_{i,j} BC_{j,t-1} + e_{i,t} \qquad (17)$$

In (19) $R_{i,t}$ is the return (inclusive of dividends) of firm i in month *t*, BC is the vector of *j* (for j=1-4) macroeconomic variables representing business cycle variables (DIV, YLD, TERM, and DEF) and $e_{i,t}$ is the error term of stock i at time *t.* These time-varying coefficients are used to estimate the one-month-ahead predicted returns for each stock. Then the stocks are ranked using the predicted returns and long and short positions taken accordingly to the momentum strategy they follow. Cooper *et al.* (2004) however, claimed that the predictive regression model of Chordia and Shivakumar reacts differently according to the market states. In other words the model, to some extend, can only explain momentum profits following down-turns and but this is not happening after following up-turns.

Avramov (2004) showed that when using predictive regressions the return predictability based on the explanatory variables can be attributed to either predictable asset mispricing or predictable risk premium or both. Driven by this conclusion Avramov and Chordia (2006) extended Chordia and Shivakumar's model by examining conditional asset pricing models whereas factor loadings could vary with firm specific market capitalization and book-to-market ratio as well as with business cycle related variables. They reported that a business cycle pattern exist within momentum profits and conclude that the momentum strategy profitability is attributable to a systematic rather than idiosyncratic component of stock returns. In other words momentum profitability in the US is entirely explained by asset mispricing that also varies with macroeconomic variables.

Following the same notion Antoniou *et al.* (2007) used a two-pass cross-sectional regression based on Avramov and Chordia's model in three major European stock markets (UK, France and Germany). The first-path regression used as dependent variable individual stocks returns. As a set of explanatory variables they used business cycle variables and well known risk factors (Fama-French three factors) varied with firm characteristics (size and Book-to-Market ratio). At the second stage returns adjusted for risk and business cycle variables are then regressed on firm specific variables (firm size, B/M ratio and past raw returns). The notion was that if the predictive power of firm characteristics was represented by the known risk factors and the business cycle variables, then the coefficients of firm characteristics and past cumulative returns from the second regression should be insignificant. If the cross-sections of residual returns continued to experience momentum after adjusting for Business Cycle variables and the three factors from Fama-French (1996) model, then the coefficient of past return variables should be significant and positive. Furthermore Antoniou et al, driven by Barberis and Thaler (2003) suggestions that the momentum effect is driven by investors' behavior divergence in (analysts') opinion, proceeded in extending the second-stage regression from Avramov and Chordia's model by adding behavioral variables such as: dispersion of analysts' earnings per share (EPS) forecasts, mean forecast error and analyst coverage.

The results of Antoniou et al (2007) study were that the early model of Chordia and Shivakumar (2002) does not prove that business cycle variables can capture momentum profits in those three European markets. Secondly the application of Avramov and Chordia (2006) model in European markets relates momentum profits to asset mispricing that systematically varies with global business conditions. Finally they concluded that the extended model of Avramov and Chordia (2006) is robust to the inclusion of behavioral variables, however their contribution is mixed across countries, leading us to the conclusion that investor's behavior is less likely to be correlated to business cycle and unlikely to explain momentum profits. To sum up, European momentum profits could be explained by unknown risk factors which are largely attributable to the business cycle.

Wu (2002) in his effort to capture return continuation phenomena as well return reversal phenomena incorporates conditioning information into the Fama-French three-factor model. His motivation was the idea that in a dynamic world, risk exposures as well as prices of risks may vary through time and depend on conditioning information (lagged macroeconomic variables such as value-weighted excess returns, one-month US T-bill rate, the yield spread between three- and one-month US T-bills, the yield spread between corporate Baa and Aaa-bonds and finally one-month lagged spread between a dividend yield and the one-month T-bill return). The exposures are assumed to be linear in the instruments. He reveals that like SMB risk, the HML risks are significantly negatively cross-correlated between short-term winners and losers, but significantly positively cross-correlated between long-term winners and losers. In other words time-variation characteristics of risks that are important in asset pricing are missed in the Fama-French unconditional analysis. Due to the fact that the conditional linear-exposure Fama-French regression model seems to remain misspecified, Wu, relaxes the linearity assumption and uses conditional cross-sectional asset pricing tests which prove that conditioning information does actually help the Fama-French model to capture the cross-sectional patterns of both return continuation as well as return reversal. In contrast to Avramov and Chordia (2006) who use individual stocks in their model, Wu uses portfolio returns.

5.2 Methodology – Data Set

In our case we will test contrarian portfolio returns within the framework of an unconditional Fama French three-factor regression model adding macroeconomic variables in order to verify if they add up to the explanatory power of the model and whether contrarian profits (and by implication the price reversals) are related to the business cycle. These are market-wide financial variables that carry information concerning the state of the economy that are useful in predicting asset returns. Contrarian portfolio return (CR) refer to the monthly abnormal average returns calculated from non-overlapping formation periods and for the following symmetric trading strategies: 1YF-1YP, 2YF-2YP and 3YF-3YP, where 1YF stands for one year portfolio formation period and similarly 1YP stands for one year performance (or holding) period of the portfolio of stocks.

For the selection of those business cycle variables we rely on the aforementioned studies (Wu (2002), Antoniou *et al.* (2007)) where the information variables have been extensively screened on their predictive power. The first macroeconomic variable employed in the present study is the three month rate on the Greek Treasury Bill (obtained from DataStream), since Fama (1981), Fama and Schwert (1977) have showed that this variable is negatively related to future stock returns and that it serves as a proxy for expectations of future economic activity. In our study we also examine the explanatory power of one-month Greek Treasury Bill (obtained also from DataStream). Other studies like Ferson and Harvey (1999) that use the loadings of stock portfolios on lagged economy-wide variables to explain the cross-section of expected returns, employ not only the one-month lagged Treasury bill as one of the instrumental variables, but also the difference between the one-month lagged returns of a three-month and a one-month Treasury-bill (Campbell (1987), Ferson and Harvey (1991)) rather than the three-month Treasury bill as a stand alone variable. Thus this variable is also employed here.

The use of default spread in the Greek stock market is not applicable as the vast majority of corporate bonds were not tradable (a variable like that could have been useful in tracking longer-term business cycle conditions, as default spread is higher during recessions and lower during expansions). Moreover as Treasury Bonds with more than 10 years maturity are rare in the Greek Capital Market, it is difficult to construct a term spread based on Greek data. However in order to proxy for this variable, we use the indices generated by Merrill Lynch (ML), available at DataStream. More specifically, we proxy term spread as the difference of the changes in the 10-year Global Government Bond Index (given by ML) minus the 3-year Global Government Bond Index. Our motivation for this action is that, as Fama and French (1988) have shown, that this variable is closely related to short-term business cycle. The assumption in using this proxy, in the absence of data for the Greek capital market is that changes in the global default spread will be reflected in the Greek market's default spread (named as SPREAD in our model).

A firm-specific characteristic variable (that is believed to be associated with the business cycle of an economy) is the Dividend yield (DY henceforth) of the General Price Index of the Athens Stock Market (available at DataStream). The Dividend Yield has been shown by Keim and Stambaugh (1986) and Fama and French (1988) that it is connected to slow mean reversion in stock returns across several economic cycles. This variable is included as a proxy for time variation in the unobservable risk premium, since a high dividend yield indicates that dividends are being discounted at a higher rate. DY equals the ratio between the dividend of a firm at the financial year-end that falls in year t-1 and the firm's market value of equity at the end of December in year t-1. Leledakis *et al.* (2003) study the Athens Stock Exchange for approximately the same time period and report a U-shaped relationship between dividend yield and average stock returns. In the context of cross-sectional regression tests (or multivariate regressions) dividend yield does not have a significant effect on stock returns. Moreover dividend yield shows a strong seasonal pattern as it is significantly negative in January months and insignificantly positive in non-January months. In Karanikas *et al.* (2006), although dividend yield is not statistically significant in the cross-sectional model, its simultaneous inclusion into the model with the natural log of the book to market value of equity offers (the second firm specific characteristic) enhances the explanatory power of the model.

Finally in our effort to increase our model explanatory power we still employ the Fama French factors as in previous chapter. First we have the SMB factor which is the difference of the returns on small- and big-stock portfolios. Then there is the HML factor which represents the difference, each month, between the returns on the high-B/M portfolios and the returns on the low- B/M portfolios.

The regression should take the following form:

$$CR_{i,t} = a_{i,t} + \sum_{j=1}^{4} \beta_{i,j} BC_{j,t-1} + \sum_{j=1}^{2} \gamma_{i,j} FF_{j,t} + e_{i,t} \qquad (18)$$

We test variations of the above model for the whole time period of the sample as well as for sub-periods, by using lagged values of business-cycle variables. Our first variation[24] model includes minimum five and maximum six independent variables. As far as macro-economic variables are concerned we initially inset lagged values of one month Treasury bill rate (TB1M), Dividend Yield (DY), Term Spread (Spread). On the second variation of our model we replace lagged values of one month T-bill rate with lagged values of the three month Treasury bill rate (TB3M) in our effort to find out whether longer term rates add to the explanatory power of the model. As a third variation we employ one-month

[24] See notes in Table 5.1 for the model variations.

lagged returns of a three-month and a one-month Treasury-bill (TB3M-TB1M) instead of the lagged values of the stand alone one (or three) month T-bill rates.

Then, as in Campbell (1987) and in Ferson and Harvey (1991), we combined (variation D) alternatively the lagged values of the yield spread between three- and one-month T-bills with the lagged values of one or three month Treasury bill rate plus the rest of the macroeconomic variables DY, SPREAD. Our scope was to find out how much this combined inclusion adds up to our models explanatory power of the contrarian portfolio profitability. In all of these variations Fama French factors (SMB and HML) are also included. Furthermore we examined these model variations for different time periods: the whole sample period (1990-2003) as well as for two equal sub-periods. The choice of the sub-period's length was taken arbitrarily. In the following section we present the most interesting results.

5.3 Results

In table 5.1 we present results concerning the first contrarian symmetric trading strategy 1YF-1YP (CR1Y). For all those variations (for the whole sample A and C, and for the 1997-2003 period variation C) where the constant term is statistically significant, we assume there is model misspecification and possibly there could be other not-included variables more appropriate to capture contrarian profitability. A general conclusion is that the inclusion of one-month lagged values of one-month T-bill rate has almost the same effect on the model's explanatory power as the one-month lagged values of three-month

T-bill rate when combined with the one month lagged values of the yield spread between 3-month and 1-month T-bill rates.

As far as the whole sample period is concerned, variations D and E indicate that the Treasury bill yield spread variable (TB3M-TB1M) is statistically significant at the 5% level of significance whereas the Dividend Yield variable is statistically significant at the 10% level. The multiple coefficient of determination R^2 for D and E is slightly higher than for all the model variations of the sample period (6.42%). Durbin Watson t-statistic shows that there is no autocorrelation in the residuals. When we apply the model and its variations to the first sub-period we observed that even if R^2 is slightly higher, on average, than that of the whole sample period none of the independent variables are statistically significant.

The second sub-period 1997-2003 includes a very volatile time period when strong upward and downward trends of the General Price Index of Athens Stock Exchange took place. The year of 1997 indicated the beginning of a new era for the Greek Economy leaving behind a long period with stagflation. The model with most variations (excluding variation C), seems to provide a better explanation for the one year contrarian portfolio returns. Dividend yield is negatively related and statistically significant for 5% level of significance. This evidence seems to be in alignment to Gombola and Liu (1993) findings where dividend yield is positively related to returns during bear markets but negatively related during bull markets. Apart from dividend's yield role we notice that for the second sub-period, SMB (the factor that is related to size) is statistically significant for only 10% level and negatively related to the one-year contrarian profitability. The statistical significance of the SMB in the second sub-sample indicates a considerable increase of the R^2 coefficient of determination up to 13.15% contrary to the modest 6.42% of the whole sample.

Table 5.2 presents the results from the second set of regressions where as an independent variable we have contrarian returns of the second symmetric strategy with two-years formation period and two years for performance period. Contrary to the results of the previous strategy Dividend Yield appears to be highly statistically significant at 5% (for A, B, C) and even at 1% level (for D and E), i.e. it plays a role in explaining contrarian profits for the whole sample period and for all possible variations. However constant coefficient estimates for A, C are statistically significant for the 1% level and B for the 5% level, indicating that other factors as well may well be responsible for the generation of the portfolios contrarian returns. This may also partially explain the lower R^2 coefficient of determination for the sum of the sample period (from 4.77% up to 5.82%).

