ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

ΜΠΣ ΣΤΗ ΧΡΗΜΑΤΟΟΙΚΟΝΟΜΙΚΗ & ΤΡΑΠΕΖΙΚΗ ΔΙΟΙΚΗΤΙΚΗ

Predictable Patterns after large stock price changes

ΝΟΥΛΑ ΓΕΩΡΓΙΑ ΜΧΡΗ 0421

ΑΘΗΝΑ 2006

ΕΠΙΒΛΕΠΩΝ ΚΑΘΗΓΗΤΗΣ	**Ν.ΠΙΤΤΗΣ**
ΕΠΙΤΡΟΠΗ	**Α.ΑΝΤΖΟΥΛΑΤΟΣ** **Χ.ΧΡΙΣΤΟΥ**

CONTENTS

Abstract

Momentum and contrarian trading strategies present challenges to the concept of efficient market theory. This paper investigates the profitability short-term trading strategies in Athens exchange stocks..

Using a sample from ASE for the period of January 2000 to January 2005, we find statistically significant abnormal profit of momentum strategy for the daily-horizon. This paper has tested the profitability of momentum trading strategies in the Greek stock market. It did so by examining profits generated portfolios formed on a daily basis, based on historical returns. Returns from daily adjusted winner portfolios are positive ,significant and systematically above the market return. There is strong evidence of momentum effect over the "spot horizon". Loser portfolios become "more losers" but the downward trend is subsidized during the last year of our observation period for both winners and losers portolios.. The preliminary result in this paper suggests further examination to investigate whether it's feasible to implement a daily strategy after accounting for transaction costs and whether the results are related to factors such as crosssectional dispersion of returns, volume (liquidity), book to market ratio, and behavioural characteristics of assets previously known to be related to price continuation and reversals. This analysis is compulsory before we suggest inefficiencies in the Greek market.

Introduction

Fama (1970) specifies that an efficient market is one in which prices reflect all available information. Predictability of security returns, with use of their past history has been a main issue in empirical finance literature. This is due to the fact that if returns of securities prove to be, by any means, predictable, it would suggest market inefficiency.
Trading strategies that apparently "beat the market" date back to the inception of trading in financial assets. A number of practitioners and academics in the pre-market efficiency era believed that predictable patterns in stock returns could lead to abnormal profits to trading strategies. In fact Keynes succinctly summarized the views of many stating that most investor's decisions can be taken only as a result of animal spirits…..
The study of the predictability of stock returns has attracted a lot of attention from researchers even before the birth of financial theory (e.g. Cowles (1933)) and the development of the efficient market hypothesis by Fama (1970). Until the beginning of the eighties, academics were quite confident that it was impossible to predict the future fluctuation of stock prices and as a consequence consruct any profitable trading rule from the study of past prices. The outcome of different strategies (based in the past) used were compatible: these portfolio rules were evidently unprofitable. Nevertheless, things have changed since that time with view to the fact that researchers have discovered a number of ways to predict future stock returns . An impressive body of empirical evidence concerning market anomalies, phenomena inconsistent with the EMH, has been widely documented in recent financial economic research. Among the most pronounced market anomalies are contrarian and momentum effects, because they demonstrate that even the weak form efficiency does not hold which means that past stock price returns can be informative of future stock return patterns. Many studies investigate profitability of return-based trading strategies, either momentum or contrarian , in international equity markets and demonstrate how these strategies could lead to abnormal returns.

The contrarian effects state that over a long time horizon stock market prices exhibit a reversal property, while momentum strategy is based in price continuations. A contrarian stock selection strategy consists of buying stocks that have been losers and selling short stocks that have been winners. A momentum investor focuses on stocks that are rising in value on increasing daily volume, and avoids stocks that are falling in price or that are perceived to be undervalued. The reasoning behind this strategy is that when a pattern of growth has been identified, it will continue to gain momentum meaning that the growth will continue.

Contrarian and momentum strategies are trading rules aiming to take advantage of the reversal and momentum profits. Clearly momentum investing is basically the opposite of contrarian investing. One of the most confusing aspects of the literature is that these two diametrically opposed strategies seem to work concurrently, although for different time horizons.

Evidence of profitability using these trading strategies (momentum and contrarian) challenges the concept of market efficiency. If they can exploit information in past prices in order to produce profits, market inefficiency would be implied. Consequently, the evidence of profitability of momentum and contrarian trading strategies presents challenges to the concepts of efficient market theory.

Different studies have tried to reconcile the concepts of market efficiency and the evidence of predictable patterns in stock trading. Researchers have attempted to identify factors such as cross sectional dispersion of returns, size, volume (liquidity), book to market ratio, and behavioural characteristics of assets to explain the profitability of momentum and contrarian strategies.

The results of these studies, however, have been inconclusive and contradictory. DeBondt and Thaler (1987) provide evidence that performance reversal of winners and losers cannot be explained by differential risk. Zarowin (1990) argues that there is still significant difference in the performance of winners and losers when size is controlled. Conrad and Kaul (1998) find that momentum and contrarian strategies have an equal chance of being successful. They also find that momentum strategy is profitable in a medium (3-12- month) horizon, while contrarian strategy is profitable in a long horizon. The lack of definitive evidence regarding trading strategies and the contradictory findings is also evident in the

Australian equity market. Brailsford (1992), using the methodology of DeBondt and Thaler (1985), found insignificant evidence of price reversal in previous winner and loser stocks.. Demir, Muthuswamy and Walter (2002) found evidence of profitability of momentum strategy that cannot be explained by size, or liquidity factors. Hurn and Pavlov (2003) also found a strong medium-term momentum effect, which cannot be completely accounted for by cross sectional dispersion of unconditional mean returns, risk adjustment and industry factors.

Efficient Market Hypothesis (EMH).

The Efficient Market Hypothesis (EMH) has been the subject of intense dispute among academics. The Efficient Market Hypothesis states that at any given time, security prices fully reflect all available information. The implications of EMH are rather profound. Most individuals that buy and sell securities, do so under the assumption that the securities they are buying are worth more than the price that they are paying, while securities that they are selling are worth less than the selling price. But if markets are efficient and current prices fully reflect all information, then buying and selling securities in an attempt to outperform the market will effectively be a game of chance rather than skill.

The Efficient Market Hypothesis evolved in the 1960s . Fama argued that in an market that includes many well-informed and active investors, securities will be appropriately priced so as to reflect all available information. Thus no information or analysis should be expected to result in strategies that could systematically outperform the market.

In an efficient market there are many rational investors who seek to maximize their profit competing actively and trying to predict future market values of individual securities. In an efficient market important current information is almost freely available to all participants and competition among the many sharp thinking participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which the market expects to happen in the future. Thus, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value.

The **random walk theory asserts** that price movements will not follow any patterns or trends and that past price movements cannot be used to predict future price movements.There are three forms of the efficient market hypothesis

1. The **"Weak" form** asserts that all past market prices and data are fully reflected in securities prices. In other words, technical analysis is of no use.
2. The **"Semistrong" form** asserts that all publicly available information is fully reflected in securities prices. In other words, fundamental analysis is of no use.
3. The **"Strong" form** asserts that all information is fully reflected in securities prices. In other words, even insider information is of no use.

Securities markets are flooded with thousands of intelligent, well-paid, and well-educated investors seeking under and over-valued securities to buy and sell. The more participants and the faster the dissemination of information, the more efficient a market should be.

The debate about efficient markets has resulted in hundreds and thousands of empirical studies attempting to determine whether specific markets are in fact "efficient" and if so to what degree. Many novice investors are surprised to learn that a tremendous amount of evidence supports the efficient market hypothesis. Early tests of the EMH focused on technical analysis and it is chartists whose very existence seems most challenged by the EMH. And in fact, the vast majority of studies of technical theories have found the strategies to be completely useless in predicting securities prices. However, researchers have documented some technical anomalies that may offer some hope for technicians, although transactions costs may reduce or eliminate any advantage.
Researchers have also uncovered numerous other stock market anomalies that seem to contradict the efficient market hypothesis. The search for anomalies is effectively the search for systems or patterns that can be used to outperform passive and/or buy-and-hold strategies. Theoretically though, once an anomaly is discovered, investors attempting to profit by exploiting the inefficiency should result its disappearance. In fact, numerous anomalies that have been documented via back-testing have subsequently disappeared or proven to be impossible to exploit because of transactions costs. Researchers that discover anomalies or styles that produce superior returns have

two choices: (1) go public and seek recognition for discovering the technique; or (2) use the technique to earn excess returns. It's common for money to flow into strategies that attempt to exploit anomalies and this in turn causes the anomaly to disappear. Further, even anomalies that do persist may take decades to pay off. Investors evaluating historical data should also consider the potential pitfalls of data mining. When searching large amounts of data, correlations between variables may occur randomly and therefore may have no predictive value. Anomalies that have existed over the longest time frames and have been confirmed to exist in international markets and out of sample periods are particularly persuasive.

The paradox of efficient markets is that if every investor believed a market was efficient, then the market would not be efficient because no one would analyze securities. In effect, efficient markets depend on market participants who believe the market is inefficient and trade securities in an attempt to outperform the market.

In reality, markets are neither perfectly efficient nor completely inefficient. All markets are efficient to a certain extent, some more so than others. In markets with substantial impairments of efficiency, more knowledgeable investors can strive to outperform less knowledgeable ones. Government bond markets for instance, are considered to be extremely efficient. Most researchers consider large capitalization stocks to also be very efficient, while small capitalization stocks and international stocks are considered by some to be less efficient. Real estate and venture capital, which don't have fluid and continuous markets, are considered to be less efficient because different participants may have varying amounts and quality of information.

The efficient market debate plays an important role in the decision between active and passive investing Active managers argue that less efficient markets provide the opportunity for outperformance by skillful managers. However, its important to realize that a majority of active managers in a given market will underperform the appropriate benchmark in the long run whether markets are or are not efficient. This is because active management is a zero-sum game in which the only way a participant can profit is for another less fortunate active participant to lose. However, when costs are added, even marginally successful active managers may underperform. If markets are efficient, the serious question for investment professionals is what role can they play (and be compensated for). Those that accept the EMH generally reason that the primary role of a portfolio manager consists of analyzing and investing appropriately based on an investor's tax considerations and risk profile. Optimal portfolios will vary according to factors such as age, tax bracket, risk aversion, and employment. The role of the portfolio manager in an efficient market is to tailor a portfolio to those needs, rather than to beat the market.

While proponents of the EMH don't believe its possible to beat the market, some believe that stocks can be divided into categories based on risk factors (and corresponding higher or lower expected returns). Faced with the inference that they cannot add value, many active managers argue that the markets are not efficient (otherwise their jobs can be viewed as nothing more than speculation). Similarly, the investment media is generally considered to be ambivalent toward the efficient market hypothesis because they make money supplying information to investors who believe that the information has value (beyond the time when it initially becomes public). If the information is rapidly reflected in prices, there is no reason for investors to seek (or purchase) information about securities and markets.

While many argue that outperformance by one or more participants in a market signifies an inefficient market, it's important to recognize that successful active managers should be evaluated in the context of all participants. Its difficult in many cases to determine whether outperformance can be attributed to skill as opposed to luck. For instance, with hundreds or even thousands of active managers, its common and in fact expected (based on probability) that one or more will experience sustained and significant outperformance. However, the challenge is to identify an outperformer before the fact, rather than in hindsight . Additionally, in many cases, strong performers in one period frequently turn around and underperform in subsequent periods. A substantial number of studies have found little or no correlation between strong performers from one period to the next. The lack of consistent performance persistence among active managers is further evidence in support of the EMH.

Return Predictability and Trading Strategies

Contrarian investing

A number of researchers interprets return predictability as the consistent overreaction of the stock market to new information. Overreaction hypothesis dictates that stock prices take temporary swings away from their fundamental values due to excess optimism and pessimism. A contrarian stock selection strategy consists of buying stocks that have been losers and selling short stocks that have been winners. The use of contrarian strategies is also known as the ‘winner-loser’ effect. The strategy is formulated on the basis that the stock market overreacts to news. Thus winners tend to be overvalued and losers undervalued. A contrarian investor who exploits this inefficiency gains when stock prices return to their fundamental values.

One of the most influential and controversial articles published on the topic, that of De Bondt and Thaler (1985), demonstrates significant changes in direction of the returns, over long periods of time. Specifically, the stocks that have hown the lowest returns(the losers) during the previous 3 or 5 years , do better during the following 3 or 5 years than those that had previously had the highest positive returns. If their results are true, the result of a zero-ivestment portfolio wit a long position on losers and shot one on winners should yield significant positive returns over a given test period. De Bondt and Thaler analyze their evidence as the result of the irrational behavior of the investors. Their theories are based on the findings of Kahneman and Tvesky (1982) in the field of cognitive psychology. According to their study people tend to overreact to unexpected and dramatic events, thus, to over-weight recent information and under-weight past information. This leads to excessive optimism about good news and extreme pessimism over bad news. Merton (1985) considers the work of De Bondt and Thaler to be particurarly noteworthy because “it represents a first attempt at a formal test of cognitive misperceptions theories as applied to the general stock market".

Chan (1988) suggests that the estimation of the abnormal turn to the contrarian investment strategy is sensitive to the model and estimation methods. Using the CAPM (a method free of problems caused by risk changes) e finds that the contrarian strategy earns a very small abnormal return which is probably economically insignificant. According to his study losers are safer at the beginning of the formation period than at the end of it and the opposite is true for the winners. A contrarian investor realizes, on average, above-market returns, but that excess return is likely to be a normal compensation for the risk in the investment strategy.

Brown Harlow and Tinic (1988) propose that rationality does not require instantaneous assimilation to new information and that in the presence of uncertainty and imperfect information risk- averse investors will initially set prices that appear to be overreactions to bad news and underreactions to good news.

Lehmann (1990) and Lo and MacKinlay (1990) were the first to find that following a selffinancing investment strategy that recommends being long in recent losers and short in recent winners yields some profitable results on the short run (from one week to one month). Lo andMacKinlay (1990) based their decomposition on the random walk hypothesis (i.e. the time series of stock returns is described with a random walk with drift under the null hypothesis)

Atkins and Dyl(1990) find results consistent with the explanation offered by De Bondt and Thaler. However, they suggest that perhaps no psychological theorizing is required to explain prices that are merely bouncing around within the bid-ask spread.

Zarowin (1990) suggests that the tendency of losers to out-perform the winners is due to the fact that losers are generally stocks from smaller companies than those of the winners. When the analysis is concentrated in companies with the same relative size the discrepancies almost disappear. The over-reaction phenomenon is in fact subsumed by the size and the January effect.

Chopra, Lakonishok and Ritter (1992) attributed long-term return reversals to investor overreaction after DeBondt and Thaler (1985) provided evidence in favour of long-term overreaction. Jegadeesh (1990) and Lehman (1990) provide evidence of short-term return reversals at shorter horizons such as monthly and weekly intervals. Profitability

of short-term contrarian strategies may also present short-term price pressure or a lack of liquidity in the market rather than overreaction.
According to Cox and Peterson(1994) short term reversals are attributed to the bid-ask bounce as well as to the degree of market liquidity. Their evidence are inconsistent with the overreaction hypothesis.

Jegadeesh and Titman(1995) provide evidence on the relationship between short-term return reversals and bid-ask spread that supports this interpretation. Lo and MacKinlay (1990) argue that a large part of the abnormal return documented by Jegadeesh and Titman is attributable to a delayed stock price reaction to common factor rather than to overreaction. The predictability of short-horizon stock returns by Mase (2000) for the UK market between January 1988 and October 1997 is shown by the subsequent return reversal of the previous period's extreme winners and losers, thus supporting the winner-loser effect. It was also found that the larger stock returns exhibit at least as much predictability as the smaller stock returns. Bowman and Iverson (1998) show evidence of short-run overreaction in the New Zealand stock market. Baytas and Chakici (1999), who based their study on seven industrialized countries, have found that returns to long-term contrarian strategies are significant except in the US market. Moreover, they have shown that returns to arbitrage portfolios based on price are higher than those based on size, and generally outperform the winner-loser arbitrage portfolios. Ahmad and Hussain (2001) investigate long run market overreaction and seasonality for stocks in the Kuala Lumpur Stock Exchange during the period 1986-1996. Stocks that exhibited extreme returns relative to the market experienced a reversal of fortune in the following 3 years.

Foort Hamelink focuses his research on stocks listed on the French stock exchange. In his paper examines the intra-day behavior of asset prices shortly before and after large price changes. Evidence is found that prices do overreact and that a correction takes place after large price movements, especially those to the downside. The correction does not take place immediately after the large price change. Prior to this, some very significant and sometimes economically important patterns can be observed. When the bid-ask spread is taken into account he still finds some ex-post profitable trading strategies that are too small in magnitude to suggest market inefficiency.

Antoniou, Galariotis and Spyrou paper investigates the existence of contrarian profits and the sources of these profits, for the Athens Stock Exchange (ASE). The empirical analysis decomposes contrarian profits to sources due to common factor reaction, overreaction to firm specific information, and profits not related to the previous two terms, as suggested by Jegadesh and Titman (1995). Furthermore, the paper examines (i) size-sorted subsamples that are rebalanced annually, and (ii) whether the results are due to the well known January seasonal. The findings suggest that, when January returns are excluded, contrarian profits in the ASE are due more to firm specific overreaction than reaction to a common factor. This implies that the delayed reaction phenomenon in the ASE is restricted to January. This result is reinforced when we allow for time variations in factor sensitivities.

Momentum investing

Until recently there has been relatively more emphasis on contrarian strategies , but there is growing evidence that price continuations result in consistent abnormal profits to momentum strategies .

Cambell (2004) defines momentum to be the inclination of stock prices to keep on moving in the same direction for several months after an initial shock. Momentum gives rise to positive autocorrelation of certain holding-period returns. Price momentum occurs when the initial shock is a change in the price itself.