Table 5.1: Variations of the regression with CR1Y dependent variable and Business Cycle-Variables, FF factors as independent variables.

			TB1M	**TB3M**	**TB3M-TB1M**	**DY**	**SPREAD**	**SMB**	**HML**			
1991-2003	CR1	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	**d-stat**	
(A)	Estimate	0,06	-1,62			-0,49	-1,41	-0,52	-0,25	3,47%	1,66<1,80<**1,87**	(+) Autocorrelation
	t-statistic	(1,79)*	(-0,92)			(-0,56)	(-0,80)	(-1,04)	(-0,51)			
(B)	Estimate	0,05		-1,15		-0,49	-1,47	-0,53	-0,21	3,10%	1,66<1,80<**1,86**	(+) Autocorrelation
	t-statistic	(1,56)		(-0,53)		(-0,54)	(-0,81)	(-1,05)	(-0,42)			
(C)	Estimate	0,05			14,28	-1,24	0,42	-0,58	-0,23	5,50%	1,66<1,80<**1,89**	(+) Autocorrelation
	t-statistic	(1,68)*			(2,01)**	(-1,37)	(0,22)	(-1,18)	(-0,50)			
(D)	Estimate	0,01	3,58		26,16	-2,08	2,25	-0,69	-0,06	6,42%	1,65<1,81<**1,91**	(+) Autocorrelation
	t-statistic	(0,44)	(1,20)		(2,16)**	(-1,83)*	(0,93)	(-1,38)	(-0,13)			
(E)	Estimate	0,01		3,58	22,57	-2,08	2,25	-0,69	-0,06	6,42%	1,65<1,81<**1,91**	(+) Autocorrelation
	t-statistic	(0,44)		(1,20)	(2,29)**	(-1,83)*	-0,93	(-1,38)	(-0,13)			
1991-1996	CR1	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	**d-stat**	
(A)	Estimate	-0,04	1,33			1,44	-1,87	0,21	0,42	5,35%	1,46<1,76<**2,29**	(+) Autocorrelation
	t-statistic	(-0,48)	(0,28)			(1,30)	(-0,79)	(0,39)	(0,53)		2,24<**2,29**<2,54	(-) Autocorrelation
(B)	Estimate	-0,06		2,99		1,31	-1,74	0,21	0,41	5,70%	1,46<1,76<**2,29**	(+) Autocorrelation
	t-statistic	(-0,78)		(0,61)		(1,46)	(-0,87)	(0,38)	(0,52)		2,24<**2,29**<2,54	(-) Autocorrelation
(C)	Estimate	0,008			11,44	-0,07	0,70	0,07	0,52	6,36%	1,46<1,76<**2,27**	(+) Autocorrelation
	t-statistic	(0,14)			(0,88)	(-0,04)	(0,22)	(0,12)	(0,66)		2,24<**2,27**<2,54	(-) Autocorrelation
(D)	Estimate	-0,02	2,51		13,15	0,06	0,35	0,09	0,48	6,74%	1,43<1,80<**2,28**	(+) Autocorrelation
	t-statistic	(-0,31)	(0,51)		(0,97)	(0,03)	(0,10)	(0,16)	(0,61)		2,20<**2,28**<2,57	(-) Autocorrelation
(E)	Estimate	-0,02		2,51	10,63	0,06	0,35	0,09	0,48	6,74%	1,43<1,80<**2,28**	(+) Autocorrelation
	t-statistic	(-0,31)		(0,51)	(0,80)	(0,03)	(0,10)	(0,16)	(0,61)		2,20<**2,28**<2,57	(-) Autocorrelation
1997-2003	CR1	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	**d-stat**	
(A)	Estimate	0,18	-7,68			-5,02	0,43	-1,45	-0,07	13,15%	1,50<1,77<**1,85**	(+) Autocorrelation
	t-statistic	(1,42)	(-0,72)			(-2,26)**	(0,08)	(-1,80)*	(-0,10)			
(B)	Estimate	0,18		-7,78		-5,12	0,44	-1,47	-0,06	13,14%	1,50<1,77<**1,85**	(+) Autocorrelation
	t-statistic	(1,39)		(-0,72)		(-2,31)**	(0,08)	(-1,85)*	(-0,09)			
(C)	Estimate	0,09			2,34	-5,12	3,31	-1,56	0,13	12,56%	1,50<1,77<**1,85**	(+) Autocorrelation
	t-statistic	(2,18)**			(0,07)	(2,26)**	(1,01)	(-1,96)*	(0,20)			
(D)	Estimate	0,18	-7,93		-3,26	-5,06	0,36	-1,45	-0,07	13,16%	1,48<1,80<**1,85**	(+) Autocorrelation
	t-statistic	(1,39)	(-0,72)		(-0,09)	(-2,23)**	(0,06)	(-1,79)*	(-0,10)			
(E)	Estimate	0,18		-14,07	-6,79	-4,53	0,36	-1,45	-0,07	13,16%	1,48<1,80<**1,85**	(+) Autocorrelation
	t-statistic	(1,39)		(-1,28)	(-0,20)	(-1,97)*	(0,06)	(-1,79)*	(-0,10)			

Table 5.1 (continued)

Notes:
1. CR1Y refers to the Contrarian portfolios returns consisted of the abnormal average returns between loser and winner portfolios taken from one year non-overlapping formation periods and for one year performance period.
TB1M is the one month government Treasury bill rate and TB3m is the three month government Treasury bill rate, and are considered to be the short term interest rate. TB3M-TB1M is the so called yield spread and shows the change of the short term interest rates.
DY is the dividend yield which is measured as the ratio between the dividend of a firm at the financial year-end that falls in year t-1 and the firms' market value of equity at the end of December in year t-1.
SPREAD is the difference the difference of the 10-year global government bond index (given by ML) minus the three-year global government index.
SMB is the difference of the returns on small- and big-stock portfolios with about the same weighted-average book-to-market equity.
HML is the difference, each month, between the simple average of the returns on the two high-B/M portfolios (S/H and B/H) and the average of the returns on the two low- B/M portfolios (S/L and B/L).
2. The business cycle variables used in estimation are lagged one-period back as it is suggested in the relevant international literature. The accounting data we employ here are from the end of financial year 1989 to that of year 2002.
3. α is the constant term of the regression, β (1,...,4) are the coefficient of the business cycle variables and the γ(1,2) are the coefficients of the two Fama – French factors SMB and HML. Finally R^2 is the multiple coefficient of determination which gives the proportion of the total sum of squares of deviations that is explained by all the repressors.
4. In order to test first-order serial correlation we use Durbin Watson d-statistic at 0.05 level of significance. Which measures the linear association between adjacent residuals from a regression model for which we have placed bounds on the critical region, creating a region where results are inconclusive. The d_L and d_U bounds have been taken from the extended Durbin-Watson tables by Savin and White (1977) which were corrected by Farebrother (1980).
5. Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level.
6.

$$(\mathrm{A})\ CR_{1,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB1M}_{t-1} + \beta_{2t}\ DY_{t-1} + \beta_{3t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{1,t}$$

$$(B)\ CR_{1,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB3M}_{t-1} + \beta_{2t}\ DY_{t-1} + \beta_{3t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{1,t}$$

$$(C)\ CR_{1,t} = \alpha_{1,t} + \beta_{1t}\ (\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{2t}\ DY_{t-1} + \beta_{3t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{1,t}$$

$$(D)\ CR_{1,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB1M}_{t-1} + \beta_{2t}\ (\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{3t}\ DY_{t-1} + \beta_{4t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{1,t}$$

$$(E)\ CR_{1,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB3M}_{t-1} + \beta_{2t}\ (\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{3t}\ DY_{t-1} + \beta_{4t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{1,t}$$

Table 5.2: Variations of the regression with CR2Y dependent variable and Business Cycle-Variables, FF factors as independent variables.

			TB1M	TB3M	TB3M-TB1M	DY	SPREAD	SMB	HML			
1992-2003	CR2	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	**d-stat**	
(A)	Estimate	0,08	0,58			-1,87	-1,03	-0,18	0,11	4,77%	1,66<1,80<**1,96**	(+) Autocorrelation
	t-statistic	(2,57)***	(0,31)			(-2,06)**	(-0,64)	(-0,37)	(0,23)			
(B)	Estimate	0,07		1,19		-2,01	-0,81	-0,20	0,14	4,90%	1,66<1,80<**1,96**	(+) Autocorrelation
	t-statistic	(2,30)**		(0,53)		(-2,10)**	(-0,48)	(-0,41)	(0,31)			
(C)	Estimate	0,08			4,97	-1,84	-0,56	-0,15	0,04	4,96%	1,66<1,80<**1,96**	(+) Autocorrelation
	t-statistic	(2,74)***			(0,61)	(-2,18)**	(-0,30)	(-0,32)	(0,09)			
(D)	Estimate	0,05	3,08		14,69	-2,58	0,96	-0,25	0,20	5,82%	1,65<1,81<**1,98**	(+) Autocorrelation
	t-statistic	(1,46)	(1,11)		(1,23)	(-2,40)***	(0,42)	(-0,52)	(0,42)			
(E)	Estimate	0,05		3,08	11,60	-2,58	0,96	-0,25	0,20	5,82%	1,65<1,81<**1,98**	(+) Autocorrelation
	t-statistic	(1,46)		(1,11)	(1,23)	(-2,40)***	(0,42)	(-0,52)	(0,42)			
1992-1997	CR2	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	**d-stat**	
(A)	Estimate	-0,02	-0,37			0,57	0,39	-0,37	0,75	2,92%	1,46<1,76<**1,97**	(+) Autocorrelation
	t-statistic	(-0,46)	(-0,11)			(0,57)	(0,17)	(-0,80)	(1,15)			
(B)	Estimate	-0,02		0,73		0,39	0,006	-0,38	0,78	2,98%	1,46<1,76<**1,91**	(+) Autocorrelation
	t-statistic	(-0,52)		(0,22)		(0,35)	(0,004)	(-0,82)	(1,20)			
(C)	Estimate	-0,01			11,04	-0,32	2,71	-0,47	0,79	4,60%	1,46<1,76<**1,90**	(+) Autocorrelation
	t-statistic	(-0,39)			(1,08)	(-0,26)	(0,99)	(-1,01)	(1,24)			
(D)	Estimate	-0,01	0,09		11,08	-0,33	2,68	-0,47	0,79	4,60%	1,43<1,80<**1,90**	(+) Autocorrelation
	t-statistic	(-0,38)	(0,02)		(1,07)	(-0,25)	(0,87)	(-1,00)	(1,22)			
(E)	Estimate	-0,01		0,09	10,99	-0,33	2,68	-0,47	0,79	4,60%	1,43<1,80<**1,90**	(+) Autocorrelation
	t-statistic	(-0,38)		(0,02)	(1,05)	(-0,25)	(0,87)	(-1,00)	(1,22)			
1998-2003	CR2	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	**d-stat**	
(A)	Estimate	0,23	-10,30			-5,00	-1,67	-0,20	-0,15	9,21%	1,46<1,76<**2,04**	(+) Autocorrelation
	t-statistic	(1,62)	(-0,84)			(-1,89)*	(-0,31)	(-0,24)	(-0,20)		**2,04**<2,24<2,54	(-) Autocorrelation
(B)	Estimate	0,22		-9,62		-4,97	-1,61	-0,23	-0,13	9,13%	1,46<1,76<**2,05**	(+) Autocorrelation
	t-statistic	(1,58)		(-0,80)		(-1,88)*	(-0,29)	(-0,28)	(-0,17)		**2,05**<2,24<2,54	(-) Autocorrelation
(C)	Estimate	0,11			3,47	-4,64	1,49	-0,30	0,08	8,25%	1,46<1,76<**2,05**	(+) Autocorrelation
	t-statistic	(2,58)**			(0,07)	(-1,77)*	(0,38)	(-0,36)	(0,12)		**2,05**<2,24<2,54	(-) Autocorrelation
(D)	Estimate	0,23	-10,28		1,29	-5,00	-1,64	-0,19	-0,15	9,22%	1,43<1,80<**2,04**	(+) Autocorrelation
	t-statistic	(1,59)	(-0,83)		(0,02)	(-1,88)*	(-0,30)	(-0,23)	(-0,20)		**2,04**<2,20<2,57	(-) Autocorrelation
(E)	Estimate	0,23	-10,28		1,29	-5,00	-1,64	-0,19	-0,15	9,22%	1,43<1,80<**2,04**	(+) Autocorrelation
	t-statistic	(1,59)	(-0,83)		(0,02)	(-1,88)*	(-0,30)	(-0,23)	(-0,20)		**2,04**<2,20<2,57	(-) Autocorrelation

Table 5.2 (continued)

Notes:

1. CR2Y refers to the Contrarian portfolios returns consisted of the abnormal average returns between loser and winner portfolios taken from two years non-overlapping formation periods and for a two-year performance period.

TB1M is the one month government Treasury bill rate and TB3m is the three month government Treasury bill rate, and are considered to be the short term interest rate. TB3M-TB1M is the so called yield spread and shows the change of the short term interest rates.

DY is the dividend yield which is measured as the ratio between the dividend of a firm at the financial year-end that falls in year t-1 and the firms' market value of equity at the end of December in year t-1.

SPREAD is the difference the difference of the 10-year global government bond index (given by ML) minus the three-year global government index.

SMB is the difference of the returns on small- and big-stock portfolios with about the same weighted-average book-to-market equity.

HML is the difference, each month, between the simple average of the returns on the two high-B/M portfolios (S/H and B/H) and the average of the returns on the two low- B/M portfolios (S/L and B/L).

2. The business cycle variables used in estimation are lagged one-period back as it is suggested in the relevant international literature. The accounting data we employ here are from the end of financial year 1989 to that of year 2002.

3. α is the constant term of the regression, β (1,...,4) are the coefficient of the business cycle variables and the γ(1,2) are the coefficients of the two Fama – French factors SMB and HML. Finally R^2 is the multiple coefficient of determination which gives the proportion of the total sum of squares of deviations that is explained by all the repressors.

4. In order to test first-order serial correlation we use Durbin Watson d-statistic at 0.05 level of significance. Which measures the linear association between adjacent residuals from a regression model for which we have placed bounds on the critical region, creating a region where results are inconclusive. The d_L and d_U bounds have been taken from the extended Durbin-Watson tables by Savin and White (1977) which were corrected by Farebrother (1980).

5. Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level.

6.

$$(\mathrm{A})\ CR_{2,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB1M}_{t-1} + \beta_{2t}\ DY_{t-1} + \beta_{3t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{2,t}$$

$$(B)\ CR_{2,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB3M}_{t-1} + \beta_{2t}\ DY_{t-1} + \beta_{3t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{2,t}$$

$$(C)\ CR_{2,t} = \alpha_{1,t} + \beta_{1t}\ (\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{2t}\ DY_{t-1} + \beta_{3t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{2,t}$$

$$(D)\ CR_{2,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB1M}_{t-1} + \beta_{2t}\ (\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{3t}\ DY_{t-1} + \beta_{4t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{2,t}$$

$$(E)\ CR_{2,t} = \alpha_{1,t} + \beta_{1t}\ \mathrm{TB3M}_{t-1} + \beta_{2t}\ (\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{3t}\ DY_{t-1} + \beta_{4t}\ SPREAD_{t-1} + \gamma_{1t}\ SMB + \gamma_{2t}\ HML + e_{2,t}$$

Table 5.3: Variations of the regression with CR3Y dependent variable and Business Cycle-Variables, FF factors as independent variables.

			TB1M	TB3M	TB3M-TB1M	DY	SPREAD	SMB	HML			
1993-2002	CR3	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	d-stat	
(A)	Estimate	0,06	-0,61			-1,2	-0,3	0,07	0,17	4,66%	1,66<**1,68**<1,80	(+) Autocorrelation
	t-statistic	(2,75)***	(-0,53)			(-2,10)**	(-0,26)	(0,22)	0,56			
(B)	Estimate	0,05		3,39		-2,79	1,42	-0,09	0,29	7,76%	1,66<**1,79**<1,80	(+) Autocorrelation
	t-statistic	(1,79)*		1,39		(-2,91)***	(0,84)	(-0,22)	0,73			
(C)	Estimate	0,06			2,22	-1,89	0,77	0,04	0,11	6,25%	1,66<**1,73**<1,80	(+) Autocorrelation
	t-statistic	(2,47)***			(0,24)	(-2,64)***	(0,43)	(0,09)	(0,29)			
(D)	Estimate	0,04	3,80		9,69	-2,89	2,04	-0,08	0,30	8,07%	1,65<1,801<**1,809**	(+) Autocorrelation
	t-statistic	(1,39)	(1,49)		(0,92)	(-2,96)***	(1,03)	(-0,19)	(0,75)			
(E)	Estimate	0,04		3,80	5,89	-2,89	2,03	-0,87	0,30	8,07%	1,65<1,801<**1,809**	(+) Autocorrelation
	t-statistic	(1,39)		(1,49)	(-0,61)	(-2,96)***	(1,04)	(-0,19)	(0,75)			
1993-1997	CR3	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	d-stat	
(A)	Estimate	0,02	-0,40			-0,21	-0,65	-0,40	1,10	3,48%	1,46<1,76<**2,45**	(+) Autocorrelation
	t-statistic	(0,43)	(-0,07)			(-0,09)	(-0,24)	(-0,64)	(1,32)		2,24<**2,45**<2,54	(-) Autocorrelation
(B)	Estimate	0,02		-0,12		-0,29	-0,77	-0,42	1,10	3,47%	1,46<1,76<**2,45**	(+) Autocorrelation
	t-statistic	(0,47)		(-0,03)		(-0,14)	(-0,37)	(-0,65)	(1,31)		2,24<**2,45**<2,54	(-) Autocorrelation
(C)	Estimate	0,02			0,90	-0,38	-0,63	0,42	1,12	3,48%	1,46<1,76<**2,45**	(+) Autocorrelation
	t-statistic	(0,50)			(0,08)	(-0,28)	(0,22)	(-0,68)	(1,31)		2,24<**2,45**<2,54	(-) Autocorrelation
(D)	Estimate	0,02	-0,52		1,12	-0,23	-0,40	-0,41	1,12	3,50%	1,43<1,80<**2,45**	(+) Autocorrelation
	t-statistic	(0,41)	(-0,09)		(0,10)	(-0,10)	(-0,10)	(-0,64)	(1,30)		2,20<**2,45**<2,57	(-) Autocorrelation
(E)	Estimate	0,02		-0,52	1,64	-0,23	-0,40	-0,41	1,12	3,50%	1,43<1,80<**2,45**	(+) Autocorrelation
	t-statistic	(0,41)		(-0,09)	(0,12)	(-0,10)	(0,10)	(-0,64)	(1,30)		2,20<**2,45**<2,57	(-) Autocorrelation
1998-2002	CR3	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	R^2	d-stat	
(A)	Estimate	-0,10	17,53			-4,34	9,07	-0,15	0,60	14,16%	1,48<**1,74**<1,80	(+) Autocorrelation
	t-statistic	(-0,97)	(1,90)*			(-1,89)*	(2,19)**	(-0,23)	(1,05)			
(B)	Estimate	-0,10		16,86		-4,43	9,16	-0,08	0,57	13,97%	1,48<**1,74**<1,80	(+) Autocorrelation
	t-statistic	(-0,94)		(1,85)*		(1,93)*	(2,18)	(-0,13)	(1,01)			
(C)	Estimate	0,08			1,16	-5,04	3,99	0,05	0,17	8,42%	1,48<**1,54**<1,80	(+) Autocorrelation
	t-statistic	(2,23)**			(0,03)	(-2,15)**	(1,21)	(0,07)	(0,31)			
(D)	Estimate	-0,10	17,61		4,78	-4,36	9,17	-0,13	0,60	14,19%	1,48<**1,74**<1,80	(+) Autocorrelation
	t-statistic	(-0,97)	(1,88)*		(0,14)	(-1,88)*	(2,16)**	(-0,20)	(1,04)			
(E)	Estimate	-0,10		17,61	-12,83	-4,36	9,17	-0,13	0,60	14,19%	1,48<**1,74**<1,80	(+) Autocorrelation
	t-statistic	(-0,97)		(1,88)*	(-0,37)	(-1,88)*	(2,16)**	(-0,20)	(1,04)			

Notes:

1. CR3Y refers to the Contrarian portfolios returns consisted of the abnormal average returns between loser and winner portfolios taken from three years non-overlapping formation periods and for a three-year performance period.
TB1M is the one month government Treasury bill rate and TB3m is the three month government Treasury bill rate, and are considered to be the short term interest rate. TB3M-TB1M is the so called yield spread and shows the change of the short term interest rates.
DY is the dividend yield which is measured as the ratio between the dividend of a firm at the financial year-end that falls in year t-1 and the firms' market value of equity at the end of December in year t-1.
SPREAD is the difference the difference of the 10-year global government bond index (given by ML) minus the three-year global government index.
SMB is the difference of the returns on small- and big-stock portfolios with about the same weighted-average book-to-market equity.
HML is the difference, each month, between the simple average of the returns on the two high-B/M portfolios (S/H and B/H) and the average of the returns on the two low- B/M portfolios (S/L and B/L).
2. The business cycle variables used in estimation are lagged one-period back as it is suggested in the relevant international literature. The accounting data we employ here are from the end of financial year 1989 to that of year 2002.
3. α is the constant term of the regression, β (1,...,4) are the coefficient of the business cycle variables and the γ(1,2) are the coefficients of the two Fama – French factors SMB and HML. Finally R^2 is the multiple coefficient of determination which gives the proportion of the total sum of squares of deviations that is explained by all the repressors.
4. In order to test first-order serial correlation we use Durbin Watson d-statistic at 0.05 level of significance. Which measures the linear association between adjacent residuals from a regression model for which we have placed bounds on the critical region, creating a region where results are inconclusive. The d_L and d_U bounds have been taken from the extended Durbin-Watson tables by Savin and White (1977) which were corrected by Farebrother (1980).
5. Where * significant for 10% level, ** significant for 5% level, *** significant for 1% level.
6.

$$(A)\; CR_{3,t} = \alpha_{1,t} + \beta_{1t}\,\mathrm{TB1M}_{t-1} + \beta_{2t}\,DY_{t-1} + \beta_{3t}\,SPREAD_{t-1} + \gamma_{1t}\,SMB + \gamma_{2t}\,HML + e_{3,t}$$

$$(B)\; CR_{3,t} = \alpha_{1,t} + \beta_{1t}\,\mathrm{TB3M}_{t-1} + \beta_{2t}\,DY_{t-1} + \beta_{3t}\,SPREAD_{t-1} + \gamma_{1t}\,SMB + \gamma_{2t}\,HML + e_{3,t}$$

$$(C)\; CR_{3,t} = \alpha_{1,t} + \beta_{1t}\,(\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{2t}\,DY_{t-1} + \beta_{3t}\,SPREAD_{t-1} + \gamma_{1t}\,SMB + \gamma_{2t}\,HML + e_{3,t}$$

$$(D)\; CR_{3,t} = \alpha_{1,t} + \beta_{1t}\,\mathrm{TB1M}_{t-1} + \beta_{2t}\,(\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{3t}\,DY_{t-1} + \beta_{4t}\,SPREAD_{t-1} + \gamma_{1t}\,SMB + \gamma_{2t}\,HML + e_{3,t}$$

$$(E)\; CR_{3,t} = \alpha_{1,t} + \beta_{1t}\,\mathrm{TB3M}_{t-1} + \beta_{2t}\,(\mathrm{TB3M} - \mathrm{TB1M})_{t-1} + \beta_{3t}\,DY_{t-1} + \beta_{4t}\,SPREAD_{t-1} + \gamma_{1t}\,SMB + \gamma_{2t}\,HML + e_{3,t}$$

As far as the second sub-sample is concerned the Dividend Yield variable is once more negatively related and statistically significant for just 10% level for all variations of the model. In variation C constant coefficient estimate becomes also statistically significant for 5% level. R^2 coefficient of determination increases to a greater extent that when we run regressions for the full sample period. A reason for this may be the up-warding business cycle and the capital market's openness that was imposed by European Union. However Durbin Watson t-statistic shows that there is negative autocorrelation in the residuals, which means that t-statistic could be biased up-wards.