Levy (1967) claims that a trading rule that buys stocks with current prices that are substancially higher than their average prices over the past 27 weeks realizes significant abnormal returns. Jensen and Bennington (1970) point out that Levy had come up with this rule after examining 68 different rules in his dissertation and because of this express scepticism about his conclusions. They analyze the profitability of his rule over a long time period outside Levy's original sample period. They find that in their sample period this trading rule does not outperform a buy and hold strategy and hence attribute the results to a selection bias. Price momentum occurs when when the initial shock is a change in the price itself. Price momentum was found in aggregate US stock prices in the late 1980's (Lo and MacKinlay 1988, Conrad and Kaul 1988 and Poterba and Summers 1988), in individual US stock prices in the early 1990's (Jegadeesh and Titman 1993) and in the international markets later in the 1990's (Rouwenhorst 1998,1999). A number of practitioners use relative strength trading rules as one of their stock selection criteria. For example a majority of the mutual funds examined by Grinblatt and Titman(1989, 1991) show a tendency to buy stocks that have increased in price over the previous quarter. Moreover Grinblatt, Titman and Wermers (1995) and Chan, Jegadeesh and Wermers (2000) find that mutual funds tend to buy past winners. Also , Womack(1996) reports that analysts generally recommend high momentum stocks more favourably than low momentum stocks.

Jegadeesh and Titman (1993) show that stocks that perform the best (worst) over a three to 12 month period tend to continue to perform well (poorly) over the subsequent three to 12 months. Their trading strategies realize significant abnormal returns over the 1965 to 1989 period. The strategy they examine in most detail , which selects stocks based on their past 6-month returns and holds them for 6 months , realizes a compounded excess return of 12,01% per year on average. However part of the abnormal returns generated in the first year after the portfolio formation dissipates in the following two years. Additional evidence indicates that the profitability of the relative strength strategies is not due to their systematic risk and cannot be attributed to lead-lag effects that result from delayed stock price reactions to common factors. However the evidence is consistent with delayed price reactions to firm-specific information. The best performers appear to be more risky than the worst performers. Therefore, standard risk adjustments tend to increase rather than decrease the return spread between past winners and past losers. The returns of a zero cost portfolio that consists of a long position in past winners and a short position in past losers makes money in every five year period since 1940. Fama and French(1996) show that long term reversals can be consistent with a multifactor model of returns , but their model fails to explain medium-term performance continuation. Despite the popularity of momentum strategies in the investment community and its visibility in the academic community there is no evidence of the effect disappearing.

According to ***K.Greet Rouwenhorst*** (1998) in his review of international momentum strategies international equity markets exhibit medium-term return continuation. Between 1980 and 1995 an internationally diversified portfolio of past medium-term winners outperforms a portfolio of medium-terms losers after correcting for risk by more than 1 percent per month. Return continuation is present in all twelve sample countries and lasts on average for about one year. The strength strategies that are suggested load negatively on conventional risk factors such as size and the market. The payoffs are therefore inconsistent with the joint hypotheses of market efficiency and commonly used asset pricing models. The European evidence in his research is remarkably similar (to findings for the United States by Jegadeesh and Titman (1993) and makes it unlikely that the U.S. experience was simply due to chance. Only the t-statistics are slightly larger for the European sample. For example , the six month/six month (choise and holding period) strategy with European stocks earns 1,16% (t-statistic= 4,02) compared with that of 0,95% (t-statistic=3,07) for the US market. Returns on European momentum portfolios are significantly correlated with relative strength strategies in the US.

Jegadeesh and Titman (2001) show that momentum strategies were profitable in the nineties as well, a period subsequent to the sample period of their previous study suggesting that the original results were not a product of data snooping bias. Using data over 1990-1998 sample period find that the strategies continue to be profitable and that past winners outperform past losers by about the same magnitude as in the earlier period. This is noteworthy given that other well known anomalies such as the small firm effect documented by Banz (1981) and the superior performance of value stocks relative to growth stocks are not observed after the sample periods examined in the original studies.

Conrad, Cooper and Hameed (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. More specifically, the profits are due to the low profits to selling losers in up markets. Moskowitz (1998) documented conflicting results; he found momentum strategies to work best in recessions and when the market is doing poorly. 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 as dated by the National Bureau of Economic Research..

Recently, Moskowitz and Grinblatt (1999) showed that momentum profits are tightly linked to industries. More specifically, momentum profits in individual stocks disappear when controlled for industries. This result is challenged by Grundy and Martin (2001) who claim that it is not the case. They found momentum strategies based on stock-specific returns to be more profitable than those based on total returns. 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.

Momentum strategies implemented on samples consisting of stocks from a number of less developed stock markets also exhibit momentum according Rouwenhorst (1999) and Chui, Titman and Wei(2000) although the momentum strategies within individual countries in their sample are often not profitable. Chui, Titman and Wei (2000) document that with the notable exceptions of Japan and Korea, momentum profits also prevail in eight Asian markets. The momentum effect is relatively stronger for firms with smaller market capitalization, which is similar to the previous finding in the US market

In addition a paper by Chan , Hameed and Tong (2000) provide evidence that international stock market indexes exhibit momentum. Clearly and Inglis (1998) show evidence that using momentum strategies could have generated abnormal profits for Canadian stocks, but this profitability represents appropriate compensation for risk and risk premiums that vary through time. They also find that the strategy may not be exploitable by average retail investors facing higher transaction costs.

Brailsford (1992) examines contrarian strategies in Australian equities for 1958 to 1987 and finds that previous winners and losers both have significantly negative returns. Returns in regard to the contrarian strategy, however, are statistically insignificant. A study by Allen and Prince (1995) for 1974 to 1991 also finds insignificant returns on contrarian strategy. Although there is a small price reversal for the winners' portfolio, and it is significant, the losers' portfolio continues to show a loss, but this loss is statistically insignificant. They find no clear evidence of the overreaction effect in the Australian stock market, unless compensation is made for changing risk premiums through time. On the other hand, a study by Gaunt (2000) for the period 1974 to 1997 finds evidence that supports price reversal in contrarian strategy by employing portfolio rebalancing. Gaunt (2000) also notes that price reversal disappeared when he used a "buy and hold" strategy. Hurn and Pavlov (2003) investigate the performance of momentum investment strategies using the top 200 of Australian stocks by market capitalization. They find the presence of a strong medium-term momentum effect, which cannot be completely accounted for by any of cross sectional dispersion of unconditional mean returns, risk adjustment and industry factors. Unlike previous US studies however there does not appear to be any abnormal profitability in following a contrarian investment strategy at least over the investment horizons they consider.

Mandalis and S.Spirou's paper examines the predictability of equity returns for the Athens Stock Exchange (ASE).They use all stocks listed in the ASE for the period 1989-2001 and find statistically significant momentum profits for short-term strategies and statistically and economically significant contrarian profits for mid- to long- term strategies. These profits are not due to changes in systematic risk or bid-ask biases. Furthermore, portfolio returns seem to be sensitive to the length of the formation period employed to construct the portfolio.

Overall

There is no direct contradiction in the profitability of both contrarian and momentum investment strategies since contrarian strategies work for a sorting period ranging from 3 to 5 years prior and a similar 3 to 5 years holding period, while momentum strategies typically work for a sorting period ranging from 1 month (or more commonly 3 months) to 12 months and a similar 1 (or 3) to 12 months holding period.2 The results correlate well with the findings of mean reversion at horizons of around 3 to 5 years and the findings of return continuation for horizons up to 12 months.3 Furthermore the overreaction hypothesis of DeBondt and Thaler (1985, 1987), as formalized by DeLong et al. (1990), and the behavioral theories of Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999) imply the observed pattern of momentum/continuation at short horizons and mean reversion at long horizons.4 Of course, apparent overreaction may also be generated in an efficient market when unanticipated persistent changes in risk or risk premia occur: For instance, when a persistent increase in systematic risk comes about, returns are initially low as prices adjust but subsequently are higher as expected returns have increased due to the increased reward for risk; similarly, if previous return realizations correlate with future risk sensitivities, as suggested by Berk et al. (1999), a price pattern resembling overreaction may result.

Factors Explaining Momentum and Contrarian Profitability

Given the persistence of the momentum and contrarian anomaly, it is important to understand its cause. Many studies have tried to identify factors that may explain the profitability of momentum and contrarian trading strategies. These factors are cross sectional dispersion of returns, behavioural model, book to market ratio, size and volume (liquidity).

1. *Cross Sectional Dispersion of Returns*

Conrad and Kaul (1998) argue that momentum strategies that involve buying winners and selling losers are by construction tilted towards stocks with high unconditional mean returns. According to this view momentum profitability can be explained completely by the cross-sectional dispersion of unconditional mean returns.

Jegadeesh and Titman (2002) empirically examine that momentum profits are attributable to cross-sectional differences in expected returns and find that momentum profits could be explained only little by the cross-sectional differences in expected returns.

2. *Behavioural Model*

Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subhrahmanyam (1998), and Hong and Stein (1999) present behavioural models that are based on the idea that momentum profits arise because of inherent biases in the way investors interpret information. The behavioural models and Conrad and Kaul's arguments make opposing predictions about the returns of past winners and losers over the period following the initial holding period. The behavioural models imply that abnormal returns in the holding period arise because of a delayed overreaction to information that pushes the prices of winners (losers) above (below) their fundamental values. These models predict that when the stock prices of winners and losers revert to their fundamental values in the subsequent period, the returns of losers should exceed the return of winners. Daniel and Titman (1999) also suggest that behavioural bias affects investment decisions, because investors are likely to be overconfident. On the contrary, Conrad and Kaul (1998) suggest that the higher returns of winners in the holding period represent their expected rates of return and thus predict that the return of the momentum portfolio will be positive, on average, in any post-ranking period. Jegadeesh and Titman (2001) evaluate various explanations for the profitability of momentum strategies documented in their study in 1993. Their evidence indicates that momentum profits have continued in the 1990s and the original results were not a product of data snooping bias. They provide support for the behavioural models, but with caution. Also, they find that a momentum portfolio yields significant positive returns in the first twelve months following the formation period. The returns of a momentum portfolio in the 13 to 60 months after the portfolio formation period were negative. They suggest that behavioural models provide a partial explanation for the momentum anomaly. Baberis, Shleifer and Vishny (1998) present a model consisting of a representative investor who believes that earnings tend to move between two different "states" or "regimes" (i.e., earnings either mean-revert or trend); even as earnings follow a random walk in the model. Berk, Green, and Naik (1999) suggest that when firms exploit advantageous investment opportunities, they tend to change their non systematic risks in a predictable manner, which will generate predictable patterns in returns.

3. Book to Market

Book to market value is one factor that can be used as a predictor of returns across securities. Fama and French (1992) show that portfolios of firms with the highest book to market ratio had an average monthly return of 1.65 %, while portfolios of the lowest ratio had an average of only 0.72 % per month.

4. Size

Basu (1977) identified P-E ratios as predictors of subsequent performance. In particular, high P-E firms underperformed and low P-E firms overperformed. Banz (1981) and Reinganum (1981) suggested that this P-E effect was related to a firm's size, that small firms tend to outperform large firms even after an allowance is made for the possibly riskier characteristics of small firms. In addition, the phenomenon of prices tending to fall during the last few days of December and rise in the first few days of January, was also found to be acute for small firms. Zarowin (1990) argues that the performance reversal of loser to winner is not due to overreaction but to the tendency for losers to be smaller-sized firms than winners. There is no significant difference between winners and losers when size is controlled in the test period performance. Chopra, Lakonishok and Ritter (1992) and Albert and Henderson (1995) however, still find an overreaction effect after controlling for size. Fama and French (1992) document significant relations between firm size, book-to-market ratios, and security returns for non-financial firms.

Barber and Lyon (1977) also document that the relation between firm size, book to-market ratios, and security returns is similar for financial and nonfinancial firms.

5. Volume (Liquidity)

Datar, Naik and Radcliffe (1998) show that low (high) volume firms earn higher (lower) future returns. Lee and Swaminathan (2000) examine the relations between momentum, volume, and long horizon returns to test the predictions of behavioural models. They show that past trading volume provides an important link between momentum and value strategies. Lee and Swaminathan show that this volume effect exists in the long term and is most pronounced among the extreme winner and loser portfolios. High (low) volume stocks earn higher (lower) average returns in each of the five years prior to portfolio formation. They show that the improvement gained by conditioning on past volume appears economically significant in price momentum strategies and the timing of price reversals is predictable, based on past trading volume. Chan and Faff (2003) in the Australian context find that turnover is negatively related to stock returns. Their finding is robust to seasonality effects and to potential nonlinearities.

6. In bibliography many more factors appear such as risk adjustment(the time-varying risk exposure to economy-wide factors) the bid-ask bounce the january effect ….

3. The Athens Stock Exchange

During much of the 1980s Greece applied a set of heavy restrictions on capital and foreign exchange markets. This made it very difficult for international investors to access local markets. However, following the adoption of European Community legislation that aimed to deregulate member states' capital markets, a wave of financial market deregulation occurred during the late 1980s and early 1990s. For much of this period, the Greek financial system was still characterised by a strong commercial banking sector that dominated equity markets. As a result, local firms, which were often characterised by family ownership, traditionally turned to banks for capital, despite the fact that an organised equity market, the Athens Stock Exchange, has been functioning for almost 120 years. More recently, this has changed with business increasingly turning to the equity market for capital. The number of listed companies in the ASE more than doubled in the 1990s. Market capitalisation grew from Dr 566 billion in 1987, to Dr 4,094 billion in 1995 and well above Dr 30,000 billion in 1999. Furthermore, the equity market capitalisation as a percentage on nominal GDP grew from 20% in 1995 to above 100% in 1999. The annual value of trade increased from nearly Dr 60 billion in 1987 to Dr 608.7 billion in 1990 and Dr 1,407.3 billion in 1995. During 1999, daily trading volumes of Dr 300-400 billion, nearly one quarter of the annual trading volume of 1995, were not uncommon. Given the growth and changes experienced by the ASE, this is a good test case to analyse the sources of contrarian profits.

Data and Methodology

Daily stock prices from ASE (ATHEX COMPOSITE) covering the period of January 2000 to January 2005 (5 years) were obtained from Datastream. The prices used were adjusted for dividends. The strategies used in this paper involve constructing portfolios in the following manner. At the end of each day (formation period) stocks are ranked n descending order based on their return. Returns are calculated as

$$R_{it} = \ln(\frac{P_t}{P_{t-1}})$$

where R_{it} is the return in day t for company i, P_t is the last traded price in day t, and P_{t-1} is the last traded price in day t-1.

We selected the ten top the five top the ten bottom and the five bottom stock performers for each day, effectively creating four portfolios. The portfolios are constructed as an equally weighted average of the stocks they include .Under the same procedure each portfolio is adjusted daily creating 4 dynamic portfolios. The portfolios with the highest stock returns are the “winner” portfolios (pos10, pos5) and the portfolios with the lowest return (neg10,neg5) are the “losers”.

In section 1 we use descriptive statistics to present special characteristics of the series we’ve created. In addition we use everyday returns on ase as a benchmark (market portfolio). We subtract these returns from the returns of the portfolios we have created in order to locate clearly any excess returns or loses.
In section two we observe the predictability of each series from their recent history(ar(1)) , meaning the movement of the returns in each day using only the return on the previous day.
In the next section we investigate the predictability of ase returns with respect to the portfolios we have created (vector autoregression)

A critical issue is the importance of transactions costs. Undoubtfully trading strategies which demand daily adjustment(all stocks in the portfolio change) can be transaction intensive. Naturally, it is possible to modify the strategy to reduce the frequency of trading. Also, institutional traders can often secure substantial trade discounts relative to individual retail investors. Second, stocks with smaller market capitalisation are more likely to be traded at a wider bid-ask spread compared to firms with larger market capitalisation. Third, it is possible to reduce overall transaction costs substantially with the use of options to achieve the same level of exposure. However, the aim of this paper is not to search for low transaction cost versions of trading strategies but rather, to identify stock price reversals and momentum in the Athens stock market . As such, portfolio profits in this study are made under non-specific transaction cost assumptions.

RESULTS

Section 1.1

Table 1 presents descriptive statistics of all the portfolios we've created through the procedure mentioned earlier and the returns of ase.

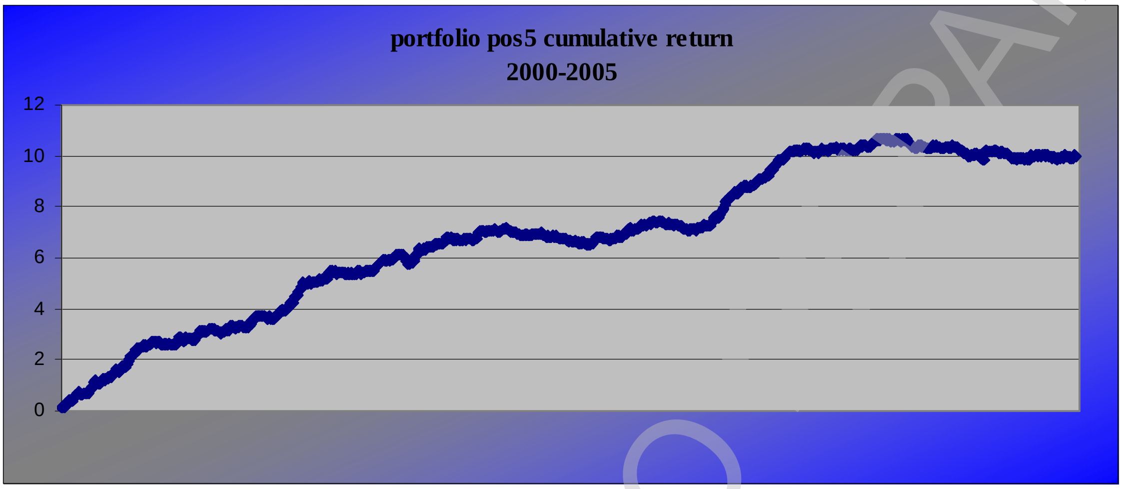
Table 1.