Finally Table 5.3 presents the relationship between the macro-variables included into the Fama-French three factor regression model and the Abnormal Average Returns coming from the contrarian strategy 3YF-3YP (CR3Y). Recall that the Abnormal Cumulative Average Returns of the 3YF-3YP for non-overlapping formation periods were the highest of all strategies even those of the employed on the overlapping formations periods. These profits were robust even after the exclusion of the transaction costs for all of their hypothetically possible levels. As we can see the variations of the regression model that present significant role of one or even two macro-variables on the explanation of the Contrarian returns outnumber any other strategy we have followed up to now.

The first three variations (A, B and C) for the total sample period show the constant coefficient to be highly statistically significant for 1% level (for A t = 2.75 and for C t = 2.47) and for second variation at 10% level. As we mentioned previously this is a sign that the power of the included variables does not offer a satisfactory explanation of the abnormal returns sources and that contrarian profitability could be driven by other variables that are not stated in this model. This is not the case for the last two variations where the variable TB3M-TB1M is introduced into the regression simultaneously with the other short term Treasury bill rates (1month or 3 month alternatively), even if all three are statistically insignificant. Furthermore the addition of the last variable causes coefficient of determination of the last two variation to improve (8.07% from 4.66%).

Dividend Yield is once again negatively related to the contrarian portfolio returns and statistically significant for all five variations. Specifically apart from the first variation DY reaches the 1% level of significance. An additional drawback of the first three variations except the fact that constant is statistically significant is that Durbin-Watson t-statistic lies between the lower and the higher boundaries signifying that the test is inclusive whether or not reject null hypothesis. The last two variations do not face this problem and seemed to be the best suitable regressions.

The model seems to be inappropriate to explain contrarian returns for the first five year sub-period of the sample period (1993-1997) as none of the variables are statistically significant. Moreover R^2 coefficient of determination is extremely low (moves from 3.47% up to 3.50%) compared to other whole sample and to the second sub-period of the sample period. The behaviour of the model during the second sub-period of the sample when there has been stock market hyper-activity is better than the first sub-period and this is why this model is more suitable for the whole sample period. An interesting outcome is that the R^2 of the models vary to higher than usual levels achieving from 8.42% up to 14.19%. The abnormal return constant is (excluding variation C) at all times not-significant and up to three variables appear to be statistically significant. Dividend

Yield once more kept its negative relation to the contrarian returns and is statistically significant for 10% level (except variation C where it reaches 5% level of significance).

The surprise is that the Spread Term is significant for the first time for 5% level for A, D and E variations and it is positively related to contrarian returns. This is a very interesting outcome as this is a variable that it has been designed to capture short-term business cycles worldwide using not-country specific data. One should take under consideration that Athens Stock Exchange especially at that particular period happened to follow a similar path (peak and bottom) with most of the Western developed capital markets and many other European emerging markets. Therefore these results reveal a highly possible connection of the contrarian profits coming from the Greek capital market to business cycles that change course within a short period of time.

Finally for the second sub-period of our sample 1998-2002 business cycle-variables such as short term T-bill rates (1month and 3month) are positively related to the contrarian profits and appear to be statistically significant at 10% level. Even though those variables significance are not as strong as other variables, it seems that they empower R^2 which reaches its maximum value 14.19%. Nevertheless Durbin-Watson statistic warns that the acceptance of the null hypothesis is inconclusive and that further examination of the model is needed before be condemned it for positive autocorrelation in the residuals.

Overall, those regressions show that contrarian profits, especially in the 3x3 year strategy, seem to be related to some extent with variables that capture variations in the business cycle. Thus, it could be possible that at least a partial explanation of contrarian profitability could be attributed to the misspecification of asset pricing models used.

5.4 Conclusion

This chapter investigates whether the profits from various term contrarian strategies are related to the business cycle. The motivation is that, as discussed above, many previous studies report that business cycle variables can explain momentum profits in international markets. Typically the variables employed in previous studies to capture the business cycle are the 3-month Treasury bill yield, the value weighted market dividend yield, the default risk premium, and the term spread.

We employ similar variables where available (due to data limitations for the Greek capital market) and examine a large number of regressions where these variables serve as explanatory variables for contrarian profits. For instance, we run regressions with and without lags, with one variable and add further variables gradually, for various sub-periods, etc.

Overall, our results suggest that contrarian profits, especially for the most profitable 3x3 year formation-testing strategy, seem to be related to some extent with variables that capture variations in the business cycle. Thus, it is argued that the failure of traditional asset pricing models to explain these profits in the literature could be due the misspecification of these models. In other words, these models may fail to adequately capture the risk that stems from business cycles, which could be at least a partial explanation of the contrarian strategy "abnormal" profitability. It should also be noted, however, that (as the low values of the coefficients of determination indicate) variables other than business cycle or macroeconomic variables (since the most important ones have been included in the analysis) may explain much better the documented price reversals. A possible hypothesis is that behavioural variables may be more relevant. It is unfortunate that data on this type of variables are not available for the ASE.

CHAPTER 6: CONCLUSION

The aim of this thesis is to investigate the existence of long-term contrarian profits in the Athens Stock Exchange (ASE) following the De Bondt and Thaler (1985) methodology and, in case these profits exist, to investigate the validity of the rational explanations of the long-run predictability.

The contribution of this thesis to the literature can be summarized as follows:

(a) Evidence is presented for ASE, a market for which evidence is scarce in relation to the contrarian profits;

(b) This is one of the very few studies in the literature that explicitly investigates the effect of transactions costs on the economic magnitude of the anomaly;

(c) Rational explanations of the anomaly such as: (i) capital gains taxes and the "January effect", (ii) microstructure biases such as bid-ask spreads, (iii) infrequent trading, (iv) short selling restrictions, are all addressed within a single study;

(d) Risk is incorporated in the analysis via the Fama and French (1992, 1993, and 1995) multifactor asset pricing model;

(e) The relation of contrarian profitability to the well known size effect is examined; the sample is also split to sub-groups based on market capitalization;

(f) Both overlapping and non-overlapping formation and testing periods are examined, and robustness tests are employed;

(g) The relationship of contrarian profits with the macro-economy and business cycles is modeled in order to see whether the profits are affected by the real economy (based on Antoniou *et al.* (2007) effort to detect a possible connection between momentum profits and business cycles).

The results seem to suggest that long-term contrarian strategies are indeed profitable in the Athens Stock Exchange irrespective of the use of overlapping/ non-overlapping formation periods. These results are also robust to various methodological adjustments. For instance, the results are not due to few outlier firms. However contrarian profits are mainly confined to medium size stocks (similar results coming from India Stock Market, Rastogi *et al.* (2009)), and to large capitalization stocks for very long term contrarian strategies only. Thus, the size effect that is often suggested by previous studies as a partial explanation for the overreaction hypothesis (Zarowin (1989, 1990)) does not hold for the ASE (confirming findings of Dissanaike (2002) for the London Capital Market).

Furthermore, on the search of a risk-based explanation of the contrarian profits we apply the Fama French three factor model and find that contrarian profits are still present (in line with Antoniou *et al.* (2005) findings relevant to the short-term contrarian strategies for Athens Stock Exchange). The argument that microstructure biases, such as bid-ask spreads or infrequent trading, may explain contrarian profits does not hold, as the ASE trading system and the methodology of excluding stocks with infrequent trading eliminates them as candidate explanations. This is also true for tax-based explanations of the anomaly based on tax loss selling (contrary to George and Hwang (2007) results for the UK stock market), since there are no capital gains taxes in the ASE (based on

Travlos and Milonas (2001), Antoniou *et al.* (2005) assertions) and the “January effect” does not affect results as in previous studies.

Finally the profitability of these strategies seems to be related, to some extent, to the business cycle an economy follows. We have argued, however, that the low values of the coefficients of determination in our regression analysis indicate that variables other than business cycle may explain much better the documented price reversals (or at least add significantly to the explanatory power). A possible hypothesis is that behavioural variables may be more relevant. It is unfortunate that data on this type of variables are not available for the ASE, and in that sense this hypothesis is very difficult to test.

An important finding of this study is that the documented contrarian profits in the ASE originate from the short leg of the strategy. That is, contrarian profits are mainly due to winners that are subsequently becoming losers, in sharp contrast to the results of previous studies for developed equity markets who arrive at the opposite conclusion. In practical terms, given the short-selling limitations in the ASE, this means that the implementation and the realisation of the profits from contrarian strategies is impossible, unless investors concentrate on the long leg of the transaction only (i.e. buy losers). Simulations of this option, with real-life transaction costs included, suggest that in real life situations extremely few strategies deliver profits that are economically meaningful.

Overall, the results of this study are quite interesting. We find that a non-rational long-term price reversal seems to take place in the ASE, probably due to investor overreaction. Due to short-sale restrictions and transactions costs, however, market *participants cannot exploit fully this anomaly in practice. Thus the market is informationally efficient with respect to this anomaly.*

The *implications* of the study are as follows:

(a) For regulators the finding of contrarian profits (even if it not fully exploitable) and the elimination of rational explanations indicate that investors are prone to behavioral biases. For instance due to representativeness they may overreact to upcoming information. As a result stock prices may not reflect all relevant information but reflect sentiment and psychology. A proposed solution would be that the authorities take steps towards better quality of information provided by firms and more careful dissemination of that info. Another practice would be to make use of the media in order to educate and train those who want to invest in the stock market;

(b) For market participants: the study shows that contrarian profits are possible for large investors who are in the position to negotiate *lower than normal* fees. Even if they take up only the long position modest profits are possible for longer-term strategies.

Future research could focus on the relationship of contrarian strategies and business cycle models. Those models can be applied on portfolios sorted through various accounting or other (psychology based) variables. Portfolios constituents could be industries or indices (FTSE 20, FTSE 40 etc). Transaction costs as a final barrier to these strategies will fade away as MIFID and Turquoise Platform will intensify competition among brokers and force stock market authorities to lower their fees. One possible avenue would be to reestimate transaction costs for a more recent period. Furthermore, as more data become available, future research should focus on the period 2004 and onwards in the ASE in order to investigate whether the relaxation of the short-selling restriction leads to higher profitability of contrarian strategies. This period should be separately examined as many changes have been occurred to the way that book value of ASE listed companies is calculated after the implications of the International Accounting Standards.

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APPENDICES

APPENDIX I

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Schools of Thought					
Boudoukh et al. (1994)	NYSE-AMEX, stocks and index Value-Line Composite Average,	US	1962-1990	Weekly autocorrelations day by day, overlapping observations, Five-size portfolios	Effect of non-synchronous trading, in case where returns are not autocorrelated, can be greater or equal to 18% for the portfolios of interest. Spot index's autocorrelation is significantly higher than futures. Futures' index autocorrelation is indistinguishable from zero.
Lo and MacKinlay (1990)	CRSP monthly returns	US	1954-1988	CAPM, APT/ size sorted portfolios, Monte-Carlo simulations	Provide a measure of the effect of data-snooping & appropriate sampling theory when snooping is unavoidable. Data-snooping biases can arise from peoples' tendency to focus on the unusual.
Conrad et al. (1997)	NASDAQ-NMS, NYSE/AMEX	US	1985-1989 for Nasdaq, 1990-1991 for NYSE/AMEX	Used Bid prices instead of transaction prices	Contrarian profits largely generated by B-A bounce in transaction prices. Use of bid prices almost eliminates profits from price reversals which disappear at trivial levels of transaction costs.
Bessembinder and Hertzel (1993)	S&P 500 future returns, CRSP	US	1964-1989	Evaluate serial dependence in returns/non-trading periods. Regress returns on prior day returns while employing indicator variable	Pattern in autocorrelation of security returns around weekend and holiday non-trading periods.
Keim (1989)	OTC National Market System, NYSE, CRSP	US	1983-1988	Blume and Stambaugh (1983,1984) methodology	Systematic trading patterns bias returns computation with closing transaction prices, largely for low-priced stocks. Dec closing prices recorded at the bid, Jan closing prices recorded at the ask (Jan effect). Weekend and Holiday effect related to B-A spread
Keim and Stambaugh (1986)	NYSE	US	1928-1978	Construct 3 ex ante observable variables - from bond market and stock market. They predict ex post risk premiums on common stocks of NYSE-listed firms of various sizes, long-term bonds of various default risks, and U.S. Government bonds of various maturities.	Expected risk premiums on many assets appear to change over time in a manner that is at least partially described by variables that reflect levels of asset prices.
Lo and MacKinlay (1997)	CRSP, S&P small stock index. Gov & Corp Bond Index	US	1947-1993	construct portfolios of stocks and bonds that are maximally predictable with respect to a set of ex-ante observable economic variables	These levels of predictability are statistically significant, even after controlling for data-snooping biases. sources of maximal predictability shift considerably across asset classes and sectors as the return horizon changes. Predictability of the maximally predictable portfolio is genuine and economically significant