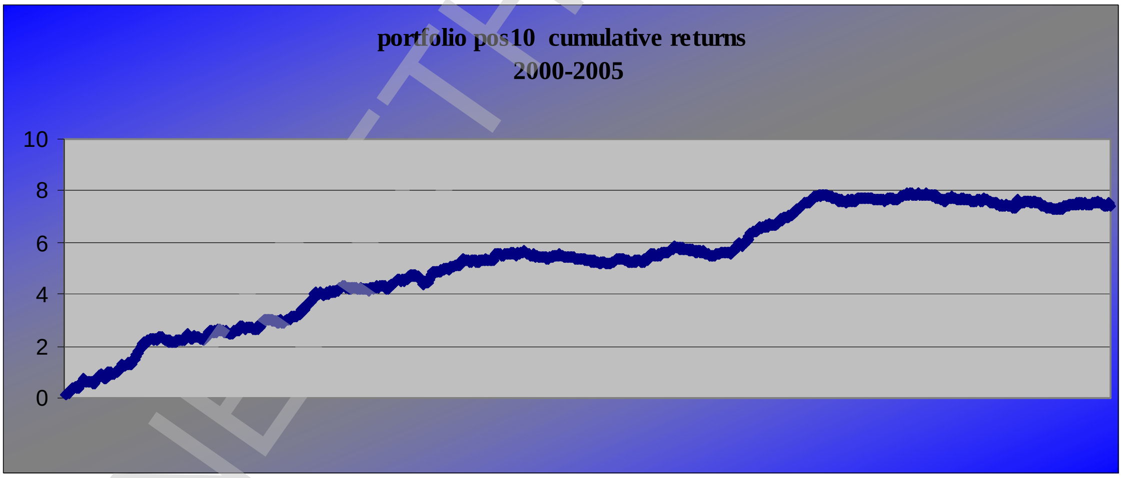
	ASE	NEG10	NEG5	POS10	POS5
Mean	-0.00058	-0.004	-0.00447	0.005957	**0.008012**
Median	-0.00083	-0.00025	-0.00082	0.002323	0.004326
Maximum	0.076202	0.102014	0.137689	0.140921	0.164022
Minimum	-0.09692	-0.14573	-0.19322	-0.12679	-0.12733
Std.Dev	**0.01477**	**0.032284**	**0.039783**	**0.031163**	**0.037736**
Skewness	-0.07131	-0.6117	-0.46632	0.456583	0.40114
Kurtosis	7.631229	4.423799	4.350795	4.367851	3.828373
Jarque-Bera	1115.474	183.0958	139.9991	140.5413	69.09705
Probability	0	0	0	0	0
Sum	-0.72658	-4.98946	-5.57663	7.42801	9.990552
Sum Sq.Dev	0.271817	1.298651	1.972039	1.210062	1.774327
Observations	1247	1247	1247	1247	1247

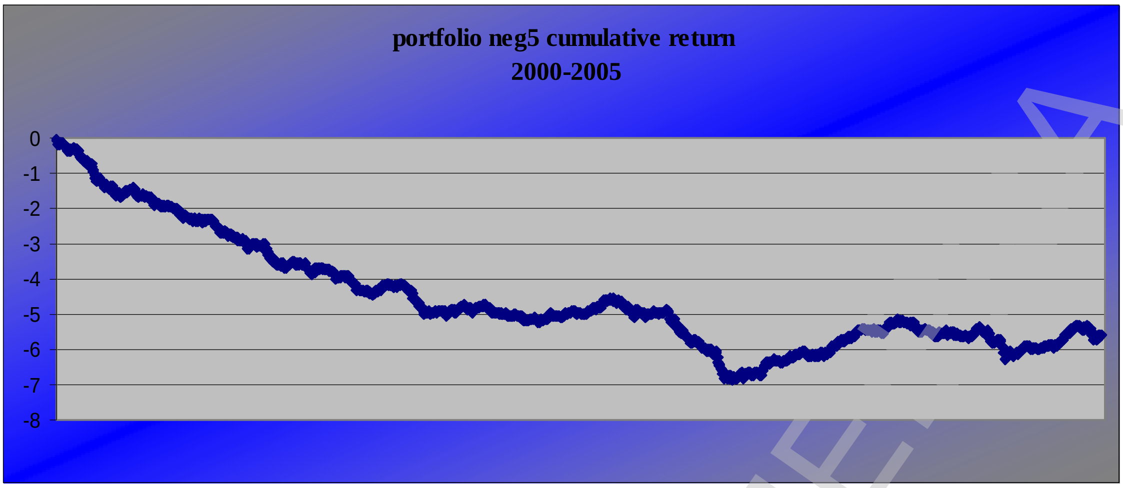
Using descriptive statistics the portfolio with the best mean returns is the pos5. The mean return of this portfolio appears to have a great difference with the market return and a much greater one with the loser portfolios. Neg5 is the portfolio with the greater loses. We observe that as we focus to the top or the bottom of the stocks ranked the winner portfolio is more profitable and the loser portfolio suffers greater loses (this result is obvious by comparing the portfolios pos5 with pos10 and neg5 with neg10). The mean market return is slightly negative but with the lowest standard deviation while the same measure appears rather increased for the portfolios under study.

The cumulative returns appear to be rather impressive but we must once again remind that there is no adjustment for transaction costs

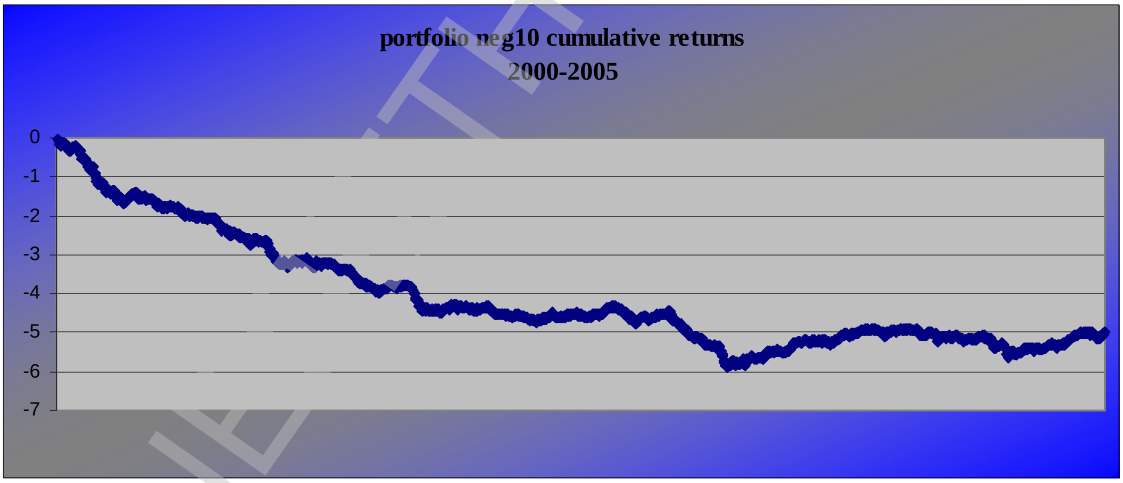
The cumulative results of each strategy are shown in the diagrams



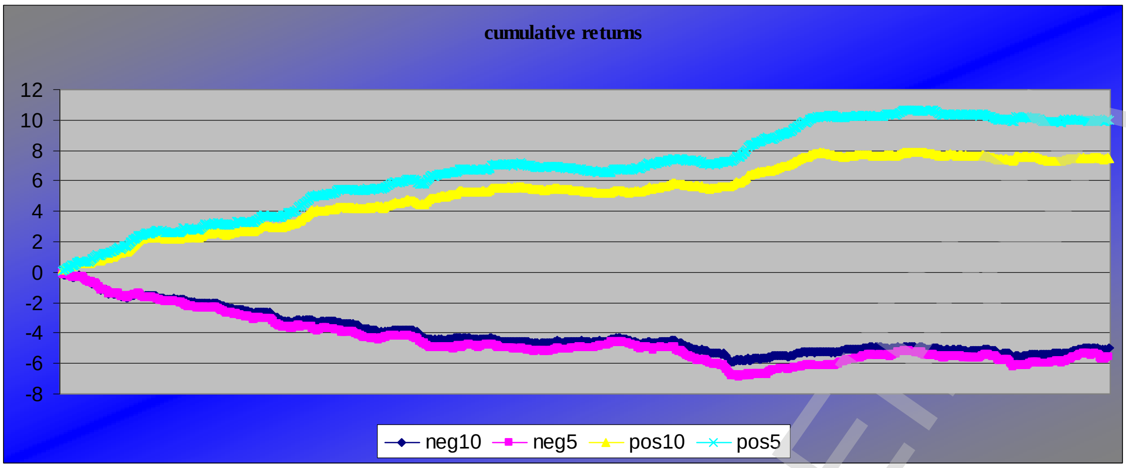




portfolio neg5 cumulative return
2000-2005
0
-1
-2
-3
-4
-5
-6
-7
-8



portfolio neg10 cumulative returns
2000-2005
0
-1
-2
-3
-4
-5
-6
-7



The cumulative return over a five year period of the portfolio we've constructed is equal to 9.990552 (999.06%) while for the pos10 portfolio reaches to 7.42801.