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Conrad and Kaul (1989)	CRSP daily return, AMEX,NYSE	US	1962-1985	Develop simple model for monthly expected returns that relies on rapidly decaying structure of weekly expected returns. Size-based portfolios	Rapid mean reversion in shorter-horizon (weekly) expected returns implies substantial higher variation through time in monthly expected returnw. 25% of small-firm return variance can be explained by time variation in monthly expected returns.
Hameed (1997)	NYSE/AMEX CRSP daily stock	US	1962-1989	Dhrymes, et al. (1984) two-stage methodology but he allows time variations in systematic factors to be modeled directly, size based portfolios, W-W closing prices	Significant cross-autocorrelations between current returns on large firms and lagged returns on small firms when trading volume is high. Asymmetric cross-autocorrelation structure in stock returns is more likely to be generated by a time-varying factor model
Data Snooping Bias					
Campbell and Limmack (1997)	London Business School (LBS) Risk Measurement Service	UK	1979-1990	Study long-term reversals in the abnormal returns, construct size categories of w-l portfolios	Momentum effect persisted for 1Y after formation. For 2nd YP smallest losers experience returns reversals (not also for smallest winners). For 2YP-5YP w-l returns reverse, not due to size effect. Seasonal in nature, Jan and Apr mostly tax-loss hypothesis.
Nagel (2001)	CRSP, Compustat,LSE	UK/US	1955-2000	examine long horizon returns of value strategies	Mom prof disappear when returns adjusted for size and BM effect both US/UK trading volume significant in predicting mom prof persistence or reversion. Cross-sectionally, the premium for value stocks and the discount on growth stocks are mean-reverting
Mai (1995)	NYSE, CRSP	France	1977-1990	DeBondt amd Thaler (1985,1987) methodology	Long-horizon contrarian strategies profitable even after controlling for size and systematic risk.
Alonso and Rubio (1990)	SSE, monthly data	Spain	1967-1984	DeBondt amd Thaler (1985,1987)	Overreaction Hypothesis accepted after correcting for size, losers >winners by 24,5% prices systematically overshoot
Chang et al. (1995)	TSE, Pacific-Basin Capital Markets Databases	Japan	1975-1991	Short-term abnormal returns to contrarian investment strategies	(i) Short-run contrarian strategy remains profitable after controlling systematic risk and firm size are taken into account (ii) Seasonality effect (including the January effect) is not a critical factor in explaining the reported short-run contrarian profits, (iii) Abnormal profits are reported regardless of whether losers are smaller or greater than winners, and the magnitude of the profits does not differ; and (iv) a strong symmetry exists between the performance of the two extreme portfolios.
Hameed and Ting (2000)	Kuala Lumpur Stock Exchange	Malaysia	1977-1996	Methodology by Lehman (1990), Lo and MacKinlay (1990)	Contrarian strategy yields significant trading profits. It generates significantly higher profits for heavily and frequently traded securities. Distinct positive relation between contrarian profits and level of trading activity in the securities even after controlling for size. asymmetric predictability of high- and low-volume portfolios is most pronounced for small firms
Kang et al. (2002)	Datastream	China	1993-2000	Lo and Mackinlay (1990) and Jegadeesh and Titman (1995)	Statistically significant abnormal profits for some short-horizon contrarian (caused by overreaction) and intermediate-horizon momentum strategies (negative cross-serial correlation). Lead –lag effect present nad varies depending on holding period horizon.
Bowman and Iverson (1998)	NZSE weekly data, University of Auckland Weekly Share Price Database	New Zealand	1967-1986	Event studies using cumulative abnormal returns	Market overreacts after a price decline and the reverses. Reversals magnitude is similar to initial price change. Results robust to risk, size, seasonal and B-A bounce.

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Schiereck et al. (1999)	Frankfurt Stock Exchange/ Deutsche Finanzmarktdatenban Karlsruhe University	Germany	1961-1991	Momentum and contrarian strategies	These strategies appeared to beat a passive approach. Factors such as beta, risk, or firm size do account for the results. Thus equity prices reflect investor forecasts of company profits that are predictably wrong
Mun et al. (2000)	Ibbotson EnCorr database (1Y Treasury returns, S&P 500 index returns for US, Morgan Stanlay Canadian market index returns	US/Canada	1986-1996	Contrarian/Overreaction Hypothesis as proposed by DeBondt and Thaler (1985, 1987) using a non-parametric methodology with a multi-factor asset pricing model	Results from risk-adjusted, non-parametric, multifactor bootstrap-simulated estimates show that, for the US, short-term and intermediate-term contrarian portfolios yield significant excess returns above the market. For the Canadian market, the intermediate term contrarian portfolio works best.
Antoniou A. et al. (2001)	Weekly data ASE	Greece	1990-2000	Jegadeesh and Titman (1995) FF (1993,1996)	Serial correlation equity returns, significant short-run con profits even after adjusted for market frictions, con prof decline from small to large stocks, overreaction hypothesis to firm specific component contribute more to con prof than underreaction to common factors
Poterba and Summers (1988)	Monthly data NYSE, IMF IFS	US, Can, UK, Austria, Belgium, Colombia, Germany, Fin, Fr, India, Netherlands, etc	1926-1986	Fama and French (1986), Lo and MacKinlay (1988)/ fads models Shiller (1994), Summers (1986)	Positive autocorrelation in returns over short horizons and negative autocorrelations over longer horizons, random walk price behavior cannot be rejected at conditional statistical levels.
Baytas and Cakici (1999)	Worldscope Disclosure Database	US, Canada, UK, Japan, Germany, France, Italy	1982-1991	Conrad and Kaul's pooled crosssection-times series (AVHP) Price- and size-based portfolios	US no evidence of overreaction. Returns to long-term contrarian strategies in other countries seem to be generally significant. returns to arbitrage portfolios based on price are higher than those based on size, the latter generally outperform the winner-loser arbitrage portfolios
Dissanaike (1997)	FT500 Index, LSPD	UK	1962-1991	Rank-period returns, B-H methodology	Past losers outperform past winners, but also less risky
Kato (1990)	TOPIX TSE, daily data	Japan	1974-1987	examine the day of the week effect for Japanese stock returns	Low Tuesday- high Wednesday returns are observed. Most positive returns arise during the nontrading period. Monday effect also observed when previous week is closed by Friday trading. Low Tuesday returns related to low Monday returns in the U.S. Weekly pattern more pronounced for smaller firms. A reverse size effect is observedduring the trading period
Brouwer et al. (1997)	Datastream	UK, France, Netherlands and Germany	June1982-Jume 1993	Value Strategies, 5 portf for 4 variables, E/P, CF/P, B/M, DY, industrial and non-industrial	Past losers for all 4 variables outperform past winners form longer-run strategies. CF/P 20,8%, E/P 5%, B/M 10% and Yld 5,2%.
Richards (1997)	Morgan Stanley Capital International (MSCI)	16 markets	1970-1995	National Stock Market Indices (for total returns in US dollars) that included high capitalization and heavily traded stocks	Long-run overreaction profits – no evidence that loser countries are riskier than winners (in term of s.t., covariance or other risk factors). Small markets have larger reversals. Stronger Revearsals for 3Y horizons.

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Balvers et al. (2000)	Morgan Stanley Capital International (MSCI)	16 OECD countries plus Hong Kong and Singapore	1969-1996	long-term contrarian strategies	Strong evidence of mean reversion in relative stock index prices consistent with the overreaction hypothesis. Imply a significantly positive speed of reversion with a halflife of 3 to 3 and one-half years. This result is robust to alternative specifications and data. Parametric contrarian investment strategies that fully exploit mean reversion across national indexes outperform buy-and-hold and standard contrarian strategies
Lead-Lag Effect					
Jegadeesh and Titman (1995b)	NYSE, AMEX weekly data	US	1963-1990	Examine price reaction to common factors and firm specific info	Delayed reaction to common factors rise lead–lag effect. Delayed reaction can't be exploited by contrarian strategies. Primary source the reversal of the firm-specific component of returns
Mech (1993)	CRSP/ Nasdaq securities	US	1972-1986	Cohen, Hawawini, Maier, Schwartz and Whitcomb [CHMSW] (1980) methodology	Transaction costs cause portfolio autocorrelation by slowing price adjustment. Transaction-cost model predicts that prices adjust faster when changes in valuation are large in relation to the bid-ask spread. Cross-sectional tests support this prediction, but time-series tests do not. Small portion of the observed cross-autocorrelations can be attributed to nonsynchronous trading
McQueen et al. (1996)	NYSE common stocks	US	1963-1994	Examine Lo and MacKinlay (1990) cross-autocorrelation puzzle	Existing explanations of the cross-autocorrelation puzzle based on data mismeasurement, minor market imperfections, or time-varying risk premiums fail to capture the directional asymmetry in the data
Kadlec and Patterson (1999)	CRSP weekly data/ ISSM, ASE, NYSE	US	1988-1992	Size (small – large) and randomly selected stocks, models for nonsynchronous trading	25% proportion of autocorrelation (and cross-autocorrelation) due to non-synchronous trading
Poshakwale and Theobald (2004)	Indian equity index series, Nifty senior, Sensex, Bseni index	India	1997-2001	Investigate analytically and empirically lead/lag relationship between large cap stocks and small cap stocks.	Large cap indices lead small cap indices and have higher speeds of adjustment towards intrinsic values. Significant contribution thin trading effect and speeds of adjustment to lead/lag effect.
Amihud and Mendelson (1987)	Daily opening and closing prices of 30 NYSE stocks	US	8/2/1982-18/2/1983	Compare open-to-open and close-to-close returns given differences in execution methods in opening and closing transaction.	Trading mechanism has a significant effect on a number of characteristics of stock returns. Opening returns are found to exhibit greater dispersion, greater deviations from normality and a more negative and significant autocorrelation pattern than closing returns.
Conrad and Kaul (1988)	CRSP	US	1962-1985	Weekly returns of 10 size-based portfolios Kalman filter by Ansley (1980)	Variation through time in short-horizon expected returns is a relatively large fraction of return variances. Variation in expected returns explains 26% of return variance for the smallest portfolio, this drops to 1% for large portfolios.
Conrad et. al (1991)	NYSE/ AMEX	US	1962-1988	Univariate and multivariate ARMA-GARCH-M parameterizations	Asymmetry in predictability of volatilities of large versus small firms. A volatility surprise to larger firms can be used to predict reliably the volatility of smaller market value firms but not vice versa.
Hou (2007)	all publicly traded securities) (CRSP) NYSE/Amex/Nasdaq data files	US	1963-2001	Focus on searching explanations for lead-lag effect as [Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993).	Strong intra-industry lead-lag effect, when they control for this effect then market-wide industry is insignificant. Largely driven by slow diffusion of bad news.