A downturn is observed in 2003 period for all portfolios while the in last year of our sample period returns on all portfolios are rather steady, maybe indicating an downturn of the phenomenon observed. This is subject to further analysis.

Section 1.2.

In the following section we present some descriptive characteristics of series we constructed by subtracting from all the portfolios we've created the market portfolio(ASE). The logic is to see the excess returns by using ase index as a benchmark. We know that riskier investments generally yield higher returns than investments that are free of risk, so that the fact that the results from the previous section have shown that returns on winner portfolios dominate returns on loser portfolios may be because the securities in the winner portfolio are riskier. With the use of Capital Asset Pricing Model (CAPM), we are able to quantify of the trade-off between risk and expected return.

With the market portfolio as exogenous and conditional on the realised return of individual assets, the CAPM model offers a testable prediction of betas. Thus, to investigate whether time varying risk beta risk explains the phenomenon observed, the Ordinary Least Squares (OLS) estimator of the slope coefficient in the market model is used to estimate the respective portfolio betas :

$$R_{it} = a_i + b_{im}R_{mt} + e_{it}$$

where R_{it} is the realised return of portfolio i at day t, R_{mt} is the realised return of the market portfolio at day t and e_{it} is the zero mean disturbance term. We use this regression method to obtain the beta of each of the respective portfolios.

The histogram view used displays the frequency distribution of our series in a histogram. The histogram divides the series range (the distance between the maximum and minimum values) into a number of equal length intervals or bins and displays a count of the number of observations that fall into each bin.

A complement of standard descriptive statistics is displayed along with the histogram. All of the statistics are calculated using observations in the current sample.

Mean is the average value of the series, obtained by adding up the series and dividing by the number of observations.

Median is the middle value (or average of the two middle values) of the series when the values are ordered from the smallest to the largest. The median is a robust measure of the center of the distribution that is less sensitive to outliers than the mean.

Max and **Min** are the maximum and minimum values of the series in the current sample.

Std. Dev. (standard deviation) is a measure of dispersion or spread in the series. The standard deviation is given by:

$$s = \sqrt{\left(\sum_{i=1}^{N} (y_i - \bar{y})^2 / (N-1)\right)}$$

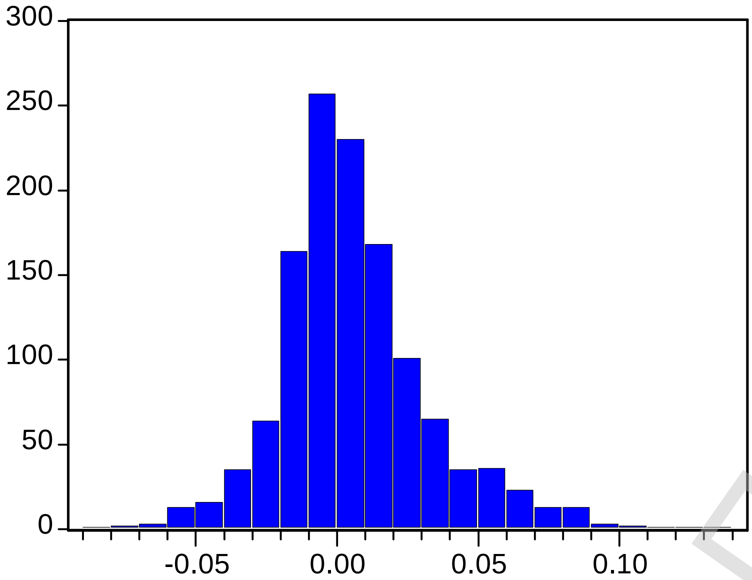
Where N is the number of observations in the current sample and $\bar{y}$ is the mean of the series.

Kurtosis measures the peakedness or flatness of the distribution of the series. Kurtosis is computed as

$$\mathrm{K} = \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \left(\frac{y_i - \bar{y}}{\hat{s}}\right)$$

Where $\hat{s}$ is again based on the biased estimator for the variance. The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

POS10-ASE

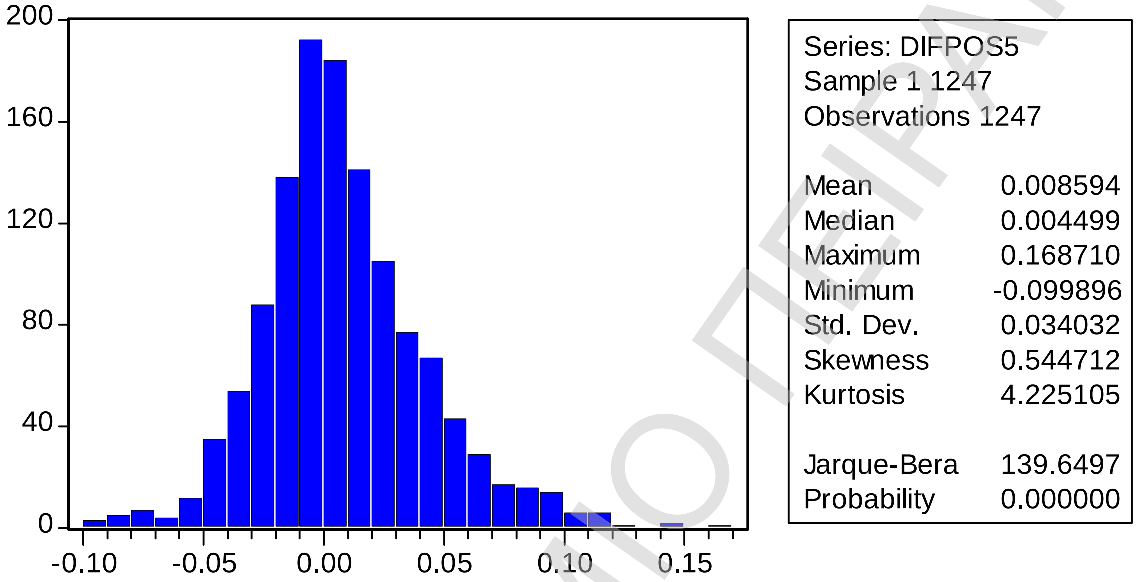


Series: DIFPOS10	
Sample 1 1247	
Observations 1247	
Mean	0.006539
Median	0.002966
Maximum	0.138359
Minimum	-0.084359
Std. Dev.	0.026771
Skewness	0.776795
Kurtosis	4.922353
Jarque-Bera	317.4177
Probability	0.000000

POS10=0.006587855902+**1.083217304***ASE

Dependent Variable: POS10				
Method: Least Squares				
Date: 06/08/06 Time: 18:04				
Sample: 1 1247				
Included observations: 1247				
POS10=C(1)+C(2)*ASE				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.006588	0.000758	8.688709	0.0000
C(2)	1.083217	0.051315	21.10909	0.0000
R-squared	0.263572	Mean dependent var		0.005957
Adjusted R-squared	0.262981	S.D. dependent var		0.031163
S.E. of regression	0.026754	Akaike info criterion		-4.402684
Sum squared resid	0.891123	Schwarz criterion		-4.394459
Log likelihood	2747.074	Durbin-Watson stat		1.563748

POS5-ASE



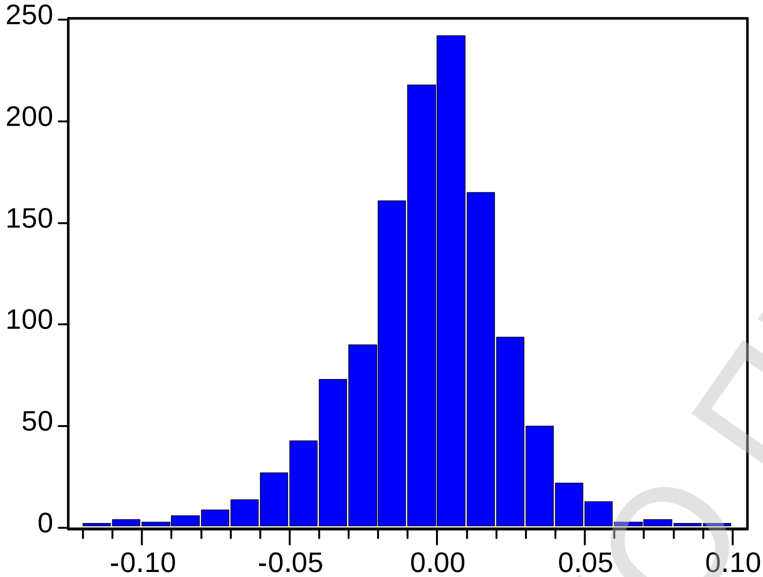
POS5=0.008658001813+**1.109270527***ASE

Dependent Variable: POS5
Method: Least Squares
Date: 06/15/06 Time: 09:30
Sample: 1 1247
Included observations: 1247
POS5=C(1)+C(2)*ASE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.008658	0.000964	8.983329	0.0000
C(2)	1.109271	0.065229	17.00591	0.0000