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Chordia and Swaminathan (2000)	CRSP NYSE/AMEX	US	1963-1996	Tests designed to take into account the issues raised by Conrad and Kaul (1988) and by Hameed (1997).	Trading volume significant determinant of lead-lag effect. Returns on high volume portfolios lead returns on low volume portfolios. differential speed of adjustment to information is a significant source of the cross-autocorrelation patterns in short-horizon stock returns
Merton (1987)				Based on Grossman-Stiglitz (1976) single-security model of asymmetric-information trading,	Recognize the importance of information costs and institutional restrictions in the information acquisition and dissemination process
Kyle (1985)				A dynamic model of insider trading with sequential auctions, structured to resemble a sequential equilibrium	Monopolistic informed trader causes his information to be incorporated into prices gradually, and, when the interval between auctions is vanishingly small, market depth is constant over time.
Holden and Subrahmanyam (1992)				Multi-period auction model in which multiple privately informed agents strategically exploit their long-lived information	Traders compete aggressively and cause most of their common private information to be revealed very rapidly. In the limit as the interval between auctions approaches zero, market depth becomes infinite and all private information is revealed immediately
Foster and Viswanathan (1993)	ISSM/ NYSE, AMEX price, quote, volume data	US	1988	Admati and Pfeiderer (1988) Foster and Viswanathan (1990) methodologies	Intraday test show that or actively traded firms trading volume, adverse selection costs, and return volatility are higher in the first half-hour of the day. Interday test results show that, for actively traded firms, trading volume is low and adverse selection costs are high on Monday
Brennan et al. (1993)	Daily stock returns/ trading volume data CRSP NYAM-NASDAQ/ IBES	US	1977-1988	Test relation number of investment analyst following a firm to the adjustment speed of stock prices to new info.	Little effect of the number of analysts on the serial correlation of portfolio returns. Granger causality regressions revealed that the returns on many analysts firm portfolios tend to anticipate those on few analysts firm portfolios. The first ones respond more rapidly to new information contained in returns. Individual security returns examination show distinct nonlinear relation between speed of adjustment and number of analysts.
Diamond and Verrecchia (1987)				Glosten and Milgrom (1985) model, market makers and traders risk neutral. Cost for shorting not the same for all.	Short sale constraints can slow down the response of stock prices to private information, especially to bad news.
Chan (1993)	CRSP daily prices	US	1980-1989	Develop a model that is related to Bossaerts (19911, Caballe and Krishnan (1992), and Bhasin (1992), who study strategic informed trading in a multiple-correlated asset environment in which market makers condition prices on order flows	Stock returns are serially uncorrelated individually but positively cross-autocorrelated. Cross-sectional differences in the signal quality can give rise to asymmetric cross-autocorrelations. Nonsynchronous trading as explanation for cros-autocorrelations among securities.
Peng and Xiong (2002)				Constructs a learning model in which incomplete information, in the form of an information capacity constraint faced by the representative investor, causes a delay in the price adjustment process.	

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Market Microstructure Effects					
Ball et al. (1995)	NYSE/Amex/ CRSP	US	1925-1984	De Bondt and Thaler (1985,1987) methodology, buy-and-hold returns, 5Y contrarian portfolios returns, monthly data.	Loser stocks are low priced and exhibit skewed return distributions. Their 163% mean return is due largely to their lowest-price quartile position. $1/8^{th}$ price increase reduces mean by 25%, thus sensitive to microstructure/liquidity effects.
Kaul and Nimalendran (1990)	NASDAQ	US	1983-1987	French and Roll (19861, Lo and Ma&inlay (1988), Fama and French (19881, and Poterba and Summers (1988)	When extract measurement errors in prices caused by the bid-ask spread, they find little evidence of market overreaction. On the contrary, security returns are positively, and not negatively, autocorrelated. They also show that bid-ask errors lead to substantial spurious volatility in transaction returns; about half of measured daily return variances can be induced by the bid-ask effect.
Park (1995)	NASDAQ/NMS CRSP	US	1984-1987	Explore a market microstructure explanation for the predictable variations in stock returns following large price changes, event study methodology	Short-run abnormal returns after large positive/negative price changes cannot be completely explained by the bid-ask effect, therefore market overreaction to info shock Average abnormal returns are not large enough to cover the transaction price movement between the bid and ask prices. Not profitable contrarian strategy.
Jegadeesh and Titman (1995a)	NYSE/CRSP/ Fitch Quatations	US	1963-1979	Ho and Stoll (1981) theoretical model of determination of prices with risk-averse dealers.	Decay of dealer inventory imbalances takes several days. Contrarian profits are compensation for bearing inventory risk and can not be realized by traders transacting at B-A prices.
Lo and Coggins (2006)	Daily and Intra-daily price at 1-h intervals of the top 200 stocks on ASX	Australia	2000-2002	Stocks divided into four quartiles. The quartiles are allocated by sorting stocks based on markets cap at the end of sampling period. Lo and MacKinlay (1990) methodology	Simple contrarian strategies applied to daily and intra-day portfolio formation, lead to small but statistically significant profits, which get eliminated by transaction costs. Source of contrarian profits market overreaction. Degree of return reversal positively related to level of order flow imbalance.
Miller et al. (1994)	S&P 500 index and futures/ CME/ KCBT/ NYSE	US	1982-1991	Alternative explanation for the observed negative autocorrelation in basis changes, that it is mainly a statistical illusion, arising because many stocks in the index portfolio trade infrequently	Significant negative autocorrelation in observed basis changes exists even when the level of the basis is well within the pricing bands imposed by index arbitrage transaction costs. Significant negative autocorrelation exists in the basis changes of the geometrically weighted Value Line index, where index arbitrage is impossible. Differences in the frequency of trading of individual stocks within the index portfolio induces the mean reversion in the basis
Ferson et al. (1993)	Common stocks DJ30, Common Stocks NYSE, low-grade bond portfolio retunrs from Ibbotson Associates, gov bond returns from CRSP	US	1963-1985 for DJ30 1928-1987 for NYSE	Gibbons and Ferson (1985) method relaxing assumption that expected returns are linear functions of predetermined instruments. Model of conditional mean-variance spanning generalizes Huberman and Kandel (1987).	More than a single risk premium is needed to model expected stock and bond returns, but the number of common factors in the expected returns is small. when size-based common stock portfolios proxy for the risk factors, they reject the hypothesis that four of them describe the conditional expected returns of the other assets.

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Trading Volume					
Conrad et al. (1994)	CRSP/ NASDAQ-NMS	US	1983-1990	Test relation between trading volume and subsequent returns patterns in individual securities' short-horizon returns. Lehman (1990) contrarian strategy	Strong evidence of a relation between trading activity and subsequent autocovariances in weekly returns. Specifically, high-transaction securities experience price reversals, while the returns of low-transactions securities are positively autocovarying.
Blume et al. (1994)				Investigate information role of volume and its applicability of technical analysis. Versions of models by Brown and Jennings (1989), Grundy et al (1989)	Volume provides information on information quality that can not be deduced from price statistic. Volume captures information contained in the quality of traders' information signals.
Campbell et al. (1993)	NYSE/ CRSP	US	1962-1988	Use a model where risk-averse market makers accommodate buying or selling pressure from liquidity or naive traders.	Stock indexes and individual large stocks the first-order daily return autocorrelation tends to decline with volume. The model implies that is more likely a stock price decline on a high-volume day than on a low-volume day
Hammed and Ting (2000)	KLSE	Malaysian	1977-1996	Lehman (1990), Lo and Mackinlay (1990) methodology	Returns from contrarian portfolio strategy are positively related to the level of trading activity in the securities. Contrarian profits higher for actively and frequently traded securities than low trading securities. Not subsumed by size effect.
Grossman and Miller (1988)				Present a simple model of market structure that captures the essence of market liquidity	Their model suggests looking to differences in the cost to market makers of maintaining a market presence and to differences in the demand by customers for immediacy for the keys to market structure and market liquidity. The greater the demand for immediacy and the lower the cost to market makers of maintaining a continuous presence, the larger the proportion of the transactions between ultimate customers effected initially through market makers, and hence the more liquid the market.
Tkac (1999)	NYSE/ AMEX large firms	US	1988-1991	Provides a theoretical rebalancing benchmark for trading volume that delivers a connection between trading activity in individual stocks and market-wide volume.	Market-related trading is an important component of the trading activity of individual firms. Excess turnover vs. the benchmark is positively related to the level of institutional ownership and option availability. firm size is negatively related to excess turnover. S&P inclusion help only previously undertrade stock
Lee et al. (2003)	AOI, ASX/ SIRCA	Australia	1994-2001	Equal-weighted strategy and a new value-weighted strategy .Following Lo and Mackinaly (1990) and Jegadeesh and Titman (1995).	Strategies yield statistically significant short-term profits, which are largely related to firm size with overreaction to firm specific information. Transaction costs eliminate profits.
Wang (1994)				Model of competitive stock trading is developed where investors are heterogeneous in their information and private investment opportunities and rationally trade for both informational and non-informational motives.	Volume is positively correlated with absolute changes in prices and dividends. He shows that informational trading and non-informational trading lead to different dynamic relations between trading volume and stock returns

Table A1: Literature Review of explanations for return reversals					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Chordia et al. (2002)	NYSE TAQ/ S&P 500/ ISSM	US	1993-1998	Focus on aggregate daily order imbalance as a measure of trading activity.	Order imbalance increases following market declines and vice versa, which reveals that investors are contrarians on aggregate. Order imbalances in either direction, excess buy or sell orders, reduce liquidity. Market-wide returns are strongly affected by contemporaneous and lagged order imbalances.
Larson and Madura (2003)	CRSP/ NYSE/ WSJI	US	1988-1995	A 10% one-day change trigger criterion for identifying events.	For Winner portfolios there is a statistical difference between uninformed and informed events even when controlling for potentially confounding factors. Uninformed events associated with overreaction whereas informed events are not. Results according to DHS (1998) where stock prices overreact to private information signals but underreact to subsequent public signals.
Pritamani and Singal (2001)	NYSE-AMEX/ ISSM	US	1990-1992	A daily stock return that represents a large abnormal price change is called an event. A change is said to be large if abnormal return after adjusting for the value-weighted CRSP index is more than three s.t. away from the mean, calculated over the 250 trading days	Unconditional abnormal returns are found to be important. As they condition on criteria like volume and public announcements, the abnormal returns become large. Out-of sample trading strategy confirms underreaction and generated abnormal returns.
Cooper (1999)	NYSE /AMEX	US	1962-1993	De Bondt and Thaler (1985,1987)	Decreasing-volume stocks experience greater reversals, whereas high-growth-in-volume stocks exhibit weaker reversals and positive autocorrelation.

APPENDIX II

Table A2: Literature Review of explanations for returns continuation

Author(s)	Data Set	Countries	Time Period	Methodological Choices	Key Results
Jegadeesh and Titman (1993)	Compustat/ NYSE/ CRSP	US	1965-1989	Trade the sources of the predictability of future stock returns based on past returns. Relates the evidence of momentum in stock prices to the evidence on the market's underreaction to earnings-related information.	Drifts in future returns over the next six and twelve months are predictable from a stock's prior return and from prior news about earnings. ach momentum variable has a separate explanatory power for future returns, as one strategy does not subsume the other. Security analysts' forecasts of earnings are also slow to incorporate past earnings news especially for the firms with the worst past earnings performance
Grundy and Martin (2001)	AMEX, NYSE/ CRSP	US	1926-1995	Investment strategies followed Assness (1995), FF (1996) methodology.	Adjusted for this dynamic risk exposure, momentum profits are remarkably stable across subperiods of the entire post-1926 era. Factor models can explain 95% of winner or loser return variability, but cannot explain their mean returns. Momentum strategies which base winner or loser status on stock-specific return components are more profitable than those based on total returns. Neither industry effects nor cross-sectional differences in expected returns are the primary cause of the momentum phenomenon.
Griffin et al. (2003)	NYSE, AMEX, CRSP, Datastream International, (IFC) index	US and 39 other countries	1990-2000	They examine whether macroeconomic risk can explain momentum profits internationally.	Momentum profits around the world are economically large and statistically reliable in both good and bad economic states. These momentum profits reverse over 1- to 5-year horizons, an action inconsistent with existing risk-based explanations of momentum.
Berk et al. (1999)				Demonstrates that a rich variety of return patterns, including momentum effects, can result from the variation of exposures over the life-cycle of a firm's endogenously chosen projects.	
Conrad and Kaul (1998)	AMEX/NYSE	US	1926-1989	Use a single unifying framework to analyze the sources of profits to a wide spectrum of return-based trading stragies.	Less than 50% of the 120 strategies yield statistically significant profits and unconditionally, momentum and contrarian strategies are equally likely to be successful. Cross-sectional variation in the mean returns of individual securities included in these strategies plays an important role in their profitability,
Ahn et al. (2003)	CRSP	US	1962-1997	Assess the profitability of momentum strategies using a stochastic discount factor approach.	They argue that the risk of the momentum strategies should be increasing in the market risk premium. Their non-parametric risk adjustment explains roughly half of momentum strategy profits, they cannot rule out the possibility of residual mispricing.
Jegadeesh and Titman (2002)	NYSE/ AMEX	US	1965-1997	Weighted relative strength strategy (WRSS) used by Conrad and Kaul (1998) intiated by Lo and MacKinlay (1990)	Object to Conrad and Kaul findings that mom profits are attributable to cross-sectional differences in expected returns as they do not take into account small sample biases.
Perez-Quiros and Timmermann (2000)	CRSP, DRI Basic Economic database	US	1954-1997	Adopts a flexible econometric model to analyze whether there are asymmetries in the variation of small and large firm risk over the economic cycle.	Consisted with theory small firms display the highest degree of symmetry in their risk across recession and expansion states, which translates into a higher sensitivity of their expected stock returns with respect to variables that measure credit conditions.

Table A2: Literature Review of explanations for returns continuation					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Momentum Profits, Macroeconomic Variables and Market States					
Chordia and Shivakumar (2002)	NYSE–AMEX/ CRSP / Moodys	US	1926-1994	Analyzes the relative importance of common factors and firm specific information as sources of momentum profit	Momentum payoffs are attributable to cross-sectional differences in conditionally expected returns that are predicted by standard macroeconomic variables. Their results provide a possible role for time-varying expected returns as an explanation for momentum payoffs.
Bernanke and Gertler (1989)				Develop a simple neoclassical model of the business cycle in which the condition of borrowers' balance sheets is a source of output dynamics. Higher borrower net worth reduces the agency costs of financing real capital revetments. Business upturns improve net worth, lower agency costs, and increase investment, which amplifies the upturn; vice versa, for downturns. Shocks that affect net worth (as in a debt-deflation) can initiate fluctuations.	
Gertler and Gilchrist (1994)	Quarterly Financial Report for Manufacturing Corporations (QFR)	US	1960-1990	Analyze the response of small versus large manufacturing firms to monetary policy. The goal is to obtain evidence on the importance of financial propagation mechanisms for aggregate activity.	They find that small firms account for a significantly disproportionate share of the manufacturing decline that follows tightening of monetary policy. They play a surprisingly prominent role in the slowdown of inventory demand. Large firms initially borrow to accumulate inventories. After a brief period, small firm; quickly shed inventories.
Kiyotaki and Moore (1997)				Idea taken from Veblen (1904), who described the positive interactions between asset prices and collateralized borrowing. Also provide a twist of Bernake nad Gertel (1989) model.	Construct a model of a dynamic economy in which lenders cannot force borrowers to repay their debts unless the debts are secured. In such an economy, durable assets play a dual role: not only are they factors of production, but they also serve as collateral for loans. The dynamic interaction between credit limits and asset prices turns out to be a powerful transmission mechanism by which the effects of shocks persist, amplify, and spill over to other sectors. They show that small, temporary shocks to technology or income distribution can generate large, persistent fluctuations in output and asset prices.
Carhart (1997)	Micropal/ Investment Company Data. FundScope Magazine, United Babson Reports, Wiesenberger Investment Companies, WSJ.	US	1962-1993	Models of Performance measurement: CAPM (Sharpe (1964), Lintner (1965)), Four-factor model by Carhart (1995)	Demonstrate that common factors in stock returns and investment expenses almost completely explain persistence in equity mutual funds' mean and risk-adjusted returns. The only significant persistence not explained is concentrated in strong underperformance by the worst-return mutual funds. Results do not support existence of skilled or informed mutual fund portfolio managers.
Cooper et al. (2004)	NYSE, AMEX/CRSP	US	1929-1995	Test overreaction theories of short momentum and long-run reversal in the cross-section of stock returns.	Momentum profits depend on the state of the market, as predicted. From 1929 to 1995, the mean monthly momentum profit following positive market returns is 0.93%, whereas the mean profit following negative market returns is −0.37%. The up-market momentum reverses in the long-run. Their results are robust to the conditioning information in macroeconomic factors. Moreover, they find that macroeconomic factors are unable to explain momentum profits after simple methodological adjustments to take account of microstructure concerns.

Table A2: Literature Review of explanations for returns continuation					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Jegadeesh and Titman (2001)	NYSE, ASE, Nasdaq	US	1965-1998	Evaluates various explanations for the profitability of momentum strategies documented in J+T (1993).	They argue that J+T 1993 findings continue to exist by the same magnitude even after 9 years. Momentum strategies continue to be profitable and that past winners outperform past losers.
Johnson (2002)	NYSE	US	1977-1992	A simple, single-firm model with a standard pricing kernel can produce momentum effects when expected dividend growth rates vary over time.	An enhanced model, under which persistent growth rate shocks occur episodically, can deliver a strong positive correlation between past realized returns and current expected returns.
Grinblatt and Moskowitz (1999)	NYSE,AMEX,NASDAQ -NMS, CRSP/ Standard Industrial Classification	US	1963-1999	Standard and normalized strategies for 6 months up to 24 months.	Documented variation in profits across stock characteristics, season, and tax environment appear inconsistent with existing theory
Hong et al. (2000)	CRSP/ NYSE, AMEX, NASDAQ/ IBES/ OCC	US	1980-1996	Their goal is to test Hong-Stein version of the under-reaction hypothesis. They look for evidence that momentum reflects the gradual diffusion of firm-specific information.	Profitability of momentum strategies drops sharply with firm size. Holding size fixed mom strategies work better among stocks with low analyst coverage. Effect of analyst coverage is greater for stocks that are past losers than for past winners. All findings consistent with hypothesis that firm-specific information, especially negative one, diffuses only gradually across the investing public.
Asness et al. (2000)	NYSE, AMEX, Nasdaq	US	1963-1998	Better proxies for the information about future returns contained in firm characteristics such as size, B/M equity, CF/P, percent change in employees, and various past return measures are obtained by breaking these explanatory variables into two industry-related components.	They find that within-industry momentum (i.e., the firm's past return less the industry average return) has predictive power for the firm's stock return beyond that captured by across-industry momentum. They also document a significant short-term (one-month) industry momentum effect which remains strongly significant when they restrict the sample to only the most liquid firms.
Lee and Swaminathan (2000)	NYSE, AMEX	US	1965-1995	Investigate the usefulness of trading volume in predicting cross-sectional returns for various price momentum portfolios	Intermediate-horizon momentum is followed by long-horizon overreaction indicating them as two elements of the same continuous process and supporting the view that initial momentum gains are partially a result of overreacting behavior of investors as postulated by De Long et al (1990). A second contribution of their work has to do with the trading volume not so much as a simple liquidity proxy but a separate volume effect which is robust to various risk adjustments
Chen and Hong (2002)	NYSE, AMEX, CRSP, Compustat	US	1928-1999	Relate Momentum to other factors driving the cross-section of expected stock returns.	Document the existence of momentum in size and B/M portfolios. Negative auto- and cross-serial covariances among the portfolios can be consistent with underreaction-based explanations. These findings are driven by the in-sample serial correlation of the market factor and not the overreaction mechanism.

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Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Bacmann et al. (2001)	Datastream Global Equity Indices/ OECD, NBER	USA, Canada, Japan, UK, France, Germany, Italy	1973-2000	Examine profitability of momentum strategies in G-7 stock market. Investigates their link with industries and the evolution of the business cycle in each of these countries.	Difference of returns (long in cyclical industries and short in defensive industries) is positive and significant (one sided t-test) with the notable exception of the Germany
Rouwenhorst (1998)	MSCI	Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, UK	1980-1995	Large country-specific sources of return variation tilt Winner and Loser portfolios towards different countries. J+T 1993 methodology	International stock markets exhibit momentum: Winners outperform Losers by about 1% per month. Momentum lasts on average for one year. Momentum is present in all twelve sample countries. Negative relationship between momentum and size. Conventional measures of risk cannot explain performance of momentum portfolios. Momentum returns survive transactions costs. Combined European and U.S. evidence makes asset pricing model mis-specification more likely. Correlation between U.S. and European momentum portfolios suggests presence of common factors.
Lewellen (2002)	NYSE, AMEX, CRSP, Compustat	US	1963-1999	Studies momentum in stock returns focusing on the role of industry, size and B/M factors.	Size and B/M exhibit momentum as strong as that in individual stocks and industries. Size, B/M portfolios are well diversified so momentum cannot be attributed to firm- or industry-specific returns. Industry, Size and B/M portfolios are negatively autocorrelated and cross-serially correlated over intermediate horizons. Evidence suggest that stocks covary too strongly with each other Excess Covariance not underreaction explains momentum in the portfolios.
Underreaction					
Daniel et al. (1998)				DHS assume that investors are overconfident about their private information and overreact to it. If investors also have a self-attribution bias, then when subsequent (public) information arrives, investors will react asymmetrically to confirming versus disconfirming pieces of news. In other words, investors attribute successes to their own skill more than they should and attribute failures to external noise more than they should. The consequence of this behavior is that investors' overconfidence increases following the arrival of confirming news. The increase in overconfidence furthers the initial overreaction and generates return momentum. The overreaction in prices will eventually be corrected in the long-run as investors observe future news and realize their errors. Hence, increased overconfidence results in short-run momentum and long-run reversal.	
Hong et al. (2000)	NYSE, AMEX,Nasdaq/ CRSP/ IBES/ OCC	US	1980 - 1996	Test the gradual-information-diffusion model of Hong and Stein (1999). Look for evidence that momentum reflects the gradual diffusion of firm-specific information	First, once one moves past the very smallest stocks, the profitability of momentum strategies declines sharply with firm size. Second, holding size fixed, momentum strategies work better among stocks with low analyst coverage. Finally, the effect of analyst coverage is greater for stocks that are past losers than for past winners. These findings are consistent with the hypothesis that firm-specific information, especially negative information, diffuses only gradually across the investing public.

Table A2: Literature Review of explanations for returns continuation					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Bernard and Thomas (1989)	NYSE, AMEX, Nasdaw	US	1974-1986	Foster, Olsen, and Shevlin (I984),CAR,SUE, Continuously balanced SUE strategy	Describe an implementable strategy, based upon the anomaly, that produces an estimated annualized abnormal return of 18% (before transactions costs) during the first quarter subsequent to the earnings announcement. Smaller abnormal returns appear to persist for at least two additional quarters. Conclude that much of their evidence cannot plausibly be reconciled with arguments built on risk mismeasurement but is consistent with a delayed price response.
Bernard and Thomas (1990)	NYSE, AMEX, Nasdaw	US	1974-1986	Form ten portfolios for each calendar quarter, based on the SUE deciles of firms announcing earnings within that quarter. They observe the relation between the SUE assignments and 3-day market reactions to earnings announcements for subsequent quarters.	Evidence presented here is consistent with a failure of stock prices to reflect fully the implications of current earnings for future earnings. Specifically, the three-day price reactions to announcements of earnings for quarters t + 1 through I + 4 are predictable, based on earnings of quarter r. Even more surprisingly, the signs and magnitudes of the three-day reactions are related to the autocorrelation structure of earnings, as if stock prices fail to reflect the extent to which each firm's earnings series differs from a seasonal random walk.
Mendenhall (1991	Compustat, CRSP, Value Line Investment Survey	US	1982-1986	Investigate whether investors similarly reassess persistence in the light of subsequent analyst earnings forecast revisions.	Analysts also underestimate the serial correlation in earnings figures. Investors also reassess the persistence of recent earnings innovations by examining subsequent analysts' forecast revisions. Security prices underreact to the information in a direct signal of upcoming earnings.
Abarbanell and Bernard (1992)	Value line forecasts/ IBES/ Compustat/ CRSP	US	1976-1986	Examine whether analysts underreact or overreact to prior earnings information and whether any such behavior could previously documented anomalous stock price movements.	Analysts' forecasts underreact to recent earnings. The undereaction in analysts forecasts are at most only about half as large as necessary to explain the magnitude of the drift. Security analysts' behavior is at best only a partial explanation for stock price underreaction to earnings and may be unrelated to stock price overreactions.
Wiggins (1991)	NYSE,AMEX/ CRSP, Cornell University Price Volume (CUPV)	US	1970-1986	This article examines the empirical bias and efficiency of Parkinson's extreme-value variance estimator for common stocks	Bias and efficiency are analyzed as a function of stock price level and trading volume. The results are sensitive to outliers in daily high and low prices. After an outlier screen is applied to the data, the efficiency of the extreme-value estimator significantly exceeds that of the close-close estimator for most price and volume groups.
Andreassen (1988)	Groups of equal number of Males-Females			Test whether the use of (buy when price fell, sell when price rise) strategy was due to a selective application of the representativeness heuristic on the price stimuli, subjects were presented either with only price information or with only price change information.	They provide strong evidence that the price-volume relationship is due, at least in part, to trading based on prices. Economists may favor this explanation because it allows the price-volume relationship to be explained without assuming that the market is dispersing information inefficiently. There may be some wasted trading, but a market can include irrational traders and still be efficient as long as a substantial number of traders follow the dictates of reason.