R-squared	0.188503	Mean dependent var	0.008012
Adjusted R-squared	0.187851	S.D. dependent var	0.037736
S.E. of regression	0.034008	Akaike info criterion	-3.922864
Sum squared resid	1.439861	Schwarz criterion	-3.914639
Log likelihood	2447.906	Durbin-Watson stat	1.629783

NEG10-ASE



Series: DIFNEG10	
Sample 1 1247	
Observations 1247	
Mean	-0.003419
Median	-0.001122
Maximum	0.099491
Minimum	-0.119371
Std. Dev.	0.026796
Skewness	-0.481717
Kurtosis	4.744824
Jarque-Bera	206.4106
Probability	0.000000

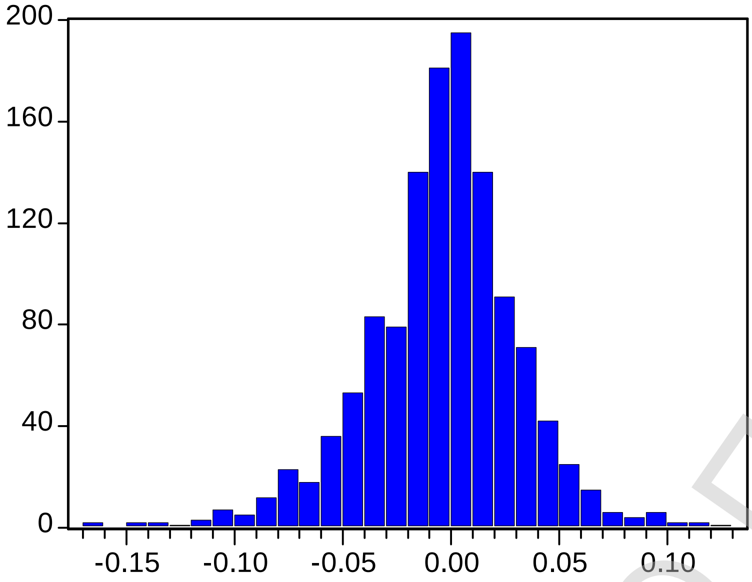
NEG10=-0.003276809668+**1.243189761***ASE

Dependent Variable: NEG10
Method: Least Squares
Date: 06/08/06 Time: 18:15
Sample: 1 1247
Included observations: 1247
NEG10=C(1)+C(2)*ASE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.003277	0.000753	-4.352585	0.0000
C(2)	1.243190	0.050952	24.39924	0.0000

R-squared	0.323488	Mean dependent var	-0.004001
Adjusted R-squared	0.322945	S.D. dependent var	0.032284
S.E. of regression	0.026564	Akaike info criterion	-4.416890
Sum squared resid	0.878553	Schwarz criterion	-4.408665
Log likelihood	2755.931	Durbin-Watson stat	1.836700

NEG5-ASE



Series: DIFNEG5	
Sample 1 1247	
Observations 1247	
Mean	-0.003889
Median	-0.001435
Maximum	0.126916
Minimum	-0.166860
Std. Dev.	0.035394
Skewness	-0.433011
Kurtosis	4.804797
Jarque-Bera	208.2119
Probability	0.000000

NEG5=-0.003740031555+**1.256302048***ASE

Dependent Variable: NEG5
Method: Least Squares
Date: 06/15/06 Time: 09:06
Sample: 1 1247
Included observations: 1247
NEG5=C(1)+C(2)*ASE

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.003740	0.000998	-3.748589	0.0002
C(2)	1.256302	0.067525	18.60499	0.0000

R-squared	0.217545	Mean dependent var	-0.004472
Adjusted R-squared	0.216916	S.D. dependent var	0.039783
S.E. of regression	0.035205	Akaike info criterion	-3.853662
Sum squared resid	1.543032	Schwarz criterion	-3.845437
Log likelihood	2404.758	Durbin-Watson stat	1.872891

There is a tendency for the betas of the loser portfolios to be slightly higher than the betas for the winner portfolios. The winner portfolios systematically report profits above the market. Though the winner portfolios report more profits do not appear to be riskier than the loser ones. The trade off earnings- risk is not observed.

Section 2

A common finding in time series regressions is that the residuals are correlated with their own lagged values. However we study the predictability of each series using their last observed returns. For example if p_t today's return on portfolio pos5 we estimate the following regression $p_t = a + bp_{t-1}$. The results are as follow:

Ase

Dependent Variable: ASE
Method: Least Squares
Date: 06/25/06 Time: 17:43
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000476	0.000414	-1.147999	0.2512
ASE(-1)	0.127730	0.028034	4.556188	0.0000
R-squared	0.016413	Mean dependent var		-0.000550
Adjusted R-squared	0.015623	S.D. dependent var		0.014731
S.E. of regression	0.014616	Akaike info criterion		-5.611801
Sum squared resid	0.265751	Schwarz criterion		-5.603571
Log likelihood	3498.152	F-statistic		20.75885
Durbin-Watson stat	1.981621	Prob(F-statistic)		0.000006

Pos 5

Dependent Variable: POS5
Method: Least Squares
Date: 06/25/06 Time: 17:58
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006312	0.001069	5.903786	0.0000
POS5(-1)	0.210170	0.027716	7.582972	0.0000
R-squared	0.044181	Mean dependent var		0.007994
Adjusted R-squared	0.043413	S.D. dependent var		0.037746
S.E. of regression	0.036918	Akaike info criterion		-3.758643
Sum squared resid	1.695475	Schwarz criterion		-3.750413
Log likelihood	2343.635	F-statistic		57.50147
Durbin-Watson stat	2.015532	Prob(F-statistic)		0.000000

Pos 10

Dependent Variable: POS10
Method: Least Squares
Date: 06/25/06 Time: 17:56
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004577	0.000876	5.225312	0.0000
POS10(-1)	0.222578	0.027619	8.058847	0.0000
R-squared	0.049616	Mean dependent var		0.005910
Adjusted R-squared	0.048852	S.D. dependent var		0.031132
S.E. of regression	0.030362	Akaike info criterion		-4.149653
Sum squared resid	1.146774	Schwarz criterion		-4.141423
Log likelihood	2587.234	F-statistic		64.94501
Durbin-Watson stat	2.024580	Prob(F-statistic)		0.000000

Neg 10

Dependent Variable: NEG10
Method: Least Squares
Date: 06/25/06 Time: 18:07
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003565	0.000917	-3.889224	0.0001
NEG10(-1)	0.093197	0.028207	3.304036	0.0010
R-squared	0.008699	Mean dependent var		-0.003942
Adjusted R-squared	0.007902	S.D. dependent var		0.032229
S.E. of regression	0.032102	Akaike info criterion		-4.038211
Sum squared resid	1.281967	Schwarz criterion		-4.029980
Log likelihood	2517.805	F-statistic		10.91666
Durbin-Watson stat	1.991607	Prob(F-statistic)		0.000980

Neg 5

Dependent Variable: NEG5
Method: Least Squares
Date: 06/25/06 Time: 18:06
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.004042	0.001129	-3.578550	0.0004
NEG5(-1)	0.082084	0.028212	2.909571	0.0037

R-squared	0.006759	Mean dependent var	-0.004409
Adjusted R-squared	0.005961	S.D. dependent var	0.039736
S.E. of regression	0.039618	Akaike info criterion	-3.617475
Sum squared resid	1.952540	Schwarz criterion	-3.609244
Log likelihood	2255.687	F-statistic	8.465605
Durbin-Watson stat	2.002826	Prob(F-statistic)	0.003684

The predictability of future (to be accurate next day) returns based on today's data is rather high and statistical significant for the series we have created. The winner series appear to be more predictable with respect to their last returns. All the results are statistically significant This may be a critical issue that explains our results and indicates market inefficiencies.

Section 3

The structural approach to time series modeling uses economic theory to model the relationship among the variables of interest. Unfortunately, economic theory is often not rich enough to provide a dynamic specification that identifies all of these relationships. Furthermore, estimation and inference are complicated by the fact that endogenous variables may appear on both the left and right sides of equations.

These problems lead to alternative, non-structural approaches to modeling the relationship among several variables

The vector autoregression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. The mathematical representation of a VAR is

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + Bx_t + e_t$$

Where y_t is a vector of k endogenous variables, x_t is d a vector of exogenous variables, $A_1, A_2, \ldots A_p$ and B are matrices of coefficients to be estimated, and e_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

Each column in the table corresponds to an equation in the VAR. For each right-hand side variable, EViews reports the estimated coefficient, its standard error, and the t-statistic.