Table A2: Literature Review of explanations for returns continuation					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Andreassen and Kraus (1990)	77 undergraduate students at a large metropolitan university, 40 men and 41 women, recruited via advertisements requesting subjects for a stock market study, - 70 men.			A model of judgmental extrapolation based on exponential smoothing is proposed in which the setting of the trend parameter is hypothesized to depend upon the relative salience of the successive changes.	Subjects were more likely to sell as prices fell and to buy as prices rose (1) as the sample size of similar changes increased; (2) when the variance of the changes was low; and (3) when the absolute value of the mean change was high.
<u>*Overreaction*</u>					
Daniel and Titman (2006)	CRSP, Compustat,	US	1968-1992	They dispute that book-to-market effect is often interpreted as evidence of high expected returns on stocks of "distressed" firms with poor past performance	Find that while a stock's future return is unrelated to the firm's past accounting-based performance, it is strongly negatively related to the "intangible" return, the component of its past return that is orthogonal to the firm's past performance. Indeed, the book-to-market ratio forecasts returns because it is a good proxy for the intangible return. Also, a composite equity issuance measure, which is related to intangible returns, independently forecasts returns.
Sirri and Tufano (1998)	Investment Company Data Institute (ICDI)	US	1971-1990	Study the flows of funds into and out of equity mutual funds	Consumers base their fund purchase decisions on prior performance information, but do so asymmetrically, investing disproportionately more in funds that performed very well the prior period. Search costs seem to be an important determinant of fund f lows. High performance appears to be most salient for funds that exert higher marketing effort, as measured by higher fees. Flows are directly related to the size of the fund's complex as well as the current media attention received by the fund, which lower consumers' search costs.
Grinblatt et al. (1995)	155 mutual funds	US	1975-1984	analyzes the extent to which mutual funds purchase stocks based on their past returns as well as their tendency to exhibit "herding" behavior (i.e., buying and selling the same stocks at the same time).	77% of the mutual funds were "momentum investors," buying stocks that were past winners; however, most did not systematically sell past losers. On average, ,funds that invested on momentum realized signi$cantly better performance than other funds. They also find relatively weak evidence that funds tended to buy and sell the same stocks at the same time.
Brunnermeier and Nagel (2004)	Nasdaq Stocks with different P/S ratios/ CRSP Compustat merged database/ CDA Sprectrum database/ HFR	US	1998-2000	The first point they want to establish is whether hedge funds were attacking the bubble in technology stocks—by selling their holdings in this segment, or even by going short—or whether hedge funds were riding the bubble	Documents that hedge funds did not exert a correcting force on stock prices during the technology bubble. Instead, they were heavily invested in technology stocks. This does not seem to be the result of unawareness of the bubble: Hedge funds captured the upturn, but, by reducing their positions in stocks that were about to decline, avoided much of the downturn. Our findings question the efficient markets notion that rational speculators always stabilize prices. They are consistent with models in which rational investors may prefer to ride bubbles because of predictable investor sentiment and limits to arbitrage.

Table A2: Literature Review of explanations for returns continuation					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Xiang et al. (2002)	Non-financial common shares from CRSP, Compustat, First Call Insider Research	US	1985-1996	Investigates the influence and explanatory power of aggregate insiders trading activities on momentum trading strategies	Find that insiders trading activities can predict cross-sectional returns and can strengthen the naive momentum effects. The risk factors such as size and BM cannot explain the strong momentum effects in our refined momentum strategies. Continuous overreaction causes the mediate term momentum effects and over pricing. correction of over pricing causes long-term reversals.
Seyhun (1992)	NYSE, ASE, Nasdaq, CRSP,	US	1975-1989	Empirically examines the effects of increases in the level and enforcement of insider-trading regulations in the 1980s on corporate insiders.	In spite of the increased statutory sanctions of the 1980s, corporate insiders earned an average of about 5.1 percent (on a dollar-weighted basis) abnormal profits over a one-year holding period between 1980 and 1984, increasing further to 7.0 percent after 1984, compared with 3.5 percent before 1980.
Lakonishok and Lee (2001)	WSJ, Baron's report/ NYSE, AMEX, Nasdaq	US	1975 - 1995	Examine the magnitude of insider trading activity and how this activity has changed over time. Examine how market reacts around insider trading and reporting dates.	Insiders are contrarians but seem to predict market better. Seem to predict cross-sectional stock returns. Result is driven by insider's ability to predict returns in smaller firms. Informativeness of insiders; activities is coming from purchases while insider selling appears to have no predictive ability.
Momentum Profits and Disposition Effect					
Grinblatt and Han (2001)	MiniCRSP/ NYSE,AMEX	US	1962-1996	Investigate the temporal pattern of stock prices in an equilibrium that aggregates the demand functions of both rational and disposition investors.	Cross-sectional empirical tests of the model find that stocks with large aggregate unrealized capital gains tend to have higher expected returns than stocks with large aggregate unrealized capital losses and that this capital gains \overhang" appears to be the key variable that generates the probability of a momentum strategy. When this capital gains variable is used as a regressor along with past returns and volume to predict future returns, the momentum effect disappears.
Oehler et al. (2003)	Graduate students of the University of Hagen and Bamberg University			Experiments were designed to test whether individual-level disposition effects attenuate or survive in a dynamic market setting. They analyze a series of 36 stock markets with 490 subjects.	The majority of investors demonstrate a strong preference for realizing winners (paper gains) rather than losers (paper losses). Disposition effect is greatly reduced only within high-pressure mechanisms like a dealer market (DM) when the last price (LP) is assumed as a reference point.
Frazzini (2006)	CRSP/Compustat, TAQ, IBES/ CDA/ Spectrum Mutual Funds	US	1980-2002	Tests whether the "disposition effect," induces "underreaction" to news, leading to return predictability. use data on mutual fund holdings to construct a new measure of reference purchasing prices for individual stocks.	show that post-announcement price drift is most severe whenever capital gains and the news event have the same sign. The magnitude of the drift depends on the capital gains (losses) experienced by the stock holders on the event date. An event-driven strategy based on this effect yields monthly alphas of over 200 basis points.

Table A2: Literature Review of explanations for returns continuation					
Author(s)	**Data Set**	**Countries**	**Time Period**	**Methodological Choices**	**Key Results**
Momentum Profits and Positive-Feedback Trading					
Nofsinger and Sias (1999)	CRSP, NYSE/ Security Owners' Stock Guides (S&P)	US	1977-1996	Investigate the cross-sectional relation between changes in institutional ownership and stock returns to assess the comparative importance of herding by institutional and individual investors.	Document strong positive correlation between changes in institutional ownership and returns measured over the same period. The result suggests that either institutional investors positive-feedback trade more than individual investors or institutional herding impacts prices more than herding by individual investors. They find evidence that both factors play a role in explaining the relation.
Shu (2007)	Expected Default Frequency (EDF) of Moody's KMV, CRSP/Compustat,	US	1969-2003	Examines the relationship between default probability and stock returns.	Document that higher default probabilities are not associated with higher expected stock returns. Within a model of bargaining between equity-holders and debt-holders in default, he shows that the relationship between default probability and equity return is (i) upward sloping for firms where shareholders can extract little benefit from renegotiation (low \shareholder advantage") and (ii) humped and downward sloping for firms with high shareholder advantage. This dichotomy implies that distressed firms with stronger shareholder advantage should exhibit lower expected returns in the cross-section. Our empirical evidence, based on several proxies for shareholder advantage, is consistent with the model's predictions.
Long-Term Momentum Hypothesis					
Kim (2002)	NYSE/AMEX/ Nasdaq	US	1931-1998	Suggests a new model that attempts to explain long-term reversal and short-term momentum in stock prices by the interaction of momentum traders and passive rational investors	The simulation results for the model confirm long-term reversal and short-term momentum and propose three new predictions that distinguish the model from other hypotheses. These predictions are synthetically described as the long-term momentum hypothesis. The primary empirical results provided by this study are consistent with the long-term momentum hypothesis.
Lesmond et al. (2004)	CRSP/ NYSE,AMEX	US	1980-1998	Re-examines the profitability of relative strength or momentum trading strategies (buying past strong performers and selling past weak performers)	They find that standard relative strength strategies require frequent trading in disproportionately high cost securities such that trading costs prevent profitable strategy execution. In the cross-section, they find that those stocks that generate large momentum returns are precisely those stocks with high trading costs. The magnitude of the abnormal returns associated with these trading strategies creates an illusion of profit opportunity when, in fact, none exists.
Berkowitz et al. (1988)	NYSE/ Data for computing volume-weighted price come from Francis Emory Fitch Co.	US	9/1/1985-29/3/1985	Develops a measure of execution costs (market impact) of transactions on the NYSE. The measure is the volume-weighted average price over the trading day. Applies this measure to a data set containing more than 14,000 actual trades.	Show that total transaction costs, commission plus market impact costs, average twenty-three basis points of principal value for our sample. Commission costs, averaging eighteen basis points, are considerably higher than execution costs, which average five basis points. They vary slightly across brokers and significantly across money managers. Though brokers do not incur consistently high or low transaction costs, money managers experience persistently high or lost costs.

APPENDIX III

In order to test for AutoRegressive Conditional Heteroscedasticity (ARCH) effect in the data we consider the following AutoRegressive Model (AR(1)) for Abnormal returns:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + u_t$$

Then we test for ARCH effects in the conditional variance of u_t ($h_t^2 = Var(u_t \mid \Omega_{t-1})$). The ARCH specification for h_t^2 is given by:

$$h_t^2 = \rho_0 + \rho_1 u_{t-1}^2 + \rho_2 u_{t-2}^2 + ... + \rho_q u_{t-q}^2$$

The null hypothesis of "NO ARCH EFFECTS" is:

$$H_0 : \rho_1 = \rho_2 = ... = \rho_q = 0$$

Against the alternative hypothesis that:

$$H_1 : \rho_1 \neq 0, \rho_2 \neq 0, ... \rho_q \neq 0$$

For illustrative purposes, in the following Table, we present results for three strategies (2x2, 3x3, 4x4) and for two lags (q=1,2). The results for other specifications are similar. As can be seen from the Table in nearly all cases the null hypothesis of "NO ARCH EFFECTS" is accepted.

TABLE

Autoregressive Conditional Heteroscedasticity Test of Residuals (OLS Case)

Panel A: LAG =1		
	Strategy 2x2	
	Lagrange Multiplier Statistic	F- Statistic
Losers	0.0055744 [0.940]	0.0048485 [0.945]
Winners	1.4309 [0.232]	1.3268 [0.263]
AP	2.1458 [0.143]	2.0579 [0.167]
	Strategy 3x3	
	Lagrange Multiplier Statistic	F- Statistic
Losers	0.081744 [.775]	0.74912 [0.786]
Winners	0.26628 [0.606]	0.24532 [0.624]
AP	0.099168 [0.753]	0.090926 [0.765]
	Strategy 4x4	
	Lagrange Multiplier Statistic	F- Statistic
Losers	1.7591 [0.185]	1.7109 [0.198]
Winners	0.26826 [0.605]	0.25257 [0.618]
AP	1.6362 [0.201]	1.5870 [0.214]
Panel B: LAG =2		
	Strategy 2x2	
	Lagrange Multiplier Statistic	F- Statistic
Losers	0.47015 [0.791]	0.19824 [0.822]
Winners	2.1197 [0.347]	0.96439 [0.399]
AP	1.9832 [0.371]	0.89646 [0.425]
	Strategy 3x3	
	Lagrange Multiplier Statistic	F- Statistic
Losers	0.38572[0.825]	0.17272 [0.842]
Winners	0.71794[0.698]	0.32461 [0.725]
AP	4.4309[.012]	2.7170 [0.134]
	Strategy 4x4	
	Lagrange Multiplier Statistic	F- Statistic
Losers	5.9476 [0.051]	3.1149 [0.055]
Winners	0.26922 [0.874]	0.12386 [0.884]
AP	1.7813 [0.410]	0.84696 [0.436]