EViews displays additional information below the coefficient summary. The first part of the additional output presents standard OLS regression statistics for each equation. The results are computed separately for each equation, using the appropriate residuals and are displayed in the corresponding column. The numbers at the very bottom of the table are the summary statistics for the VAR system as a whole.

Our aim is to test the predictability of ase returns with regard to the four portfolios we have created (each one separately). Assuming that the VAR contains one lagged value of the endogenous variables end let a constant be the only exogenous variable, the equation estimated is of the following form:

$$ase_t = a_{11} ase_{t-1} + a_{12} pos5_{t-i} + c_1 + e_{1t}$$

$$pos5_t = a_{21} ase_{t-1} + a_{22} pos5_{t-1} + c_2 + e_{2t}$$

Where a_{ij} and c_i are the parameters to be estimated.

Ase & pos5

Vector Autoregression Estimates
Date: 06/25/06 Time: 19:46
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	ASE	POS5
ASE(-1)	0.112352	0.066166
	(0.03112)	(0.07861)
	[3.61067]	[0.84165]
POS5(-1)	**0.013863**	0.198926
	(0.01218)	(0.03077)
	[1.13825]	[6.46478]
C	-0.000596	0.006441
	(0.00043)	(0.00108)
	[-1.39325]	[5.96279]
R-squared	0.017437	0.044725
Adj. R-squared	0.015856	0.043188
Sum sq. resids	0.265474	1.694509
S.E. equation	0.014614	0.036922
F-statistic	11.02969	29.09818
Log likelihood	3498.801	2343.990
Akaike AIC	-5.611238	-3.757608
Schwarz SC	-5.598892	-3.745262
Mean dependent	-0.000550	0.007994
S.D. dependent	0.014731	0.037746
Determinant Residual Covariance		2.37E-07
Log Likelihood (d.f. adjusted)		5967.226
Akaike Information Criteria		-9.568582
Schwarz Criteria		-9.543890

Ase & pos10

Vector Autoregression Estimates
Date: 06/25/06 Time: 19:47
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	ASE	POS10
ASE(-1)	0.114196	-0.010969
	(0.03268)	(0.06791)
	[3.49411]	[-0.16153]
POS10(-1)	0.012492	0.225251
	(0.01550)	(0.03221)
	[0.80591]	[6.99398]
C	-0.000558	0.004554
	(0.00043)	(0.00089)
	[-1.30790]	[5.13374]
R-squared	0.016927	0.049636
Adj. R-squared	0.015345	0.048107
Sum sq. resids	0.265612	1.146750
S.E. equation	0.014618	0.030374
F-statistic	10.70125	32.46013
Log likelihood	3498.478	2587.247
Akaike AIC	-5.610719	-4.148069
Schwarz SC	-5.598373	-4.135723
Mean dependent	-0.000550	0.005910
S.D. dependent	0.014731	0.031132
Determinant Residual Covariance		1.44E-07
Log Likelihood (d.f. adjusted)		6277.870
Akaike Information Criteria		-10.06721
Schwarz Criteria		-10.04251

Ase & neg5

Vector Autoregression Estimates
Date: 06/25/06 Time: 19:49
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	ASE	NEG5
ASE(-1)	0.127996	0.110020
	(0.03171)	(0.08588)
	[4.03701]	[1.28103]
NEG5(-1)	-0.000212	0.063033
	(0.01177)	(0.03189)
	[-0.01797]	[1.97687]
C	-0.000477	-0.004063
	(0.00042)	(0.00113)
	[-1.14302]	[-3.59768]
R-squared	0.016414	0.008069
Adj. R-squared	0.014831	0.006473
Sum sq. resids	0.265751	1.949966
S.E. equation	0.014622	0.039608
F-statistic	10.37124	5.055500
Log likelihood	3498.152	2256.509
Akaike AIC	-5.610197	-3.617189
Schwarz SC	-5.597851	-3.604843
Mean dependent	-0.000550	-0.004409
S.D. dependent	0.014731	0.039736
Determinant Residual Covariance		2.64E-07
Log Likelihood (d.f. adjusted)		5900.398
Akaike Information Criteria		-9.461312
Schwarz Criteria		-9.436620

Ase & neg10

Vector Autoregression Estimates
Date: 06/25/06 Time: 19:51
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	ASE	NEG10
ASE(-1)	0.140708	0.101205
	(0.03411)	(0.07488)
	[4.12511]	[1.35164]
NEG10(-1)	-0.010441	0.066798
	(0.01563)	(0.03430)
	[-0.66820]	[1.94741]
C	-0.000510	-0.003613
	(0.00042)	(0.00092)
	[-1.22190]	[-3.93975]
R-squared	0.016766	0.010154
Adj. R-squared	0.015184	0.008561
Sum sq. resids	0.265656	1.280086
S.E. equation	0.014619	0.032091
F-statistic	10.59805	6.375427
Log likelihood	3498.376	2518.720
Akaike AIC	-5.610556	-4.038074
Schwarz SC	-5.598210	-4.025728
Mean dependent	-0.000550	-0.003942
S.D. dependent	0.014731	0.032229
Determinant Residual Covariance		1.50E-07
Log Likelihood (d.f. adjusted)		6253.080
Akaike Information Criteria		-10.02742
Schwarz Criteria		-10.00272

Examining the results we do observe that winner portfolios returns estimate better ase returns than the losers but the coefficient estimated while it is statistically important is not rather significant. In appendix A we present a total Var constructed with all portfolios

Conclusions

This paper has tested the profitability of momentum trading strategies in the Greek stock market. It did so by examining profits generated portfolios formed on a daily basis based on historical returns. Returns from daily adjusted winner portfolios are positive ,significant and systematically above the market return There is strong evidence of momentum effect over the short almost “spot horizon”. Loser portfolios become “more losers” but the downward trend is subsidized during the last year of our observation period for all portfolios.

The preliminary result in this paper suggests further examination to investigate whether it’s feasible to implement a daily strategy after accounting for transaction costs and whether the results are related to factors such as crosssectional dispersion of returns, volume (liquidity), book to market ratio, and behavioural characteristics of assets previously known to be related to price continuation and reversals. This further analysis is compulsory in order to account for the inefficiencies in Greek stock market that we have observed.

Appendix A

Vector Autoregression Estimates with all the portfolios

Vector Autoregression Estimates
Date: 07/03/06 Time: 09:55
Sample(adjusted): 2 1247
Included observations: 1246 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	ASE	POS5	POS10	NEG5	NEG10
ASE(-1)	0.129982	0.028091	-0.018486	-0.010411	0.042595
	(0.03700)	(0.09345)	(0.07679)	(0.10007)	(0.08110)
	[3.51329]	[0.30060]	[-0.24074]	[-0.10405]	[0.52519]
POS5(-1)	0.018829	0.126823	0.103889	0.032225	0.053554
	(0.02278)	(0.05754)	(0.04728)	(0.06161)	(0.04994)
	[0.82658]	[2.20412]	[2.19726]	[0.52304]	[1.07245]
POS10(-1)	-0.004851	0.108299	0.111192	0.013979	0.004370
	(0.02911)	(0.07353)	(0.06042)	(0.07874)	(0.06381)
	[-0.16665]	[1.47285]	[1.84027]	[0.17754]	[0.06848]
NEG5(-1)	0.020662	-0.007388	-0.014524	-0.038537	-0.051890
	(0.02089)	(0.05276)	(0.04336)	(0.05650)	(0.04579)
	[0.98913]	[-0.14001]	[-0.33500]	[-0.68209]	[-1.13319]
NEG10(-1)	-0.035272	0.008048	0.027434	0.158612	0.114800
	(0.02793)	(0.07055)	(0.05797)	(0.07554)	(0.06123)
	[-1.26283]	[0.11408]	[0.47323]	[2.09960]	[1.87497]
C	-0.000646	0.006346	0.004448	-0.004287	-0.004139
	(0.00043)	(0.00110)	(0.00090)	(0.00117)	(0.00095)
	[-1.49033]	[5.79254]	[4.94033]	[-3.65400]	[-4.35328]
R-squared	0.018773	0.046445	0.053473	0.013437	0.014867
Adj. R-squared	0.014816	0.042600	0.049656	0.009459	0.010895
Sum sq. resids	0.265114	1.691459	1.142121	1.939413	1.273991
S.E. equation	0.014622	0.036933	0.030349	0.039548	0.032053
F-statistic	4.744753	12.07939	14.01043	3.377695	3.742628
Log likelihood	3499.649	2345.112	2589.767	2259.890	2521.694
Akaike AIC	-5.607783	-3.754594	-4.147299	-3.617800	-4.038032
Schwarz SC	-5.583091	-3.729903	-4.122607	-3.593108	-4.013340
Mean dependent	-0.000550	0.007994	0.005910	-0.004409	-0.003942
S.D. dependent	0.014731	0.037746	0.031132	0.039736	0.032229
Determinant Residual Covariance		1.31E-17			
Log Likelihood (d.f. adjusted)		15380.69			
Akaike Information Criteria		-24.63995			
Schwarz Criteria		-24.51649			

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